Essays on Macroeconomics and Labor Economics

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Dedication

To my parents and my wife. Your encouragement and support has made everything possible.

Abstract

This dissertation consists of three chapters. The first chapter (joint with Bledi Taska) examines the role of technological change in explaining the large and persistent decline in earnings following job loss. Using detailed skill requirements from the near universe of vacancies posted online, we estimate technological change at the occupation level and find that approximately 50% of the decline in earnings after job loss is due to technological change. We integrate technological change, occupation choice, and employment risk into a Bewley-style economy to rationalize our empirical results and examine the optimal combination of public insurance transfers and retraining subsidies for unemployed workers. We find there are welfare gains from increasing the generosity of public insurance transfers and retraining subsidies relative to the current U.S. policy, both in the steady state as well as along the transition path.

The second chapter (joint with Kyle Herkenhoff and Gordon Phillips) examines the credit access and usage among unemployed individuals. We show that unemployed individuals maintain significant access to credit. Following job loss, the unconstrained borrow, while the constrained default and delever. We quantitatively show that long-term credit relationships and credit-registries allow the unemployed to partially offset income losses using credit. We estimate the model and find that the optimal provision of public insurance is unambiguously lower with greater credit access.

The third chapter investigates the impact of declining labor force growth on the allocation of workers across firms and aggregate output. Theoretically, I demonstrate as labor force growth declines the probability a worker meets a firm declines, which decreases hiring. Quantitatively, the observed decline in labor force growth leads to a modest decline in hiring for employed and unemployed workers. Despite lower reallocation of workers across firms, output per worker increases since the average worker has greater labor market experience, is more productive, and is better sorted across firms.

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Chapter 1

Technological Change and the Consequences of Job Loss

1.1 Introduction

A large empirical literature has documented that job loss causes a large and persistent decline in earnings (e.g., Davis and von Wachter (2011) and references therein). Existing theories of the large and persistent decline in earnings typically rely on either human capital declines following job loss (e.g., Ljungqvist and Sargent (1998), Huckfeldt (2014), and Jarosch (2015)) or workers undergoing a lengthy process of reclimbing the job ladder (e.g., Jarosch (2015), Krolikowski (2017), and Jung and Kuhn (2018)).[1] In this paper, we explore the role of technological change in explaining the large and persistent decline in earnings following job loss. We find that approximately 50% of the decline in earnings after job loss is due to technological change. Technological change affects earnings losses after job loss by changing the skills needed to work in a given occupation. Given the importance of technological change in generating earnings losses after job loss, we examine the optimal provision of subsidies for retraining in addition to public insurance transfers for the unemployed. We find there are welfare gains from increasing the generosity of public insurance transfers and retraining subsidies relative to the current U.S. policy, both in the steady state as well as along the transition path.

This paper makes three contributions. First, our empirical contribution is to measure the impact of technological change on the outcomes of displaced workers. Using detailed skill requirements from the near universe of vacancies posted online, we estimate technological change by measuring the change in computer and software requirements by occupation over

[1] Davis and von Wachter (2011) show that the canonical search and matching model in the spirit of Mortensen and Pissarides (1994) cannot account for the size and persistence of earnings losses following job loss.

time.[2] We document three facts that suggest that technological change plays a significant role in the large and persistent decline in earnings following job loss. We show that workers who are displaced from occupations undergoing a greater increase in computer and software requirements: (1) experience a larger decline in earnings following job loss, (2) are more likely to switch occupations following job loss, and (3) move to occupations with lower computer and software requirements relative to their initial occupation. Additionally, we show that the decline in earnings due to increases in computer and software requirements is concentrated among occupation switchers.

Our empirical results suggest that technological change plays a key role in the decline in earnings following job loss. Technological change introduces new skill requirements into newly created jobs within an occupation. Not all workers have these new skills. If displaced, workers who do not have the new skills that have become common in their occupation are forced to search for a job in another occupation with lower skill requirements, which tend to be lower paying.

Our second contribution is to integrate technological change (e.g., Chari and Hopenhayn (1991), Mortensen and Pissarides (1998), and Violante (2002)), occupation choice (e.g., Lucas and Prescott (1974) and Wiczer (2015)), and employment risk (e.g., Moen (1997), Burdett, Shi, and Wright (2001), and Menzio and Shi (2011)) into a Bewley-style economy that can rationalize our empirical findings and be used for policy analysis. We calibrate the model to match aggregate labor market moments and show that the model successfully replicates our empirical finding that workers displaced from occupations undergoing greater increases in technology experience larger earnings losses and that the larger earnings losses are concentrated among occupation switchers. In the model, technological change increases the skill requirements to work in an occupation, and occupations experience heterogeneous changes in skill requirements. The model generates large and persistent earnings losses when workers are displaced and, as a result of technological change, no longer have the required skills to work in their original occupation. These unemployed workers then direct their search for a new job to an occupation, with a lower level of technology used in production, where their skills are still employable but wages are lower.

In the model, the government provides insurance to unemployed workers through public insurance transfers as well as by subsidizing the cost of a retraining program. The model is estimated so that public insurance transfers represent all transfers that unemployed workers

[2] We follow recent work by Hershbein and Kahn (2018) and Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2018b), who argue that the skill requirements listed in vacancy postings are informative on the technology of the firm posting the vacancy. We choose computer and software requirements as our measure of technological change since computers and software are present in nearly all (four-digit) occupations, and there is heterogeneity in the degree to which occupations have adopted new computer and software technologies over the past decade.

receive from the government. We model the retraining program as enrolling in community college classes. To enroll in the retraining program, unemployed workers pay a tuition cost and their human capital increases probabilistically. We calibrate the parameters of the retraining program to match the share of displaced workers who enroll in community college classes as well as their change in earnings as measured by Jacobson, LaLonde, and Sullivan (2005), who link administrative earnings records to community college records for the state of Washington. Finally, agents are also able to partially self-insure through savings in an incomplete asset market.

Given the model's ability to generate earnings losses after displacement that are consistent with the data, we use the model as a laboratory in which to examine the cause of earnings losses. We estimate the relative importance of a given channel by removing that feature from the model and measuring the average size of earnings losses generated by the model. We find that approximately 50% of the decline in earnings after job loss is due to technological change. We find that the remaining half of earnings losses are due to the loss of occupation-specific human capital. The importance of technological change in the size of earnings losses motivates retraining as being part of the optimal policy for unemployed workers.

Our third contribution is quantitative. We perform a policy experiment in which we solve for the optimal combination of public insurance transfers and subsidies to retraining. We evaluate the policies using lifetime consumption equivalents and a utilitarian welfare criterion, which places equal weight on all individuals. The government finances the public insurance transfer and retraining subsidy using taxes on labor income. The government faces an equity-efficiency trade-off wherein the government provides equity through transfers and retraining subsidies but must balance the distortionary effects of raising taxes to finance these programs. We find that the utilitarian government sets the optimal policy so that it replaces 50.3% of lost earnings with transfers and subsidizes 30% of the retraining cost. The optimal policy provides more generous transfers and retraining subsidies relative to the current U.S. policy of replacing 41.2% of lost earnings via transfers and subsidizing 0% of tuition for retraining.[3] On average, an individual would be willing to give up 0.75% of lifetime consumption to transition from an economy with the current policy for unemployed workers to move to an economy with the optimal combination of public insurance transfers and retraining subsidies.

The introduction of transfers and retraining subsidies generates welfare gains through both

[3]Osikominu (2013) and Kambourov, Manovskii, and Plesca (2012) comment that in the United States since the mid-1990s, programs for displaced workers have focused on job search assistance (i.e., getting individuals reemployed quickly) rather than on teaching new skills through retraining. On exception is Trade Adjustment Assistance (TAA), which offers retraining services for workers who are displaced because of trade. However, a very small fraction of displaced workers are covered by TAA (e.g., Kondo (2018)). See LaLonde (2003) and Barnow and Smith (2015) for detailed histories of retraining in the United States.

a short-run and long-run impact on consumption after job loss. Immediately after job loss, more generous transfers increase the consumption of unemployed workers. In the years after job loss, the introduction of retraining subsidies increases consumption: more generous retraining subsidies enable more workers to retrain after job loss, which increases their human capital and subsequently increases employment and wages. Hence, transfers insure consumption in the short-run following job loss, whereas retraining provides long-run insurance. Both of these channels generate welfare gains.

To evaluate the role of technological change in shaping the optimal policy for unemployed workers, we solve for the optimal combination of public insurance transfers and retraining subsidies in an environment with constant technology (i.e., without technological change). With constant technology, the utilitarian government sets the optimal policy so that it replaces 51.6% of lost earnings with transfers, and retraining subsidies are set to 0%. With constant technology, unemployment generates a temporary (short-run) decline in both earnings and consumption, which can be partially offset with more generous public insurance transfers. The introduction of technological change creates more persistent (long-run) declines in earnings and consumption for unemployed workers and creates a motive for the utilitarian government to subsidize retraining.

Finally, we solve the transition path of the economy from the initial baseline policy to the optimal policy, which replaces 50.3% of lost earnings with transfers and subsidizes 30% of retraining costs. We find that along the transition path, there is a utilitarian welfare gain among individuals who are alive at the time of the policy transition. On average, an individual alive at the time of the reform would be willing to give up 0.54% of remaining lifetime consumption to undergo the policy transition. While there is a utilitarian welfare gain, the policy transition is not Pareto improving. We find that lower human capital individuals have the largest welfare gains (up to 1.75% of remaining lifetime consumption) and that individuals with human capital in the top two quintiles at the time of the policy change experience welfare losses from the policy change (as much as 0.25% of remaining lifetime consumption).

Related Literature. Our work contributes to the recent literature that aims to reconcile the predictions of equilibrium models of the labor market with the empirical evidence on the large and persistent decline in earnings following job loss.[4] From this literature, two

[4] Papers documenting a larger and persistent decline in earnings after job loss include Jacobson, LaLonde, and Sullivan (1993), Couch and Placzek (2010), and Davis and von Wachter (2011). This paper emphasizes the role of occupation switching. Prior work (e.g., Stevens (1997), Kambourov and Manovskii (2009), and Huckfeldt (2014)) has shown that occupation switching plays a central role in the persistent decline in earnings following job loss. However, there has been limited work examining what causes individuals to switch occupations after job loss. We contribute to this literature by showing that workers displaced from occupations undergoing a greater increase in computer and software requirements are more likely to switch

theories have gained prominence for the large and persistent decline in earnings: (1) workers suffer permanent declines in human capital while unemployed (e.g., Ljungqvist and Sargent (1998), Huckfeldt (2014), and Jarosch (2015)); and (2) workers engage in a lengthy process of reclimbing the job ladder in order to return to a good match (e.g., Jarosch (2015), Krolikowski (2017), and Jung and Kuhn (2018)). The results of this paper are most closely related to the papers that examine human capital declines upon job loss. This paper adds to this prior work by introducing technological change as a cause for the decline in human capital following job loss, as well as by empirically identifying a set of skills (computer and software) where workers are falling behind the technological frontier over the past decade. Among the papers that consider human capital declines upon job loss, the paper most closely related to ours is Huckfeldt (2014). Huckfeldt (2014) examines why the decline in earnings following job loss is larger in recessions and documents that workers displaced in a recession are: (1) more likely to switch occupations following displacement and (2) more likely to move to an occupation that pays a lower average wage. Huckfeldt (2014) rationalizes these findings in a directed search model of the labor market with a skill-intensive and skill-neutral occupation where the hiring standards of each occupation evolve endogenously over the business cycle and workers lose human capital while unemployed.[5] In this paper, we provide novel evidence that workers displaced from occupations undergoing greater technological change (as measured by changes in computer and software requirements) experience larger declines in earnings, with the earnings losses concentrated among occupation switchers. Motivated by this empirical finding, we develop a Bewley-style economy with technological change, occupation choice, and employment risk to rationalize our empirical observations and to estimate the optimal combination of public insurance transfers as well as retraining subsidies to insure unemployed workers.

Our paper contributes to the literature that introduces technology growth into models of frictional labor markets (e.g., Mortensen and Pissarides (1998), Violante (2002), Postel-Vinay (2002), Eyigungor (2010), and Restrepo (2015)). The paper most closely related to ours is Restrepo (2015), who examines how structural change can lead to persistently higher unemployment through a mismatch of the skills available in unemployed workers and the skills demanded by firms. Restrepo (2015) applies his theory to the decline in routine-cognitive jobs from the 1990s to 2000s. The present paper differs by considering how technological change contributes to the outcomes of displaced workers rather than the level of unemployment. Additionally, we focus on a different application, namely, the spread of computer and software requirements across occupations between 2010 and 2017.

occupations.

[5]In his model, workers are subject to a gradual decay of human capital while unemployed, as well as an obsolesence shock, which causes workers to redraw their human capital from lower in the distribution.

This paper also contributes to recent papers that have examined how occupations change over time in terms of their task and skill requirements (e.g., Lindenlaub (2017), Burstein, Morales, and Vogel (2018), Hershbein and Kahn (2018), Atalay et al. (2018b), Atalay et al. (2018a), and Deming and Noray (2019)).[6] Much of this literature (e.g., Lindenlaub (2017), Burstein, Morales, and Vogel (2018), and Atalay et al. (2018b)) examines how the changing nature of occupations over time has contributed to the increase in income inequality over the past several decades. The paper most closely related to ours is Deming and Noray (2019), who examine how the rapid pace of newly introduced skill requirements in occupations that are concentrated in STEM majors (science, technology, engineering, and mathematics) accounts for the flattening of the earnings profile for workers employed in these STEM occupations over their first 10 years in the occupation. The present paper adds to this literature by considering how changes in the technology used in an occupation affect the outcomes of workers displaced from that occupation.

Finally, this paper contributes to recent work that has examined the optimal policy for unemployed workers in labor search models with incomplete asset markets (e.g., Lentz (2009), Krusell, Mukoyama, and ahin (2010), Koehne and Kuhn (2015), Chaumont and Shi (2017), Braxton, Herkenhoff, and Phillips (2018), and Birinci (2019)). The novel features of this paper relative to prior work are: (1) considering the role of technological change in determining the optimal policy for unemployed workers and (2) considering the mix of the optimal policy between unemployment insurance (transfers) and subsidized retraining programs. Previous work has used quantitative models of the labor market to estimate the welfare (and income) effects of increases in retraining for unemployed workers, where retraining is modeled as a reduction in occupation mismatch (Macaluso (2017)), reducing the cost of switching occupations (Hawkins and Mustre-del-Rio (2016)), or removing skill loss while unemployed (Jung and Kuhn (2018)).[7] This paper adds to the literature by using micro-estimates of the impact of retraining through community colleges to discipline the impact of retraining in an equilibrium model of the labor market, and solving for the optimal subsidy to retraining programs in conjunction with public insurance transfers received by

[6] Recent work has also used patents to measure technological innovation (e.g. Kogan, Papanikolaou, Seru, and Stoffman (2017)). In a related paper, Kogan, Papanikolaou, Schmidt, and Song (2018) examine how innovation as measured through the stock-valuation of a newly issued patent at a worker's own firm versus a competitor firm impacts their subsequent earnings. A recent literature has also examined the impact of automation on wages and inequality (e.g., Acemoglu and Restrepo (2018), Arnoud (2018), Leduc and Liu (2019), and Moll, Rachel, and Restrepo (2019)). While automation is the replacement of workers with a new technology, the focus of this paper, technological change, is about the introduction of new technologies that are complementary to workers conditional on the worker having the skills to use the technology.

[7] Spinnewijn (2013) characterizes the optimal path of training and unemployment insurance over an unemployment spell using a Hopenhayn and Nicolini (1997) style framework. There is also a quantitative literature that examines the welfare effects of policy reforms for active labor market programs (e.g., Albrecht, Van den Berg, and Vroman (2009) for Finland, Nie (2010) for Germany, and Gautier, Muller, van der Klaauw, Rosholm, and Svarer (2018) for Denmark).

the unemployed.[8]

The paper proceeds as follows. Section 2.2 describes our main empirical results on technological change and the outcomes of displaced workers,

1.2 Empirics

Does technological change contribute to the decline in earnings following job loss? What are the mechanisms through which technological change affects the outcomes of displaced workers? We answer these questions by measuring the change in computer and software requirements at the occupation level using detailed skill requirements from the near universe of vacancies posted online and merging our measure of technological change into a sample of displaced workers. We find that individuals displaced from occupations undergoing a greater increase in computer and software requirements experience larger declines in earnings, are more likely to switch occupations, and move to occupations with lower computer and software requirements relative to their original occupation. Our results highlight that technological change contributes to the decline in earnings following job loss and works through occupation switching.

1.2.1 Data Overview

In this subsection, we give an overview of the data used in the paper. First, we discuss how we measure technological change by using changes in skill requirements from online vacancies. We then discuss our sample of displaced workers.

Measuring Technological Change with Online Vacancies

In this section, we discuss how we measure technological change using changes in skill requirements from online vacancies. Burning Glass Technologies (hereafter Burning Glass) provides us with their database of online vacancy postings. Burning Glass examines approximately 40,000 online job boards and company websites daily to collect information on vacancy posting. Their algorithms identify newly posted ads, remove duplicate advertisements, and collect detailed information about the occupation, employer, and location, as well as the skill and education requirements for the posted vacancy. Given the breadth of coverage, Burning Glass believes their database covers the near universe of jobs that are posted online.[9]

[8] An extensive empirical literature has examined the effects of training programs on the outcomes of participants. For a recent survey of the effects of retraining programs, see Card, Kluve, and Weber (2017).

[9] Recent papers using the Burning Glass database include Azar, Marinescu, Steinbaum, and Taska (2018), Deming and Kahn (2018), Hershbein and Kahn (2018), Hazell and Taska (2018), and Hershbein, Macaluso, and Yeh (2018).

The database of vacancies for this paper covers the years 2010-2017. For each vacancy, the occupation (up to a six-digit SOC code) is recorded along with detailed information on the skill requirements. Burning Glass collects the text posted for each job vacancy, and their algorithms code keywords and phrases as additional job requirements. Thousands of specific skills are codified, such as knowledge of Microsoft Excel, and are available for each vacancy collected. These codified skills will be used to measure technological change as discussed below. During our sample period, Burning Glass records information for, on average, 1.5 million vacancies per month, each with 10 skill requirements.[10]

In this paper, as an example of technological change, we examine the spread of computers and software within an occupation. Following Hershbein and Kahn (2018), we define a vacancy to contain a computer or software related skill if any of its reported skill requirements contain the keyword "Computer" or if any of the reported skill requirements are classified by Burning Glass as a software skill. We then measure for each occupation the share of vacancies in a given year that contain a computer or software related skill. Let $z_{o,t}$ denote the share of vacancies in occupation o and year t that contain a computer or software related skill.

To examine whether the share of vacancies in an occupation listing a computer or software requirement is informative about the use of computers and software in that occupation, we compare the estimates from Burning Glass with data from O*NET. O*NET asks individuals working in a given occupation as well as occupational experts to rate the level of knowledge needed in an occupation for a given set of skills/tasks and has been commonly used to measure the tasks performed in an occupation (e.g., Acemoglu and Autor (2011)). The level of knowledge is scored 0-7, with higher values indicating that a greater level of knowledge is required. Panel (a) of Figure 1.1 compares the share of vacancies listing a computer skill requirement (*y-axis*) to the level of computer knowledge recorded in O*NET (*x-axis*) for each four-digit occupation. The graph shows that our measure of computer and software requirements based on the skill content listed in online vacancies is highly correlated with the measure from O*NET. This finding suggests that the share of vacancies listing a computer or software requirement is informative about the use of computers and software in an occupation.

Given the measure $z_{o,t}$ of computer and software requirements in each occupation, we estimate technological change by measuring the change in the share of vacancies in a given occupation that contain a computer or software skill. Let $\Delta z_o = z_{o,2017} - z_{o,2010}$ denote the change in the share of vacancies in occupation o that list a computer or software skill

[10] Appendix A.1 benchmarks the Burning Glass data against other measures of vacancy posting (JOLTS), as well as measures of employment. In short, the distribution of vacancies in Burning Glass across industries largely resembles the distribution of vacancies in JOLTS, while the distribution of vacancies across occupations is consistent with the distribution of employment in the OES.

requirement between 2010 and 2017.[11] Panel (b) of Figure 1.1 presents a scatter plot of computer and software requirements in 2010 (*x-axis*) against the change in computer and software requirements between 2010 and 2017 by occupation (*y-axis*). The scatter plot shows that the majority of occupations saw an increase in computer and software requirements between 2010 and 2017. Additionally, the scatter plot shows that there is significant heterogeneity in the adoption of computer and software requirements across occupations between 2010 and 2017. This heterogeneity in the adoption of computer and software requirements is critical for our identification of the impact of technological change on the outcomes of displaced workers, as we will compare the outcomes of workers displaced from occupations with large increases in computer and software requirements to the outcomes of workers displaced from occupations with a small increase (or decrease) in computer and software requirements.

Table 1.1 provides an example of two occupations that experienced a large increase in computer and software requirements, as well as occupations that experienced a small increase or decrease in computer and software requirements between 2010 and 2017. Advertising and marketing managers (SOC code 1120) experienced an increase of over 11 percentage points in the share of vacancies listing computer and software requirements between 2010 and 2017. Over this time period, there has been an increase in the demand for specific software packages and platforms to be used by advertising and marketing managers. For instance Salesforce, Software as a Service (SaaS), and Google Analytics / Google Adwords are forms of software and platforms that were commonly listed in vacancies in 2017 but were rarely seen in 2010. Similarly, sales representatives for wholesale and manufacturing trades (SOC code 4140) have seen an increase of nearly 7 percentage points in the share of vacancies listing computer and software requirements, with the increase coming from the listing of specific forms of software including SaaS and Salesforce. Examples of occupations with a small increase or a decline in computer and software requirements include machinists and machine operators (SOC code 5140) and health practitioners (SOC code 1911).

We will use this measure of technological change to estimate how the outcomes of displaced workers vary by the rate of technological change in the occupation from which they were displaced. In the next subsection, we discuss our sample of displaced workers.

CPS Displaced Workers Supplement (DWS)

To measure the outcomes of displaced workers, we use the Displaced Workers Supplement (DWS) to the Current Population Survey (CPS). The DWS is conducted every two years as part of the January or February CPS. Individuals are identified as displaced workers

[11] In Appendix A.3.1, we present robustness results where we consider the change in computer skill requirements over a different set of years, and find nearly identical results.

and included in the DWS if they have lost their job within the past three years because of their company or plant shutting down, their shift or position being eliminated, or having insufficient work.[12] These reasons for becoming unemployed are designed to identify workers who lost their job for reasons that are exogenous to their characteristics. The DWS collects information on individuals' earnings and occupation both for the job from which they were displaced, and for their current job if they are employed at the time of the survey. We use the 2012, 2014, 2016, and 2018 waves of the DWS, and to align with the Burning Glass data, examine individuals who were displaced from their job between 2010 and 2017.
From the DWS, we construct two samples that will be used in this paper:

1. **Employed sample:** Our first sample includes all individuals who are employed both at the time of the DWS and prior to displacement. We additionally require that individuals have non top-coded earnings both prior to displacement and after displacement.[13] This results in a sample of 4,672 individuals. We use this sample to measure the earnings loss around displacement as well as the propensity to switch occupations by degree of technological change in their original occupation.

2. **Population sample:** Our second sample includes all individuals who were identified as displaced in the DWS with non-top coded earnings prior to displacement.[14] This results in a sample of 6,887 individuals. We use this sample to examine whether individuals who are displaced from occupations that experienced a greater amount of technological change were less likely to regain employment.

Table 2.1 contains summary statistics for both samples. The first column of Table 2.1 presents summary statistics for the employed sample, while the second column presents summary statistics for the population sample. We observe, on average, individuals two years after being displaced. These individuals on average have weekly real earnings that are nearly 6.5% below their pre-displacement earnings.[15] Additionally, column (1) of Table

[12] Additionally, since the 1998 wave of the DWS, individuals who identify as being displaced are also not self-employed, and do not expect to be recalled to their job within the next six-months.

[13] Some individuals report being employed but also report zero earnings. To be in the sample, we require that an individual have real weekly earnings greater than $100 (in 2012 dollars) both prior to displacement and after displacement. Our results are robust to different values of this minimum earnings threshold.

[14] We impose the non-top coded earnings condition to maintain consistency with our employed sample. We additionally require that an individual have weekly real earnings greater than $100 (in 2012 dollars) prior to displacement. Our results are robust to this minimum earnings threshold.

[15] An average decline of 6.5% of pre-displacement earnings two years following job loss is smaller than the estimates of Davis and von Wachter (2011), who estimate an earnings decline of approximately 16% of prior earnings for expansion periods. There are two discrepancies between our sample and the one used by Davis and von Wachter (2011). First, Davis and von Wachter (2011) restrict their sample to individuals who have at least three years of tenure at the firm from which they are displaced. Second, we require individuals to be employed both prior to and following displacement, whereas Davis and von Wachter (2011) make no requirements about regaining employment. Using the DWS, Huckfeldt (2014) obtains a similar estimate of the average decline in earnings following job loss (8.5% of prior earnings). Compared to Huckfeldt (2014), we do not consider recessionary periods, when the average size of earnings losses is known to be larger.

2.1 shows that 63.4% of displaced workers who have regained employment at the time of the DWS are employed in a different (four-digit) occupation than the one from which they were displaced.[16] Column (3) of Table 2.1 presents summary statistics for non-displaced individuals from the monthly CPS.[17] Non-displaced workers are employed in occupations with similar levels of computer and software requirements in 2010 as well as occupations that experienced the same average increase in computer and software requirements as our sample of displaced workers.[18] Non-displaced workers are approximately one year older than our sample of displaced workers and have similar years of completed education. The primary margin in which our sample of displaced workers differs from non-displaced workers is their current weekly earnings. Non-displaced workers have average weekly earnings of over $820, whereas our sample of displaced workers (who have regained employment) have average weekly earnings of just over $730. This comparison suggests that our sample of displaced workers is not selected from particular occupations and is generally similar to the sample of non-displaced workers.

In the following sections, we examine the role of technological change, as measured through changes in computer and software requirements, in driving earnings losses after job loss and examine the mechanisms through which technological change affects the earnings of displaced workers.

1.2.2 Graphical Evidence

In this section, we present graphical evidence on the link between increases in computer and software requirements and the size of earnings losses among displaced workers. In the following subsection, we will formalize the empirical relationship between changes in computer and software requirements and the outcomes of displaced workers using cross-sectional regressions and find results consistent with the results presented in this section.

We begin by documenting that there has been significant heterogeneity in the change in computer and software requirements across occupations. To observe this heterogeneity, we place displaced workers into quintiles based on the change in the share of vacancies

[16] The high percentage of individuals switching occupations is not specific to displaced workers. Examining all unemployment spells in the monthly CPS, we find that over 50% of individuals regain employment in a different occupation. Using a coarser definition of occupations (13-occupations), Fujita (2018) also finds that over 50% of individuals switch occupations after an unemployment spell.

[17] To identify non-displaced individuals from the monthly CPS, we consider the DWS waves of the CPS and identify individuals who do not report being a displaced worker within the past three years. To be consistent with the construction of the samples from the DWS, we additionally require individuals to be currently employed with real weekly earnings of at least $100 (in 2012 dollars) and to be non top-coded. The requirement that real weekly earnings be at least $100 requires us to only use the outgoing rotation groups of the CPS, which limits the sample size to a quarter of the monthly CPS.

[18] In Appendix A.2.1, we compare the distribution of occupations among displaced workers and non-displaced workers and find they are very similar.

that listed a computer or software requirement between 2010 and 2017 in the occupation from which they were displaced. Panel (a) of Figure 1.2 presents the average change in computer and software requirements by quintile. The figure shows that workers in the bottom quintile lost their job in occupations that were experiencing a decline in computer and software requirements between 2010 and 2017. Individuals in the second quintile lost their job in occupations that on average experienced virtually no change in computer and software requirements. Conversely, individuals in the top three quintiles lost their job in occupations that experienced an increase in computer and software requirements. For example, workers in the fifth quintile lost their job in occupations where the share of vacancies listing a computer and software requirement increased by nearly 10 percentage points. This heterogeneity allows us to estimate how the outcomes of displaced workers are affected by changes in computer and software requirements in the occupations from which they were displaced, which we turn to next.

We find that individuals displaced from occupations undergoing a larger increase in computer and software requirements experience a larger decline in earnings. Panel (b) of Figure 1.2 shows the average change in earnings following displacement by quintile of the change in computer and software requirements for the occupation from which an individual was displaced. The figure shows that individuals displaced from an occupation in the first quintile (occupations that experienced a decline in computer and software requirements) experienced relatively small declines in earnings of approximately 2% of pre-displacement earnings. Conversely, individuals in the fifth quintile, who were displaced from occupations undergoing the largest increase in computer and software requirements, have nearly a 15% decline in earnings. This observation suggests that changes in computer and software requirements play a significant role in explaining the earnings losses of displaced workers. We next examine the mechanisms through which changes in computer and software requirements affect the outcomes of displaced workers.

We find that changes in computer and software requirements affect earnings following displacement through occupation switching. Panel (c) of Figure 1.2 presents the average change in earnings following displacement for individuals who switch occupations (black bars) and individuals who do not switch occupations (orange bars) by quintile of the change in computer and software requirements. The figure shows that for individuals in the first two quintiles, the decline in earnings following job loss is small and the outcomes of occupation switchers and stayers are nearly identical. Conversely, for individuals in the top three quintiles, there are large declines in earnings, and the decline in earnings is almost entirely driven by occupation switchers. For instance, among individuals in the fifth quintile, occupation switchers experience, on average, nearly a 19% decline in earnings, while non-switchers experience just over a 3% decline in earnings.

The individuals who switch occupations after job loss may be doing so because they no longer have the skills to work in their prior occupation. To test this hypothesis, we examine the nature of occupation switching and show that individuals displaced from an occupation experiencing a larger increase in computer and software requirements are more likely to move to an occupation with lower computer and software requirements. Panel (d) of Figure 1.2 shows the share of individuals who move to an occupation with lower computer and software requirements relative to their original occupation following displacement.[19] In the first quintile, approximately 25% of individuals switch occupations and move to an occupation with lower computer and software requirements. Conversely, nearly 45% individuals displaced from occupations in the fifth quintile move to an occupation with lower computer and software requirements.

The results presented in Figure 1.2 demonstrate that the decline in earnings following job loss occurs almost exclusively among individuals displaced from occupations undergoing an increase in computer and software requirements. Further, this decline in earnings is concentrated among individuals who switch occupations following job loss. We additionally find that individuals displaced from an occupation undergoing a larger increase in computer and software requirements are more likely to move to an occupation with lower computer and software requirements. We view these results as consistent with the notion that the decline in earnings following job loss is driven by technological change, which requires workers to have new skills to perform newly created jobs in their prior occupation. Displaced workers who do not have the new skills that have become required in their prior occupation search for a job in another occupation with a lower use of technology, where their skills are still employable, but they are paid a lower wage. In the next section, we formalize the empirical relationship between changes in computer and software requirements, earnings, and occupation switching using a series of cross-sectional regressions and obtain results consistent with those presented here.

1.2.3 Empirical Approach

In this section, we present our empirical approach for examining the impact of changes in computer and software requirements on the outcomes of displaced workers.

Let $Y_{i,o,t}$ denote the outcome variable of interest for individual i, who was displaced in occupation o and is in the DWS in year t (such as the change in log real earnings following displacement or an indicator variable for switching occupations following displacement).[20]

[19] In particular, we compare the share of vacancies that list a computer or software requirements in 2017 for individuals' current occupation and the occupation from which they were displaced. Note in the figure we do not condition on switching occupations. We find similar results if we use the share of vacancies listing computer and software requirements in 2010.

[20] Note that given the construction of the DWS, this individual was displaced during years $t-3$ to $t-1$.

Let Δz_o denote the change in the share of vacancies listing computer or software requirements for occupation o between the years 2010 and 2017. Let $X_{i,t}$ denote a vector of controls, which includes the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, and years of educational attainment, as well as a series of dummy variables including the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey.[21] The specification we use is of the form

$$Y_{i,o,t} = \alpha + \beta \Delta z_o + \Gamma X_{i,o,t} + \epsilon_{i,o,t}. \tag{1.1}$$

The coefficient of interest is β, which gives the change in the outcome variable $Y_{i,o,t}$ of a 100 percentage point increase in computer and software requirements in the occupation from which an individual was displaced. If $\beta < 0$, then we have evidence that an increase in the share of vacancies listing computer and software requirements is associated with a decrease in the variable of interest.

Impact of Technological Change on the Outcomes of Displaced Workers

The first column of Table 1.3 shows the results of estimating equation 1.1 where the dependent variable is the difference in log real earnings between individuals' current earnings and their earnings prior to displacement.[22] The negative coefficient on the change in computer requirements in column (1) indicates that an increase in computer and software requirements in the occupation from which an individual was displaced results in larger earnings losses following displacement. When we compare a displaced worker at the 75th percentile of the distribution of changes in computer and software requirements with a worker at the 25th percentile, we see that on average, the worker at the 75th percentile experiences a decline in earnings that is nearly 4 percentage points larger.[23] The result presented in column (1) suggests that technological change as measured through changes in computer and software requirements contributes to the decline in earnings following job loss. We next consider a series of additional outcome variables to investigate the mechanism through which technological change affects earnings following job loss.

[21] Note that when the outcome variable of interest is employment at the time of the DWS, we drop control variables that contain employment information at the time of the survey (i.e., the dummy variable for working full-time at the time of the DWS and the duration of the unemployment spell after layoff).

[22] To remove the impact of outliers on the estimation results, we winsorize the change in log earnings and the change in the share of vacancies listing computer and software requirements at the 2.5% level. We find similar results at different levels of winsorizing and with the raw data.

[23] At the 75th percentile of the distribution, the change in the share of vacancies listing computer skill requirements is 6.1 percentage points. At the 25th percentile, the change in the share of vacancies listing computer skill requirements is -0.5 percentage points.

The prior literature that has examined the earnings losses of displaced workers has emphasized that individuals who switch occupations following job loss incur larger earnings losses than individuals who do not switch occupations (e.g., Stevens (1997), Kambourov and Manovskii (2009), Huckfeldt (2014)). Occupation switching then presents a potential mechanism through which technological change affects earnings following job loss. We next examine how changes in computer and software requirements in the occupation from which individuals were displaced affects their probability of switching occupations after job loss. The second column of Table 1.3 shows the results of estimating equation 1.1 where the dependent variable is an indicator variable for an individual switching occupations following displacement, where an occupation is measured at the four-digit SOC code level. The positive coefficient estimate in column (2) indicates that an increase in computer and software requirements in the occupation from which an individual was displaced, increases the probability that the individual is reemployed in a different occupation. When we compare a displaced worker at the 75th percentile of the distribution of changes in computer and software requirements with a worker at the 25th percentile, we see that on average, the worker at the 75th percentile is approximately 4 percentage points more likely to switch occupations. This result suggests that occupation switching may play a role in linking increases in computer and software requirements to lower earnings for displaced workers. In the following subsection, we will further examine the role of occupation switching.

An alternative mechanism is that technological change lengthens individuals' unemployment spells and lowers their subsequent earnings through a duration dependence style mechanism. The third column of Table 1.3 shows the results of estimating equation 1.1 where the dependent variable is the log number of weeks an individual was unemployed after displacement.[24] The results presented in column (3) show that changes in computer and software requirements do not affect the length of a displaced worker's unemployment spell after layoff. In addition to not being statistically significant, the coefficient estimate in column (3) on the change in computer and software requirements is economically small. The coefficient estimate implies that an individual displaced at the 75th percentile of the change in computer and software requirements distribution has an unemployment spell that is approximately 5 percent (0.7 weeks) longer than an individual displaced at the 25th percentile. This result indicates that the larger decline in earnings following displacement for workers who were displaced from occupations undergoing larger increases in computer and software requirements (as shown in column (1) of Table 1.3) is not driven by those individuals having longer unemployment spells.

We find a similar result when we look at the probability that an individual is employed

[24]Note that we obtain similar results when using the level of unemployment duration. When the duration of unemployment is the dependent variable, we drop it as a control variable.

following displacement. The fourth column of Table 1.3 shows the results of estimating equation 1.1 where the dependent variable is an indicator variable equal to one when an individual is employed at the time of the DWS. The coefficient estimate displayed in column (4) implies that changes in computer and software requirements are not associated with changes in the probability of being employed after displacement.[25]

The results presented in Table 1.3 show that individuals who are displaced from occupations undergoing greater technological change (measured as a larger increase in the share of vacancies listing a computer or software requirement) experience larger earnings losses. The results also point to occupation switching as a potential mechanism linking technological change to larger earnings losses. One could worry that the occupations which are undergoing greater technological change are simply using the introduction of new technologies as a means to replace workers, and our results are being driven by a decline in the demand for workers in the occupations that are increasing their use of technology. To account for this potential explanation, we include the change in the share of total employment in an occupation between 2010 and 2017 as a control variable in equation 1.1.[26] Table 1.4 presents the results of estimating equation 1.1 where we control for the change in employment share in each four-digit occupation. Controlling for changes in employment share in an occupation does not alter the message or magnitude of our empirical results. We continue to find that increases in computer and software requirements are associated with larger earnings declines following job loss and that occupation switching serves as a potential mechanism. In Section 1.2.4 we show that our results are robust to a series of additional explanations as well as different measures of technological change. In the following subsection, we further examine the role of occupation switching as a mechanism that links technological change to larger earnings losses following job loss.

Role of Occupation Switching

We next further examine occupation switching as a mechanism that links technological change to larger declines in earnings following job loss.

Let $S_{i,o,t}$ be a dummy variable equal to 1 if individual i, who is in the DWS in year t and was displaced from occupation o, switches occupations following displacement. Let $\Delta ln(Earn_{i,o,t})$ denote the change in log real earnings of individual i, who is in the DWS in year t and was displaced from occupation o. To examine the role of occupation switching in generating lower earnings for workers displaced from occupations experiencing greater

[25] We additionally find that changes in computer skill requirements are not associated with being unemployed at the time of the DWS, or with dropping out of the labor force.

[26] We use data from the OES statistics to measure employment share within each four-digit occupation for the years 2010-2017.

technological change, we estimate the following regression

$$\Delta ln(Earn_{i,o,t}) = \alpha + \beta \Delta z_o + \gamma S_{i,o,t} + \eta(\Delta z_o \times S_{i,o,t}) + \Gamma X_{i,t} + \epsilon_{i,o,t}. \tag{1.2}$$

The coefficient of interest is η, which reports whether individuals who switch occupations experience a different change in log real earnings due to changes in computer and software requirements relative to individuals who do not switch occupations. In particular, if $\eta < 0$, then individuals who switch occupations experience a larger decline in earnings for a given increase in computer and software requirements relative to individuals who do not switch occupations.

Table 1.5 returns the coefficient estimates of estimating equation 1.2. In column (1), the coefficient estimate on the change in computer requirements indicates that the earnings of individuals who do not switch occupations following displacement are not affected by changes in computer and software requirements. Alternatively, the coefficient estimate on the interaction of changes in computer and software requirements and occupation switching is negative and statistically significant. The fact that the coefficient on the interaction term is negative and statistically significant indicates that the relationship between increases in computer and software requirements and lower earnings following job loss is concentrated among occupation switchers. Among individuals switching occupations, an individual displaced at the 75th percentile of the distribution of changes in computer and software requirements has a decline in earnings that is 5.8 percentage points larger than an individual displaced at the 25th percentile. Conversely, among individuals who *do not* switch occupations, individuals displaced at the 75th percentile have a decline in earnings that is 0.5 percentage points *smaller* than a displaced worker at the 25th percentile. In column (2) of Table 1.5, we present the results of estimating equation 1.2 while controlling for changes in employment share and find nearly identical results. The results presented in Table 1.5 provide evidence that the mechanism through which technological change (as measured by increases in computer and software requirements) leads to lower earnings following job loss works through occupation switching.

The results of Table 1.5 indicate that individuals who are displaced from occupations undergoing greater technological change experience greater earnings losses and that these earnings losses are driven by switching occupations. Potentially, these individuals are switching occupations following job loss because they no longer have the skills to work in their original occupation. To examine this hypothesis, we estimate equation 1.1 where the dependent variable is a dummy variable that is equal to 1 if an individual switches occupations after displacement and their new occupation has a lower level of computer and software requirements relative to their original occupation.[27] Table 1.6 presents the estimation results. Column (1) shows that individuals who are displaced from an occupation undergoing a greater increase in computer and software requirements have a higher probability of switching occupations and moving to an occupation with lower computer and software requirements. When we compare a displaced worker at the 75th percentile of the distribution of changes in computer and software requirements with a worker at the 25th percentile, we see that on average, the worker at the 75th percentile is 9.5 percentage points more likely to move to an occupation with lower computer and software requirements relative to their original occupation. In column (2) of Table 1.6, we include the change in employment share as a control variable and find similar results. Finally, column (3) of Table 1.6 shows that we obtain similar results when we restrict the sample to individuals who switch occupations following displacement. The results presented in Table 1.6 are suggestive that individuals who switch occupations are doing so because they no longer have the skills to work in their prior occupation.

The results presented in this section provide evidence that the mechanism through which technological change decreases earnings following job loss works through occupation switching. We showed that the relationship between greater technological change and larger declines in earnings is concentrated among occupation switchers. We then showed that these individuals are, on average, moving to occupations with lower levels of computer and software requirements, which suggests that these individuals no longer have the skills to work in their prior occupation. In the next subsection, we discuss the results of a series of robustness exercises.

1.2.4 Robustness

In this section, we briefly summaize a set of robustness exercises for the results presented in Section 1.2.3.

We conduct a series of robustness exercises and show that our results are robust to (1) an alternative set of years to measure technological change in the Burning Glass database (Appendix A.3.1); (2) an alternative way of measuring technological change, which uses the share of all skills listed for an occupation that are computer or software skills to measure the importance of computers and software in an occupation (Appendix A.3.1); and (3) measuring changes in computer and software skill requirements using data from O*NET

[27] We compare the share of vacancies listing computer or software requirements in 2017 for the occupation from which an individual was displaced as well as the individual's current occupation. We obtain similar results if we use the 2010 share of vacancies listing computer or software requirements. Additionally, we include as a control variable the share of vacancies listing computer or software requirements in 2010 in the occupation from which the individual was displaced.

(Appendix A.3.1). Using computer and software requirements collected from newspaper vacancies provided by Atalay et al. (2018b) for the time period 1982-2000 we show in Appendix A.3.1 that our results are robust to considering a different time period.

We additionally conduct a series of exercises to show that our results are distinct from the literature that has emphasized (1) routine versus non-routine employment (Appendix A.3.2); (2) declining manufacturing employment (Appendix A.3.2); and (3) changes in other types of skill requirements (e.g., cognitive, social, manual) (Appendix A.3.2).

1.2.5 Taking Stock

The empirical results presented in this section showed that individuals displaced from occupations undergoing greater increases in computer and software requirements experience larger declines in earnings. We showed that these larger declines in earnings occur through occupation switching. We additionally showed that individuals who are displaced from occupations undergoing a greater degree of technological change are more likely to move to occupations with lower computer and software requirements. We interpret these results as providing evidence that technological change contributes to the decline in earnings following job loss by requiring workers to have new skills to perform newly created jobs in their prior occupation. Displaced workers who do not have the new skills that have become common in their prior occupation must search for a job in another occupation where their skills are still employable, but they are paid a lower wage. These empirical observations suggest that retraining may play a role as part of the optimal policy for unemployed workers. In the next section, we integrate technological change, occupation choice, and employment risk into a Bewley-style economy to rationalize our empirical findings and to solve for the optimal combination of public insurance transfers as well as subsidies for retraining.

1.3 Model

This section introduces a Bewley-style economy with the following three features. First, there is exogenous technology growth that is embodied in new matches between workers and firms. Second, workers direct their search for jobs across occupations, where occupations are heterogeneous in their use of technology. Third, agents face exogenous employment risk. We show that the model is able to replicate our empirical observation that workers who are displaced from occupations undergoing greater technological change experience larger declines in earnings, with the larger earnings losses concentrated among occupation switchers. Given the model's ability to match the size of earnings losses in the data, we use the model as a laboratory in which to decompose the source of earnings losses after job loss and measure the share of earnings losses that are accounted for by technological change.

Finally, we use the model to solve for the optimal mix of public insurance transfers and subsidized retraining programs.

1.3.1 Model Overview

Agents and Technology. Time is discrete and runs forever. There is a unit measure of workers and a continuum of potential entrant firms. Let z_j denote the level of technology at time j. We assume the level of technology grows at a constant rate $g > 0$ over time.

Occupations and Vacancy Posting. In the labor market, there are $K \geq 2$ occupations, or islands in the spirit of Lucas and Prescott (1974). Occupations differ in the level of technology that they use in production. Let $c_k \in [0, 1]$ denote the technology intensity of an occupation $k \in \mathcal{K}$. At time j, all vacancies posted in occupation k use technology level $z_{k,j} = c_k z_j$. The heterogeneity in occupations, where some occupations employ a greater amount of technology in production (and pay a high wage) while other occupations use lower levels of technology (and pay a lower wage), is similar to the vertical ranking of occupations documented in Groes et al. (2014).

Potential entrant firms pay an entry cost κ_j to post a vacancy at time j and choose which occupation $k \in \mathcal{K}$ to post a vacancy in, subject to a free-entry condition. Vacancies that go unfilled exit the labor market. Workers direct their search across occupations (e.g., Lucas and Prescott (1974), and Wiczer (2015)). Once a match is formed, the level of technology in the match is fixed for the duration of the match. This form of technological change is *embodied* in matches, as in Mortensen and Pissarides (1998), Violante (2002), Postel-Vinay (2002), and Eyigungor (2010). In order for a worker to become employed with a newer vintage of technology, they must match with a new vacancy either through on-the-job search or after a spell of unemployment.

Workers. There are T overlapping generations of workers, as in Menzio et al. (2016) Workers live T periods. Workers are either employed ($e = W$) or unemployed ($e = U$) and direct their search for jobs across occupations both while they are employed and while they are unemployed. Workers are heterogeneous in their human capital (or skills), which is denoted by $h \in \mathcal{H} \equiv [\underline{h}, \bar{h}]$. Workers are also either inexperienced ($x = N$) or experienced ($x = E$) in their current occupation k. Workers become experienced with probability λ_E when they remain employed in an occupation k. Becoming experienced raises a worker's production and wages in an occupation by a factor $A_E > 1$. When experienced workers are unemployed, they become inexperienced with probability λ_N. Additionally, experienced workers become inexperienced by accepting a job in a new occupation. Human capital

h can be thought of as general human capital, while experience x can be thought of as occupation-specific human capital.[28]

Workers are risk averse and discount the future at rate $\beta \in (0,1)$. New workers enter as inexperienced unemployed workers and draw their human capital from a distribution $\Gamma_j(h) : \mathcal{H} \to [0,1]$. Agents have access to a savings market where they are able to save at the risk-free rate r. Let $a \in \mathcal{A} \equiv [0, \bar{A}]$ denote the net asset position of an individual.

Labor Market. In the labor market, workers direct their search for jobs across occupations both while employed and while unemployed. Let $M(s,v)$ denote the labor market matching function, and define labor market tightness to be the ratio of vacancies (v) to searching workers (s).[29] Since search is directed, there is a separate labor market tightness for each submarket, defined by the time period j, and the occupation of the firm k, as well as the worker's age (t), human capital (h), experience (x), and assets (a).[30] In each submarket the job finding rate for individuals, $p(\cdot)$, is a function of the labor market tightness $\theta^x_{j,t}(h,a,k)$, such that $p(\theta^x_{j,t}(h,a,k)) = \frac{M(s^x_{j,t}(h,a,k), v^x_{j,t}(h,a,k))}{s^x_{j,t}(h,a,k)}$. The hiring rate for firms $p_f(\cdot)$ is also a function of labor market tightness and is given by $p_f(\theta^x_{j,t}(h,a,k)) = \frac{M(s^x_{j,t}(h,a,k), v^x_{j,t}(h,a,k))}{v^x_{j,t}(h,a,k)}$. Matches end exogenously each period with probability δ.

Production and Wages. When workers with human capital h and experience x match with a firm in occupation k at time j, they produce $f(c_k z_j, h, x)$. We use an "up-to-the-task" production function (e.g., Albrecht and Vroman (2002) and Jarosch and Pilossoph (2018)), which requires that workers have a minimum amount of human capital to produce with a given level of technology. We use the up-to-the-task production function because it introduces a notion of skill requirements to work in a given occupation. As we will discuss in Section 1.4, we will use our data from Burning Glass to calibrate the skill requirements for each model occupation. For tractability, workers are paid a piece-rate $\omega \in [0,1]$ of their production as a wage, as in Herkenhoff et al. (2015). Paying workers a piece-rate of their output is similar to the outcome of a Nash bargaining game between risk-neutral workers and firms, where the worker and firm each receive a constant share of the match surplus as compensation for forming the match.

[28] Modeling the acquisition of occupation-specific human capital as a stochastic process from being inexperienced to experienced follows Kambourov and Manovskii (2009). Workers losing their occupation-specific human capital stochastically while being unemployed is similar to the notion of turbulence presented in Den Haan et al. (2001) and Fujita (2018).

[29] Searching workers include both employed and unemployed individuals. We assume that employed workers have the same search efficiency as unemployed workers.

[30] As in Chaumont and Shi (2017), the firm conditions on the worker's assets since the worker's asset position influences their on-the-job search decision and hence the probability that the worker separates from the firm.

Unemployment Insurance and Retraining. Agents receive a public insurance transfer $b_j > 0$ from the government if unemployed at time j. The public insurance transfer incorporates all forms of assistance that unemployed workers receive, such as unemployment insurance benefits, emergency unemployment assistance, and general transfer programs such as welfare and food stamps.[31] In the model, public insurance transfers are funded through a proportional labor income tax τ that is levied on all employed workers. Additionally, unemployed workers have access to home production $d_j > 0$. Home production proxies for other resources that the unemployed have access to following job loss, such as transfers from friends and family or changes in spousal labor supply.

Unemployed workers also have access to a retraining program. To enter the retraining program, the worker pays a cost $(1-s)\kappa_{R,j}$, where $\kappa_{R,j}$ is the tuition cost of the retraining program in period j and $s \in [0,1]$ is the share of the retraining tuition costs that is subsidized by the government. After entering the retraining program, an unemployed worker's general human capital (h) increases with probability λ_R. The retraining program also inflicts a utility penalty $\psi > 0$ on enrolled students, which can be interpreted as lost leisure due to time spent in the retraining program. Enrolling in the retraining program also imposes a cost $\zeta\kappa_{R,j}$ on the government, which is also funded through the proportional labor income tax.[32]

Stationarity. In equilibrium, the cost of posting a vacancy κ_j, the tuition cost of retraining $\kappa_{R,j}$, the value of public insurance transfers b_j, and the distribution of human capital of new workers $\Gamma_j(h)$ must grow at the rate of technological progress g for the economy to be stationary. It is convenient to analyze a transformed economy where the cost of posting a vacancy, the cost of retraining, the value of public insurance, and the distribution of human capital for new workers are constant over time. In the transformed economy, the latest vintage of technology is held fixed and is denoted by $\bar{z}$. The level of technology in a match (z) and workers' general human capital (h) evolve relative to the latest vintage of technology, which requires that they depreciate at rate $\mu = \frac{1}{1+g}$. In the estimation, we model the depreciation of match technology (z) and human capital (h) as occurring stochastistically so that they depreciate by factor μ, on average, over a model year.

[31]In our baseline model, unemployed workers receive the public insurance transfer every period that they are unemployed. In additional results that are available upon request, we consider an extension of the model where unemployment insurance benefits expire as in Mitman and Rabinovich (2015). In the model with unemployment insurance benefit expiration we find similar welfare gains at the optimal policy from Section 1.5.1 as in the baseline version of the model.

[32]We model the retraining program as incurring a cost to the government since we will calibrate the model to estimates of the impact of community college classes on the outcomes of displaced workers. Kane and Rouse (1999) find that the costs of community colleges are largely paid by the government rather than via the tuition of enrolled students.

Timing and Aggregate State. The timing of the period is such that at the start of the period, shocks to human capital, match technology, job destruction, and experience are realized. After the shocks are realized, agents then search for jobs in the labor market. After the labor market closes, agents make their consumption, savings, as well as retraining decisions and the model period ends.
The aggregate state of the economy is given by $\Omega(e, h, x, k, z, a) \to [0, 1]$, which is a distribution of workers across employment status (e), human capital (h), experience (x), occupations (k), vintages of technology (z), and assets (a). We prove in Appendix A.4.4 that the model is conditionally Block Recursive (e.g., Menzio and Shi (2011)) and that the aggregate state does not affect the behavior of agents in the economy.[33] For presentation purposes, in the next section where we present the Bellman equations that govern the behavior of agents in the economy, we exclude the aggregate state.

1.3.2 Bellman Equations

This section presents the Bellman equations that govern the behavior of workers and firms in equilibrium. In the Bellman equations below, we present an agent's problem after the labor market has closed for the period.

Unemployed Workers. Let $U_t^N(h, a, 0)$ denote the value of being an inexperienced, unemployed worker of age t, with assets a and human capital h. The unemployed worker makes their consumption and savings decision, as well as their retraining decision. Upon entering the retraining program, the worker pays cost $(1-s)\kappa_R$ and has their human capital updated from h to $h + \Delta_R$ with probability λ_R. Those who retrain incur a utility penalty of ψ, which can be thought of as lost leisure due to enrolling in the retraining program. At the start of the next period after shocks to human capital are realized, the unemployed worker searches for a job in the inexperienced labor market by searching across the set of occupations, and applying for a job in the occupation with the highest continuation value. The value to an inexperienced unemployed worker is

$$U_t^N(h, a, 0) = \max_{a' \geq 0, R \in \{0,1\}} u(c) - R\psi + \beta \mathbb{E}\left[\hat{U}_{t+1}^N(h', a', 0)\right] \quad \forall t \leq T$$

$$U_{T+1}^N(h, a, 0) = 0,$$

[33] As we discuss in greater detail in Section 1.3.3, the model is block recursive conditional on a given tax rate τ.

where $\hat{U}^N_{t+1}(h^{'}, a^{'}, 0)$ denotes the expected value of search for an inexperienced unemployed worker, which is given by

$$\begin{aligned}\hat{U}^N_{t+1}(h^{'}, a^{'}, 0) = \max_{k \in \mathcal{K}} \, & p(\theta^N_{t+1}(h^{'}, a^{'}, k))W^N_{t+1}(h^{'}, a^{'}, \bar{z}, k) \\ & + \left(1 - p(\theta^N_{t+1}(h^{'}, a^{'}, k))\right) U^N_{t+1}(h^{'}, a^{'}, 0),\end{aligned}$$

subject to the budget constraint,

$$c + \frac{a^{'}}{1+r} + R(1-s)\kappa_R \leq b + a + d,$$

and the law of motion for a worker's human capital, which is indexed by employment status U and their retraining decision $R \in \{0, 1\}$,

$$h^{'} = H(h, U, R).$$

Experienced unemployed workers face a problem similar to that of inexperienced unemployed workers. The main difference is that experienced unemployed workers search in the experienced labor market for a job in their own occupation and in the inexperienced market for jobs in all other occupations. Appendix A.4.1 contains the Bellman equation for experienced unemployed workers.

Employed Workers. Let $W^N_t(h, a, z, k)$ denote the value of being an inexperienced worker with human capital h and assets a, who is employed at a firm in occupation k that uses technology $z \leq \bar{z}$. The agent makes their consumption and savings choice, and receives utility from consumption. At the start of the next period, shocks to human capital and match technology are realized, and the worker becomes unemployed with probability δ. Workers who become unemployed are immediately allowed to search in the labor market.[34] If the worker is not hit by the separation shock δ, then the worker becomes experienced in occupation k with probability λ_E. After the experience shock is revealed, the worker engages in on-the-job search. If the worker becomes experienced, then they search for a job in their own occupation in the experienced labor market and search for a job in all other occupations in the inexperienced labor market. If the worker did not become experienced, then they search in the inexperienced labor market for all occupations. The continuation

[34]Given the quarterly timing of the model to match labor market flows, we allow workers to search immediately after being hit by the job separation shock. In the model, all separations to unemployment are exogenous. Numerically, we have verified that employed workers would never choose to quit their match and become unemployed.

value of the inexperienced employed worker is

$$W_t^N(h,a,z,k) = \max_{a' \geq 0} u(c) + \beta \mathbb{E}\Big[\delta \hat{U}_{t+1}^N(h',a',k) \\ + (1-\delta)\Big(\lambda_E \hat{W}_{k,t+1}^E(h',a',z',k) + (1-\lambda_E)\hat{W}_{t+1}^N(h',a',z',k)\Big)\Big] \quad \forall t \leq T$$

$$W_{T+1}^N(h,a,z,k) = 0,$$

where $\hat{W}_{t+1}^N(h',a',z',k)$ denotes the value of on-the-job search for an inexperienced employed worker from occupation k, and is given by

$$\hat{W}_{t+1}^N(h',a',z',k) = \max_{\tilde{k} \in \mathcal{K}} p(\theta_{t+1}^N(h',a',\tilde{k}))W_{t+1}^N(h',a',\bar{z},\tilde{k}) \\ + \Big(1 - p(\theta_{t+1}^N(h',a',\tilde{k}))\Big) W_{t+1}^N(h',a',z',k),$$

and $\hat{W}_{t+1}^E(h',a',z',k)$ denotes the value of on-the-job search for a worker who is experienced in occupation k, and is given by

$$\hat{W}_{t+1}^E(h',a',z',k) = \max\Big\{ p(\theta_{t+1}^E(h',a',k))W_{t+1}^E(h',a',\bar{z},k) + \Big(1 - p(\theta_{t+1}^E(h',a',k))\Big) W_{t+1}^E(h',a',z',k), \\ \max_{\tilde{k} \in \mathcal{K}/\{k\}} p(\theta_{t+1}^N(h',a',\tilde{k}))W_{t+1}^N(h',a',\bar{z},\tilde{k}) + \Big(1 - p(\theta_{t+1}^N(h',a',\tilde{k}))\Big) W_{k,t+1}^E(h',a',z',k)\Big\},$$

subject to the budget constraint,

$$c + \frac{a'}{1+r} \leq (1-\tau)\omega f(c_k z, h, N) + a,$$

and the laws of motion for worker's human capital, and the firm's technology,

$$h' = H(h,W), \quad z' = Z(z).$$

Experienced employed workers face a problem similar to that of inexperienced employed workers. Appendix A.4.2 contains the Bellman equations for experienced employed workers.

Matched Firms. Let $J_t^N(h,a,z,k)$ denote the value to a firm in occupation k of being matched with an age t inexperienced worker with human capital h, assets a, and using technology $z \leq \bar{z}$. In the current period, the firm produces and makes wage payments. At the start of the period, shocks to the worker's human capital and technology within the match are realized, and with probability δ the match ends exogenously. If the match avoids the separation shock, then the worker becomes experienced with probability λ_E and searches in the labor market.

If the worker does not match with another job via on-the-job search, then the match continues and the firm continues to receive the benefits of the match. The probability that the worker leaves the firm via on-the-job search depends on their asset choice in the current period as well as where the worker searches for a new match in the next period. Let $y = (t, h, a, z, x, k)$ denote the state of the individual that the firm is matched with in the current period, and let $a^{'}(y)$ denote the agents asset choice. Let $y^{'} = (t{+}1, h^{'}, a^{'}(y), z^{'}, x^{'}, k)$ denote the agent's state in the next period when making their decision about which occupation to search for a job in (i.e., after shocks to human capital, match technology, and experience are realized), and let $\hat{k}(y^{'})$ denote the occupation where the worker searches for a job. With probability $p(\theta_{t+1}^{x(\hat{k})}(h^{'}, a^{'}(y), \hat{k}(y^{'})))$ the worker matches with another job via on-the-job search.[35] The value to the firm is given by

$$\begin{aligned}
J_t^N(h, a, z, k) = &(1-\omega) f(c_k z, h, N) \\
&+ \frac{1-\delta}{1+r}\mathbb{E}\left[(1-\lambda_E)\left(1 - p(\theta_{t+1}^{N}(h^{'}, a^{'}(y), \hat{k}(y^{'})))\right) J_{t+1}^N(h^{'}, a^{'}(y), z^{'}, k)\right] \\
&+ \frac{1-\delta}{1+r}\mathbb{E}\left[\lambda_E\left(1 - p(\theta_{t+1}^{x(\hat{k})}(h^{'}, a^{'}(y), \hat{k}(y^{'})))\right) J_{t+1}^E(h^{'}, a^{'}(y), z^{'}, k)\right] \quad \forall t \le T
\end{aligned}$$

$$J_{T+1}^N(h, a, z, k) = 0,$$

and the laws of motion for worker's human capital and the firm's technology,

$$h^{'} = H(h, W), \quad z^{'} = Z(z).$$

Firms matched with experienced workers face a similar problem as firms matched with inexperienced workers. Appendix A.4.3 contains the Bellman equations for a firm matched with an experienced worker.

Vacancies. Potential firms enter the market and post vacancies to hire an age t worker with experience $x \in \{E, N\}$, human capital h, and assets a for occupation k subject to the free-entry condition

$$\kappa \ge p_f(\theta_t^x(h, a, k)) J_t^x(h, a, \bar{z}, k) \text{ for } x \in \{E, N\}, \tag{1.3}$$

where $p_f(\theta_t^x(h, a, k))$ is the matching rate for firms in occupation k with an age t worker with skills h, assets a, and experience $x \in \{E, N\}$. The free-entry condition binds for all

[35] Note that when the worker becomes experienced, their choice of which occupation to search for a new job in determines whether they search in the experienced market (i.e., if they choose to search in their current occupation k) or the inexperienced market (i.e., if they choose to search in any other occupation $\tilde{k} \in \mathcal{K}/\{k\}$). For this reason, we denote the market the agent searches in as $x(\hat{k})$.

submarkets such that $\theta_t^x(h,a,k) > 0$.

Government. The government provides public insurance transfers to unemployed workers and can subsidize the tuition cost of the retraining program. We assume the government must maintain budget balance in every period.

All unemployed individuals receive a public insurance transfer b. A fraction $R_t(h) \in [0,1]$ of age t unemployed individuals with human capital h enroll in the retraining program. Each individual that enrolls in the retraining programs generates a cost to the government of $\zeta\kappa_R + s\kappa_R$, which represents the cost of running the program (ζ) and subsidies to unemployed workers who enroll (s). Public insurance and the retraining program are paid for by a proportional labor income tax, τ, which is levied on all employed individuals to satisfy

$$\sum_{(h,t)} u_t(h)\left[b + R_t(h)(\zeta\kappa_R + s\kappa_R)\right] = \sum_{(t,h,z,x,k)} \tau\omega f(c_k z, h, x) e_{k,t}^x(h,z), \tag{1.4}$$

where $u_t(h)$ is the mass of individuals with human h that are unemployed at age t, and $e_{k,t}^x(h,z)$ is the mass of age t agents with skill h that are employed at the firm with technology z in occupation k.

1.3.3 Equilibrium

A recursive competitive equilibrium for this economy is a list of household policy functions for assets $\{a'_{e,x,t}(h,a,z,k)\}$, occupations to search for employment in $\{\hat{k}_{e,t}^x(h,a,z,k)\}$, and retraining decisions $\hat{R}_t^x(h,a,k)$, a labor market tightness function $\{\theta_t^x(h,a,k)\}$, a tax rate τ, and a distribution of individuals across states Ω such that

1. Given prices, the households' policy functions solve their respective dynamic programming problems.

2. The labor market tightness in each occupation is consistent with the free-entry condition in equation 1.3.

3. The tax rate τ balances the government's budget constraint (equation 2.12).

4. The distribution of individuals across states Ω is consistent with individual policy functions.

In Appendix A.4.4, we prove that if the government's budget constraint is ignored and the tax rate τ is taken as given, then the model is Block Recursive (e.g., [Menzio and Shi (2011)). Given an exogenous tax rate, the Block Recursive nature of the model means that the individual and firm problems can be solved independent of the distribution of workers across states. In practice, we iterate on the tax rate to solve the model, and in the transition path experiment we iterate on a path of taxes to satisfy the government's budget constraint. This feature of the model will allow us to tractably solve for the transition path of the economy following the policy reform.

1.4 Calibration and Estimation

In this section, we discuss the calibration and estimation of the model.[36] First, we discuss the calibration of the model and then show the results from a series of untargeted moments, which serve as a model validation exercise. Finally, we use the model as a laboratory in which to decompose the sources of earnings losses after layoff and measure the share of earnings losses that are due to technological change.

The model is estimated at a quarterly frequency. We use the increase in the share of vacancies listing computer or software requirements to set the growth rate of technology g. Between 2010 and 2017, the share of vacancies listing computer or software requirements increased from 26.27% of vacancies to 29.18%.[37] This corresponds to an annual growth rate of 1.5%. We normalize the value of the frontier technology to 1 (i.e., $\bar{z} = 1$) and then assign a grid of values for technology $z \in \mathcal{Z}$ where the grid points are spaced so that moving up one grid point is consistent with a growth rate of $g = 1.5\%$.[38] All matches between workers and firms start at the frontier technology ($\bar{z}$) and then evolve according to the following stochastic process:

$$Z(z) = z' = \begin{cases} z\mu & \text{w/ pr. } \iota \\ z & \text{w/ pr. } 1-\iota, \end{cases}$$

where $\mu = \frac{1}{1+g}$ governs the size of technological decay caused by technology growth, and $\iota \geq 0$ governs the probability of technology decay. To be consistent with the quarterly timing of the model and the annual rate of technology growth g, we set $\iota = 0.25$.

In the labor market, we set the job destruction rate to 10% per quarter, $\delta = 0.10$ (Shimer (2005)). Matching in the labor market is defined using a constant returns to scale matching function that yields well-defined job finding probabilities:

$$M(s,v) = \frac{sv}{(s^{\xi} + v^{\xi})^{1/\xi}} \in [0,1).$$

[36] In Appendix A.5, we present the algorithm for solving the model.

[37] These estimates are weighted using employment shares by occupation from the CPS between 2010 and 2017.

[38] We use a grid with seven grid points where $\mathcal{Z}= [0.9145, 1]$. Increasing the number of grid points on the technology grid (which would add points to the bottom of the grid) does not alter the results, as virtually all workers in a match exit the match before the match hits the bottom level of the technology grid.

The matching elasticity parameter is chosen to be $\xi = 1.6$, as estimated in Schaal (2012). The entry cost of posting a vacancy κ is estimated by targeting an unemployment rate of 6.8%, which is the average reported by the Bureau of Labor Statistics from 2010 to 2017. When workers and firms match with one another, they produce according to an "up-to-the-task" production function, as in Albrecht and Vroman (2002) and Jarosch and Pilossoph (2018). The production function $f(c_k z, h, x)$ is given by

$$f(c_k z, h, x) = \begin{cases} A_x c_k z & A_x h \geq c_k z \\ 0 & \text{o.w.,} \end{cases}$$

where the parameter A_x denotes the relative productivity of workers with experience $x \in \{E, N\}$.[39] We normalize the relative productivity of inexperienced workers to 1 (i.e., $A_N = 1$). Following the estimates on the returns to occupation tenure from Kambourov and Manovskii (2009), we set the relative productivity of experienced workers to $A_E = 1.12$, which generates a 12% increase in productivity and wages for experienced workers. Workers become experienced (on average) after being in an occupation for five-years; given the quarterly timing of the model we set the probability of becoming experienced to $\lambda_E = 0.05$. When workers are unemployed, they become inexperienced with probability λ_N. We calibrate the probability of becoming inexperienced while unemployed to match the share of individuals who switch occupations after layoff. In Section 1.2.1 we measured that 63.4% of displaced workers switch occupations following job loss.[40] Finally, wages are determined as a piece-rate $\omega \in [0, 1]$ of production. As in Herkenhoff et al. (2015), we set $\omega = 0.67$. Workers' general human capital (h) also evolves while in the labor market. The grid on human capital $\mathcal{H}$ is taken as given by agents and is spaced such that moving up by a grid point is associated with an increase in human capital of $g = 1.5\%$. The general human capital of employed individuals evolves according to

$$H(h, W) = h^{'} = \begin{cases} h\mu & \text{w/ pr. } \iota \\ h & \text{w/ pr. } 1 - \iota. \end{cases}$$

[39] This production function imposes the restriction that workers with low levels of skills (measured via both their general and their occupation-specific human capital) are unable to work in occupations with high levels of technology. As commented in Jarosch and Pilossoph (2018), the "up-to-the-task" production function is consistent with estimates by Lise and Robin (2017), who estimate a flexible production function and find that low skill workers have limited ability to match with highly productive firms.

[40] Note that the high rate of occupation switching is not an artifact of considering displaced workers. Using all unemployment to employment (UE) transitions in the CPS over this time period, we find that approximately 53% of transitions involve an occupation switch. The results of Fujita (2018) are similar using a much broader classification of occupations.

Unemployed agents receive public insurance transfers from the government (b) as well as the value of home production (d). The value of the public insurance transfer (b) is calibrated to match the change in transfers to the change in lost earnings as measured in the PSID. Using the PSID from the period 2001 to 2013, Braxton et al. (2018) estimate that public insurance to the unemployed replaces 41.2% of lost earnings. The value of home production (d) is estimated by targeting the decline in consumption following job loss. From the PSID, Braxton et al. (2018) estimate that having an involuntary unemployment spell of at least one quarter results in annual consumption being 93.8% of its level prior to layoff.

The unemployed also have the ability to engage in a retraining program. The parameters for retraining are set to be consistent with estimates based on retraining occurring through community colleges. The cost of the training program κ_R is calibrated to match the ratio of the tuition cost to average earnings. Using data on community college tuition costs from Kane and Rouse (1999) and average earnings from the CPS, we estimate that a quarter of community college costs 5.12% of average quarterly earnings. The tuition subsidy to retrain is set to zero in the baseline estimation of the model (i.e., $s = 0$).[41] From the estimates of Kane and Rouse (1999), we set the cost to the government of an additional student enrolled in community college classes to be equal to four-times the costs of tuition to enrolled students (i.e., $\zeta = 4$).[42] The probability of increasing human capital through retraining λ_R is calibrated to match the average increase in earnings for individuals who enroll in community college classes following displacement. Jacobson et al. (2005) link administrative earnings data to community college records for the state of Washington and estimate that one-year of community college classes increases post-displacement earnings by 9% annually for men and by 13% for women.[43] To be conservative, we focus on the earnings gain among men and target an average gain in quarterly earnings of 2.25% per quarter of retraining. The evolution of human capital among unemployed workers who

[41] Jacobson et al. (2005) comment that most of the displaced workers in their study attended community college at their own expense. Kambourov et al. (2012) and Osikominu (2013) comment that in the U.S. since the mid-1990s, programs for displaced workers have focused on job search assistance (i.e., getting individuals reemployed quickly) rather than on teaching new skills through retraining.

[42] Kane and Rouse (1999) provide estimates of the costs of enrolling in community college. They estimate the cost to students of one-year of community college to be $2,300 (in 2012 dollars). The authors comment that the costs of community college are largely borne to the government, and estimate the cost to the government per year of classes is $9,150 per-student. Their estimates correspond to the year 1997. Using the CPS, we measure average annual earnings in 1997 to be $44,899.3 (in 2012 dollars).

[43] Kambourov et al. (2012) find similar returns to training (not only training that occurs via community colleges) in the U.S., while Osikominu (2013) finds similar returns in Germany. These estimates are based on non-experimental data. Using experimental data from the National Job Training and Partnership Act Study, Heckman et al. (2000) find comparable gains in earnings resulting from training. In a recent paper Hyman (2018), uses quasi-experimental variation in the leniency of judges who rule on Trade Adjustment Assistance (TAA) eligibility to estimate the impact of TAA on worker outcomes and finds that average annual returns to training are approximately 9.3% of prior earnings.

engage in the retraining program is given by

$$H(h, U, 1) = h^{'} = \begin{cases} h\mu & \text{w/ pr. } \iota \\ h & \text{w/ pr. } 1 - \iota - \lambda_R \\ h(1+g) & \text{w/ pr. } \lambda_R. \end{cases}$$

The general human capital of unemployed workers who do not enroll in the retraining program ($R = 0$) evolves in the same fashion as employed workers,

$$H(h, U, 0) = H(h, W).$$

The utility cost of enrolling in the retraining program ψ is calibrated to match the share of displaced workers who enroll in community colleges following displacement. Jacobson et al. (2005) estimate that 16.6% of displaced workers enroll in community college classes following displacement.

We next discuss the mapping between occupations in the data and the model. In the empirical analysis of Section 2.2, our notion of an occupation was a four-digit SOC code, which classifies 108 unique occupations. For tractability in the quantitative model, we consider $K = 10$ occupations. To map occupations in the data to occupations in the model, we group occupations with similar computer and software requirements together.[44] To obtain the technology intensity in each occupation ($\{c_k\}_{k=1}^{k=10}$), we use variation in earnings across the 10 occupation groups. Given the production function and wage process specified above, the technology intensity of an occupation governs the level of the wage in that occupation, and occupations with higher levels of technology pay higher wages.[45] Let $\bar{e}_k$ denote smoothed earnings in occupation k.[46] We calibrate the technology intensity of the first occupation (c_1) to match the ratio of smoothed earnings in the first occupation to average earnings among all workers. Using the outgoing rotation groups from the CPS, we measure this ratio to be 0.797. We calibrate the remaining technology parameters ($\{c_k\}_{k=2}^{k=10}$) to match the ratio of smoothed earnings in occupation k relative to the first occupation ($\frac{\bar{e}_k}{\bar{e}_1}$).

A worker's life span is set to $T = 120$ quarters (30 years). Newly born agents enter the model as unemployed, inexperienced workers with zero assets. Newly born agents draw their

[44] In Appendix A.6.1, we show the cutoffs used to generate the 10 occupation groups.

[45] As discussed in Appendix A.6.1, we find a similar pattern in the data that occupations with greater usage of computer and software pay higher wages on average.

[46] We generated smoothed earnings by averaging the predicted values from a regression of computer and software requirements in 2010 on individuals' earnings in the occupation in which they are employed. In Appendix A.6.1, we present the details for our estimation of the smoothed earnings, and the process for calibrating c_k.

initial human capital from an inverted exponential distribution with parameter λ_H, which is calibrated to match the share of workers employed in the occupation with the highest technology level.[47] The agent's preferences over non-durable consumption are given by

$$u(c) = \frac{c^{1-\sigma} - 1}{1 - \sigma}.$$

We set the risk aversion parameter to a standard value, $\sigma = 2$. The discount factor of workers β is calibrated to hit the 75th percentile of the net liquid asset to income (NLATI) ratio. We measure the 75th percentile of the NLATI ratio to be 21.2% using data from the 2010 and 2013 waves of the SCF.[48] We set the annualized risk-free rate (r) to 4%.

Table 2.6 contains a summary of the model parameters, and Table 3.2 displays the calibrated parameters and their calibration targets.[49] The estimated model matches the targeted moments very well. We discuss non-targeted moments in the next subsection.

1.4.1 Model Impact of Technology Growth on Displaced Workers

In this subsection, we analyze the model's predictions on the role of technology growth on the outcomes of displaced workers. These moments were untargeted in the calibration of the model and serve as a model validation exercise.

In the model, occupations are heterogeneous in their technology intensity c_k. For a given change in the frontier technology Δz, occupations with greater technology intensity experience a larger increase in the human capital (skill) requirement necessary to work in that occupation.[50] We estimate the outcomes of displaced workers by the change in technology (skill requirements) in the occupation from which they were displaced and discuss how these estimates compare to the estimates from the data presented in Section 2.2. These moments were not targeted in the calibration.

To facilitate the comparison between the model and data, we sample agents in the model using identical criteria to the Displaced Workers Supplement (DWS) to the CPS. To simulate a DWS, we identify individuals who have been displaced within the past three-years and observe their occupation, earnings, and employment both at the time of the "survey" and in the quarter prior to displacement. Based on a model agent's occupation prior to displacement, we form quintiles of displaced workers based on the change in technology in

[47] We use an inverted exponential distribution, which places a large mass of agents on the right-hand side of the distribution, since an individual's human capital decays over time in the model.

[48] As in Herkenhoff et al. (2015), to measure the NLATI ratio for each individual, we sum cash, checking, money market funds, CDs, corporate bonds, government savings bonds, stocks, and mutual funds less credit card debt over annual gross income.

[49] For ease of exposition, we present the parameter estimates for all of the technology intensity terms in Table A.13 in Appendix A.6.1.

[50] Recall that the production function is such that a worker's human capital must exceed the technology used in production to be able to produce in a given occupation.

their occupation (i.e., the technology intensity (c_k) of their occupation).[51] We then measure the change in earnings, as well as the change in earnings by occupation switchers and stayers across these quintiles, and compare to the data estimates from Section 2.2.

Panel (a) of Figure 1.3 shows the average change in earnings following displacement by quintile of the change in technology as estimated in the model (dashed red line) as well as in the data (solid black line). The figure shows that workers in the fifth quintile (those who experience the largest change in technology requirements) experience the largest decline in earnings of nearly 10% of pre-displacement earnings. Conversely, workers in the first quintile experience the smallest decline in earnings of just over 3% of pre-displacement earnings. These patterns are qualitatively consistent with the estimates from the data, which show that individuals displaced from occupations undergoing larger increases in computer and software requirements experience a larger decline in earnings. As we will discuss in greater detail below, the model generates larger declines in earnings for workers in the occupations experiencing the largest changes in technology, as these workers fall behind the technological frontier for their occupation and then move to an occupation with lower skill requirements, where they are paid a lower wage.

We next examine the model's predictions on the role of occupation switching in the outcomes of displaced workers. Panel (b) of Figure 1.3 shows the change in earnings by technology change quintile for individuals who switch occupations following job loss, while panel (c) shows the change in earnings among individuals who do not switch occupations. The figure shows that the model is able to replicate the empirical observation that occupation switchers incur larger declines in earnings compared to occupation stayers. Occupation switchers incur large losses in the model, as occupation switching after job loss occurs when an individual has fallen behind the technological frontier for their occupation and no longer has the skills to work in their prior occupation. The worker then directs their search to an occupation where their skills are still employable, but they make a permanently lower wage. This induces occupation switchers to have large declines in earnings in the model. Conversely, among occupation stayers, in both the model and the data, the size of the change in technology does not significantly affect the size of earnings losses.

The results of this section showed that the estimated model qualitatively captures the empirical patterns documented in Section 2.2. In particular, in the model individuals displaced from occupations that experience a larger increase in technology experience a larger decline in earnings, and the decline in earnings is concentrated among occupation switchers. In the next section, we decompose the decline in earnings to estimate the share of the decline that is due to technological change.

[51] As discussed above, occupations with higher technology intensity c_k experience a greater change in technology (skill requirements).

1.4.2 Decomposing Earnings Losses after Displacement

In this section, we use the model as a laboratory in which to decompose the sources of earnings losses after displacement. In particular, we examine the role of technological change and occupation-specific human capital in generating earnings losses after displacement. To measure the relative importance of these channels, we remove each feature of the model sequentially and measure the average size of earnings losses generated by the model. We find that technological change and occupation-specific human capital each account for approximately 50% of the decline in earnings following job loss.

We start by removing technological change from the model, which requires setting the technology growth rate to zero (i.e., $g = 0$).[52] As in Section 1.4.1, we measure earnings losses in the model using a model-simulated Displaced Worker Supplement, where on average agents are two years removed from job loss, and restrict our sample to agents who have regained employment. In the model with constant technology, the average decline in earnings is 3.04%. In the baseline model, the average decline in earnings is 6.04%. Hence, technological change accounts for approximately 50% of the decline in earnings following job loss in the baseline model.

We next remove occupation-specific human capital (experience) from the model (i.e., $A_E = A_N = 1$). In the model with constant technology and no occupation-specific human capital, earnings are 0.18% higher after layoff relative to before layoff. Hence, occupation-specific human capital accounts for the remaining decline in earnings generated in the baseline model. Table 1.9 summarizes the results of the decomposition exercise.[53]

The results of this section showed that technological change accounts for approximately 50% of the decline in earnings following job loss. Loss of occupation-specific human capital accounts for the remaining half of the decline. Technological change generates earnings losses after job loss as workers fall behind the technological frontier for their occupation and no longer have the skills to work in their prior occupation. The importance of technological change in the size of earnings losses motivates retraining as being part of the optimal policy for unemployed workers. In the next section, we perform a welfare experiment in which we compare the welfare effects of insuring unemployed workers with public insurance transfers versus a subsidized retraining program, and solve for the optimal combination of the two policies.

[52] We recalibrate the model with constant technology (i.e., without technological change). Appendix A.6.2 discusses the calibration with constant technology and presents the model fit.

[53] We obtain similar results if we remove occupation-specific human capital first, and then remove technological change.

1.5 Optimal Policy for Unemployed Workers

In this section, we use the model to perform a policy experiment in which we solve for the optimal public insurance transfer and retraining tuition subsidy for unemployed workers. In our baseline economy, transfers to the unemployed replace 41.1% of lost earnings on average, and the retraining tuition subsidy is set to 0%. We first compute the optimal policy for unemployed workers across steady states of the model. To solve for the optimal policy in steady state, we use a utilitarian welfare criterion, which is an equally weighted average of newly born individuals' consumption equivalent gains from moving to the new policy. We find that the optimal policy sets the replacement rate of public insurance transfers to 50.3% of lost earnings and the retraining tuition subsidy to 30%.

After solving for the optimal steady state policy, we solve the transition path from the baseline policy to the new optimum. When assessing welfare along the transition path, we measure the consumption equivalent gains of all individuals alive at the time of the policy reform. We find that there is a utilitarian welfare gain along the transition path.

1.5.1 Optimal Policy in Steady State

We first compute the optimal policy for unemployed workers in steady state. To compute the optimal policy for unemployed workers, we compare a utilitarian welfare criterion across steady states of the model with differing levels of public insurance transfers and subsidies to retraining programs.[54] In particular, we measure the welfare effects of moving from the current U.S. policy to the optimal level of public insurance transfers, holding the current subsidy to retraining programs fixed; the optimal tuition subsidy for retraining, holding current public insurance transfers fixed; and the optimal combination of public insurance transfers and tuition subsidies for retraining.

Table 1.10 presents the results of the welfare experiment. Column (1) corresponds to the baseline estimation of the model, which represents the current U.S. policy of transfers to unemployed workers replacing 41.1% of lost earnings and a 0% subsidy to the retraining program. Column (2) reports the optimal replacement rate of public insurance transfers to unemployed workers, holding the retraining subsidy fixed at 0%. Welfare is maximized when the public insurance transfer replaces 49.3% of lost earnings. On average, individuals are willing to give up 0.64% of lifetime consumption to be born in an economy with a 49.3% replacement rate rather than in an economy with a 41.1% replacement rate. With more generous public insurance transfers, individuals have higher consumption following

[54]See Appendix B.6.1 for details of the estimation of the share of lifetime equivalent consumption an individual would be willing to give up (or must receive) to be willing to move from the current policy to an alternative policy.

displacement. However, due to more generous transfers, the tax rate on labor income must be raised to maintain a balanced budget. The utilitarian government balances the welfare gains of greater consumption following displacement with the efficiency losses of higher labor income taxes at a replacement rate of 49.3%.

We next consider the optimal subsidy to retraining programs, holding public insurance transfers fixed. Column (3) of Table 1.10 reports the optimal subsidy to retraining programs, holding public insurance transfers fixed. Welfare is maximized when the retraining subsidy is increased to 27%. On average, individuals are willing to give up 0.47% of lifetime consumption to be born in an economy with a 27% retraining subsidy rather than in an economy with no subsidy to retraining. With more generous subsidies to retraining, the share of individuals who enroll in retraining increases. With greater retraining, the level of human capital in the economy increases, and the unemployment rate declines slightly, due to job finding rates increasing from individuals' having higher human capital. As consumption is higher among the employed, decreasing the unemployment rate generates a welfare gain. As the size of the subsidy to retraining increases past the optimum, more individuals enroll in the retraining program, which requires higher taxes to maintain budget balance, which generates efficiency losses. The government balances these forces at a subsidy of 27%.

The results presented in columns (2) and (3) of Table 1.10 show that there are welfare gains from increasing both the generosity of public insurance transfers and the retraining subsidy for unemployed workers. We now examine the optimal combination of public insurance transfers and retraining subsidies to the unemployed. Column (4) of Table 1.10 reports the optimal combination of public insurance transfers and retraining subsidies to the unemployed. The utilitarian government maximizes welfare with public insurance transfers that replace 50.3% of lost earnings on average and a 30% retraining subsidy. On average, individuals are willing to give up 0.75% of lifetime consumption to be born in an economy with the optimal combination of public insurance transfers and retraining subsidies relative to the baseline economy.

The results of the policy experiment show that the utilitarian government can increase welfare by increasing the generosity of both transfers to the unemployed and retraining subsidies. The utilitarian government increases welfare by using both policies because transfers and retraining each provide insurance at different horizons after job loss. Panel (a) of Figure 1.4 plots consumption 1 quarter after job loss relative to 4 quarters before job loss for different values of the public insurance transfer in an economy with a 0% retraining subsidy (solid black line) and an economy with a 30% retraining subsidy (dashed red line).[55]

[55] Note that consumption after displacement, as reported in Table 1.10, is annual consumption measured in a two-year window around job loss. This annual measure of consumption after layoff was used in the

The figure shows that immediately after job loss, more generous transfers increase the consumption of the unemployed.[56] Thus, transfers provide short-run insurance against job loss. Alternatively, the retraining subsidy provides long-run insurance after job loss. Panel (b) of Figure 1.4 plots consumption 12 quarters (3 years) after job loss relative to 4 quarters before job loss for different levels of the public insurance transfer with a 0% retraining subsidy (solid black line) and a 30% retraining subsidy (dashed red line).[57] The figure shows that 3 years after job loss, consumption is higher in the economy with a 30% retraining subsidy relative to an economy without a retraining subsidy. The introduction of retraining subsidies increases consumption by reducing the probability that individuals are unemployed and by increasing wages. Hence, the introduction of retraining increases welfare by providing long-run insurance against unemployment. Together, transfers and retraining subsidies increase welfare by raising the path of consumption following job loss over both the short and long run.

The results of this section show that there are welfare gains from increasing the generosity of both transfers to the unemployed and retraining subsidies. In the next subsection, we examine the role of technological change in influencing the optimal policy for unemployed workers.

Role of Technological Change in Setting Optimal Policy. We now turn off technological change ($g = 0\%$) and perform the steady state policy experiment of solving for the optimal combination of public insurance transfers and retraining subsidies. This exercise allows us to examine how technological change influences the optimal policy for unemployed workers. Column (5) of Table 1.10 presents the optimal policy in an environment with constant technology (i.e., without technological change). The optimal policy with constant technology replaces 51.6% of lost earnings with transfers and sets the retraining subsidy to 0%. From the comparison of optimal policies with and without technological change, we see that accounting for technological change introduces a motive for the government to include retraining subsidies as part of the optimal policy for unemployed workers.

Technological change alters the policy response to unemployment because of its impact on the nature of income shocks and their pass-through to consumption. Panel (a) of Figure 1.5 plots the path of earnings for displaced workers in the model with technological change (solid black line) and the model with constant technology (dashed red line). In the model

calibration of the model, and the two-year window was used to mimic the sampling structure of the PSID from which our consumption moment was measured.

[56]The introduction of retraining subsidies slightly lowers consumption immediately after job loss because of a larger number of individuals enrolling in retraining and paying the tuition cost.

[57]The persistent decline in consumption after job loss is consistent with the estimates of Saporta-Eksten (2013).

with constant technology, unemployment causes a temporary decline in earnings, with earnings returning to their pre-layoff level after three years. This pattern of temporary earnings losses in an environment with constant technology and permanent earnings losses in an environment with technological change is mirrored in the consumption paths of the two economies. Panel (b) of Figure 1.5 plots the path of consumption following job loss in the model with technological change (solid black line), and the model with constant technology (dashed red line). With constant technology, an individual's consumption exhibits an almost complete recovery within four-years of job loss. Conversely, with technological change, an individual's consumption remains permanently lower after job loss. These permanent declines in consumption are less able to be insured via transfers and create a motive for retraining subsidies to be included as part of the optimal policy for unemployed workers.

The results of this section showed that there are steady state welfare gains from increasing the generosity of public insurance transfers and retraining subsidies. We additionally showed that incorporating technological change creates a motive for the government to provide insurance to the unemployed via retraining subsidies. In the next subsection, we show that there are welfare gains along the transition path after incorporating the optimal policy for unemployed workers.

1.5.2 Transition Path to Optimal Policy for Unemployed Workers

In this section, we compute welfare along the transition path to the optimal steady state policy for unemployed workers, which sets the replacement rate of public insurance to 50.3% and the retraining subsidy to 30%. We measure welfare along the transition path for all individuals who are alive at the time of the reform and measure welfare in terms of their remaining lifetime consumption.[58]

To solve the transition path to the economy with the optimal policy for unemployed workers, we start from the steady state of the baseline economy. We simulate an unexpected and permanent increase in the replacement rate of public insurance transfers from 41.1% to 50.3% and the retraining subsidy from 0% to 30%. After the unexpected increase in public insurance transfers and the subsidy to retraining, individuals in the economy have rational expectations that the new policy for unemployed workers is permanent. Individuals in the economy also have rational expectations on the path of taxes that balances the government's budget constraint along the transition path.[59]

Figure 1.6 presents the results of the transition path experiment. Panel (a) shows the

[58]Appendix A.7.2 presents the details of how we measure welfare along the transition path in terms of remaining lifetime consumption.

[59]Solving the transition path of the economy is tractable due to the Block Recursive nature of the model (see Section 1.3.3 and Appendix A.4.4). Appendix B.7 provides the computational details for solving the transition path.

path of public insurance transfers along the transition, and panel (b) presents the path of the retraining subsidy. Panel (c) presents the path of the tax rate on labor income that maintains budget balance in each year of the transition. In the first year of the transition, the tax rate increases from 3.15% to just under 4.10%. The tax rate remains elevated for five-years and then settles at its new steady state value of 3.78%. The tax rate is elevated (relative to its new steady state value) in the first years of the transition due to the unemployment rate being elevated over this time period.

Panel (d) of Figure 1.6 presents the path of consumption for unemployed workers following the policy change. Consumption of the unemployed is measured as the average consumption of unemployed workers divided by the average consumption of employed workers. After the policy change, the consumption of the unemployed increases sharply by nearly 5 percentage points before slowly settling at its new steady state level 2.25 percentage points above the initial steady state. The consumption of the unemployed initially spikes as unemployed workers decrease their quantity of precautionary savings that were accumulated under the less generous policy for unemployed workers.

We find that there are welfare gains along the transition path. The average individual who is alive at the time of the policy transition has a 0.54% consumption equivalent gain. While there is a welfare gain for the average individual, some individuals do experience welfare losses along the transition path. Figure 1.7 presents the average consumption equivalent gain (loss) by the quintile of an individual's human capital at the time of the policy transition. The figure shows that the welfare gains of the policy change are decreasing in an individual's human capital at the time of the policy change. Individuals in the bottom three quintiles of human capital experience welfare gains from the policy transition, whereas individuals in the top two quintiles experience a decline in welfare.

1.5.3 Policy Experiment: Robustness and Extensions

In this section, we present the results of the policy experiment for various robustness exercises and extensions to the model. In particular, we examine the optimal combination of transfers to the unemployed and subsidies for retraining in a version of the model, where we allow workers to search across occupations and wage-piece rates. We find that allowing agents to search over occupations and wage piece-rates causes only a minor change to the optimal policy for unemployed workers. We additionally present results for the welfare gains at the optimal policy found in Section 1.5.1 for extensions of the model where (1) benefits are subject to expire, and (2) agents are able to borrow up to a limit. We find there are welfare gains from moving to the optimal policy under both of these extensions to the model.

Robustness: Search Over Occupations and Wages

In this section, we present results from a policy experiment where we allow agents to search for jobs across occupations and wage piece-rates.[60] In the baseline version of the model agents search over occupations, and wages are determined as a piece-rate ($\omega \in [0, 1]$) of output with a single wage-piece rate for all matches. In this extension of the model, workers search over a grid of wage piece-rates in addition to searching over occupations. This extension allows for wages to be determined endogenously by the search behavior of agents, and for wages to respond to changes in policy. With this extension of the model we repeat our policy experiment of solving for the optimal combination of public insurance transfers to the unemployed and the retraining tuition subsidy.

Table 1.11 presents the results of this welfare experiment. Column (2) of Table 1.11 presents the optimal policy for unemployed workers, where workers can search over wage piece-rates and occupations. The optimal policy calls for setting the generosity of transfers to the unemployed so that they replace 49.3% of lost earnings, and setting retraining subsidies to cover 25% of the tuition cost of retraining. These polices are more generous than the current U.S. policy of a 41.2% replacement rate from transfers, and a 0% tuition subsidy for retraining. Additionally, the optimal policy with search over wage piece-rates and occupations, is very similar to the optimal policy from the baseline model which called for a 50.3% replacement rate from transfers and a 30% tuition subsidy.

Model Extensions

In this section, we present the welfare gains under various extensions to the model at the optimal policy found in Section 1.5.1, which sets the replacement rate of public insurance transfers to 50.3% and subsidizes 30% of the retraining tuition cost. In particular, we consider extensions of the model that take into account unemployment insurance benefit expiration and borrowing. Under these extensions, we continue to find steady state welfare gains from moving to the optimal policy. The results are summarized in Table 1.12.

Benefit Expiration. In our baseline estimation of the model, unemployed workers receive the public insurance transfer every period that they are unemployed. However, in reality, unemployment insurance benefits, which are a major component of public insurance transfers, typically expires after 26 weeks of unemployment. In this subsection, we examine an extension of the model where a portion of the public insurance transfer to unemployed workers expires. As in Mitman and Rabinovich (2015) individuals become

[60] We present the model with search over wage piece-rates and occupations in Appendix A.9.1. In this Appendix, we also present the calibration and model fit.

ineligible for unemployment insurance (UI) benefits stochastically each period that they are unemployed.[61] After becoming ineligible for unemployment insurance benefits, unemployed workers only receive the non-UI component of transfers to the unemployed. Using the model with benefit expiration, we perform the steady state policy experiment of moving to the optimal policy from Section 1.5.1, which sets the replacement rate of public insurance transfers to 50.3% and subsidizes 30% of the retraining tuition cost. We find that there is a 0.59% utilitarian welfare gain from the policy transition.

Borrowing. Finally, we consider an extension of the model where agents are able to borrow. We model borrowing as occurring through credit cards. In particular, we set the borrowing limit to match the median ratio of credit card limits to income as reported in the SCF, and we set the interest rate on borrowing to match the average real interest rate on credit cards from the SCF.[62] We then we perform the steady state policy experiment of moving to the optimal policy from Section 1.5.1, which sets the replacement rate of public insurance transfers to 50.3% and subsidizes 30% of the retraining tuition cost. We find that there is a 0.26% utilitarian welfare gain from the policy transition.

1.6 Conclusion

In this paper, we examine the cause of the large and persistent decline in earnings following job loss, and explore the optimal policy to insure unemployed workers. We make three contributions. First, we show that technological change, as measured through changes in computer and software requirements, plays a significant role in the earnings losses of displaced workers. In particular, we show that workers displaced from occupations that are undergoing a larger increase in computer and software requirements (1) experience a larger decline in earnings, (2) are more likely to switch occupations, and (3) are more likely to move to an occupation with lower computer and software requirements. Second, we integrate technological change, occupation choice, and employment risk into a Bewley-style economy. The model is able to replicate the empirical facts documented in this paper. We find that technological change accounts for approximately 50% of the decline in earnings following job loss. Third, we show that there are welfare gains from increasing the generosity of public insurance transfers and retraining subsidies both in the steady state as well as along the transition path.

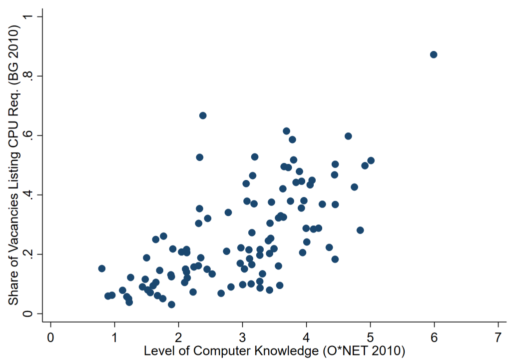
[61] Using a stochastic process for unemployment insurance expiration allows us to tractable incorporate benefit expiration, and avoid having to keep unemployment duration as a state variable in the analysis. See Appendix A.9.2 for details on the model with benefit expiration.

[62] We use the 2010 and 2013 waves of the SCF. We measure the median ratio of credit card limits to be 10% of annual earnings. We measure the (annualized) average real credit card interest rate to be 13%.

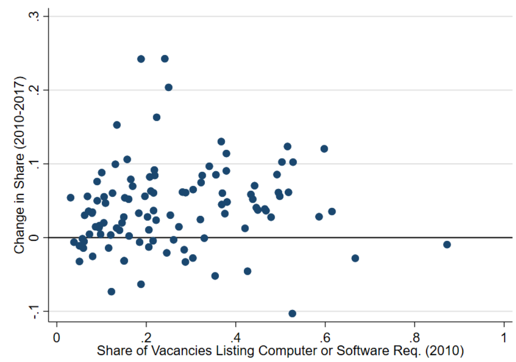
Figures and Tables

Figure 1.1: Technological Change by Occupation

(a) Computer & Software Req. by Occupation



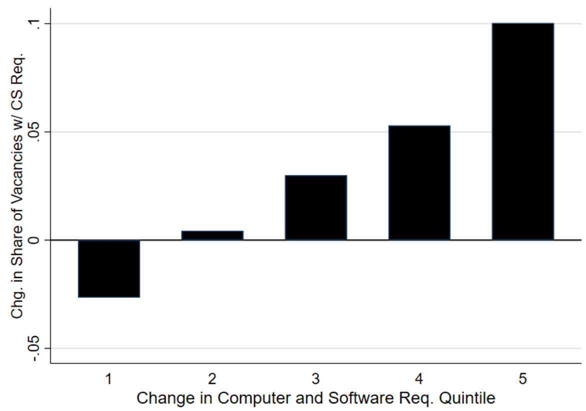
(b) Chg. Computer & Software Req. by Occupation



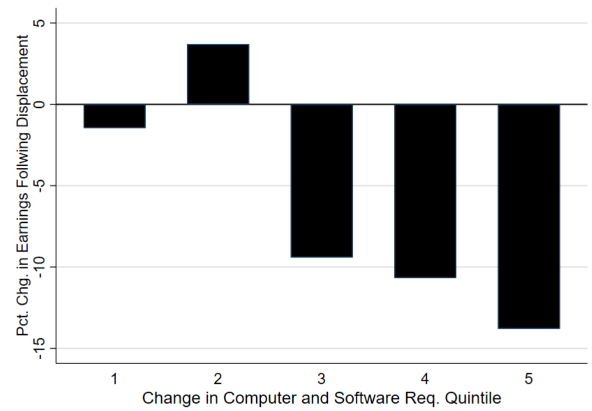
*Notes: Panel (a) displays the level of knowledge in computers reported in O*NET (x-axis) and the share of vacancies listing a computer or software requirement by occupation as measured in the Burning Glass database in 2010 (y-axis). Panel (b) displays the share of vacancies listing a computer or software requirement by occupation in 2010 (x-axis), and the change in the share of vacancies listing a computer or software requirement between 2010 and 2017 (y-axis) as measured in the Burning Glass database. Occupations are measured using four-digit SOC codes.*

Figure 1.2: Change in Computer & Software Req. and Displaced Worker Outcomes

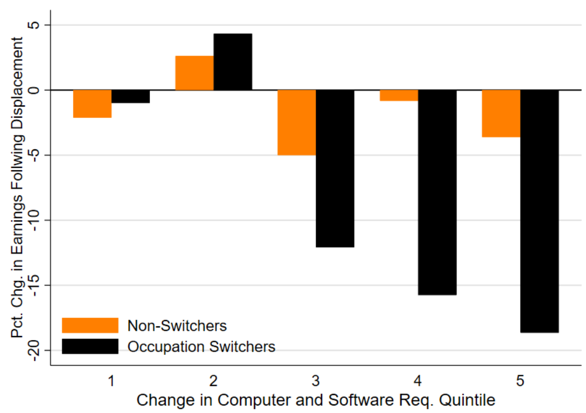
(a) Changes in Computer & Software Requirements



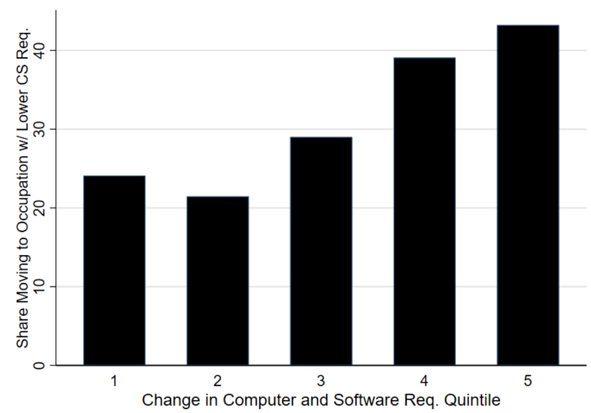
(b) Change in Earnings Following Displacement



(c) Change in Earnings Following Displacement



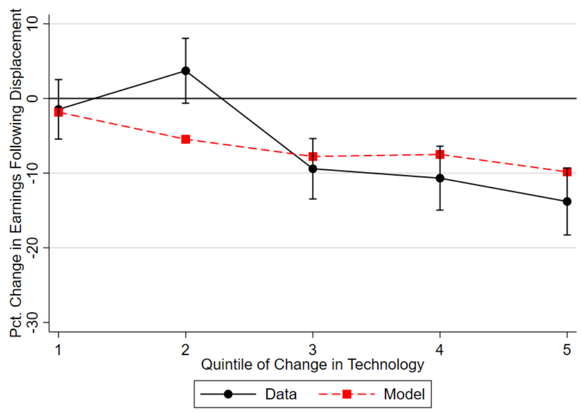
(d) Moving to Occ. w/ Lower Computer & Software Req.



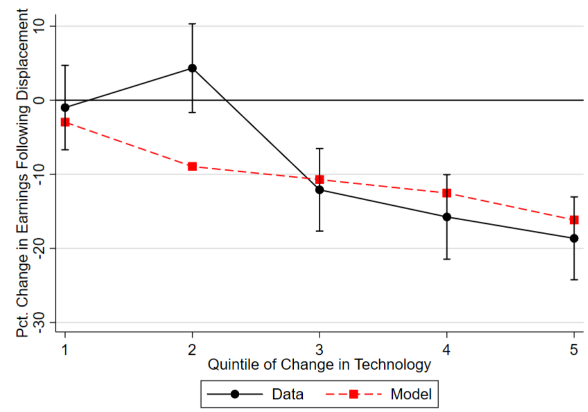
Notes: Panel (a) shows the average change in computer and software requirements by quintile of changes in computer and software requirements. Panel (b) shows the average change in earnings for displaced workers by quintile of change in computer and software requirements. Panel (c) shows the average change in earning by quintile for occupation switchers and non-switchers. Panel (d) shows the share of individuals who move to an occupation with lower computer and software requirements relative to their original occupation. Individuals are placed into quintiles based on the occupation from which they were displaced. Occupations are defined using four-digit SOC codes.

Figure 1.3: Model Predictions of Non-Targeted Moments

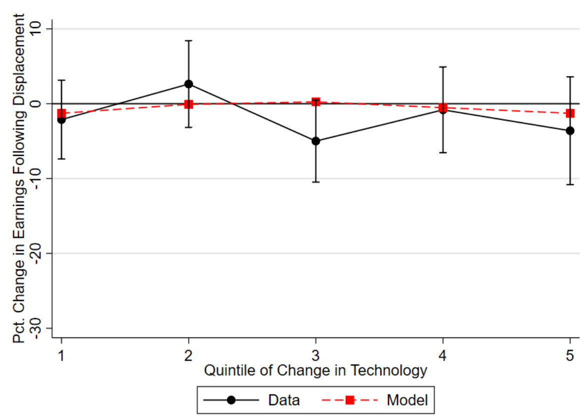
(a) Change in Earnings



(b) Change in Earnings: Occupation Switchers



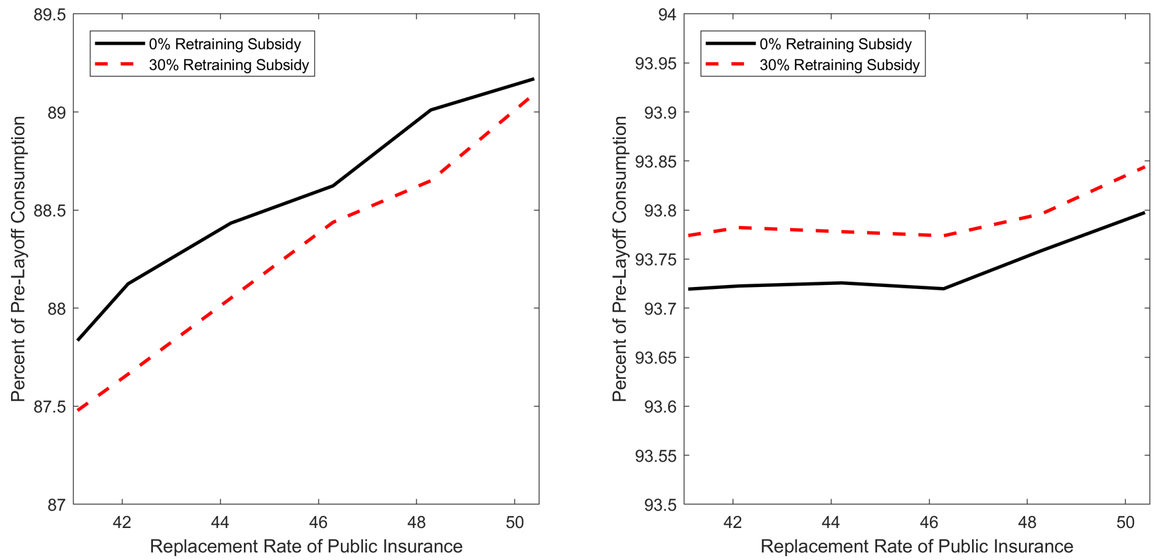
(c) Change in Earnings: Occupation Stayers



Notes: This figure presents model and data estimates on the outcomes of displaced workers by quintile of the change in technology in the occupation from which they were displaced. In the model, quintiles are determined based on the technology intensity of individuals' occupation prior to displacement. The solid black line represents estimates from the data, and the dashed red lines represent estimates from the model. The vertical black lines represent 95% confidence intervals of data estimates.

Figure 1.4: Consumption after Job Loss

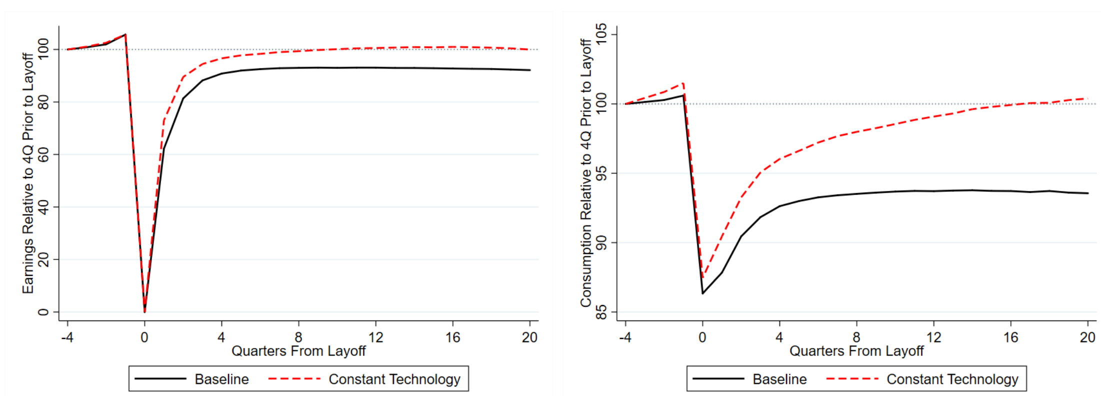
(a) Consumption 1 Quarter after Job Loss (b) Consumption 3 Years after Job Loss



Notes: The figure shows consumption after job loss under alternative public insurance transfers and retraining subsidies. Panel (a) plots consumption in the quarter after job loss relative to 4 quarters prior to job loss. Panel (b) plots consumption 12 quarters (3 years) after job loss relative to 4 quarters prior to job loss. The solid black line corresponds to an economy with a 0% retraining subsidy, and the dashed red line corresponds to an economy with a 30% retraining subsidy.

Figure 1.5: Impact of Technological Change on Outcomes of Displaced Workers

(a) Earnings (b) Consumption

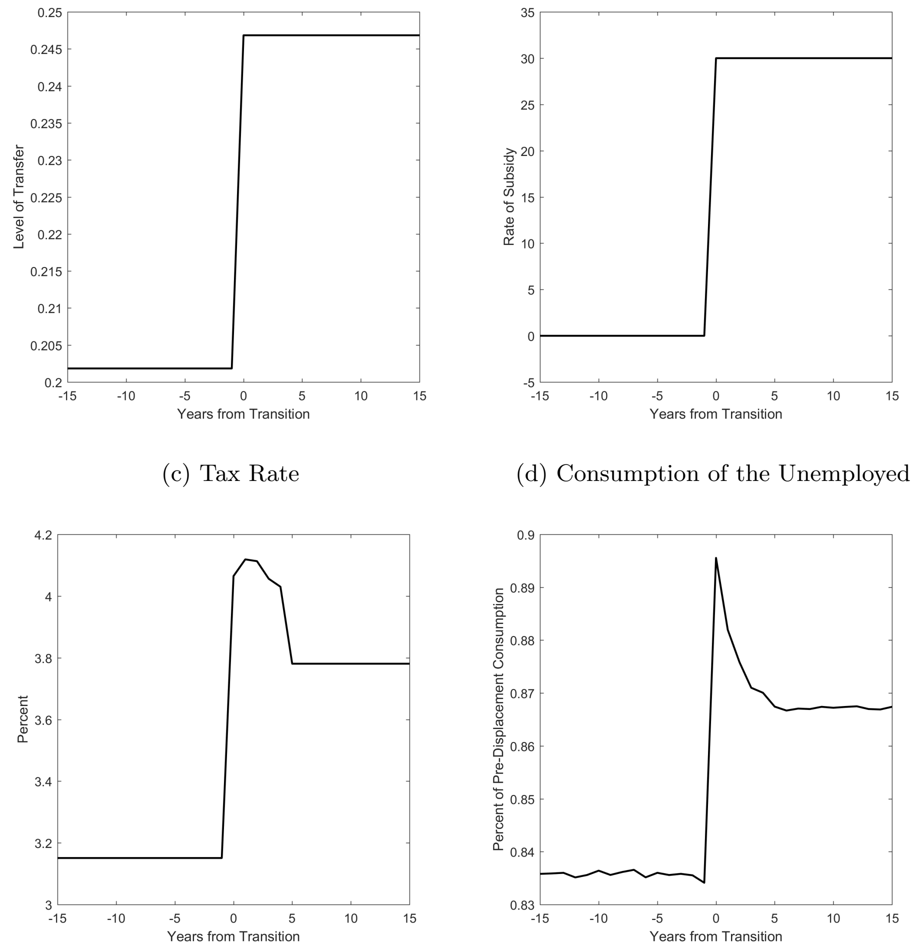


Notes: The figure shows the path of earnings (panel (a)) and consumption (panel (b)) following layoff in the baseline estimation of the model with technological change (solid black line) and estimation of the model with constant technology (dashed red line). Earnings and consumption are both measured relative to four quarters prior to layoff.

Figure 1.6: Transition Path Experiment

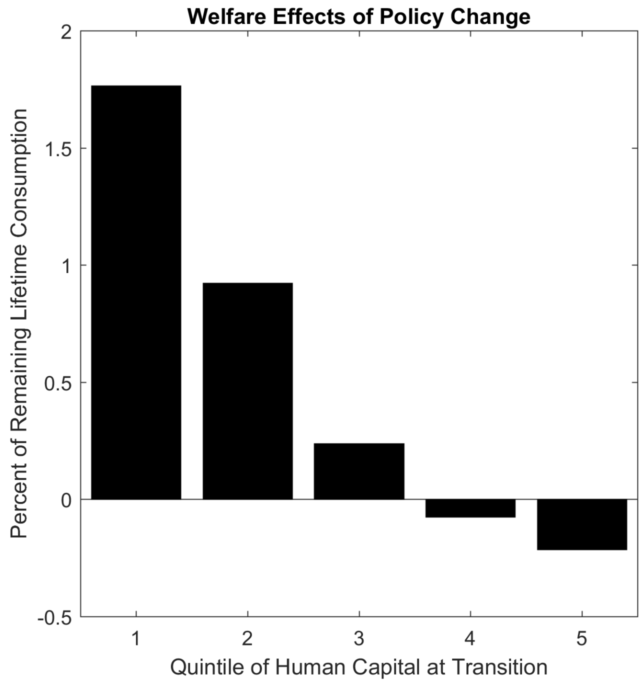
(a) Public Insurance Transfer (b) Retraining Subsidy

(c) Tax Rate (d) Consumption of the Unemployed



Notes: The figure shows output from the transition path experiment inwhich the replacement rate of public insurance to the unemployed as well as the retraining subsidy is adjusted from their baseline values to the optimal policy.

Figure 1.7: Welfare Effects Along the Transition Path



Notes: The figure shows the welfare effects of the policy transition along the transition path. Individuals alive at the time of the policy reform are placed into quintiles based on their human capital at the time of the policy transition.

Table 1.1: Occupations with Changes in Computer and Software Skill Requirements

Occupations with Large Increase in Computer & Software Skill Requirements		
Occupation	SOC Code	Change in Share of Vacancies w/ Computer & Software Req.
Advertising & Marketing Managers	1120	0.112
Sales Rep. Wholesale & Manufacturing	4140	0.068
Occupations with Decrease/Small Increase in Computer & Software Skill Requirements		
Occupation	SOC Code	Change in Share of Vacancies w/ Computer & Software Req.
Machinists and Machine Operators	5140	-0.028
Health Practitioners	2911	0.014

Notes: This table provides summary statistics for occupations experiencing a large increase in computer and software requirements between 2017 and 2010, as well as occupations that experienced a small increase (or decrease) in computer and software requirements over this time period.

Table 1.2: Summary Statistics

	(1) Employed Sample	(2) Population Sample	(3) CPS Non-Displaced
Chg. Computer Req.	0.030	0.030	0.030
Share Vacancies w/ Computer or Software Req. (2010)	0.278	0.278	0.268
Weekly Real Earnings (Displaced Job)	781.54	774.93	-
Weekly Real Earnings (Current Job)	731.69	-	823.01
Years Since Displacement	1.89	1.76	-
Weeks Unemployed After Displacement	13.15	-	-
Switch Occ. (d)	0.634	-	-
Age	40.29	40.97	42.11
Years of Education	13.98	13.85	14.02
Observations	4,672	6,887	37,787

Notes: See Section 1.2.1 for sample selection criteria for employed and population samples. The change in computer requirements, and the share of vacancies listing a computer or software requirement are measured in the occupation from which the worker was displaced for the employed and population samples. For the non-displaced sample these variables are based on the worker's current occupation. Weekly earnings are measured in 2012 dollars. Occupation switching is measured between the occupation from which individuals were displaced and their current occupation, where occupation is measured using a four-digit SOC code. The symbol (d) denotes a dummy variable.

Table 1.3: Impact of Technological Change on Outcomes of Displaced Workers

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Log Unemp. Duration	(4) Emp. (d)
Chg. Computer Req.	-0.591***	0.598***	0.794	0.0948
	(0.228)	(0.203)	(0.535)	(0.141)
Observations	4,672	4,672	4,672	6,887
R-squared	0.263	0.016	0.077	0.115
	Emp. Sample	Emp. Sample	Emp. Sample	Pop. Sample
Controls	Yes	Yes	Yes	Yes

Notes: This table shows regression results from the estimation of equation 1.1. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, and years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In column (3) we remove the control variable for the log of unemployment duration, and in column (4) we remove the control variables for unemployment duration and full-time employment after displacement. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 1.4: Impact of Technological Change Accounting for Employment Change

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Log Unemp. Duration	(4) Emp. (d)
Chg. Computer Req.	-0.602**	0.499**	0.843	0.133
	(0.233)	(0.207)	(0.541)	(0.141)
Chg. Emp. Share	-0.811	-7.648*	3.746	2.870
	(3.596)	(3.971)	(9.735)	(2.610)
Observations	4,672	4,672	4,672	6,887
R-squared	0.263	0.017	0.077	0.116
	Emp. Sample	Emp. Sample	Emp. Sample	Pop. Sample
Controls	Yes	Yes	Yes	Yes

Notes: This table shows regression results from the estimation of equation 1.1. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, and years of educational attainment as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In column (3) we remove the control variable for the log of unemployment duration, and in column (4) we remove the control variables for unemployment duration and full-time employment after displacement. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 1.5: Role of Occupation Switching

	(1) Chg. Log Real Earnings	(2) Chg. Log Real Earnings
Chg. Computer Req.	0.0781	0.0618
	(0.262)	(0.267)
Swith Occ. (d)	-0.0498***	-0.0501***
	(0.0176)	(0.0177)
Chg. Computer Req. X Switch Occ. (d)	-0.953**	-0.948**
	(0.375)	(0.376)
Observations	4,672	4,672
R-squared	0.269	0.269
	Emp. Sample	Emp. Sample
Controls	Yes	Yes
Control Emp. Share	No	Yes

Notes: This table shows regression results from the estimation of equation 1.2. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 1.6: Switching to Occupations with Lower Computer and Software Requirements

	(1) Switch Occ. Lower (d)	(2) Switch Occ. Lower (d)	(3) Switch Occ. Lower (d)
Chg. Computer Req.	1.437***	1.219***	1.441***
	(0.202)	(0.203)	(0.230)
Observations	4,672	4,672	2,984
R-squared	0.124	0.129	0.227
	Emp. Sample	Emp. Sample	Emp. Sample
Controls	Yes	Yes	Yes
2010 Comp. Req.	Yes	Yes	Yes
Emp. Share	No	Yes	Yes
Only Occ. Switchers	No	No	Yes

Notes: This table shows regression results from the estimation of equation 1.1, where the dependent variable is a dummy variable equal to one when an individual switches occupations following displacement and moves to an occupation with lower computer and software requirements than their original occupation. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria and sample definitions. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, the share of vacancies listing a computer or software requirement in 2010 in the occupation from which the individual was displaced, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. The symbol (d) indicates a dummy variable. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 1.7: Model Parameters

Variable	Value	Description
		Non-estimated
Variable	Value	Description
g	1.5%	Annual technology growth rate
ι	0.25%	Quarterly probability of technology decay
r	0.04	Risk-free rate
δ	0.1	Exogenous job destruction rate
A_N	1.00	Inexperienced worker productivity
A_E	1.12	Experienced worker productivity
λ_E	0.05	Probability of becoming experienced
ω	0.67	Worker piece-rate
ξ	1.6	Labor search match elasticity
ζ	4	Relative cost to government of training
T	120	Life span in quarters
		Jointly estimated
Variable	Value	Description
b	0.202	Public insurance transfer to unemployed
κ	0.519	Firm entry cost
d	0.085	Home production
κ_R	0.024	Tuition cost of retraining
ψ	0.303	Utility cost of retraining
λ_R	0.226	Probability of human capital gain from retraining
λ_N	0.677	Probability of becoming inexperienced when unemployed
λ_H	0.177	Exponential parameter for initial human capital
c_1	0.561	Technology intensity first occupation
β	0.981	Worker's discount factor

Table 1.8: Model Calibration

Var.	Value	Target	Model	Data	Source
b	0.202	Transfer to Income Loss	41.1%	41.2%	PSID
κ	0.519	Unemployment Rate	6.8%	6.8%	BLS
κ_R	0.024	Retraining Cost / Avg. Earnings	4.8%	5.1%	KR
ψ	0.303	Retraining Rate	17.8%	16.6%	JLS
λ_R	0.226	Earnings Gain from Retraining	2.42%	2.25%	JLS
λ_N	0.677	Share Switching Occ. After Layoff	55.8%	63.4%	CPS
λ_H	0.177	Share Emp. in Highest Tech Occ.	16.8%	15.6%	CPS
c_1	0.561	Ratio of Occ. Earnings / Avg. Earnings	0.762	0.797	CPS
β	0.981	P75 Net Liquid Assets to Income	20.7%	21.1%	SCF
d	0.085	Consumption After Displacement	90.5%	93.8%	PSID

Table 1.9: Decomposing Earnings Losses after Displacement

	Change in Earnings after Displacement
Data	-6.42%
Baseline Model	-6.04%
Model w/ Constant Technology	-3.04%
Model w/ Constant Technology & w/o Experience	0.18%

Notes: The table shows the percent change in earnings after displacement in the data as well as for different estimations of the model. In all cases, individuals have regained employment and are on average 2-years after displacement.

Table 1.10: Optimal Policy for Unemployed Workers

	(1) Baseline	(2) Optimal Transfer	(3) Optimal Subsidy	(4) Optimal Combination	(5) Optimal Combination w/ Constant Tech.
Transfer/Income Loss	41.1%	49.3%	41.1%	50.3%	51.6%
Retraining Subsidy	0%	0%	27%	30%	0%
Mean Welfare Chg.	-	0.64%	0.47%	0.75%	0.52%
Unemployment Rate	6.8%	7.3%	6.5%	7.0%	7.0%
Share Retraining	17.8%	9.9%	24.1%	13.3%	10.5%
Consumption After Disp.	90.5%	91.4%	90.5%	91.8%	93.1%
Marginal Tax Rate	3.15%	3.81%	3.10%	3.78%	4.11%

Notes: 'Welfare' is the consumption equivalent of leaving an economy with the U.S. policy of a 41.1% *replacement rate and* 0% *subsidy to retraining and moving to an economy with an alternate replacement rate or retraining subsidy. For example, in column (2), the mean welfare change of* 0.64% *indicates that an individual, on average, would give up* 0.64*% of lifetime consumption to have a* 49.3% *replacement rate as opposed to a* 41.1% *replacement rate, holding the current tuition subsidy fixed. See Appendix B.6.1 for details on the estimation of the welfare effect in steady state.*

Table 1.11: Optimal Policy for Unemployed Workers

	(1) Baseline	(2) Optimal Combination
Transfer/Income Loss	40.3%	49.3%
Retraining Subsidy	0%	25%
Mean Welfare Chg.	-	0.27%
Unemployment Rate	4.6%	5.2%
Share Retraining	17.6%	14.7%
Consumption After Disp.	91.0%	92.4%
Marginal Tax Rate	2.13%	2.90%

Notes: This table presents the results of the policy experiment where agents search over occupations and wage piece-rates. See Appendix A.9.1 *for model details. 'Welfare' is the consumption equivalent of leaving an economy with the U.S. policy of a* 40.3% *replacement rate and* 0% *subsidy to retraining and moving to an economy with an alternate replacement rate or retraining subsidy. For example, in column (2), the mean welfare change of* 0.27% *indicates that an individual, on average, would give up 0.27% of lifetime consumption to have a* 49.3% *replacement rate and 25% retraining tuition subsidy as opposed to a* 40.3% *replacement rate and* 0% *retraining tuition subsidy. See Appendix B.6.1 for details on the estimation of the welfare effect in steady state.*

Table 1.12: Welfare Gains Under Model Extensions

	(1) Welfare Gains
Baseline	0.75%
Model with benefit expiration	0.59%
Model with borrowing	0.26%

Notes: This table presents the welfare gains of moving to the optimal policy under various extensions of the model. 'Welfare' is the consumption equivalent of leaving an economy with the U.S. policy of a 41.1% *replacement rate and* 0% *subsidy to retraining and moving to an economy with a* 50.3% *replacement rate and* 30% *subsidy to retraining. See Appendix B.6.1 for details on the estimation of the welfare effect in steady state.*

Chapter 2

Can the Unemployed Borrow? Implications for Public Insurance

2.1 Introduction

By the first quarter of 2018, aggregate credit card limits exceeded 17% of GDP. In this paper, we explore how the presence of this well developed credit market affects optimal labor market policy. To what extent can – and do – displaced workers offset income loss and thus self-insure using credit? Given the degree to which displaced workers can privately self-insure, what is the optimal provision of public insurance?[1]

Our empirical contribution is to measure the borrowing behavior and borrowing ability of unemployed individuals. Using newly linked administrative earnings and credit bureau data, we document four facts which suggest that credit markets play an important role in the way workers self-insure: (1) prior to displacement, workers who lose their jobs can replace a significant fraction of their prior income with unused credit (44% with unused revolving credit, on average), (2) credit limits and credit scores do not immediately respond to job loss and do not decline in an economically significant manner within five years after job loss, (3) unconstrained individuals, those with credit scores in the top two quintiles prior to job loss, borrow and replace a significant fraction of lost earnings with credit, and (4) constrained individuals, who have credit scores in the bottom two quintiles prior to job loss, default and delever. Both borrowing and defaulting allow job losers to transfer resources across time and states of the world, allowing unemployed individuals to partially

[1]This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191 and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

self-insure their losses.

Our empirical results reconcile two literatures with seemingly conflicting results. Studies based on checking-account data suggest that there is roughly zero net borrowing, on average, by workers who lose their jobs (e.g. Gelman et al. (2015), and Ganong and Noel (2015)). On the other hand, direct questions about borrowing among workers who lose their jobs and other survey data imply that roughly 20% of the unemployed borrow, and roughly 30% become delinquent on debt obligations (e.g. Sullivan (2008), Hurd and Rohwedder (2010), and Gerardi et al. (2015)).[2] Papers that show ex-post default include Hurd and Rohwedder (2010), Gerardi et al. (2015), Herkenhoff et al. (2015), and Keys (2018). Surveys of bankruptcy also cite job loss as a factor (e.g. Sullivan et al. (1999)). Lastly, Baker and Yannelis (2017) illustrate significant differences in consumption losses between constrained and unconstrained individuals (see also Crossley and Low (2011)). We reconcile these results by showing that some job losers borrow, while other job losers default and delever. While these offsetting forces yield zero net-borrowing by the unemployed, both the borrowers and defaulters are using credit to smooth consumption.

Our quantitative contribution is to compute optimal public insurance to the unemployed in an environment that replicates our empirical findings while also matching current levels of credit access in the U.S. We do so by integrating long-term credit lines (e.g. Mateos-Planas and Ros-Rull (2010)) and employment risk (e.g. Moen (1997), Burdett et al. (2001), and Menzio and Shi (2011)) into a defaultable debt framework (e.g. Eaton and Gersovitz (1981), Chatterjee et al. (2007), and Livshits et al. (2007)).

To generate the credit access and borrowing patterns we observe in the data, our theory relies on two features of the U.S. credit market: (i) the credit registry generates reputation concerns in the form of exclusion from credit markets in the event of default, and (ii) lenders issue long-term contracts in the form of revolving lines of credit, such as credit cards and home equity lines of credit, whose limits and interest rates are not contingent on subsequent income changes. Because the unemployed value future access to credit markets, most job losers repay, and therefore lenders offer credit contracts to individuals both before and after job loss. Conversely, in a model without credit lines, where debt is individually priced each period, unemployed agents would face a sudden change in borrowing capacity, which is inconsistent with the facts we establish. As Athreya et al. (2009) have shown, credit markets are poor insurance markets in economies with one-period debt. It is the presence of credit lines which allows us to match both the level of credit access and the non-responsiveness of credit limits to layoff.

After estimating our framework to match aggregate credit access and borrowing moments in

[2]Papers that show ex-post borrowing following job loss include Sullivan (2008), Hurd and Rohwedder (2010), Herkenhoff (2013), Collins et al. (2015).

the early 2000s, we show that our model successfully replicates the non-targeted responses of borrowing, credit limits, and defaults upon job loss. Similar to the data, the model economy's borrowing limits do not respond to job loss, while defaults increase. Additionally, as in the data, the model generates heterogeneity in borrowing following job loss. Both groups of individuals, borrowers and defaulters, smooth consumption using credit markets. In particular, when individuals borrow they pay a premium in the form of a spread over the risk free rate, reflecting default risk. In bad states of the world, such as when a borrower loses their job, they may default to smooth consumption. Similar to Zame (1993), default partially completes the market in our framework.

Given our model's ability to replicate the micro data, we use our framework to compute optimal transfers to the unemployed (we express the optimal transfers as a *replacement rate* of lost earnings during unemployment). We evaluate policies using a utilitarian welfare criterion, in which equal weight is placed on all individuals. We assume the government raises funds to cover transfers with a distortionary labor income tax. Therefore, the government faces an equity-efficiency tradeoff that is affected by the presence of a credit market. Simultaneously cutting taxes and public insurance improves efficiency (lower distortionary taxes) but also generates equity losses (larger consumption losses upon layoff). In the presence of a well-developed credit market, the ability to borrow mitigates consumption losses upon layoff and therefore lowers the equity losses if public insurance is cut. Given levels of credit access observed in the early 2000s, the utilitarian government's optimal steady-state replacement rate is 38.3%, which is lower than the current U.S. replacement rate of 41.2%. If credit markets were shut down, the optimal steady-state policy is an unambiguously higher replacement rate of 43.2%.

Our optimal policy exercise implies a low degree of substitutability between public insurance and private forms of self-insurance. There are two general equilibrium forces which limit the desire of the government to substitute out of public insurance. First, for low levels of public insurance, precautionary savings increase and individuals become less likely to borrow. Second, default rates rise and credit becomes more costly if public insurance becomes sufficiently low. In other words, public insurance and private self-insurance are complementary at the aggregate level (aggregate transfers and aggregate borrowing comove positively for low values of public insurance), even though at the individual level they are substitutes (*ceteris paribus*, individuals borrow more if the public transfer is reduced). Therefore, moderate levels of public insurance are necessary to sustain access to credit markets among the unemployed.

Lastly, we compute welfare along the transition path when we reduce the replacement rate from 41.2% to 38.3%. Individuals who were alive at the time of this policy change have a utilitarian welfare gain of .05% of lifetime consumption after the transition. We find that the majority of individuals experience a welfare gain. However, while over 80% of individuals with the highest human capital (at the time of the policy change) experience a welfare gain, only 65% of individuals with the lowest human capital have a welfare gain. Even though our model does not have search effort in the labor market, directed search generates moral hazard. As a consequence, cutting transfers raises the employment rate by approximately .5% as workers search in areas of the job market with higher job finding rates.

Related Literature. Our paper contributes to recent work which has integrated credit markets into models with labor markets (e.g. Athreya and Simpson (2006), Herkenhoff (2013), Bethune et al. (2013), Bethune (2017), Athreya et al. (2015), Luo and Mongey (2016), and Ji (2018)). The most closely related paper is by Athreya and Simpson (2006) who compute the responsiveness of bankruptcies to public insurance provision, showing that more generous unemployment insurance may actually raise bankruptcies. We build on Athreya and Simpson (2006) in three key ways. We model long-term credit contracts which allows us to match the degree of self-insurance provided by the credit market, we model the labor market in general equilibrium, and we calculate the optimal provision of public insurance.

Our model adds to a small but growing literature on individual credit lines, credit scoring, and long-term relationships between borrowers and lenders.[3] Of particular note, work by Mateos-Planas and Ros-Rull (2010) analyzes bankruptcy reform in an economy with credit lines and private information about endowments. We depart from Mateos-Planas and Ros-Rull (2010) by modeling the labor market and we obtain tractability via competitive search over credit contracts.

Our paper is related to studies which integrate unemployment insurance into Bewley-Huggett-Aiyagari frameworks (e.g. Lentz and Tranaes (2001), Krusell et al. (2010), Nakajima (2012a), and Nakajima (2012b)) as well as studies of optimal unemployment insurance with assets (*inter alia* Shimer and Werning (2005), Chetty (2008), Lentz 2009, Koehne and Kuhn (2015), Chaumont and Shi (2017), and Griffy 2017).[4] Related papers by Shimer and Werning (2005) and Lentz 2009 compute optimal UI in models with savings. Relative to these studies we make several contributions: (i) we empirically document the large income-replacement or self-insurance role that credit markets play in the US economy, (ii) we incorporate the institutions that allow this self-insurance to exist in our model

[3] See Mateos-Planas and Seccia (2006), Mateos-Planas and Ros-Rull (2010), and Mateos-Planas (2013) on models of credit lines; Chatterjee et al. (2008a), Chatterjee et al. (2008b), and Chen (2012) on models of credit scoring; and Mitman (2011) and Hedlund (2011) for models of long term relationships between borrowers and lenders.

[4] Our paper also complements studies on optimal UI over the business cycle (Mitman and Rabinovich (2011), Birinci and See (2017), and references therein).

(long-term contracts, reputation concerns, and defaultable debt), and (iii) we quantify the substitutability between private borrowing and public forms of insurance.

Our article is also related to the literature on private unemployment insurance (e.g. Chiu and Karni (1998) and Hendren (2015)). We contribute to this literature in two ways, (i) we focus on private self-insurance or income replacement through credit markets, and (ii) Hendren (2015) focuses on two-period models which abstract from reputation concerns and long-run interactions present in our data and model. While both papers take very different approaches to the question of how substitutable private and public forms of insurance are, our results are consistent with Hendren (2015) in the sense that the scope for private self-insurance is limited, even with long-term contracts and strong dynamic reputation concerns.

The paper proceeds as follows. Section 2.2 describes our main empirical results, Section 2.3 describes the model, Section 2.4 describes the calibration, Section 2.5 computes optimal transfers to the unemployed, and Section 2.6 concludes.

2.2 Empirical Results Using Administrative Data

Do the unemployed have access to credit? Do they borrow or default? We answer these questions by studying time-series and cross-sectional credit market outcomes for workers who lose their jobs. To mitigate endogeneity of job loss, we focus on mass layoffs (e.g. Jacobson et al. (1993)). We first compare the average response of borrowing, credit limits, and scores between workers who lose their jobs and those that do not. We find that workers who lose their jobs have significant amounts of credit access, and that credit access does not respond in an economically meaningful way to job loss. The mean amount borrowed by workers who lose their jobs is approximately zero.

We show that the zero-net-borrowing result is driven by heterogeneity among workers who lose their jobs. Using the cross-section of workers who lose their jobs, we show that roughly 1/3 of workers who lose their jobs borrow, 1/3 default or delever, and roughly 1/3 do not alter their borrowing. We establish that unconstrained individuals, those with credit scores in the top two quintiles prior to job loss, borrow and replace a significant fraction of lost earnings with credit, and constrained individuals, those with credit scores in the bottom two quintiles prior to job loss, default and delever.

2.2.1 Data

Our main dataset is a randomly drawn panel of 5 million TransUnion credit reports linked through a scrambled social security number to the Longitudinal Employment and Household Dynamics (LEHD) administrative records database. The TransUnion database contains information on the balance, credit score, limit, and status (delinquent, current, etc.)

across different types of consumer debt held by individuals at an annual frequency from 2001 through 2008. The LEHD database is a matched employer-employee dataset covering 95% of U.S. private sector jobs. The LEHD includes quarterly data on earnings, worker demographic characteristics, firm size, firm age, and average wages. Our primary sample of employment records includes individuals with credit reports between 2001 and 2008 from the 11 states for which we have LEHD data: California, Illinois, Indiana, Maryland, Nevada, New Jersey, Oregon, Rhode Island, Texas, Virginia, and Washington.

Since job dismissal and reason of dismissal are not recorded in the LEHD, we follow Jacobson et al. (1993) and focus on mass layoffs. Unlike Jacobson et al. (1993) who focus on workers from Pennsylvania with 6 years of tenure prior to job loss, we focus on a representative cross-section of workers with 3 years of tenure prior to job loss. We show that much of earnings losses in our sample are temporary and that nearly 1/3 of the workers who lose their jobs immediately find a job that pays more than their prior job (e.g. of 31k displaced workers only 19k have a loss 1 year after displacement), and thus their earnings losses are purely transitory. In a companion paper, Braxton et al. (2019), we use filtering methods to recover permanent and transitory income shocks. We show that individuals borrow in response to negative transitory shocks and default in response to negative permanent shocks.

Our analysis focuses on revolving credit because it can be drawn down immediately after job loss, with no additional application or income verification, and it can be repaid slowly. The main components of revolving credit include bank revolving (bank credit cards), retail revolving (retail credit cards), finance revolving credit (other personal finance loans with a revolving feature), and mortgage related revolving credit (HELOCs). Appendix B.2 includes an analysis of bank cards as well as total credit, each of which exhibit similar patterns to revolving credit. However, it is important to note that not all types of credit balances affect the budget constraint in the same way. A first mortgage *lowers* liquid resources on hand (buying a house involves handing money to the bank), whereas an increase in revolving debt augments liquid resources on hand. We also study the response of credit scores, delinquencies (30 days late and 60 days late), and chargeoffs to job loss.

2.2.2 Sample Descriptions and Summary Statistics

We use two samples in this paper.[5]

1. **Panel Sample:** Our first sample includes all 18 to 64 year olds who were at a firm that underwent a mass layoff episode, had at least 3 years of tenure at the time of the

[5] All sample sizes are rounded to the nearest thousand in compliance with Census Bureau disclosure rules.

mass layoff and made at least $5,000 dollars at the firm in the prior year.[6] We split this sample into a treatment group of 31,000 individuals who were displaced as part of the mass layoff, and a randomly selected control group of roughly equal size that includes individuals who worked at a firm with a mass layoff but were not displaced. We require that individuals in the treatment group are never displaced as part of another mass layoff episode, and we require the control group is never displaced as part of a mass layoff episode.

2. **Cross Sectional Sample:** Our second sample includes 19,000 displaced workers in the treatment group who had a decline in annual earnings comparing the year after displacement relative to the year prior to displacement.

Table 2.1 includes summary statistics for both samples. Panel (A) of Table 2.1 provides summary statistics for the treatment and control groups in the Panel Sample in the year prior to the mass layoff event. Annual earnings, as well as credit limits and balances are deflated by the CPI. Column (1) of Table 2.1 summarizes the treatment group while column (2) summarizes the control group. The treatment group earned $44k in the year prior to displacement while the control group earned over $49k. In the empirical analysis we include individual fixed effects, controls for age, and proxies for wealth to account for differences across treatment and control groups.

The treatment and control groups are very similar in terms of their credit market variables. Our measure of the credit score is the TransUnion "bankruptcy score," which is designed to measure the probability of bankruptcy.[7] The bankruptcy score lies between 0 and 1000 and higher scores reflect lower odds of bankruptcy. The treatment group has an average credit score in the year before displacement of 427, while the control group's average score is 437. Revolving credit balances, limits and unused limits to income are also very similar across treatment and control groups.

Individuals have substantial revolving credit limits in the year before job loss, with an average of nearly $27k for the treatment group. Individuals in the treatment group can replace, on average, 44 percent of their income with unused revolving debt in the year before job loss.[8] The magnitude of unused credit prior to layoff indicates that these individuals have significant reserves of unused credit which can be drawn down when they enter into unemployment.

[6]These restrictions on tenure and prior earnings are common in the literature, e.g. Davis and Von Wachter (2011), and are used to mitigate issues associated with seasonal employment or weak labor force attachment.

[7]Rather than using a traditional credit risk score, we use the TransUnion bankruptcy score in the regression analysis. Bankruptcy scores are used only by more sophisticated lenders, and when they are used, they are used in conjunction with a traditional credit risk score.

[8]Note unused revolving credit to income is winsorized at the 1 percent level at the top and bottom of the distribution.

Panel (B) of Table 2.1 includes summary statistics for the cross sectional sample in the year prior to mass layoff. In the analysis that follows, we define credit constraints using the credit score. Table 2.1 shows that unused credit is monotonically increasing by credit score quintile. The table also shows that in the year prior to mass layoff, the majority of individuals have a substantial amount of unused credit. Individuals with the highest credit scores have unused revolving credit that totals more than their annual income, while individuals in the third credit score quintile are able to replace 27 percent of their annual income with revolving credit.

The summary statistics of Table 2.1 indicate that individuals have, on average, a large stock of credit prior to layoff. We next examine how access to – and use of – credit evolves following job loss.

2.2.3 Average Response of Earnings and Credit Following Job Loss

Our first approach is to estimate the average response of credit variables following job loss using a distributed lag framework as in Jacobson et al. (1993) around a mass layoff episode.[9] This empirical strategy compares displaced to nondisplaced individuals before and after the mass layoff episode to identify how individuals use credit following job loss.

Let i index individuals and t index years. Let α_i denote a set of individual fixed effects and γ_t denote year dummies. Let $Y_{i,t}$ denote the outcome of interest (such as real earnings, credit score, real revolving debt balance, etc.). Let $D_{x,i,t}$ be a dummy variable taking the value 1 when an individual is x periods before (if x is negative) or after (if x is positive) displacement. For example, $D_{-1,i,t}$ is a dummy variable indicating an individual is 1 period before displacement. The vector $X_{i,t}$ contains control variables, including a quadratic in age and deciles for lagged cumulative earnings. We include deciles for lagged cumulative earnings to proxy for an individual's wealth prior to displacement. The specification we use is of the following form:

$$Y_{i,t} = \alpha_i + \gamma_t + \sum_{j=-4}^{5} \beta_j D_{j,i,t} + \mathit{\Gamma} X_{i,t} + \varepsilon_{i,t} \tag{2.1}$$

The objects of interest are $\beta_0, \beta_1, ..., \beta_5$, which summarize the impact of job loss on the outcome variable in the year of displacement and subsequent years. To examine the validity of the point estimates, we show that the treatment and control groups have parallel trends prior to displacement (i.e. $\beta_{-4}, \beta_{-3}, .., \beta_{-1}$ are not statistically different from zero).

Table 2.2 documents the average response of earnings and borrowing behavior following job loss. The coefficients in Table 2.2 correspond to $(\beta_{-4}, \beta_{-3}, ..., \beta_4, \beta_5)$ in equation (2.1), and

[9] Appendix B.1 includes details on the identification of mass layoffs.

are interpreted as the difference in the outcome variable between displaced and nondisplaced individuals. Figure 2.1 plots the coefficient estimates from Table 2.2 along with 95 percent confidence intervals.

Panel (a) of Figure 2.1 plots the differences in real annual earnings between displaced and non-displaced individuals. The figure shows that earnings losses following job loss are large and persistent. In the year of job loss, a displaced individual makes nearly $3k less than a nondisplaced individual, and one year later, this difference in earnings increases to nearly $14k. Five years after job loss, a displaced individual still earns $3k less than a nondisplaced individual. These large and persistent effects of job loss are consistent with prior studies, e.g. Jacobson et al. (1993), Davis and Von Wachter (2011), Jarosch (2014), and Huckfeldt (2014).[10]

Panel (b) of Figure 2.1 shows the impact of job loss on an individual's credit score. The graph shows that displaced and nondisplaced workers exhibit parallel pretrends. However, in the year of layoff, a displaced individual's credit score declines by nearly 6.5 points, on average, relative to nondisplaced individuals. In the following year, the difference in credit scores between displaced and nondisplaced individuals is roughly 16 points. While statistically significant, these changes are economically small. The average credit score for an individual in the treatment group is 427 points in the year prior to displacement, with a standard deviation of 268 points. Relative decreases of 6 and 16 points, then represent less than a 1.5 percent and 4 percent decline in credit scores, respectively. As credit scores represents the marginal cost of borrowing, our results indicate that the marginal cost of borrowing is unresponsive to job loss.

Panel (c) of Figure 2.1 demonstrates that the stock of credit is also largely unresponsive to job loss. Panel (c) compares the revolving credit limits of displaced and nondisplaced individuals around a layoff episode. In the year of displacement, a displaced individual's credit limit decreases relative to a nondisplaced individual by $1k, on average. One year after displacement, the difference in credit limits between displaced and nondisplaced individuals increases to just over $1,700. In the year prior to displacement, individuals in the treatment group had, on average, a revolving credit limit of nearly $27k. Thus, by the year following displacement, the borrowing limit declines to $25k, on average. These results indicate that following job loss, individuals maintain substantial lines of credit.

Panel (d) of Figure 2.1 measures the impact of job loss on borrowing. We focus on revolving credit since it can be drawn down immediately, without notice or further income verification, upon job loss. Panel (d) shows that, on average, displaced individuals do not borrow more than nondisplaced individuals. This zero response of borrowing following job

[10] The increase in earnings of the treatment group relative to the control group prior to displacement is also observed in Davis and Von Wachter (2011) and Jarosch (2014).

loss is consistent with the recent work of Gelman et al. (2015) and Ganong and Noel (2015).[11] However, the cross-sectional analysis in Section 2.2.4 reveals that there is significant heterogeneity among workers who lose their jobs as nearly two-thirds of workers alter their balances and default upon job loss, and a significant fraction use the credit market to borrow.

Default Following Job Loss

We now investigate whether individuals can use credit markets to relax their budget constraint by defaulting and not making scheduled debt repayments. When a lender and borrower enter into a debt contract, both sides know that there is potential for the borrower to not repay the loan. Lenders price contracts accordingly by charging a premium over the risk free rate, and in bad states of the world, an indebted individual may default to smooth consumption. Table 2.3 and Figure 2.2 document the propensity of individuals to smooth consumption via default following job loss.

Panel (a) of Figure 2.2 shows the difference in the probability of having a 60 day delinquency within the past year for displaced and nondisplaced individuals around a mass layoff episode. One year after job loss, displaced individuals are 3.1 percentage points more likely to be 60 days delinquent.[12] This result suggests that individuals use the skipping of payments as a means to smooth consumption following job loss.

After a sufficient amount of time (typically 6 months) the creditor ceases to try to collect missing payments and they notify the credit bureau to "chargeoff" the debt. Panel (b) of Figure 2.2 shows the difference in the probability of having a debt chargeoff within the past year for displaced and nondisplaced individuals. Prior to job loss, displaced and nondisplaced individuals are not significantly different in their probability of having a debt chargeoff. However, in the year of job loss, the probability a displaced individual will have a debt chargeoff is nearly 0.9 percentage points higher than a nondisplaced individual. One year after displacement, the difference is nearly 3 percentage points.

After charging off a debt, the creditor can sell the debt obligation to a collection agency who will attempt to collect on the debt. The collection agency reports to the credit bureau, and the credit bureau flags individuals in collection. Panel (c) of Figure 2.2 displays the difference in the probability of having a debt enter into collections within the past 12 months for displaced and nondisplaced individuals around a mass layoff. In the year they are laid off, the probability a displaced individual enters collections is 1.1 percentage points higher

[11] The results presented in Table 2.2 and Figure 2.1 include all types of revolving credit (HELOCs, etc.) rather than just credit cards. In Appendix B.2.2, we present results for credit card (bank card) balances as well as limits. The pattern of the results for credit card balances are nearly identical to revolving balances.

[12] These results are robust to using other measures of default or delinquencies. See Appendix B.2.2 for additional average response results for measures of credit access, usage and default.

than a nondisplaced individual. This represents a 10% increase relative to the average collection rate of 11.2 percent between 2001 and 2008.[13]

The effect of job loss on collections is very persistent. Four years after job loss, displaced individuals remain nearly 2 percentage points more likely to be in collections than nondisplaced individuals. The persistent emergence of collections following job loss indicates that individuals relax their budget constraint by missing debt payments following job loss for a substantial period of time.

Panel (d) of Figure 2.2 shows the difference in the probability of having a derogatory public flag within the past year for displaced and non-displaced individuals.[14] One-year after job loss, displaced individuals are 0.7 percentage points more likely to have a derogatory flag on their credit report relative to a non-displaced individual.

The results presented in Table 2.3 and Figure 2.2 indicate that individuals use missed debt repayments and default in response to job loss. A striking feature of these results is their persistence. Two years after job loss, individuals remain significantly more likely to have their outstanding debts charged off. Four years after displacement, individuals are still more likely to be in collections. The results in this section show that despite not borrowing on average, credit markets play a central role in an individual's response to unemployment through the use of defaults (e.g missed payments, chargeoffs, and collections). In the next section, we show that while there is zero borrowing on average, this result masks substantial heterogeneity in borrowing behavior following job loss.

2.2.4 Heterogeneous Responses: Credit Replacement Rates

We now explore the cross-sectional patterns of borrowing by workers who lose their jobs. Despite the fact that there is zero net borrowing following job loss, we now show that roughly 1/3 of workers who lose their jobs borrow, 1/3 delever or default, and roughly 1/3 do not alter their borrowing patterns. Both defaulters and borrowers are using credit markets to smooth consumption.

To formalize the analysis of heterogeneous responses of borrowing to job loss, we measure *revolving credit replacement rates* (we will refer to this as the 'replacement rate' in this section). Let t denote year of displacement and i denote the individual. The replacement rate is the ratio of an individual's change in their revolving debt balance to the change in their earnings, where we measure the change in revolving debt balance and earnings from the year

[13]The share of consumers in collections comes from the Federal Reserve Bank of New York's Quarterly Report on Household Debt and Credit. Accessed from "https://www.newyorkfed.org/microeconomics/databank.html" on 6/14/2017.

[14]Individuals obtain a derogatory flag on their credit report for bankruptcy, tax liens, foreclosure, civil judgments, etc.

prior to displacement to the year after displacement ($RR_{it} = \frac{-(debt_{i,t+1} - debt_{i,t-1})}{earnings_{i,t+1} - earnings_{i,t-1}}$).[15] Since the replacement rate is only defined for those with an earnings loss, we restrict our sample to individuals with an earnings loss between the year prior to displacement and the year after displacement. The numerator in the replacement rate is the *negative* of the change in revolving debt to ease interpretation. Figure 2.3 presents a smoothed density of the replacement rates in our cross-sectional sample. The density exhibits significant variance, with some individuals replacing over 70 percent of their earnings loss with revolving debt (replacement rate of 0.7) and some individuals who decrease their balances by over 70 percent of their earnings loss (replacement rate of -0.7).[16]

In Figure 2.3, 39% of the displaced workers delever. Among those who delever, a large fraction default. Table 2.4 reveals that roughly 43.6% (=.17/.39) of those who delever enter delinquency in the year after layoff. Moreover, 21% (=.08/.39) of those who delever receive a debt chargeoff. Among those who delever without a deliquency flag, it may be the case that the banks renegotiated the loan without charging it off (Adelino et al. (2013)), however, we cannot identify renegotiations.

Our theory, which we present later in Section 2.3, as well as existing theories, predict that credit constraints are an important determinant of the borrowing decision. To proxy for credit constraints, we separate individuals into credit score quintiles based on their credit score in the year prior to displacement.[17] Let $C_{y,i,t-1}$ be a dummy variable taking the value 1 when individual i is in credit score group y in year $t-1$ and will be displaced in year t. For example, $C_{3,i,t-1}$ is a dummy variable indicating an individual is in credit score quintile 3 one year before being displaced in year t. The vector $X_{i,t}$ contains control variables, including a quadratic in age and deciles for lagged cumulative earnings. Using our cross sectional sample of displaced workers who had an earnings loss, we estimate regressions of the replacement rate (RR_{it}) on credit score quintiles:

$$RR_{it} = \lambda_1 + \lambda_2 C_{2,i,t-1} + \lambda_3 C_{3,i,t-1} + \lambda_4 C_{4,i,t-1} + \lambda_5 C_{5,i,t-1} + \gamma_t + \Phi X_{it} + \varepsilon_{it} \qquad (2.2)$$

The objects of interest are $(\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5)$. The coefficient λ_k for $k \geq 2$, gives the difference in replacement rates for individuals in the k^{th} credit score quintile relative to

[15] We measure the change in earnings and revolving debt balances over a two year window since Panel (a) of Figure 2.2 shows that the decline in earnings due to job loss is concentrated in the year after displacement. Our previous draft used a one year window (comparing t to t-1) and found similar results – those results are available upon request.

[16] In Appendix B.2.4, we show that the credit replacement rate for the unemployed measured in the 2007-09 SCF panel reveals a similar pattern of credit usage around job loss.

[17] Note the credit score quintiles are defined among all displaced individuals in our cross sectional sample. These individuals experienced an earnings loss in the 2-year window around displacement, which compares real annual earnings in the year after displacement relative to the year before displacement.

individuals in the first credit score quintile, holding all else constant.
To estimate the average replacement rate for an individual in the k^{th} credit score quintile we take the average values of the control variables for individuals in the sample denoted by $\bar{X}_i$ and use the OLS coefficients in the following expression:

$$\hat{RR}_k = \hat{\lambda}_k + \hat{\lambda}_1 + \hat{\Phi}\bar{X}_i \tag{2.3}$$

The statistic $\hat{RR}_k$ can be interpreted as the average replacement rate for the k^{th} group conditional on the controls. Additionally, taking the difference between $\hat{RR}_k$ and $\hat{RR}_1$ returns the marginal effect at the mean of moving from credit score group 1 to credit score group k.
Table 2.5 documents the role that credit scores prior to displacement play in determining an individual's replacement rate. The coefficients in column (1) of Table 2.5 correspond to $(\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5)$ in equation (2.2). The first column of Table 2.5 documents significant differences in replacement rates across credit score quintiles.[18] Holding all else constant, an individual in the fifth credit score quintile has a replacement rate that is 18.4 percentage points higher than an individual in the first credit score quintile.
Figure 2.4 displays the estimated replacement rate ($\hat{RR}_k$) by credit score quintile. The figure shows that average replacement rates are an increasing function of credit score quintile. Individuals in the bottom two credit score quintiles reduce their revolving debt balances while individuals in the top three credit score quintiles replace earnings losses with revolving debt. Individuals in the fourth credit score quintile replace 9 percent of their lost earnings by borrowing, while individuals in the highest credit score quintile replace 15 percent of their lost earnings by borrowing. For comparison, in Section 2.4, we estimate that job losers replace 41.2% of lost earnings with public transfers. Hence the amount of income-replacement that individuals with the highest credit scores obtain through increasing their revolving credit balances is equivalent to over a third of the amount of public insurance currently offered in the U.S.
While replacement rates are easy to interpret and capture overall credit market use during job loss, replacement rates may be driven by factors other than earnings losses (e.g. high score individuals may simply borrow more, on average). In the next section, we isolate the portion of the replacement rate attributable to earnings losses.

[18] Note the replacement rate used in the estimation of equation (2.2) is winsorized at the top and bottom of the distribution by 10 percent.

2.2.5 Heterogeneous Response: Role of Earnings Losses

Our final approach is to estimate the heterogeneous responses of credit outcomes to earnings losses across individuals with different credit scores. Let $\Delta e_{i,t+1,t-1} = e_{i,t+1} - e_{i,t-1}$ be the change in earnings between year $t+1$ and year $t-1$ for an individual i who was displaced in year t and had an earnings loss. As above, let $C_{y,i,t-1}$ be a dummy variable taking the value 1 when individual i is in credit score group y in year $t-1$ and will be displaced in year t. Let $Y_{i,t+1}$ be the outcome variable of interest (such as the change in real revolving debt balances, or an indicator variable for having a 60-day delinquency). We estimate the following specification:

$$Y_{i,t+1} = \gamma_t + \eta + \mu \Delta e_{i,t+1,t-1} + \sum_{j=2}^{5} (\eta_j C_{j,i,t-1} + \mu_j C_{j,i,t-1} \times \Delta e_{i,t+1,t-1}) + \Psi X_{i,t} + \varepsilon_{i,t} \quad (2.4)$$

The objects of interest are $(\mu, \mu_2, \mu_3, \mu_4, \mu_5)$. The coefficient μ summarizes the marginal change in the outcome variable for each dollar lost among individuals in the lowest credit score group, and the sum of the coefficients $\mu + \mu_j$ return the marginal effect for individuals in the jth credit score group. We relegate the corresponding tables to Appendix B.2.3.

We first consider the heterogeneous responses of borrowing to changes in earnings. Panel (a) of Figure 2.5 plots the marginal effect of a \$10k earnings loss on revolving credit balances by credit score quintile. Individuals with the highest credit scores replace 5.39% of lost earnings by borrowing. So for every \$10k of lost earnings, they borrow \$539 ($= -10,000 \times [0.0210 - 0.0749]$). Individuals in the lowest credit score quintile reduce their credit balances by 2.1% of lost earnings (the p-value of this point estimate is just slightly larger than .1). For every \$10k of lost earnings, they reduce borrowing by \$210 ($-10,000 \times 0.021$). These results highlight that there is heterogeneity in the role that earnings losses play in an individual's borrowing behavior following displacement. Hence part of the heterogeneity in replacement rates observed in Figure 2.4 is attributable to differences across credit score groups in the response of revolving debt balances to earnings losses. Thus, some component of the borrowing response to job loss may be consistent with contemporaneous and innovative work by Hundtofte and Pagel (2017) who use Icelandic data and attribute delevering upon job loss to heterogeneous preferences to smooth debt.

We next consider the heterogeneous responses of default to changes in earnings. Panel (b) of Figure 2.5 plots the marginal effect of a \$10k earnings loss on the probability of a 60-day delinquency in the year after displacement. For individuals in the lowest two credit score quintiles, a \$10k decline in earnings increases the probability of a 60-day delinquency by 1.23 percentage points. For individuals in the three highest credit score groups, a decline in earnings is not associated with higher delinquency rates. Panels (c) and (d) of Figure 2.5

plot the marginal effect of a $10k earnings loss on the probability of a debt chargeoff and a derogatory public flag, respectively. For those in the lowest credit score quintiles, a $10k decline in earnings increases the probability of a chargeoff by .74 percentage points and increases the probability of a derogatory public flag by .61 percentage points. For those in the highest credit score quintiles, the chargeoff and derogatory flag response is roughly two to four times weaker.

2.2.6 Taking Stock: Heterogeneous Responses

Across credit score quintiles, individuals use credit markets to smooth consumption in very different ways. Unconstrained individuals in the highest credit score quintile increase their revolving credit balances in response to income losses. Conversely, constrained individuals in the middle and bottom of the credit score distribution default and chargeoff loans in response to income losses. Both groups of individuals are using credit markets in response to job and income loss. In the subsequent sections, we develop a quantitative model to replicate these observations from the data. We then quantify the optimal degree of public insurance given the level of credit access observed in the data.

2.3 Model

In this section, we compute optimal transfers to the unemployed (which we will also call 'public insurance') in an environment that replicates the borrowing behavior documented in Section 2.2. Our framework is a labor search model (e.g. Menzio and Shi (2011)) with long-term credit lines (e.g. Mateos-Planas and Ros-Rull (2010)). By modeling credit lines, we are able to replicate the non-responsiveness of credit access to job loss. In the calibrated model, when public insurance becomes sufficiently low, high asset individuals precautionary save, while low asset individuals become more likely to default, and the credit market endogenously contracts. This complementarity between public and private insurance limits the willingness of the government to substitute out of public insurance.

Time is discrete and runs forever. There is a unit measure of individuals, a continuum of potential risk-neutral lenders, and a continuum of potential entrant firms. There are $T \geq 2$ overlapping generations of risk averse individuals that face idiosyncratic risk, similar to Menzio et al. (2012). Each individual lives T periods. Individuals have heterogeneous discount factors. Let β_i be a type i individual's discount factor, where $i \in \{H, L\}$ denotes an individual's type and types are both observable and permanent. We set $0 < \beta_H < \beta_L < 1$, i.e. type L individuals are more patient ('low profit' to lenders) than type H individuals ('high profit' to lenders). The share of type i individuals in the economy is π_i.

Heterogeneous discount factors will allow us to match the cost of credit and use of credit observed in the U.S. data.

At the start of each period, individuals direct their search for jobs (e.g. Moen (1997), Burdett et al. (2001), and Menzio and Shi (2011)). Individuals then participate in an asset market where they make asset accumulation, borrowing, and default decisions. Let t denote age and t_0 denote birth cohort. We assume that individuals must apply (i.e. search) for credit contracts at utility cost κ_S. Let $S_{i,t,t+t_0}$ be a dummy that equals 1 if a type i, age t individual searches for credit in period $t+t_0$. Individuals may default on their loans $b_{i,t,t+t_0}$ at utility cost $\psi_D(b_{i,t,t+t_0})D_{i,t,t+t_0}$, where $D_{i,t,t+t_0}$ is a dummy that equals 1 in the event of default. The objective of an individual is to maximize the present discounted value of utility over non-durable consumption ($c_{i,t,t+t_0}$) net of any utility penalties of default and application costs:

$$\mathbb{E}_{t_0}\left[\sum_{t=1}^{T}\beta_i^t\left(u(c_{i,t,t+t_0})-\psi_D(b_{i,t,t+t_0})D_{i,t,t+t_0}-\kappa_S S_{i,t,t+t_0}\right)\right]$$

For the remainder of the paper we focus on a recursive representation of the problem, dropping the time subscript $t+t_0$.

In addition to types, individuals are heterogeneous along multiple dimensions. Individuals are either employed or unemployed, with employed value functions denoted W, and unemployed value functions denoted U. Let $e \in \{W,U\}$ denote employment status. Let $b \in \mathcal{B} \equiv [\underline{B}, \bar{B}] \subset \mathbb{R}$ denote the net asset position of the individual, where $b > 0$ indicates saving and $b < 0$ indicates borrowing. Let $\vec{h} \in \mathcal{H} \equiv [\underline{\tilde{h}}, \bar{\tilde{h}}] \times [\underline{\epsilon}, \bar{\epsilon}] \subset \mathbb{R}^2$ be a tuple representing an individual's human capital. Human capital is comprised of two components, a persistent component ($\tilde{h}$) and a transitory component (ϵ). Human capital follows a Markov chain which depends on an individual's employment status, and it is calibrated to match earnings changes of the employed, as well as earnings losses following job loss. Workers differ with respect to their piece-rate $\omega \in [0,1]$ which denotes the share of their per-period match output that they receive as a wage. Individuals also differ with respect to their credit access $a \in \{C,N\}$, where $a = C$ denotes those with credit access who can borrow, and $a = N$ denotes those without credit access who are unable to borrow. Individuals that have credit access are heterogeneous with respect to their borrowing limit $\underline{b} \in \underline{\mathcal{B}} \equiv [\underline{B}, 0]$ as well as their interest rate $r \in \mathcal{R} \equiv [\underline{r}, \bar{r}] \subset \mathbb{R}_+$.

Unemployed individuals direct their search for employment across vacancies which specify a fixed piece rate ω for the duration of the employment match. Let $M(u,v)$ denote the labor market matching function, and define labor market tightness to be the ratio of vacancies (v) to unemployment (u). Since search is directed, there is a separate labor market tightness for each submarket, defined by an agent's age (t), requested piece-rate (ω), and human capital ($\vec{h}$). Although individuals differ along other dimensions, an agent's age, human capital, and requested piece-rate are the only characteristics that matter for firm profitability. In each submarket, the job finding rate for individuals, $p(\cdot)$, is a function of labor market tightness $\theta_t(\omega, \vec{h})$, such that $p(\theta_t(\omega, \vec{h})) = \frac{M(u_t(\omega,\vec{h}),v_t(\omega,\vec{h}))}{u_t(\omega,\vec{h})}$. On the other side of the market, the hiring rate for firms $p_f(\cdot)$ is also a function of labor market tightness and is given by $p_f(\theta_t(\omega, \vec{h})) = \frac{M(u_t(\omega,\vec{h}),v_t(\omega,\vec{h}))}{v_t(\omega,\vec{h})}$. Once matched with a firm, a worker produces $f(\vec{h}) : \mathcal{H} \to \mathbb{R}_+$ and keeps a share ω of this production as their wage. Matches end exogenously each period with probability δ. It is important to note that because we model piece-rate contracts, workers' wages grow over time with their human capital. This generates a motive for employed workers to borrow against future income, and we need newly laid off workers to be indebted prior to job loss in order to generate defaults and delevering.

Every period individuals without credit access choose whether or not to search for a credit line, which entails a utility cost κ_S. After incurring the utility cost, the agent then directs their search over the menu of credit lines, which specify a borrowing limit $\underline{b}$, and interest rate r. Let $M_C(u_C, v_C)$ denote the credit market matching function, and define the credit market tightness to be the ratio of vacant credit contracts (v_C) to individuals searching for a credit contract (u_C). As in the labor market, since search is directed, credit market tightness is specific to each submarket. A submarket is defined by an agent's age (t), type (i), employment status ($e \in \{W, U\}$), piece-rate wage (ω), prior debt (b), human capital ($\vec{h}$), and the requested contract ($\underline{b}, r$). In each submarket, the credit finding rate for individuals, $p^c(\cdot)$, is a function of the credit market tightness. For unemployed individuals, the tightness is given by $\theta^{c,U}_{i,t}(b, \vec{h}; \underline{b}, r)$ where $p^c(\theta^{c,U}_{i,t}(b, \vec{h}; \underline{b}, r))$ is the associated credit finding rate.[19] On the other side of the market, the probability a lender matches with a borrower, denoted $p^c_f(\cdot)$, is also a function of credit market tightness and is given by $p^c_f(\theta^{c,U}_{i,t}(b, \vec{h}; \underline{b}, r))$.[20] An individual remains matched with a lender until the individual defaults, or the match is destroyed exogenously at rate δ_C.

The timing is such that individuals enter the credit search stage and must decide whether to apply for a credit line. They then make borrowing, saving, and consumption decisions. Idiosyncratic human capital risk is then realized. At the start of the next period individuals enter the labor market and apply for jobs, and they may endogenously separate from lenders

[19]For the unemployed, $p^c(\theta^{c,U}_{i,t}(b, \vec{h}; \underline{b}, r)) = \frac{M_C(u_{C,i,U,t}(b,\vec{h};\underline{b},r),v_{C,i,U,t}(b,\vec{h};\underline{b},r))}{u_{C,i,U,t}(b,\vec{h};\underline{b},r)}$. For the employed, the tightness depends on the wage piece-rate, $\theta^{c,W}_{i,t}(\omega, b, \vec{h}; \underline{b}, r)$ and $p^c(\theta^{c,W}_{i,t}(\omega, b, \vec{h}; \underline{b}, r)) = \frac{M_C(u_{C,i,W,t}(\omega,b,\vec{h};\underline{b},r),v_{C,i,W,t}(\omega,b,\vec{h};\underline{b},r))}{u_{C,i,W,t}(\omega,b,\vec{h};\underline{b},r)}$.

[20]For the unemployed, $p^c_f(\theta^{c,U}_{i,t}(b, \vec{h}; \underline{b}, r)) = \frac{M_C(u_{C,i,U,t}(\omega,b,\vec{h};\underline{b},r),v_{C,i,U,t}(\omega,b,\vec{h};\underline{b},r))}{v_{C,i,U,t}(\omega,b,\vec{h};\underline{b},r)}$. For the employed, the credit finding rate depends on the wage piece-rate, $p^c_f(\theta^{c,W}_{i,t}(\omega, b, \vec{h}; \underline{b}, r)) = \frac{M_C(u_{C,i,W,t}(\omega,b,\vec{h};\underline{b},r),v_{C,i,W,t}(\omega,b,\vec{h};\underline{b},r))}{v_{C,i,W,t}(\omega,b,\vec{h};\underline{b},r)}$.

by defaulting or they may receive an exogenous credit separation shock.

Let $U^S_{i,t}(b,\vec{h};0,0)$ denote the value of entering the credit search stage for an unemployed, age t, type i individual with net worth b, and human capital $\vec{h}$. The last two elements of the state space are zero, reflecting the fact that the agent does not have a credit contract, and thus $\underline{b}=0$ and $r=0$. This agent must decide whether to pay the utility cost κ_S of searching for a credit contract or remaining without credit,

$$U^S_{i,t}(b,\vec{h};0,0) = \max\left\{-\kappa_S + U^A_{i,t}(b,\vec{h};0,0),\ U^N_{i,t}(b,\vec{h};0,0)\right\} \quad \forall t \leq T$$

$$U^S_{i,T+1}(b,\vec{h};0,0) = 0$$

where $U^N_{i,t}(b,\vec{h};0,0)$ is the value of an unemployed individual without credit access, specified below, and $U^A_{i,t}(b,\vec{h};0,0)$ is the value of applying for a credit contract which is given by

$$\begin{aligned} U^A_{i,t}(b,\vec{h};0,0) = &\max_{(\underline{b},r)\in\underline{\mathcal{B}}\times\mathcal{R}} p^c(\theta^{c,U}_{i,t}(b,\vec{h};\underline{b},r))U^C_{i,t}(b,\vec{h};\underline{b},r) \\ &+ \left(1-p^c(\theta^{c,U}_{i,t}(b,\vec{h};\underline{b},r))\right)U^N_{i,t}(b,\vec{h};0,0) \end{aligned}$$

After the asset market closes, the agent makes their consumption and savings decisions with savings accruing interest at the risk free rate r_f. For an agent that did not receive a credit contract, their consumption and savings problem is constrained in that the agent is not allowed to borrow. An unemployed individual receives a public transfer z. This transfer incorporates all forms of assistance that unemployed workers receive, which can include unemployment compensation and emergency unemployment assistance as well as general transfer programs such as welfare and food stamps that unemployed individuals may be enrolled in. As discussed in Section 2.4, we will calibrate z to be consistent with the change in total transfers relative to the change in income for job losers. The transfer to unemployed individuals is funded through a proportional tax τ on labor income that is levied across all employed individuals. Additionally, unemployed individuals receive the value of home production g, which is assumed to be constant across the duration of unemployment as well as homogeneous across unemployed individuals. In the model, home production proxies for other resources that individuals have access to following job loss, such as transfers from friends and family, or changes in spousal labor supply. We will calibrate the value of home production to match estimates of consumption following job loss.

After consuming, idiosyncratic human capital risk is realized. Unemployed individuals, on average, lose human capital, while employed individuals gain human capital. Individuals then enter the labor market where they direct their search over piece-rate wage contracts

ω. At the end of the period, individuals without credit access enter the credit search stage. The continuation value of an unemployed agent without credit access is,

$$U_{i,t}^{N}(b,\vec{h};0,0) = \max_{b^{'}\geq 0} u(c) + \beta_i \mathbb{E}\left[\max_{\tilde{\omega}} p(\theta_{t+1}(\tilde{\omega},\vec{h}^{'}))W_{i,t+1}^{S}(\tilde{\omega},b^{'},\vec{h}^{'};0,0) + \left(1-p(\theta_{t+1}(\tilde{\omega},\vec{h}^{'}))\right)U_{i,t+1}^{S}(b^{'},\vec{h}^{'};0,0)\right] \quad \forall t \leq T$$

$$U_{i,T+1}^{N}(b,\vec{h};0,0) = 0$$

subject to the budget constraint,

$$c + q(b^{'},0)b^{'} \leq z + g + b$$

and the law of motion for human capital, which is indexed by employment status U,

$$\vec{h}^{'} = H(\vec{h},U) \tag{2.5}$$

The bond price $q(b^{'},r)$ includes both the discount on the face-value of loans as well as the savings rate,

$$q(b^{'},r) = \mathbb{I}\{b^{'}<0\}\frac{1}{1+r} + \mathbb{I}\{b^{'}\geq 0\}\frac{1}{1+r_f}$$

For an agent that received a credit contract, their consumption and savings problem is constrained by their borrowing limit $\underline{b}$. The agent chooses their asset position, searches for jobs, and then decides whether to default on any outstanding debts. The value function of an agent with credit is given by,

$$U_{i,t}^{C}(b,\vec{h};\underline{b},r) = \max_{b^{'}\geq \underline{b}} u(c) + \beta_i \mathbb{E}\left[\max_{\tilde{\omega}} p(\theta_{t+1}(\tilde{\omega},\vec{h}^{'}))W_{i,t+1}^{D}(\tilde{\omega},b^{'},\vec{h}^{'};\underline{b},r) + \left(1-p(\theta_{t+1}(\tilde{\omega},\vec{h}^{'}))\right)U_{i,t+1}^{D}(b^{'},\vec{h}^{'};\underline{b},r)\right] \quad \forall t \leq T \tag{2.6}$$

$$U_{i,T+1}^{C}(b,\vec{h};0,0) = 0$$

subject to the budget constraint,

$$c + q(b^{'},r)b^{'} \leq z + g + b$$

and the law of motion for unemployed individuals' human capital (equation (2.5)). After directing their search over firms in the labor market, the agent observes if their credit relationship has been exogenously destroyed. With probability δ_C, the agent looses their credit market access. After the realization of the credit separation shock, the agent decides whether or not to default. The default decision and the resulting continuation value for an unemployed worker is given by

$$\begin{aligned} U^D_{i,t+1}(b', \vec{h}'; \underline{b}, r) = \delta_C \max\{U^N_{i,t+1}(0, \vec{h}'; 0, 0) - \psi_D(b'),\ U^N_{i,t+1}(b', \vec{h}'; 0, 0)\} \\ + (1 - \delta_C) \max\{U^N_{i,t+1}(0, \vec{h}'; 0, 0) - \psi_D(b'),\ U^C_{i,t+1}(b', \vec{h}'; \underline{b}, r)\} \end{aligned} \tag{2.7}$$

Let $D^{N,U}_{i,t+1}(b', \vec{h}'; \underline{b}, r)$ be an indicator function denoting an individual's default decision when they are unemployed and are hit by the credit separation shock ($D^{N,U}_{i,t+1}(b', \vec{h}'; \underline{b}, r) = 1$ when the individual defaults and is equal to zero otherwise). Let $D^{C,U}_{i,t+1}(b', \vec{h}'; \underline{b}, r)$ be an indicator function denoting an individual's default decision when they are unemployed and are not hit by the credit separation shock.

Employed individuals in the economy face similar credit constraints as unemployed individuals. The two main differences between the employed and unemployed are that (1) with probability δ, employed individuals are laid off and must search for a new job, and (2) employed individuals pay a proportional labor income tax τ which is used to fund the public insurance transfer. The Appendix B.3.1 contains the Bellman equations for employed workers.

2.3.1 Lenders

There is a continuum of potential lenders who are risk neutral and can obtain funds without constraint at the risk free rate r_f. Lenders discount their stream of future profits at rate $\beta_{lf} \in (0, 1)$. Lenders offer credit contracts which specify a borrowing limit $\underline{b} < 0$ and an interest rate r. Let $\Pi^U_{i,t}(\vec{x})$ denote the profits to a lender of being matched with a type i, age t, unemployed individual where an individual's state is given by $\vec{x} = (b, \vec{h}; \underline{b}, r)$.[21] Let $b'_{i,t}(\vec{x})$ and $\hat{D}^{N,U}_{i,t+1}(\vec{x}')$ denote the asset and default policy functions of the individual. The profits to the lender of offering a contract with borrowing limit $\underline{b}$, and interest rate r are given by,

$$\begin{aligned} \Pi^U_{i,t}(b, \vec{h}; \underline{b}, r) = \beta_{lf} b'_{i,t}(\vec{x}) \left(\frac{(r_f - r)}{1 + r} + \mathbb{E}\left[\delta_C \hat{D}^{N,U}_{i,t+1}(\vec{x}') + (1 - \delta_C)\hat{D}^{C,U}_{i,t+1}(\vec{x}')\right]\right) \times \mathbb{I}\{b'_{i,t}(\vec{x}) < 0\} \\ + \beta_{lf}(1 - \delta_C)\mathbb{E}\left[\left(1 - \hat{D}^{C,U}_{i,t+1}(\vec{x}')\right) \hat{\Pi}^U_{i,t+1}(\vec{x}')\right] \end{aligned} \tag{2.8}$$

At the end of the period an age t agent makes their savings decision, $b'_{i,t}(\vec{x})$. If the individual is borrowing, $b'_{i,t}(\vec{x}) < 0$, then in the next period the lender earns the spread between the interest rate r and the risk free rate r_f. However, the lender faces default risk on the

[21] For employed individuals the state is $\vec{x} = (\omega, b, \vec{h}; \underline{b}, r)$, and lender profits are defined analogously in Appendix B.3.2. Let $\vec{x}'$ denote the state space of the individual in the next period.

outstanding loan $b'_{i,t}(\vec{x})$. The default risk faced by the lender incorporates the probability of the credit separation shock, as well as shocks to human capital and the individual's job search decision. The default probability of the agent who receives the credit separation shock is denoted $\hat{D}^{N,U}_{i,t+1}(\vec{x}')$, and is given by:[22]

$$\hat{D}^{N,U}_{i,t+1}(\vec{x}') = p\left(\theta_{t+1}(\hat{\omega}, \vec{h}')\right) D^{N,W}_{i,t+1}(\hat{\omega}, b', \vec{h}'; \underline{b}, r) + \left(1 - p\left(\theta_{t+1}(\hat{\omega}, \vec{h}')\right)\right) D^{N,U}_{i,t+1}(b', \vec{h}'; \underline{b}, r) \tag{2.9}$$

where $\hat{\omega}$ is the unemployed worker's choice of where to search for a job.[23] If the agent does not default and the credit match is not hit by the credit separation shock, then the match between the lender and borrower continues to the next period. The profits to the lender in the next period are denoted by $\hat{\Pi}^{U}_{i,t+1}(\vec{x}')$ and take into account the agent's choice of where to search for a job. The continuation profits to the lender are

$$\hat{\Pi}^{U}_{i,t+1}(\vec{x}') = p\left(\theta_{t+1}(\hat{\omega}, \vec{h}')\right) \Pi^{W}_{i,t+1}(\hat{\omega}, b', \vec{h}'; \underline{b}, r) + \left(1 - p\left(\theta_{t+1}(\hat{\omega}, \vec{h}')\right)\right) \Pi^{U}_{i,t+1}(b', \vec{h}'; \underline{b}, r)$$

Free entry determines the number of lenders who enter each submarket in equilibrium. The free entry condition is

$$\kappa_C \geq p^c_f\left(\theta^{c,U}_{i,t}(b, \vec{h}; \underline{b}, r)\right) \Pi^{U}_{i,t}(b, \vec{h}; \underline{b}, r) \tag{2.10}$$

The free entry condition binds for all submarkets such that $\theta^{c,U}_{i,t}(b, \vec{h}; \underline{b}, r) > 0$. Note that individuals who are searching for credit contracts are not currently able to borrow, $b \geq 0$. Lenders in a match with an employed individual face a similar problem, but their continuation value must take into account the probability that the individual becomes unemployed. Appendix B.3.2 contains the Bellman equation for a lender in a match with an employed worker.

2.3.2 Firms

Firms are assumed to have access to a linear production technology, and to have an exogenous job destruction rate δ. Firms have the same discount factor β_{lf} as lenders. The continuation value of a firm that has committed to pay piece rate ω to their age t employee

[22] The default probability when the agent is not hit by the credit separation shock is denoted $\hat{D}^{C,U}_{i,t+1}(\vec{x})$. It follows the same structure as equation (2.9), but with the policy functions for default when the agent is not hit by the credit separation shock, $D^{C,W}_{i,t+1}$ and $D^{C,U}_{i,t+1}$.

[23] Note the choice of where to search for a job is a function of state variables which are suppressed for convenience.

with human capital $\vec{h}$ is

$$J_t(\omega,\vec{h}) = (1-\omega)f(\vec{h}) + \beta_{lf}\mathbb{E}\left[(1-\delta)J_{t+1}(\omega,\vec{h}^{'})\right] \quad \forall t \leq T$$
$$J_{T+1}(\omega,\vec{h}) = 0$$

subject to the law of motion for human capital for employed individuals,

$$\vec{h}^{'} = H(\vec{h}, W)$$

Firms must pay cost κ to post a vacancy. A vacancy specifies a wage piece rate ω, as well as a human capital requirement $\vec{h}$, and age t. Free-entry requires that:

$$\kappa \geq p_f\left(\theta_t(\omega,\vec{h})\right) J_t(\omega,\vec{h}) \tag{2.11}$$

The free entry condition binds for all submarkets such that $\theta_t(\omega,\vec{h}) > 0$.

2.3.3 Government

The government determines the level of transfers to the unemployed, i.e. public insurance. We assume the government must maintain budget balance in every period.
All unemployed individuals receive public transfers z. Public transfers are paid for by a proportional labor income tax, τ, which is levied on all employed individuals to satisfy

$$z\sum_{(i,t)}\sum_{\vec{x}} \hat{u}_{i,t}(\vec{x}) = \sum_{(i,t)}\sum_{\vec{x}} \tau\left(\omega f(h)\hat{e}_{i,t}(\vec{x})\right) \tag{2.12}$$

where $\hat{u}_{i,t}(\vec{x})$ is the share of individuals with state $\vec{x}$ that are type i and age t who are unemployed, and $\hat{e}_{i,t}(\vec{x}) = 1 - \hat{u}_{i,t}(\vec{x})$ is the share who are employed.[24]

2.3.4 Equilibrium

In equilibrium, individual decision rules are optimal, free entry holds in both the credit and labor market, the government balances its budget, and the distribution of individuals across states is consistent with the decision rules. The formal definition of equilibrium is given in Appendix B.4.
In Appendix B.4, we prove that if the government budget constraint is ignored and τ is exogenously given, then the model is *Block Recursive* (e.g. Menzio and Shi (2011)). Given

[24]There is a slight abuse of notation where $\vec{x} = (b, \vec{h}; \underline{b}, r)$ for the unemployed and $\vec{x} = (\omega, b, \vec{h}; \underline{b}, r)$ for the employed.

an exogenous τ, Block Recursivity means that the individual, lender, and firm problems can be solved independently of the distribution of individuals across states.

The equilibrium tax rate that balances the government budget constraint will ultimately depend on the distribution of individuals across states and, in the case of transition dynamics, the path of tax rates will also depend on the path of the distribution of individuals across states. However, the fact that equilibrium prices and the distribution of individuals across states are only linked by τ greatly simplifies our computation of the transition path.

2.4 Calibration

Due to the computationally demanding nature of the model, our calibration strategy is to assign values from the literature to standard parameters wherever possible and then estimate the remaining non-standard parameters to match moments from the data.[25] We estimate our steady state to match moments from 1995 to 2007, although several of our moments are only available at different points in time.

The period is one quarter. We set the annualized risk free rate to 4%, and the corresponding quarterly discount factor for firms and lenders is $\beta_{lf} = 0.99$. The low worker type (who generates *low* profits to the lender) also discounts the future at the same rate, $\beta_L = 0.99$. We estimate the discount factor of the high type (who generates high profits for the lender), $\beta_H = .632$, to match the 95th percentile of the real credit card interest rate distribution. We measure the 95th percentile of real credit card interest rates to be 19.03% in the SCF between 1995 and 2007.[26]

We calibrate the fraction of individuals that are high types, denoted $\pi_H = 1 - \pi_L = .096$, to target the fact that 31.38% of individuals report having a ratio of net liquid assets to annual gross income that is less than 1 percent in the SCF between 1995 and 2007. This measure allows us to capture the large mass of individuals at, or marginally above, zero net liquid assets.[27]

In terms of labor market variables, we set the job destruction rate to a constant 10% per quarter, $\delta = 0.1$ (Shimer (2005)). For the labor market matching function, we use a constant returns to scale matching function that yields well-defined job finding probabilities:

$$M(u, v) = \frac{u \cdot v}{(u^\zeta + v^\zeta)^{1/\zeta}} \in [0, 1)$$

The matching elasticity parameter is chosen to be $\zeta = 1.6$ as measured in Schaal (2012).

[25] Appendix B.5 describes our solution algorithm in detail.

[26] Interest rates are made real by subtracting the CPI inflation rate in a given year.

[27] As in Herkenhoff et al. (2015), for each individual we sum cash, checking, money market funds, CDs, corporate bonds, government savings bonds, stocks, and mutual funds less credit card debt over annual gross income.

The labor vacancy posting cost $\kappa = .995$ is estimated to target an unemployment rate of 5.0%, which is the average reported by the Bureau of Labor Statistics from 1995 to 2007.
Human capital evolves following a Markov chain with a persistent and transitory component. Let $\vec{h} = (\tilde{h}, \epsilon)$, denote the human capital of an agent, where $\tilde{h}$ denotes the individual's persistent human capital, and ϵ denotes the transitory component. We assume the production function is linear and additive in the human capital of the worker, $f(\vec{h}) = \tilde{h} + \epsilon$. The process for the persistent component of human capital is governed by two parameters $p_{\tilde{h},L}$ and $p_{\tilde{h},H}$.

$$H_P(\vec{h}, U) = \tilde{h}' = \begin{cases} \tilde{h} - \Delta & \text{w/ pr. } p_{\tilde{h},L} \text{ if unemployed} \\ \tilde{h} & \text{w/ pr. } 1 - p_{\tilde{h},L} \text{ if unemployed} \end{cases}$$

$$H_P(\vec{h}, W) = \tilde{h}' = \begin{cases} \tilde{h} + \Delta & \text{w/ pr. } p_{\tilde{h},H} \text{ if employed} \\ \tilde{h} & \text{w/ pr. } 1 - p_{\tilde{h},H} \text{ if employed} \end{cases}$$

The grid for the persistent component of human capital $\tilde{h} \in [0.6,\ 0.7,\ 0.8,\ 0.9,\ 1,\ 1.1,\ 1.2]$ as well as the step size $\Delta = 0.1$ between grid points are taken as given. To estimate the probability that the persistent component of a worker's human capital increases while employed $p_{\tilde{h},H} = 0.083$, we target the semi-elasticity of earnings with respect to age using the 1995 to 2007 Current Population Surveys.[28] To estimate the probability that a worker's productivity decreases while unemployed $p_{\tilde{h},L} = 0.651$, we target the 6.9% decline in earnings 5 years following job loss as measured in Section 2.2.3. The rapid pace at which workers lose the persistent component of their human capital tends to dampen the importance of credit for self-insurance. Smaller values of $p_{\tilde{h},L}$ considered in earlier drafts of this paper resulted in greater substitutability between credit and public insurance.
The process for the transitory component of human capital is governed by the parameters $p_{\epsilon,L}$ and and $p_{\epsilon,H}$:

$$H_T(\tilde{h}', W) = \epsilon' = \begin{cases} \Delta_\epsilon(\tilde{h}') & \text{w/ pr. } p_{\epsilon,H} \\ 0 & \text{w/ pr. } 1 - p_{\epsilon,L} - p_{\epsilon,H} \\ -\Delta_\epsilon(\tilde{h}') & \text{w/ pr. } p_{\epsilon,L} \end{cases} \tag{2.13}$$

[28]We estimate the earnings gain associated with an increase in age using the following regression of age on earnings on a cross-section of individuals in period t: $ln(Y_{i,t}) = \alpha + \beta_{age} Age_{i,t} + \varepsilon_{i,t}$,where $Y_{i,t}$ denotes the earnings of individual i in year t, and $Age_{i,t}$ denotes the age of individual i in year t. The coefficient β_{age} estimates the average increase in log earnings associated with an increase in age. Using data from the CPS for the years 1995-2007 among full-time workers between the ages of 25 and 54, we estimate a relative gain in earnings with a 1-year increase in age of 0.93%. We additionally include educational attainment dummies, as well as industry and year dummies in the estimation.

The step size $\Delta_\epsilon(\tilde{h}^{'}) = 0.095\tilde{h}^{'}$ is taken as given, and we estimate the parameters $p_{\epsilon,H} = 0.252$ and $p_{\epsilon,L} = 0.111$ to target the share of employed workers who experience a 9.5% wage increase and decrease over a given year, respectively, as reported in Kurmann and McEntarfer (2017).[29] Given the processes for the transitory and persistent components of human capital, the evolution of human capital proceeds as:

$$
\begin{aligned}
H(\vec{h}, W) &= (H_P(\vec{h}, W), H_T(H_P(\vec{h}, W), W)) \\
H(\vec{h}, U) &= (H_P(\vec{h}, U), 0)
\end{aligned}
$$

The public transfer to unemployed workers $z = .327$ is estimated to match the 41.2% public transfer replacement rate (change in public transfers divided by change in annual income) among laid-off workers observed in the PSID between 2001 and 2013.[30] We focus on the change in transfers around job loss rather than the level of transfers to focus on the transfers that are received upon job loss.

The value of home production $g = 0.146$ is calibrated to target the decline in consumption associated with job loss. Using the PSID, we estimate that, on average, individuals who experience at least 1-quarter of unemployment have annual consumption that is 93.8% of their consumption level prior to layoff.[31]

In terms of credit market variables, we set the quarterly exogenous credit separation rate to 2.6% per quarter, $\delta_C = 0.026$, based on Fulford (2015). For the credit market matching function, we again use a constant returns to scale matching function that yields well-defined credit finding probabilities:

$$
M_C(u_C, v_C) = \frac{u_C \cdot v_C}{(u_C^{\zeta_C} + v_C^{\zeta_C})^{1/\zeta_C}} \in [0, 1)
$$

[29] Kurmann and McEntarfer (2017) report that between 2009 and 2010, 7.65% of job stayers (individuals who report being at the same establishment (SEIN) for 10 consecutive quarters) experienced a wage decline of at least 9.5% during that year. They report 19% of job stayers experienced a wage increase of 9.5% or higher during that year.

[30] Our measure of income from the PSID is household income less transfers, which is the sum across household members of (1) wage and salary income; (2) business income; and (3) interest dividend income. Transfers are also measured at the household level. We measure the public transfer replacement rate (change in transfers over the change in household income less transfers), for households where either the head of household or spouse has an involuntary unemployment spell with a duration of greater than 1 quarter. We additionally require an income decline of at least $1k, and we winsorize the replacement rate at the 1% level. We focus on involuntary layoffs to avoid unemployment spells due to quits, and as involuntary layoffs are more consistent with the notion of a layoff in the model. We similarly use individuals with an unemployment duration of at least three months given the quarterly timing of the model where unemployed individuals are out of work for at least a full quarter. Using the SIPP, Rothstein and Valletta (2017) estimate a replacement rate (changes in transfers over changes in earnings) of 43.6%.

[31] In the PSID, we measure the change in family consumption across survey waves for families where the head of household had an involuntary unemployment spell with a duration of at least one quarter between 2005 and 2013. Additionally, we require that the household have at least $5k of consumption both before and after layoff, and that the head of household was employed in the prior wave of the PSID. We winsorize the change in consumption among this sample at the 5% level.

The matching elasticity parameter is chosen to be $\zeta_C = 0.37$ as measured in Herkenhoff (2013).

There is an exogenously given grid of interest rates for credit contracts over the interval $[\underline{r}, \bar{r}]$. We set the minimum annual interest rate ($\underline{r}$) to be 10.5%, which comes from taking the sum of average interest charges and total fees as reported in Agarwal et al. (2014) for individuals with FICO scores greater than 800. We set the maximum interest rate ($\bar{r}$) to be 22.5%, which is the 99th percentile of the real credit card interest rate distribution in the SCF from 1995 to 2007.

Credit contracts also specify a borrowing limit which must lie in the interval $[\underline{B}, 0)$, where $\underline{B} < 0$ is the minimum value of the asset grid. We estimate $\underline{B} = -1.149$, so that the average unused credit (credit limit less outstanding balance) to income ratio is 23.5% as measured in the SCF from 1995 to 2007.[32] The credit posting cost $\kappa_C = 2.214 \times 10^{-5}$ is estimated so that the credit finding rate in the model matches the new-borrower credit approval rate of 65.0%, which can only be measured in the 2007 to 2009 SCF panel. The utility cost of searching for a credit contract $\kappa_S = 1.272 \times 10^{-4}$ is calibrated to match the fact that 69.8% of the population has credit access in the SCF from 1995 to 2007.

A worker's life span is set to $T = 120$ quarters (30 years). Newly born individuals enter as unemployed workers, with zero assets and without a credit contract. Their initial persistent human capital is drawn from an exponential distribution with parameter λ_H. We calibrate the parameter λ_H to match the P75-P25 earnings ratio of young workers (workers between 25 and 29), which we measure as $\frac{\tilde{earnings}_{p75} - \tilde{earnings}_{p25}}{earnings_{avg}}$, where $\tilde{earnings}_j$ is the jth percentile of residualized earnings.[33] Using the CPS from 1995 to 2007 we measure the P75-P25 earnings ratio among workers age 25 to 29 to be 0.4843. Individual preferences over non-durable consumption are given by:

$$u(c) = \frac{c^{1-\sigma} - 1}{1 - \sigma}$$

We set the risk aversion parameter to a standard value, $\sigma = 2$. The utility penalty of default is assumed to be linear in the amount of assets defaulted upon:

$$\psi_D(b) = -b \cdot \psi$$

We set the default penalty $\psi = 14.771$ to match the bankruptcy rate in the U.S. from 1998-2007 of 0.145% per quarter.[34]

[32] Using the SCF from 1995-2007, we estimate an unused credit to income ratio of 23%.

[33] We residualize earnings by removing year and industry fixed effects, and controlling for the years of education.

[34] This is computed using the SCF from 1998 (the date they first record bankruptcies) to 2007. We measure that 0.58% of individuals with a credit card report having filed for bankruptcy within the past

Table 2.6 contains a summary of the model parameters, and Table 3.2 displays the calibrated parameters and their calibration targets. The estimated model matches the targeted moments very well. We discuss non-targeted moments in the next section.

2.4.1 Model Estimated Borrowing and Default Responses to Job Loss

In this section, we compare the model estimated borrowing and default responses of displaced workers to the data. These moments were not targeted in the calibration.

To measure the average effect of job loss on credit access and usage, we estimate the distributed lag regression model of equation (2.1) on model simulated data. We impose the same sampling requirements in the simulation as in the data. In particular, we require individuals to have 3 years of tenure at a firm in order to be in either the treatment or control samples.

Figure 2.6 plots the estimated coefficients. To facilitate the comparison between model estimates and the data, we normalize reported coefficients by pre-displacement earnings. Panel (a) presents the difference in earnings between displaced and non-displaced individuals from the model simulation. Similar to the data, displaced individuals' earnings drop by approximately 30%, on average. The shorter term recovery of earnings is quicker in the model than in the data; however, the losses 5 years after layoff are closer to the data since they are targeted in our calibration.

Despite the large and persistent decline in earnings, Panel (b) shows that borrowing limits are largely unaffected by job loss. Individuals take out credit lines prior to job loss and thus borrowing limits are unresponsive to job loss, similar to the data. The change in credit limits is effectively zero in the model. In the data, credit limits fall in years 1 and 2, but are insignificantly different from zero elsewhere. This stands in contrast to models which have one period debt, e.g. Herkenhoff (2013) and Athreya et al. (2009).

Borrowing follows a similar pattern. Panel (c) reveals that debt is largely unresponsive to job loss in both the model and data. Borrowing increases marginally in the model. In the data, borrowing is indistinguishable from zero in all years.

Panel (d) examines the propensity of individuals to default in the model following job loss. When we compare the model to the data, we consider default to be any derogatory public flag which includes bankruptcy, foreclosure, tax liens and other debt discharges. While our model's concept of default is Chapter 7 bankruptcy, these derogatory public flags (including bankruptcy) are typically correlated and result in the same end-result of debt discharge. These are rare events in the data, and so we use public derogatory flags in the data to maximize power. Between the year before layoff (t=-1) and the year after layoff (t=1),

year.

the default rate rises by .261% in the model and by .639% in the data. Thus, the model accounts for nearly 41% (=.261/.639) of the rise in defaults following job loss.

Lastly, Figure 2.7 shows the model's heterogeneous response of borrowing and default to job loss. We plot the model's distribution of credit replacement rates following job loss versus the distribution of credit replacement rates in the 2007 to 2009 SCF panel (the change in debt can only be measured in the panel years). The model is able to partially replicate the distribution of replacement rates observed in the data. The model produces too little deleveraging, but it successfully captures the large mass at zero and a significant fraction of borrowing.

The relatively weak deleveraging response is driven by too little net and gross borrowing among the employed, which is a common problem in consumer credit models (e.g. Herkenhoff (2013)). Upon job loss, too few individuals have debts which limits how many job losers default or pay down existing debt. Our framework partially addresses this issue by allowing human capital and wages to grow over the lifecycle, generating a role for borrowing among young, employed workers. In our baseline calibration 6.2% of job losers delever after job loss, whereas in the SCF data, 24% of job losers delever over the same period.[35] Therefore our model captures roughly 25% of observed delevering among job losers.

Overall, we view Figures 2.6 and 2.7 as evidence that the model generates similar unemployed borrowing and default patterns as the data. We view the model's ability to reproduce unresponsive borrowing among job losers, despite featuring strong precautionary motives and rising defaults, as providing validation of the model.

2.5 Optimal Public Insurance to the Unemployed

In this section, we compute optimal public transfers to the unemployed under various levels of credit access. Our benchmark U.S. economy features a transfer to the unemployed that replaces 41.2% of lost earnings on average. We first compute optimal transfers in steady state. When assessing optimality in steady-state, we use a utilitarian welfare criterion, which is an equally weighted average of newly born individuals' consumption-equivalent gains of moving to the new policy.[36] We find that the optimal replacement rate of public insurance is 38.3%.

Second, we compute the general equilibrium transition path from current U.S. policy to

[35] In the SCF, we identify an individual to be unemployed in a given wave if they are either unemployed at the time of the survey or have had an unemployment spell of longer than 4 weeks within the past year. We measure the replacement rate and share of individuals deleveraging among household heads and their spouses who were not identified as unemployed in the 2007 wave, but were identified as unemployed in the 2009 wave and had an earnings loss between the 2007 and 2009 waves.

[36] See Appendix B.6 for details on the estimation of the share of lifetime consumption an individual would be willing to give up to move across economies.

the new optimum. When assessing welfare along the transition path, we compute the consumption-equivalent gains of all individuals alive at the time of the policy reform.[37] We find that there are small positive welfare gains along the transition path when the replacement rate of public insurance is lowered from 41.2% to 38.3%.

2.5.1 Optimal Policy in Steady State

We first compute optimal transfers to the unemployed in steady state. We do so by comparing utilitarian welfare across steady states of the model with differing levels of public transfers, z. As we have done throughout the paper, instead of reporting z, we report the replacement rate of public transfers which is the average fraction of lost earnings replaced by a given level of z. Table 2.8 summarizes our findings. Column (1) replicates the baseline U.S. calibration in which 41.2% of lost earnings is replaced by the government, 19.6% of individuals borrow, the default rate is .142% per quarter, and annual consumption falls by 6.0% for individuals who have an unemployment spell.

Column (2) reports the optimal replacement rate in the baseline U.S. calibration, where all parameters except for z are held fixed at their values in Table 2.6. Welfare is maximized when the public insurance transfer, z, replaces 38.3% of lost earnings. The fraction of individuals who borrow increases to 20.4%, and annual consumption falls by 6.1% for individuals who have an unemployment spell, which are both marginally greater than in the baseline calibration. With a weaker safety net, workers now find jobs faster, and the unemployment rate declines by .5%. Although our environment does not feature search effort, the model still features moral hazard because of directed search. With lower public transfers, individuals direct their search into submarkets where they find jobs more quickly. At a moderately lower public insurance replacement rate of 38.3%, the default rate declines. In our framework, the cost of default is preclusion from future credit access. In an economy with a marginally weaker safety net, individuals value future credit access more. Therefore, they are less likely to default and the quarterly default rate declines to .135%. Importantly for our exercise, the default rate is non-monotonic in the replacement rate of public transfers. We will illustrate this property of the default rate in the next section.

On average, individuals are willing to give up 0.129% of lifetime consumption to be born in an economy with a 38.3% replacement rate as opposed to our baseline economy with a 41.2% replacement rate. Figure 2.8 graphically illustrates steady-state utilitarian welfare for various replacement rates. Welfare is single peaked with respect to the replacement rate. Lowering the replacement rate too much generates significant welfare losses. We discuss the mechanisms behind this result in the next section.

[37] See Appendix B.6.2 for details on the estimation of welfare along the transition path.

We now counterfactually shut down credit markets (i.e. no borrowing, $\underline{\mathcal{B}} = \{0\}$ and thus $\underline{b} = 0$ for all contracts) and redo our optimal steady-state policy analysis. This exercise allows us to study how optimal policy interacts with the presence of a well-developed credit market. Column (3) of Table 2.8 reports our results. The optimal replacement rate increases to 43.2% when credit markets are shut down. This replacement rate exceeds the current U.S. replacement rate of 41.2%.

Without credit, there is limited private self-insurance for low asset individuals. A consequence is that the government can partially complete the market by raising the public insurance replacement rate from 41.2% to 43.2%. Because of moral hazard, however, when the safety net expands, the unemployment rate increases by .1%. The relatively weak moral hazard effects from expanding the safety net are in line with existing quantitative and empirical exercises (e.g. see Nakajima (2012a) for a recent summary). To cover the cost of the expanded safety net, the equilibrium labor tax rate increases by .15%.[38]

Public insurance replacement rates can only be cut by 4.9 percentage points (=43.2-38.3) as we move from a steady state in which 0% of individuals have access to credit (Column (3) of Table 2.8) to a steady state in which 70.5% of individuals have access to credit (Column (2) of Table 2.8). Therefore our steady state results suggest a limited scope for substitution between public and private insurance. In what follows, we explore which features of the environment generate this lack of substitutability.

2.5.2 What limits the substitutability of public and private insurance?

Despite extremely well developed credit markets in the U.S., Column (2) of Table 2.8 reveals that it is only optimal to moderately cut public insurance. What limits further substitution out of public insurance and into borrowing? When public insurance is cut, there are two effects. First, those who enter unemployment with zero assets have a much weaker safety net and borrow more, ceteris paribus. This is what we refer to as *micro substitutability* between public insurance and borrowing. Second, in general equilibrium, individuals save more in order to avoid entering unemployment with zero assets. Fewer job losers borrow, and this is what we refer to as *macro complementarity* between public insurance and borrowing.

We measure the micro substitutability between public insurance and credit by analyzing the borrowing patterns of unemployed individuals with zero net worth. By conditioning on zero net worth, we are able to measure how borrowing responds to public insurance separately from precautionary shifts in the wealth distribution. Let $\bar{b}'_0$ denote the asset choice of a typical unemployed individual with zero net worth. Panel (A) of Figure 2.9

[38]We find that the effects of taxation are close to linear in our framework. In results available upon request, we endow the government with necessary spending level G in order to generate reasonable initial labor income tax levels. We find very similar results to what is reported in the text.

plots $\bar{b}'_0$ as a function of the public insurance replacement rate. As the government replaces less income with public insurance, individuals with zero net worth monotonically borrow more ($\bar{b}'_0$ becomes more negative). With a weaker safety net, individuals with zero net worth optimally replace a greater share of their lost income through borrowing. Therefore, we call public insurance and credit *micro substitutes*. This property holds globally.

At the center of the optimal public insurance decision is the endogenous cost of credit. Panel (B) of Figure 2.9 plots the default rate, which is the key determinant of the cost of credit. The relationship between public insurance and the default rate is non-monotonic. First, consider the region with public insurance replacement rates greater than 38%. In this region, the default rate rises when the public insurance replacement rate *increases* from 38% to 42%. To understand why this is the case, consider the default punishment. Households borrow to smooth consumption, and if they do not repay, they are excluded from future credit markets for a stochastic period of time. Exclusion from credit markets is significantly less costly when the safety net expands, and therefore the default rate rises when transfers increase.

Now consider the region with public insurance replacement rates less than 38%. In this region, the default rate rises when the public insurance replacement rate *decreases* from 38% to 28%. With a smaller safety net, smaller income shocks trigger default. Consequently, default rates rise in this region.

Panel (C) of Figure 2.9 plots the interest rate, and Panel (D) of Figure 2.9 plots the credit finding rate. Profit maximizing lenders understand the relationship between the default rate and the safety net.[39] In an environment with higher overall default rates, they adjust their behavior accordingly by providing credit offers (v_C) in submarkets with higher interest rates as well as reducing the number of credit offers. The individual credit finding rate falls, and the cost of credit, conditional on obtaining credit, rises. Panel (C) illustrates that the interest rate follows the same non-monotonic pattern as the default rate. Panel (D) illustrates that the individual credit finding rate declines when public insurance replacement rates fall beyond 38%. The higher interest rate and lower credit finding rate both represent an increasing cost to credit as public transfers are cut.

We now turn to the macro complementarity of public transfers and credit. We measure the macro complementarity between public insurance and credit by analyzing the fraction of individuals who borrow. When public insurance is cut, individuals save more in order to avoid large consumption losses following an income shock. The fraction of individuals who borrow summarizes how strong these general equilibrium precautionary motives are.

Panel (E) of Figure 2.9 plots the fraction of individuals borrowing as a function of the public

[39]The negative relationship between defaults and UI replacement rates, whether internalized by lenders or not, is quite strong in the data, e.g. Hsu et al. (2014).

insurance replacement rate. At high levels of public insurance which replace more than 36.9% of lost earnings, public insurance and credit are aggregate substitutes. Increasing the replacement rate from 38% to 42% lowers the fraction of individuals who borrow. However, at low levels of public insurance which replace less than 36.9% of lost earnings, the fraction of individuals who borrow declines as replacement rates are cut. The size of the credit market begins to contract for further cuts to public insurance. Therefore, for low levels of public insurance, we call credit and public insurance *macro complements*. The macro complementarity between credit and public insurance at low levels of replacement rates is ultimately what prevents the government from substituting further out of public insurance and into credit.

Two key drivers of the macro complementarity are precautionary credit line accumulation and precautionary savings. Panel (F) of Figure 2.9 plots the unused credit limit to income ratio which rises monotonically as benefits are cut. Despite a falling fraction of borrowers, individuals' precautionary motives dominate, and more individuals pay the utility cost of applying for credit. Since so many more individuals apply for credit, the fraction of individuals with credit access rises despite the lower credit finding rate. As a consequence, aggregate unused credit limits rise.

In terms of precautionary saving, Panel (G) of Figure 2.9 plots the top and bottom deciles of the wealth distribution. A result of lower replacement rates is rising wealth dispersion. Conditional on borrowing, individuals must borrow more since there is a weaker safety net. The 10th percentile of the wealth distribution falls. On the other hand, employed individuals now save more in order to avoid borrowing at higher rates. The 90th percentile of the wealth distribution rises. The net effect is significantly more wealth dispersion as the safety net is weakened.

Ultimately, the overall substitutability between public insurance and credit is quite low and the consumption of job losers declines as the replacement rate is cut. Panel (H) of Figure 2.9 plots the year-over-year consumption loss of individuals who are displaced. Even thought there is increased saving, the rising cost of credit and lower credit approval rate imply larger consumption losses upon layoff as transfers are cut.

What Panels (A) through (H) of Figure 2.9 establish is that despite micro substitutability between credit and public insurance, public insurance and credit are macro complements at low levels of public insurance replacement rates. This limits the government's willingness to substitute out of public insurance and into private borrowing. A consequence is that moderate amounts of public insurance are necessary to keep the costs of borrowing low.

Distribution of gains and losses. While the policy of decreasing the replacement rate of public insurance from 41.2% to 38.3% raises welfare on average, it is not Pareto-improving. Figure 2.10 presents the welfare change of moving from a 41.2% to 38.3% replacement rate by the persistent component of an individual's initial human capital. The majority of individuals with the lowest initial level of human capital have a welfare loss when public insurance is cut. On the other hand, the majority of individuals with the highest initial level of human capital have a welfare gain when public insurance is cut. In our framework, human capital and assets are highly correlated. Low asset, low human capital individuals must increasingly rely on more costly debt when public insurance is cut, and thus they have welfare losses from the policy change.

2.5.3 Transition Path

In this section, we compute welfare gains along the transition path when public insurance replacement rates are cut from current U.S. levels of 41.2% to 38.3%. We measure welfare along the transition path for all individuals alive at the time of the policy reform.[40]

To conduct the experiment, we start from the steady state of the baseline economy. We simulate an unexpected decline in the generosity of the public insurance to the unemployed, where the replacement rate is lowered to 38.3%. After the initial unexpected decline, individuals in the economy have rational expectations that the lower replacement rate is permanent. What makes the transition experiment tractable is the fact that our model is Block Recursive conditional on τ (see Section 2.3.4 and Appendix B.4). We allow the labor income tax rate, τ, to adjust non-linearly during the transition to the new steady state. See Appendix B.7 for computational details of the transition path experiment.

Panel (A) of Figure 2.11 illustrates the path of the public insurance replacement rate. We let $t = 0$ correspond to the year in which public insurance is cut from 41.2% to 38.3%. Panel (B) of Figure 2.11 illustrates the path of the labor income tax, τ, which is levied on employed individuals to fund the public transfer. The tax rate declines by .27% in the first year after the policy change, and then marginally declines thereafter to the new steady state.

Panel (C) of Figure 2.11 plots the fraction of individuals borrowing. Since the initial U.S. steady state prior to date $t = 0$ features a high public insurance transfer, when benefits are cut, the fraction of individuals borrowing increases by roughly 1 percentage point. As Panel (E) of Figure 2.9 made clear, the government cuts transfers up until the point where fraction of individuals borrowing reaches it maximum. Further cuts to public insurance would reduce borrowing.

Panel (D) of Figure 2.11 illustrates that the unemployment rate declines along the transition path with a weaker safety-net. What drives the decline in unemployment is that individuals direct their search toward submarkets with greater job finding rates since they are less able

[40] See Appendix B.6.2 for details on the estimation of welfare effects in the transition experiment.

to smooth consumption through either public or private means. Even though our framework features wealth accumulation, our model produces very fast transition dynamics, which is common in linear-utility Diamond-Mortensen-Pissarides models as well as frameworks that incorporate risk aversion (Krusell et al. (2010)).

We find that the average individual who is alive at the time that the transition occurs has a 0.05% consumption equivalent gain. Figure 2.12 plots the fraction of individuals, alive at the time of the reform, who have welfare gains along the transition path. We stratify the welfare gains by the persistent component of human capital at the time of the policy change. The figure shows that at higher (lower) levels of persistent human capital, approximately 80% (65%) of individuals have a welfare gain from the policy change. In summary, at all levels of persistent human capital, the majority of individuals experience a welfare gain as the economy transitions from the current 41.2% replacement rate to a 38.3% replacement rate.

2.6 Conclusions

In this paper we ask two questions: Can the unemployed borrow? What does the presence of a well-developed credit market imply for optimal public insurance to the unemployed?

To answer the first question, we built a new dataset which links employment records to TransUnion credit reports. Our empirical contribution is to show that workers who lose their jobs maintain access to credit and that unconstrained workers who lose their jobs borrow, while constrained workers who lose their jobs default and delever. We reconcile previous studies by showing that displaced workers do not borrow on average, but roughly 1/3 of displaced workers default and delever, and roughly 1/3 of displaced workers borrow more. Thus credit markets are important for both sets of workers in their borrowing and consumption decisions.

To answer the second question, we develop a new framework that integrates credit lines (e.g. Mateos-Planas and Ros-Rull (2010)) into a competitive labor search model with employment risk (e.g. Moen (1997), Burdett et al. (2001), and Menzio and Shi (2011)). Our quantitative contribution is to measure the optimal degree of public insurance in an economy that features current levels of U.S. credit access, and matches the responsiveness of credit access following job loss.

We validate our model using our new micro facts, and we find that the optimal provision of public insurance is unambiguously lower as credit access expands. In our benchmark economy, the utilitarian government would prefer to have the income replacement rate from public unemployment insurance lowered from the current US policy of 41.2% to 38.3%. We find this policy change would generate welfare gains both in the new steady state as well as along the transition path.

We then use the framework to explore the factors that limit the ability to further substitute out of public insurance and into private borrowing. We find that for low levels of public insurance, there is a strong *macro-complementarity* between credit markets and public insurance: credit markets and public insurance comove positively. Cutting public insurance too much increases the cost of credit and individuals precautionarily save. Consumption losses upon layoff increase and individuals are strictly worse off. Individuals default more and thus, in anticipation of default, lenders increase interest rates and provide fewer credit offers. Despite reputation concerns and significant expansions of long-term credit, the U.S. government is quite close to the optimal public insurance replacement rate.

Beyond the contributions made in this paper, this paper documents basic facts regarding job loss, default, and borrowing. These new facts can also be used to calibrate or examine policy relevant mechanisms in incomplete-market frameworks. Moreover, the long-term credit model developed in this paper is extremely flexible and allows us to better characterize the interaction between credit and income. In concurrent work, we are using credit bureau data and modifying the model framework to (i) identify permanent and transitory income processes (Braxton et al. (2019)), and (ii) study the impact of credit access on earnings mobility (in progress).

Tables and Figures

Table 2.1: Summary Statistics

(A) Panel Sample (Year Prior to Mass Layoff)		
	(1) Treatment	(2) Control
Annual Earnings	$44,230	$49,260
Credit Score	427	437
Age	40.6	41.3
Revolving Credit Balance	$10,680	$11,200
Revolving Credit Limit	$26,910	$28,580
Unused Revolving Credit to Income	0.44	0.41
Observations (Rounded to 000s)	31000	30000

(B) Cross Sectional Sample (Year Prior to Mass Layoff)	
	Avg. Unused Revolving Debt to Income
Credit Score Quintile 1	0.06
Credit Score Quintile 2	0.12
Credit Score Quintile 3	0.27
Credit Score Quintile 4	0.58
Credit Score Quintile 5	1.04

Note: Sample selection criteria in Section 2.2.2. Annual earnings, revolving credit balance and revolving credit limit are in 2008 dollars. Credit score refers to the TransUnion bankruptcy score. Unused revolving credit to income is winsorized at the 1-percent level at the top and bottom of the distribution.

Table 2.2: Average Response of Earnings and Credit Variables to Displacement

	(1) Earnings	(2) Credit Score	(3) Revolving Credit Limit	(4) Revolving Credit Balance
4 Years Before Displacement	1,169***	0.0699	-217.5	39.66
	(167.2)	(1.664)	(232.3)	(149.9)
3 Years Before Displacement	2,757***	-0.964	-363.8	-49.26
	(220.1)	(2.013)	(334.7)	(202.9)
2 Years Before Displacement	5,049***	1.019	-365.1	-36.50
	(262.8)	(2.210)	(403.0)	(240.8)
1 Year Before Displacement	5,157***	-4.488*	-347.4	47.28
	(296.8)	(2.427)	(473.4)	(281.0)
Year of Displacement	-2,850***	-6.352**	-996.4*	-473.2
	(353.5)	(2.595)	(533.7)	(315.8)
1 Year After Displacement	-13,830***	-15.79***	-1,738***	-583.7*
	(410.6)	(2.714)	(572.3)	(336.9)
2 Years After Displacement	-9,735***	-15.40***	-1,503**	-455.1
	(429.0)	(2.966)	(624.8)	(368.3)
3 Years After Displacement	-7,246***	-12.52***	-1,223*	-211.5
	(446.3)	(3.216)	(693.2)	(414.8)
4 Years After Displacement	-5,293***	-11.99***	-1,423*	-186.9
	(491.2)	(3.554)	(783.8)	(474.0)
5 Years After Displacement	-3,081***	-9.055**	-1,667*	-653.4
	(556.1)	(4.146)	(889.9)	(552.1)
Individual Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Age and Wealth Controls	Y	Y	Y	Y
R-squared	0.153	0.019	0.026	0.017
Indiv-Yr Obs.	472000	472000	472000	472000
No. of Indiv	61000	61000	61000	61000

Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. The set of variables "K Years Before (After) Displacement" are dummy variables equal to one when an individual is K years before (after) displacement, and equal to zero otherwise. Annual earnings, revolving credit balance and revolving credit limit are in 2008 dollars. Credit score refers to the TransUnion bankruptcy score.*

Table 2.3: Average Response of Default Measures to Displacement

	(1) 60 Day Delinq. (d)	(2) Chargeoff (d)	(3) Collections (d)	(4) Derogatory Public Flag (d)
4 Years Before Displacement	0.000733	0.00274	0.00353	-0.00147
	(0.00428)	(0.00350)	(0.00388)	(0.00230)
3 Years Before Displacement	-0.000547	0.00445	-0.000502	-0.000245
	(0.00473)	(0.00357)	(0.00408)	(0.00237)
2 Years Before Displacement	-0.0118**	-0.00644*	0.00228	0.000440
	(0.00490)	(0.00354)	(0.00424)	(0.00245)
1 Year Before Displacement	-0.00520	-0.00171	0.00351	0.000849
	(0.00516)	(0.00374)	(0.00452)	(0.00253)
Year of Displacement	0.00688	0.00872**	0.0109**	0.00385
	(0.00544)	(0.00391)	(0.00480)	(0.00262)
1 Year After Displacement	0.0308***	0.0287***	0.0278***	0.00724***
	(0.00563)	(0.00406)	(0.00495)	(0.00270)
2 Years After Displacement	0.0186***	0.0151***	0.0298***	0.00743**
	(0.00618)	(0.00438)	(0.00538)	(0.00297)
3 Years After Displacement	0.00993	0.00666	0.0251***	0.00408
	(0.00685)	(0.00483)	(0.00585)	(0.00322)
4 Years After Displacement	-0.00834	0.00111	0.0187***	0.00267
	(0.00771)	(0.00535)	(0.00649)	(0.00354)
5 Years After Displacement	-0.0190**	-0.00704	0.0123	-0.00284
	(0.00947)	(0.00648)	(0.00776)	(0.00423)
Individual Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Age and Wealth Controls	Y	Y	Y	Y
R-squared	0.007	0.003	0.010	0.001
Indiv-Yr Obs.	472000	472000	472000	472000
No. of Indiv	61000	61000	61000	61000

Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. The symbol (d) indicates a dummy variable. The set of variables "K Years Before (After) Displacement" are dummy variables equal to one when an individual is K years before (after) displacement, and equal to zero otherwise. All outcome variables are indicators for having the outcome occur within the past 12 months.*

Table 2.4: The Fraction of Displaced Workers who Delever or Default in the Year of Layoff

Fraction of Displaced Workers with...	
Decline in Revolving Credit Balances	0.39
Decline in Revolving Credit Balances and 60-day Delinquency	0.17
Decline in Revolving Credit Balances and Debt Chargeoff	0.08

Note: Summary statistics for cross-sectional sample in Figure 2.3.

Table 2.5: Replacement Rates of Revolving Credit by Credit Score Quintile

	(1) OLS Replacement Rate (2-Year)	(2) Predicted Value Replacement Rate (2-Year)
Credit Score Quintile 1		-0.0359***
		(0.00435)
Credit Score Quintile 2	-0.00804	-0.0439***
	(0.00651)	(0.00502)
Credit Score Quintile 3	0.0319***	-0.00395
	(0.00790)	(0.00660)
Credit Score Quintile 4	0.124***	0.0883***
	(0.00823)	(0.00696)
Credit Score Quintile 5	0.184***	0.148***
	(0.00822)	(0.00685)
Constant	-0.0742*	
	(0.0390)	
Year FE	Y	Y
Age and Wealth Controls	Y	Y
R squared	0.040	NA
No Obs.	19000	19000

Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. *Replacement rate is the negative of the change in revolving credit balance over the change in earnings, where the change in earnings and the change in borrowing is measured from the year after displacement relative to the year before displacement. The replacement rate is only defined for individuals who had a decline in earnings around displacement. A replacement rate of 0.2 indicates that an individual replaced 20 percent of their lost earnings with revolving credit. Credit score quintiles are based upon an individuals TransUnion bankruptcy score in the year prior to displacement. Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. Column (1) reports OLS estimates of equation* (2.2) *which estimates the replacement rate as a function of credit score quintile. The replacement rate used in the estimation is winsorized at the top and bottom at the 10 percent level. Column (2) reports predicted values of the replacement rate by credit score quintile implied by the results of Column (1), where the control variables are evaluated at their sample means, as in equation* (2.3).

Table 2.6: Model Parameters

Variable	Value	Description
	Non-estimated	
Variable	Value	Description
r_f	0.04	Risk free rate
β_{lf}	0.99	Discount factor: lenders and firm
β_L	0.99	Discount factor low worker type
δ	0.1	Exogenous job destruction rate
ζ	1.6	Labor match elasticity
δ_C	0.026	Exogenous credit destruction rate
ζ_C	0.37	Credit match elasticity
$\underline{r}$	10.5%	Minimum (annualized) interest rate
$\overline{r}$	22.5%	Maximum (annualized) interest rate
σ	2	Risk aversion
T	120	Lifespan in quarters
	Jointly-estimated	
Variable	Value	Description
z	0.327	Public insurance transfer to unemployed
κ	0.995	Firm entry cost
κ_C	2.214×10^{-5}	Lender entry cost
κ_S	1.272×10^{-4}	Utility penalty of searching for credit
ψ_D	14.771	Utility penalty of default
$p_{\tilde{h},L}$	0.651	Prob. persistent human capital decrease
$p_{\tilde{h},H}$	0.083	Prob. persistent human capital increase
$p_{\epsilon,L}$	0.111	Prob. transitory human capital low
$p_{\epsilon,H}$	0.252	Prob. transitory human capital high
λ_H	2.943	Exponential parameter initial persistent human capital
g	0.146	Home production
$\underline{B}$	-1.149	Lower bound for borrowing limit
β_H	0.632	Discount factor: high worker type
π_L	0.904	Share of low type individuals

Table 2.7: Model Calibration

Variable	Value	Target	Model	Data	Source
z	0.327	Transfer to Income Loss	41.2%	41.2%	PSID 2001-2013
κ	0.995	Unemployment Rate	5.3%	5.0%	BLS 1995-2007
κ_C	2.214×10^{-5}	Credit Finding Rate	64.1%	65.0%	SCF 2007-2009
κ_S	1.272×10^{-4}	Share of Individuals w/ Credit Access	69.9%	69.8%	SCF 1995-2007
ψ	14.771	Bankruptcy Rate	0.142%	0.145%	SCF 1998-2007
$p_{\tilde{h},L}$	0.651	Earnings Loss 5 Yr. After Layoff	6.6%	6.9%	LEHD/TU 2003-2008
$p_{\tilde{h},H}$	0.083	Earnings Gain With Age	0.92%	0.93%	CPS 1995-2007
$p_{\epsilon,L}$	0.111	Share of Indiv. w/ 9.5% Wage Decline	8.6%	7.65%	KM (2017)
$p_{\epsilon,H}$	0.252	Share of Indiv. w/ 9.5% Wage Increase	17.2%	19.0%	KM (2017)
λ_H	2.943	P75-P25 Earnings Ratio Among Young Workers	0.479	0.484	CPS 1995-2007
g	0.146	Consumption After Layoff	94.0%	93.8%	PSID 2005-2013
$\underline{B}$	-1.149	Unused Credit Limit to Income	23.5%	23.0%	SCF 1995-2007
β_H	0.632	P95 Real Credit Card Interest Rate	16.0%	19.0%	SCF 1995-2007
π_L	0.904	Share of Individuals w/ Net Liquid Assets to Income $< 1\%$	31.6%	31.4%	SCF 1995-2007

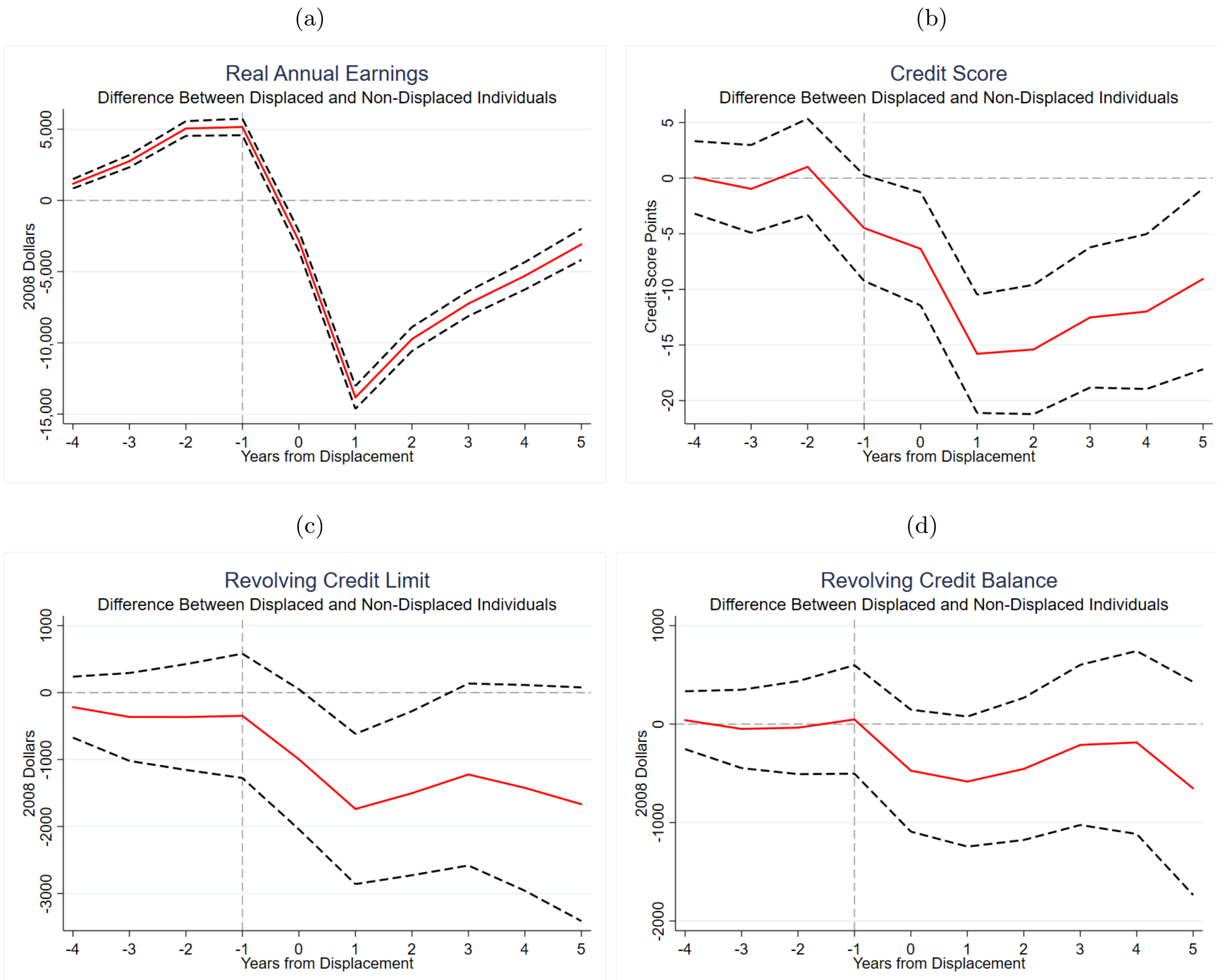
Notes: KM (2017) refers to Kurmann and McEntarfer (2017).

Table 2.8: Optimal Public Insurance to the Unemployed

	(1) Baseline	(2) Optimal Policy w/ Credit	(3) Optimal Policy w/o Credit
Transfer/Income Loss	41.2%	38.3%	43.2%
Mean Welfare Chg.	-	0.129%	0.084%
Unemployment Rate	5.3%	4.8%	5.4%
Fraction of Individuals Borrowing	19.6%	20.4%	-
Default Rate	0.142%	0.135%	-
Fraction of Individuals w/ Credit Access	69.9%	70.5%	-
Consumption Loss 1Q After Job Loss	94.0%	93.9%	94.0%
Marginal Tax rate	2.12%	1.77%	2.27%

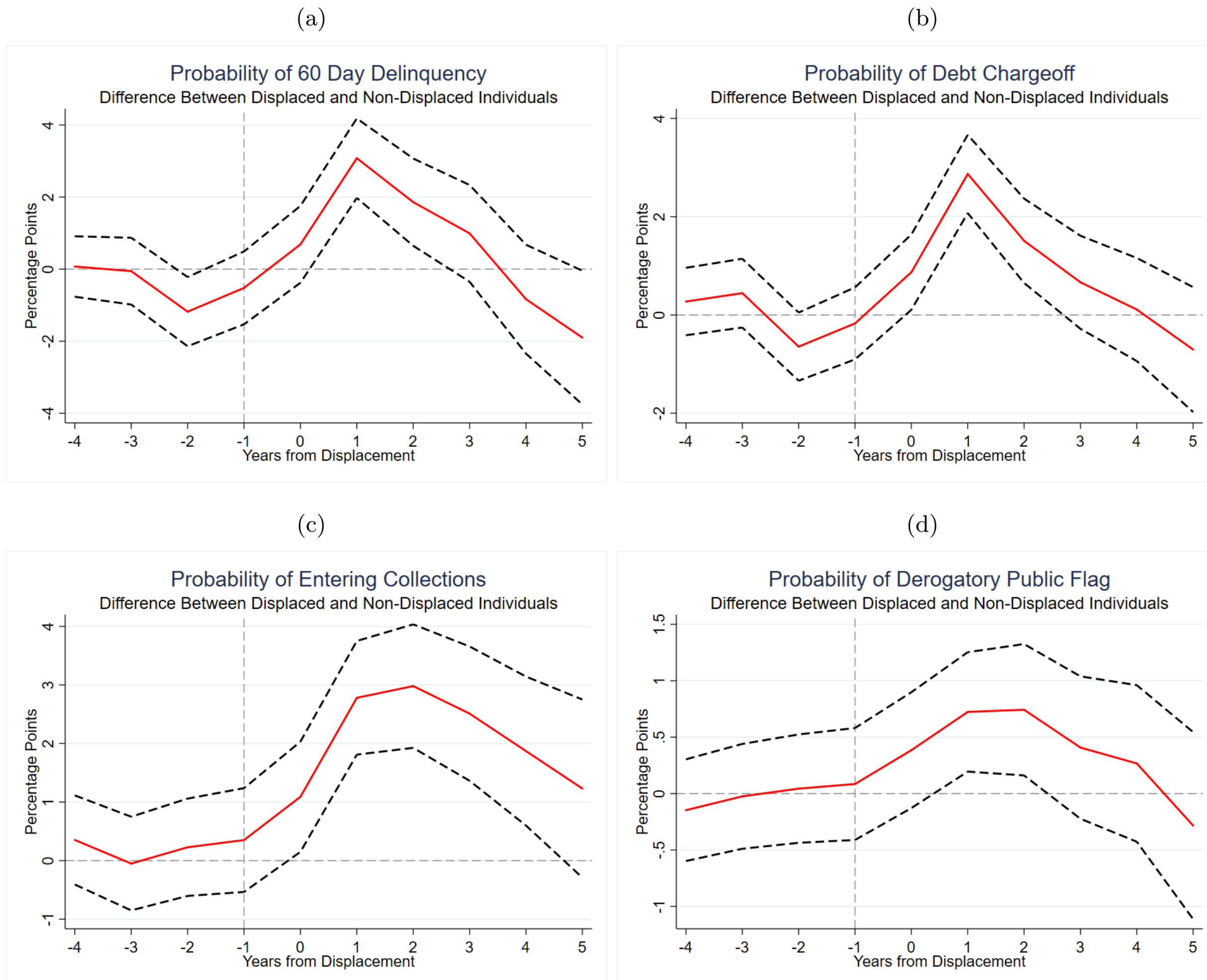
Notes: 'Welfare' is the consumption equivalent of leaving an economy with the US policy of a 41.2% *replacement rate to an economy with an alternate replacement rate. For example, in column (2), the mean welfare change of* 0.129% *indicates that an individual, on average, would give up* 0.129% *of lifetime consumption to have a* 38.3% *replacement rate as opposed to a* 41.2% *replacement rate. See Appendix B.6 for details on the estimation of the welfare effect.*

Figure 2.1: Average Response of Earnings and Credit Variables to Displacement



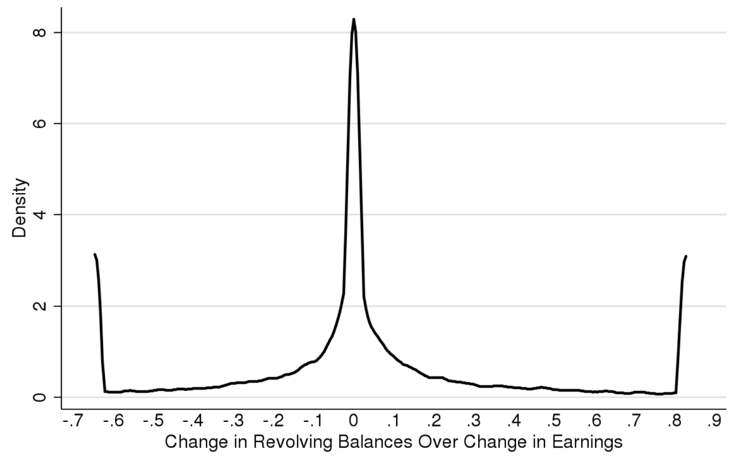
Notes: Figure presents estimates of the effect of job loss on earnings and credit variables. Solid line is the difference in the outcome variable between displaced and nondisplaced individuals. Dashed line represents a 95 percent confidence interval. Figures present coefficient estimates from Table 2.2.

Figure 2.2: Average Response of Default Measures to Displacement



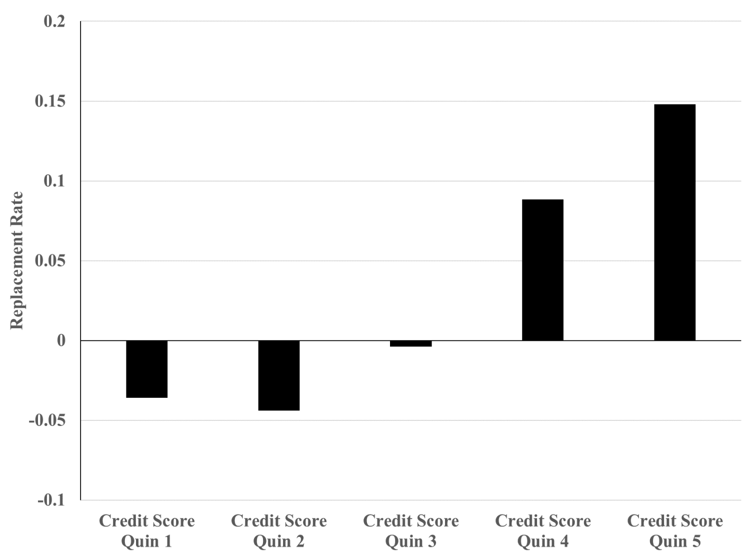
Notes: Figure presents estimates of the effect of job loss on measures of default and delinquency. Solid line is the difference in the outcome variable between displaced and nondisplaced individuals. Dashed line represents a 95 percent confidence interval. Figures present coefficient estimates from Table 2.3.

Figure 2.3: Replacement Rate of Lost Earnings with Revolving Credit



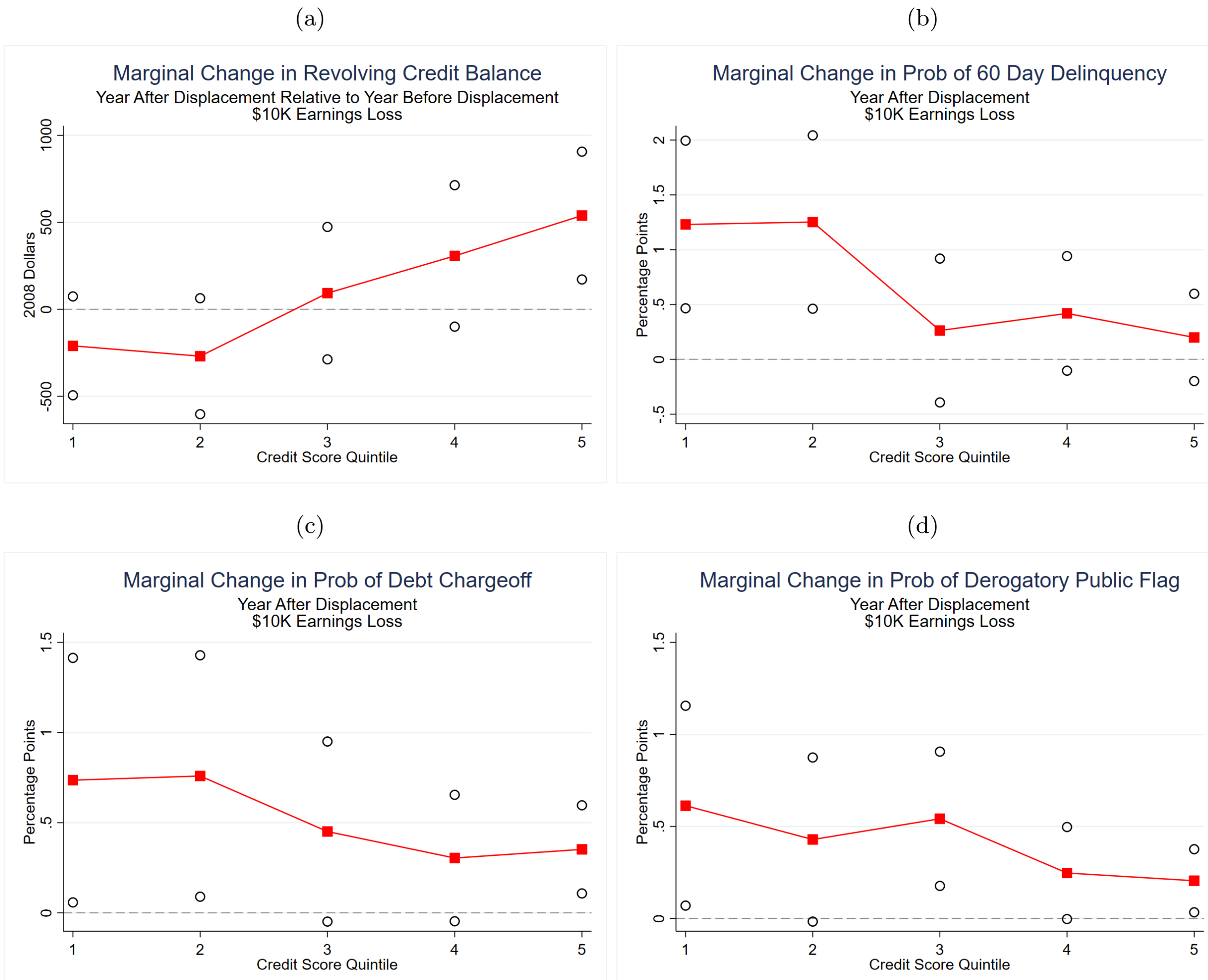
Notes: Figure shows the distribution of replacement rates using a kernel density. Replacement rate is the negative of the change in revolving credit balance over the change in earnings, where the change in earnings and the change in borrowing are measured from the year after displacement relative to the year before displacement. The replacement rate is defined for individuals who had a decline in earnings around displacement. A replacement rate of 0.2 indicates that an individual replaced 20 percent of their lost earnings with revolving credit.

Figure 2.4: Replacement Rate of Lost Earnings with Revolving Credit by Credit Score Quintile



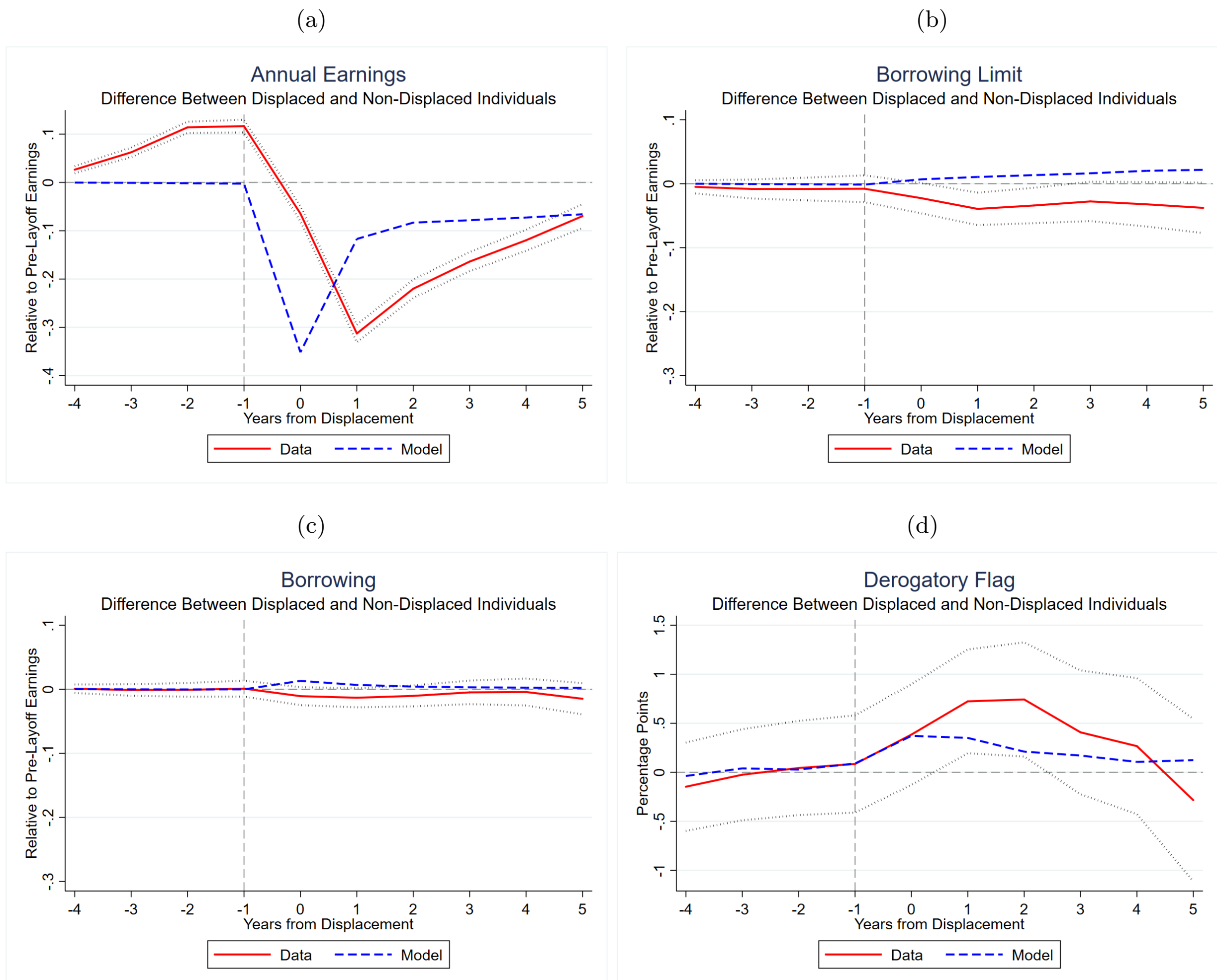
Notes: Replacement rate estimates are from Column (2) of Table 2.5. See notes to Figure 2.3 for definition of replacement rate. Credit score quintiles are based upon an individual's TransUnion bankruptcy score in the year prior to displacement.

Figure 2.5: Marginal Effect of Earnings Loss on Borrowing and Default Activity



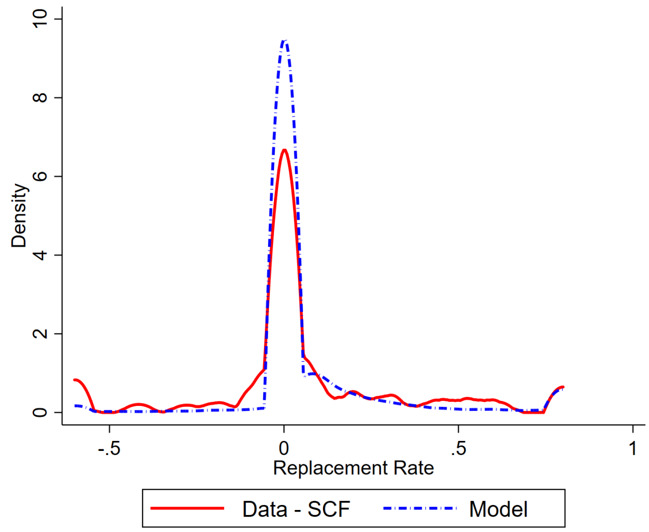
Notes: Squares in the figures present the marginal effect of earnings loss on the variable of interest. Earnings loss is measured as the difference in real annual earnings in the year after displacement relative to the year before displacement. The estimates are taken from Column (3) of Tables B.4-B.7. The coefficient for Credit Score Quintile 1 correspond to the coefficient 2 Yr. Chg. Earnings from the table, while the coefficient for Credit Score Quintile k corresponds to the sum of the coefficients 2 Yr. Chg. Earnings and 2 Yr. Chg. Earnings Credit Quin k. The dots represent a 95 percent confidence interval.

Figure 2.6: Model Predictions of the Average Response of Earnings and Credit Variables to Displacement



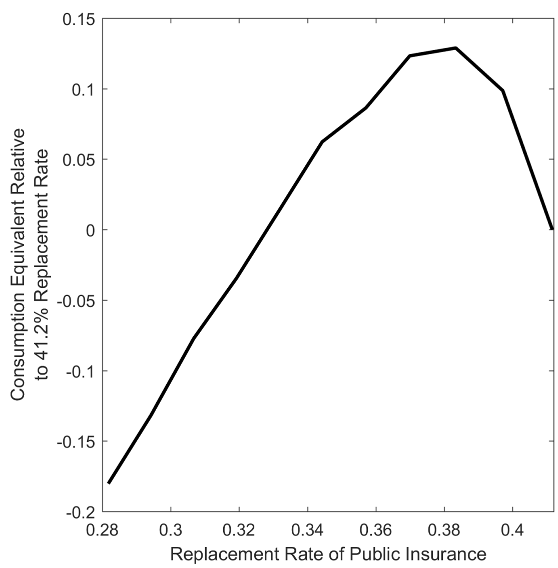
Notes: Figure presents estimates of the effect of job loss on earnings and credit variables comparing estimates from the data (red solid line) to estimates from the model (blue dashed line). The gray finely dashed lines represent 95 percent confidence intervals of data estimates.

Figure 2.7: Kernel Density of Replacement Rates, Model versus Data



Notes: Figure presents the models estimate of the replacement rate of credit (blue dashed line) following job loss compared to the data estimate of the replacement rate of credit around job loss as measured in the 2007-2009 SCF panel (red solid line).

Figure 2.8: Welfare Effect of Change in Public Transfer to Unemployed

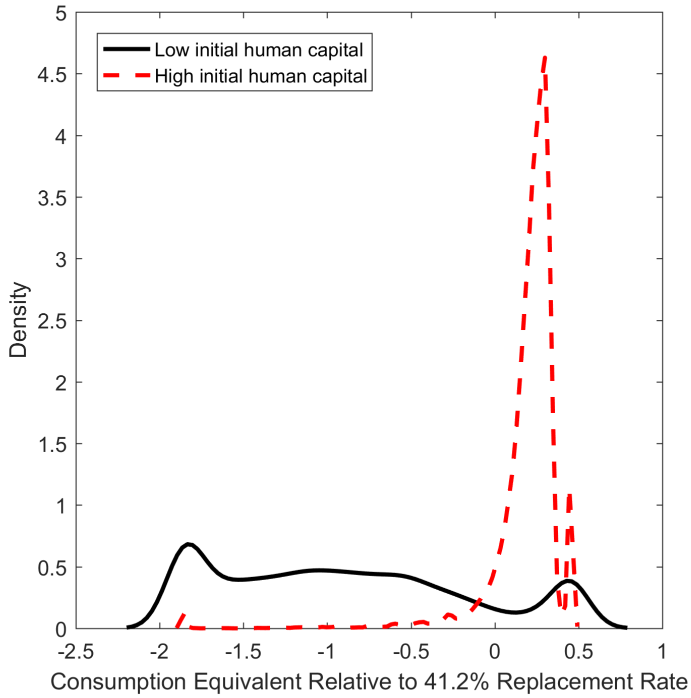


Notes: 'Welfare' is the consumption equivalent of leaving an economy with the US policy of a 41.2% *replacement rate to an economy with an alternate replacement rate. For example, the welfare change of* 0.129% *indicates that an individual, on average, would give up* 0.129% *of lifetime consumption to have a* 38.3% *replacement rate as opposed to a* 41.2% *replacement rate. See Appendix B.6 for details on the estimation of the welfare effect.*

Figure 2.9: Steady State Welfare Experiment

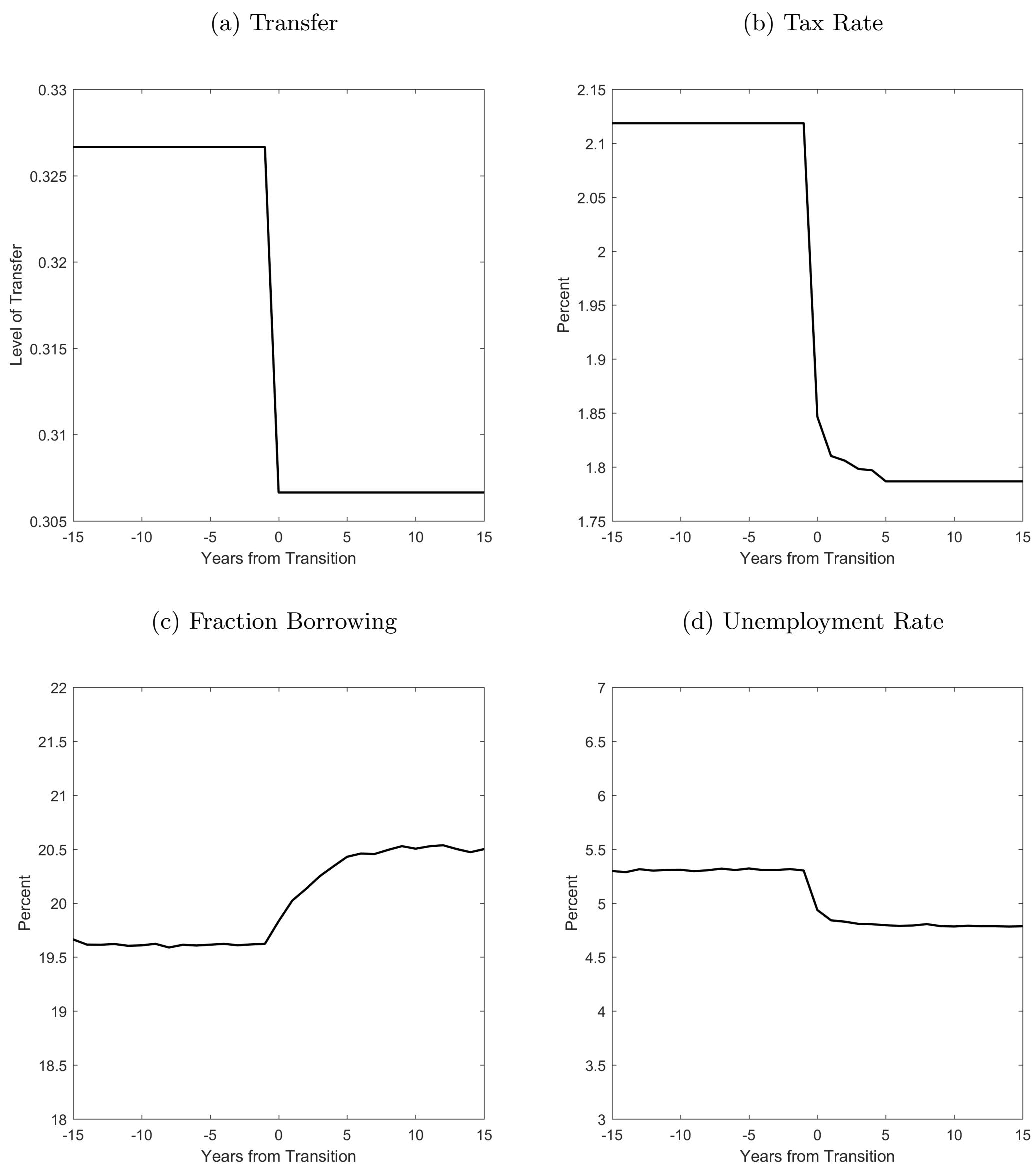
Notes: Figure shows output from the steady state welfare experiment where the replacement rate of public insurance to the unemployed is adjusted.

Figure 2.10: Distribution of Welfare Changes from Changing Public Transfer to Unemployed



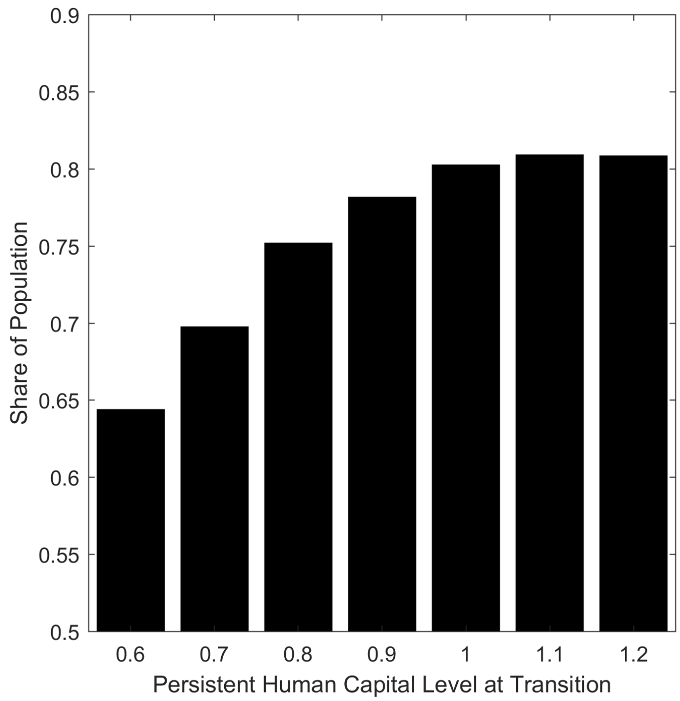
Notes: 'Welfare' is the consumption equivalent of leaving an economy with the US policy of a 41.2% replacement rate to an economy with a 38.3% replacement rate. See Appendix B.6 for details on the estimation of the welfare effect.

Figure 2.11: Transition Path Experiment



Notes: Figure shows output from the transition path welfare experiment where the replacement rate of public insurance to the unemployed is adjusted.

Figure 2.12: Welfare Gains by Persistent Human Capital Along Transition Path



Notes: The figure shows the share of the population alive at the time of the transition that has a welfare gain when the replacement rate is lowered from 41.2% to 38.3%, where welfare is measured using consumption equivalents. The population is stratified by the persistent level of human capital.

Chapter 3

The Impact of Labor Force Growth on the Allocation of Workers Across Firms and Aggregate Output

3.1 Introduction

The trend labor force growth rate has steadily declined from over 2.3 percent per year in 1975 to under 0.7 percent in 2016 (Figure 3.1). This decline in labor force growth is part of the demographic transition to an older population and workforce that is occurring in the United States as well as in much of the developed world.[1] Prior research has shown that the decline in labor force growth has reduced the entry of new firms (e.g. Hopenhayn et al. (2018), Karahan et al. (2019), and Peters and Walsh (2019)), while the aging of the population contributes to a lower unemployment rate (e.g. Shimer (2001)) as well as reduced job creation and hiring (e.g. Engbom (2019)). In this paper, I evaluate how changes in the labor force growth rate impact the allocation of workers across firms, and aggregate output. Answering this question requires analyzing the impact of declining labor force growth on the rate workers are hired both while employed and unemployed as well as the vacancy posting decision of firms. I find that the decline in the labor force growth rate has led to a modest decline in the rate at which workers are hired both while employed and unemployed, a decline in the vacancy creation by firms, but higher output per worker as the labor market becomes comprised of older workers who are more productive and better

[1]There has been a similar trend decline in working age population growth in the U.S. from over 1.7 percent in 1975 to less than 0.5 percent in 2016.

sorted across firms.

In evaluating the impact of changes in the labor force growth rate on the allocation of workers across firms and aggregate output I make two contributions. First, I establish a theoretical link between declining labor force growth and lower hiring due to reduced vacancy creation by firms. To establish this link I integrate labor force growth into the labor sorting model of Lise and Robin (2017). In the model as the labor force growth rate declines, the pool of unemployed workers shrinks, which shifts the pool of potential hires for firms to more expensive employed workers that must be poached away from other firms. Firms respond by posting fewer vacancies, and hiring declines. Consistent with the theory, Figure 3.2 shows that since 1975 there has been a decline in: (i) the unemployment rate, (ii) vacancy creation, (iii) the rate employed workers switch jobs (job to job transitions), and (iv) the rate unemployed workers are hired (unemployment to employment (UE) transitions). This relationship between labor force growth, vacancy creation, and hiring motivates the notion that changes in the labor force growth rate may alter the allocation of workers across firms, and hence aggregate output.

The second contribution of the paper is to quantitatively evaluate the theory using the decline in the labor force growth rate in the U.S. over the past 40 years. I calibrate the model to be consistent with the U.S. labor market and then feed in the observed path of labor force growth rates since 1975.[2] Solving the transition path of the model economy, I find that the decline in labor force growth has led to a modest decline in hiring for employed and unemployed workers as well as vacancy posting by firms. However, output per worker is over 4.5 percent higher following the decline in labor force growth due to a shift in the pool of workers being older, more experienced, and better sorted across firms.

I integrate labor force growth and human capital accumulation into the labor sorting model of Lise and Robin (2017) to evaluate the impact of changes in labor force growth on the labor market. In the model, a new cohort of workers arrive each period, and draw their productivity from a distribution which is calibrated to reflect the productivity of labor force entrants. By matching with a firm and maintaining employment, workers are able to increase their productivity over time as in Ljungqvist and Sargent (1998). This feature gives a life cycle element to the model where, on average, workers enter the labor market with relatively low productivity and gradually increase their productivity over their careers. Firms are heterogeneous in their productivity. In each period, firms observe the rate of labor force growth and decide how many vacancies to post. The number of vacancies posted by each firm is endogenously determined through a free entry condition which equates the cost

[2] I start the analysis in 1975 since from this year onward I have an annual panel of labor force growth, job to job transitions, unemployment to employment transitions, employment to unemployment transitions, and vacancy rates. Appendix C.4 provides details on all data used in the paper.

of posting an additional vacancy with the expected benefit of posting the vacancy. Workers search among the posted vacancies both while unemployed and employed, with employed workers moving to firms where they are more productive through on the job search.

Using a standard bargaining procedure (e.g. Postel–Vinay and Robin (2002)), I show that a decrease in the labor force growth rate decreases the probability that a worker meets a firm, which lowers hiring. As the labor force growth rate declines the share of unemployed workers declines. This decline in unemployed workers makes firms more likely to meet an employed workers when posting a vacancy. To poach a currently employed worker, a firm must offer to pay a higher wage relative to hiring an equally skilled unemployed worker. Hence, having a smaller share of unemployed workers in the labor market reduces the expected benefit to firms from posting a vacancy. However, free-entry requires that the benefit of posting a vacancy remain equal to the cost. Thus, for the free-entry condition to be satisfied firms must become more likely to meet a worker while searching, which *decreases* the probability that a worker meets a firm. When the probability of a worker meeting a firm is lower, both employed and unemployed workers are less likely to be hired. Hence following a decline in the labor force growth rate, employed workers are less likely to move to firms where they are more productive. This link between declining labor force growth and reduced hiring motivates how changes in the labor force growth rate can influence the allocation of workers across firms as well as aggregate output. I refer to this channel where a change in the labor force growth rate impacts the labor market through a change in the probability of workers and firms meeting one another as the *meeting channel.*

When the labor force growth rate is lower, the labor market has a larger share of older workers. Due to the human capital process, where workers acquire human capital while working, older workers tend to be more experienced. Additionally, older workers have had more time in the labor market to search for firms where they can be more productive and make higher wages, i.e. older workers tend to be better sorted across firms. These two effects, being more productive and better sorted, make it so that having a labor market with a larger share of older workers may actually have greater output per worker, even if the rate of hiring is lower. I refer to this channel where a change in the labor force growth rate impacts the labor market by altering the composition of workers in the labor market as the *labor composition channel.*

I calibrate the model to be consistent with the flows of workers across labor market states and firms, as well as the dynamics of earnings over a working career as measured in the Current Population Survey. In particular, for worker flows, I target the rate unemployed workers become employed (UE transitions), the rate employed workers become unemployed (EU transitions), and the rate employed workers switch jobs (job to job transitions). To discipline the distribution of productivity that labor force entrants draw from and the evolution of human capital over an individuals career, I target aggregate moments for the relative earnings of young workers compared to older workers, and the average increase in earnings per year of experience, respectively. The model generates endogenous distributions of the earnings of recent labor force entrants, as well as a path of earnings over a working career that closely resembles what is observed in the data. This provides support for the evolution of human capital in the model where individuals start their careers as relatively low productivity workers, and the notion that higher labor force growth increases the share of the labor force that has relatively low productivity.

I then use the model as a laboratory to estimate the impact of the decline in the labor force growth rate on the allocation of workers across firms, and aggregate output. In particular, I feed into the model the path of the labor force growth rate from 1975 to 2016, and solve the transition path of the economy. I find that the decline in the labor force growth rate decreases the unemployment rate by nearly 8%. As the pool of available workers shifts to more expensive employed workers, vacancy creation decreases along the transition path by nearly 2.5%. With the decline in vacancy posting, hiring for employed and unemployed workers also declines along the transition path. The model predicts that based upon the path of labor force growth, the rate at which employed workers switch jobs (job to job transitions) declines by nearly 4.5%, while the rate that unemployed workers are hired (UE transitions) declines by nearly 0.5% percent.

Despite the decline in hiring, and vacancy creation following the decrease in labor force growth, output per worker increases. In particular, following the decline in labor force growth, output per worker is over 4.5 percent higher in 2016. The decrease in the labor force growth rate alters the composition of workers in the labor market to being comprised of more experienced, productive workers, who are also better sorted across firms. Hence, for output per workers, the labor composition channel of lower labor force growth dominates the meeting channel.

As a final exercise, I hold a worker's productivity fixed over their working career and estimate the impact of lower labor force growth on the labor market. In this exercise, the labor composition channel only takes into account that older workers tend to be better sorted across firms, but are, on average, equally productive as younger workers. Solving the transition path of the economy with fixed worker productivity, there are similar declines in vacancy posting and hiring as in the baseline model. However, output per worker increases by just over 1.5 percent along the transition path. This exercise serves as a decomposition of the labor composition channel, and indicates that approximately 1/3 of the increase in output per worker from the baseline model comes through improved sorting of workers across firms, while the remaining increase occurs as firms match with more experienced and productive workers.

Related Literature. This paper adds to the labor sorting literature through its introduction of labor force growth. Relative to existing labor sorting models (e.g. Shimer and Smith (2000), Lise et al. (2016), Hagedorn et al. (2017), and Lise and Robin (2017)) the model in this paper is novel in allowing for changes in the labor force growth rate to influence the probability that workers and firms meet one another as well as the allocation, or sorting, of workers across firms. The quantitative results indicate that the decline in the labor force growth rate since the 1970s have led to a modest decline in vacancy creation and worker reallocation, but an increase in output per worker.

On a technical level, this paper builds off of the work of Lise and Robin (2017), who provide a framework to tractably estimate transition paths in labor sorting models with two-sided heterogeneity by deriving a block-recursivity style (e.g. Menzio and Shi (2010), and Menzio and Shi (2011)) result for random search models of the labor market. Relative to Lise and Robin (2017), this paper incorporates labor force growth and the accumulation of human capital.

This paper also contributed to the literature that has examined how changing demographics in the U.S. are impacting the labor market (e.g. Shimer (2001), Hopenhayn et al. (2018), Engbom (2019), Karahan et al. (2019), and Peters and Walsh (2019)). The most closely related paper is Engbom (2019), who examines the role of the aging of the U.S. population on worker flows and aggregate output. He finds that the aging of the U.S. population has led to a decline in worker flows and a reduction in aggregate output. There are three main differences between the present paper and Engbom (2019). First, Engbom (2019) considers the role of the aging of the population, while the present paper considers the decline in labor force growth. Second, Engbom (2019) does not consider how the sorting or the allocation of workers across firms is impacted by changing demographics. Third, the present paper does not allow workers to transition into become an entrepreneur and start their own firm, which is critical to the mechanism of Engbom (2019).

Another closely related paper is Karahan et al. (2019), who examine the role of the decline in labor force growth on the entry of new firms. They find that the decline in the labor force growth rate has played an important role in the decline in new firm entry since the 1970s. They do not however consider how changes in the labor force growth rate impact the matching of workers and firms, or the allocation of workers across firms. Consistent with the results of Karahan et al. (2019) the quantitative model of this paper predicts following a decline in the labor force growth rate there is a decline in vacancy creation by firms.

Finally, this paper appeals to the literature on the declining dynamism of the U.S. economy, which has documented a decline in firm entry, as well as hiring and job switching rates over the past several decades (e.g. Decker et al. (2013), Hyatt and Spletzer (2013), Davis and Haltiwanger (2014), and Molloy et al. (2016) among others). This paper adds to the literature by examining the role of declining labor force growth in driving the decline in vacancy creation and hiring. While the decline in vacancy creation and hiring from the transition path experiment is qualitatively consistent with the data since 1975, the magnitude of the declines are smaller than what is observed in the data. These results indicate that declining labor force growth has only played a minor role in the observed declines in vacancy creation and hiring.

The paper proceeds as follows. Section 3.2 presents a stylized, steady state, version of the model where workers are homogeneous, and I establish a theoretical link between labor force growth, vacancy creation, and hiring. In Section 3.3, I incorporate heterogeneous workers and calibrate the model to be consistent with the U.S. labor market. In Section 3.4, I solve the transition path of the model economy by feeding in the path of labor force growth rates from 1975 to 2016 and examine the impact on the allocation of workers across firms and aggregate output. Section 3.5 concludes.

3.2 Theoretical Model

I add labor force growth and human capital accumulation to the Lise and Robin (2017) labor sorting model to examine the role of changes in the labor force growth rate on the allocation of workers across firms. I begin by presenting a steady state version of the model with homogeneous workers to illuminate the mechanism where a decline in the labor force growth rate lowers the hiring of both employed and unemployed workers by reducing the benefit to firms of creating vacancies. I introduce worker heterogeneity and allow for workers' human capital to evolve over their working career in Section 3.3. The formulation of the quantitative model in Section 3.3 allows for solving the transition path of the economy using the realized path of labor force growth rates over the past 40 years.

3.2.1 Ingredients

Agents and Entry to the Labor Market

Workers are homogeneous in their productivity, and are either employed or unemployed. Workers have linear utility and consume wages when employed and unemployment benefits when unemployed.

The labor force grows at an exogenous rate λ each period, and workers enter the labor market as unemployed workers.[3] Variables denoted by a hat have been deflated by the size of the labor force (l) in that period, that is $\hat{a} = \frac{a}{l}$.

[3] In Section 3.3, the rate of labor force growth will be allowed to vary each period.

Firms are heterogeneous, with productivity denoted by $y \in \mathbb{Y}$, and their type is fixed indefinitely. Firms observe the rate of labor force growth and decide how many vacancies to post to satisfy a free entry condition. Posting v vacancies costs the firm $c(v)$, where $c(\cdot)$ is an increasing and convex function.

Search, Production and Wages

Workers and firms engage in random search for employment opportunities. Workers search both while unemployed and employed, with employed workers searching with relative search intensity ϕ. Aggregate search intensity in the labor market is given by $\hat{s} = \hat{u}+\phi\hat{e}$, where $\hat{u}$ is the unemployment rate (share of population unemployed) and $\hat{e} = 1-\hat{u}$ is the employment rate (share of the population employed). The unemployment rate and employment rate are measured going into the searching stage of the period. Firms pay flow cost $c(v)$ to post vacancies, and in a given period a firm y posts $v(y)$ vacancies. The vacancy rate (number of vacancies over size of the labor force) is given by $\hat{v} = \int_{\mathbb{Y}} \hat{v}(y)dy$.

The process for matching is described in Section 3.2.2, but for a worker and firm to *match* with one another they must *meet* one another first. Meetings between workers and firms occur according to a CRS function $M(\hat{s}, \hat{v})$, which takes as inputs aggregate search intensity $\hat{s}$ and vacancies $\hat{v}$. Define $\theta = \frac{\hat{v}}{\hat{s}}$ as the labor market tightness, and denote $p(\theta) = \frac{M(\hat{s},\hat{v})}{\hat{s}}$ as the probability an unemployed worker meets a firm, while $\phi p(\theta)$ is the probability an employed worker meets a firm. Finally, $q(\theta) = \frac{M(\hat{s},\hat{v})}{\hat{v}}$ denotes the probability a firm meets a worker.

When a worker and a firm y are matched with one another they produce $f(y)$, which is assumed to be strictly increasing in y. Firms pay wages to the worker, which are determined through a bargaining process described in Section 3.2.2. Unemployed workers receive unemployment benefit b. I assume that $f(y) > b$, $\forall(y) \in \mathbb{Y}$, which will allow all firms to be able to hire a worker. Finally, matches between workers and firms are destroyed at an exogenous rate δ.

Match Surplus

When a worker and firm are matched with one another they create match surplus $S(y)$, which is defined as the surplus to the worker and firm of being in the match rather than being unmatched. The surplus to a worker of being in a match is given by $W(y, y_0) - U$, where $W(y, y_0)$ is the value to a worker of being employed at firm y and having outside option y_0, and U is the value of being unemployed.[4] The surplus to a firm with productivity

[4]The outside option is the worker's outside option in the bargaining procedure presented in Section 3.2.2. A worker outside option in the bargaining process can be unemployment or employment at another firm.

y of being in a match with a worker whose outside option is y_0 is given by $J(y, y_0)$.[5] Adding the surplus to the worker and firm of being in a match generates the following match surplus:

$$S(y) = W(y, y_0) - U + J(y, y_0)$$

With the assumption of transferable utility a worker's outside option, which impacts the wage payments between the worker and firm, does not alter the amount of match surplus but only the allocation of the surplus between the worker and firm. I assume $S_t(y, y_0) = S_t(y)$, and then verify that $W_t(y, y_0)$ and $J_t(y, y_0)$ are consistent with this assumption. I additionally show below that the match surplus is independent of the rate of labor force growth.

Timing

At the beginning of each period the labor force grows and labor force entrants arrive in the economy as unemployed workers. Firms observe the rate at which the labor force grows and decide how many vacancies to post. Workers and firms then search and match in the labor market. After the labor market closes, production and wage payments occur. The separation shock then occurs at the end of the period.

3.2.2 Bargaining and Matches Between Workers and Firms

In this section, I introduce the bargaining procedure for wages and define how workers and firms decide with whom to match.

Wages are determined following a sequential bargaining procedure as in Postel-Vinay and Robin (2002), which defines wages as a function of the match surplus between a worker and firm. The bargaining procedure proceeds as follows:

- When a firm meets an *unemployed* worker, the firm makes a take it or leave it offer to the unemployed worker. Hence, the firm offers the unemployed worker their reservation wage, which equates the value of working to the value of being unemployed, i.e. $W(y, U) = U$.[6]

- When a firm meets an *employed* worker, the firm enters into Bertrand competition with the worker's current employer. Suppose firm $\tilde{y}$ meets a worker, who is currently employed at firm y. There are two cases to consider:

[5] Expressions for the value of being unemployed, employed and a firm in a match are given in Section 3.2.4.

[6] In the quantitative model presented in Section 3.3 the assumption that firms make take it or leave it offers to the unemployed will be critical in being able to solve for the transition path.

1. $S(\tilde{y}) > S(y)$: The worker will switch to firm $\tilde{y}$, and receives promised value $W(\tilde{y}, y) - U = S(y)$. That is the worker is poached by firm $\tilde{y}$ by being given the entire surplus from their prior match, and the worker's prior firm y becomes the worker's outside option. The value of this match to firm $\tilde{y}$ is $J(\tilde{y}, y) = S(\tilde{y}) - S(y)$.
2. $S(y) \geq S(\tilde{y})$: The worker remains employed at firm y, but depending on how much the worker is being compensated by firm y they may be able to use meeting firm $\tilde{y}$ to increase their compensation. Suppose the worker is currently receiving $S(y_0)$ from firm y, where y_0 is the worker's current outside option. There are two scenarios to consider:
   (a) $S(y) \geq S(\tilde{y}) > S(y_0)$: In this case firm $\tilde{y}$ has the potential to pay the worker more than firm y is currently paying the worker, and the worker uses meeting firm $\tilde{y}$ to renegotiate their wage at firm y. The firms enter into Bertrand competition over the worker, and firm y retains the worker by compensating them with $W(y, \tilde{y}) - U = S(\tilde{y})$, which is all of the surplus that firm $\tilde{y}$ could have offered the worker. The worker's outside option is now $\tilde{y}$, and firm y receives the remaining match surplus $J(y, \tilde{y}) = S(y) - S(\tilde{y})$.
   (b) $S(y) \geq S(y_0) > S(\tilde{y})$: In this case firm $\tilde{y}$ cannot pay the worker more than firm y is currently paying the worker. The worker cannot use firm $\tilde{y}$ to renegotiate their wage and the worker's outside option remains y_0.

The bargaining procedure also specifies how employed workers and firms decide with whom to match. Define the *matching set* for a worker who is employed at firm y as: $m_1(y) = \{\tilde{y} \in \mathbb{Y} | S(\tilde{y}) > S(y\}$. This is the set of all firms $\tilde{y}$ that can provide the worker employed at firm y with all of the surplus from their current match at firm y, which entices the worker to switch firms. Define the *renegotiation set,* for a worker, who is employed at firm y, and has outside option y_0 as: $m_2(y, y_0) = \{\tilde{y} \in \mathbb{Y} | S(y) \geq S(\tilde{y}) > S(y_0)\}$. This is the set of all firms $\tilde{y}$, that can provide the worker with more surplus than they are currently receiving from firm y, but not enough surplus to entice the worker to leave firm y. Finally, define the *matching set* for firm y as: $m_F(y) = \{\tilde{y} \in \mathbb{Y} | S(y) > S(\tilde{y})\}$. This set defines the set of all firms that firm y is able to hire workers away from.

With the matching sets established, recursive expressions for the distribution of workers across firms as well as the evolution of the unemployment rate can be defined.

3.2.3 Laws of Motion and Aggregate Output

In this section, I outline the law of motion for unemployment as well as matches across firms. These laws of motion define the distribution of workers across firms, which allows for the definition of aggregate output in the model.

Unemployment

Let there be l_t individuals in the labor force in period t of which u_t are unemployed and $e_t = l_t - u_t$ are employed.[7] In period $t+1$, there are l_{t+1} individuals in the labor force, where $l_{t+1} = (1+\lambda)l_t$ and λ is the growth rate of the labor force. The number of unemployed workers in period $t+1$, u_{t+1}, is then given by the following recursive expression:[8]

$$u_{t+1} = u_t\left[1 - p(\theta_t)(1-\delta)\right] + \delta e_t + \lambda l_t$$

Individuals unemployed in period $t+1$ are classified into three mutually exclusive groups: (1) individuals unemployed in period t who did not meet a firm and avoid the exogenous separation shock, (2) individuals employed in period t who were hit by the separation shock, and (3) labor force entrants. Dividing by the size of the labor force in period $t+1$, and using the fact that individuals are either employed or unemployed returns the following recursive expression for the unemployment rate in period $t+1$:

$$\hat{u}_{t+1} = \frac{\hat{u}_t\left[1 - p(\theta_t)(1-\delta)\right] + \delta\left(1 - \hat{u}_t\right) + \lambda}{1+\lambda} \tag{3.1}$$

Solving equation 3.1 for the steady state unemployment rate returns:

$$\hat{u} = \frac{\delta + \lambda}{\lambda + p(\theta)(1-\delta) + \delta} \tag{3.2}$$

Equation 3.2 shows that holding all else fixed, as the labor force growth rate λ increases the steady state unemployment rate increases. Hence, holding all else fixed, changes in the labor force growth rate alters the composition of workers across employment and unemployment. I show below that this change in the composition of workers across employment and unemployment influences the value to the firm of posting a vacancy, which is the critical step in showing how changes in the labor force growth rate impact the probability that a worker meets a firm while searching.

Density of Matches

In this subsection, I define a recursive expression for the density of matches across firms. In levels, let $e_t(y)$ be the number of matches at firm y going into the search stage in period t. Let $e_{t+}(y)$ be the number of matches at firm y after the search stage in period t, which

[7]Note these are the stocks of employed and unemployed workers at start of the labor search stage of period t.

[8]In this section, I consider a steady state environment. However, to ease the presentation of the laws of motion, I will discuss the flows of workers across states between periods t and $t+1$.

is given by:

$$e_{t+}(y) = e_t(y)\left(1-\phi p(\theta_t)\int_{m_1(y)}\frac{v_t(\tilde{y})}{v_t}d\tilde{y}\right) + u_t p(\theta)\frac{v_t(y)}{v_t}\mathbb{I}\{y\in m_1(U)\}$$
$$+\int_{\mathbb{Y}_0} e_t(y_0)\phi p(\theta_t)\frac{v_t(y)}{v_t}\mathbb{I}\{y\in m_1(y_0)\}dy_0$$

Matches after the search stage in period t can be classified into three mutually exclusive groups: (1) workers who were employed by firm y going into the search stage today and did not match with another firm (2) workers who entered the search stage today as unemployed workers and matched with firm y, and (3) workers who entered the search stage in period t employed at firm y_0, and matched with firm y. Using matches after the search stage from period t, we can obtain the distribution of matches going into the search stage in period $t+1$, denoted $e_{t+1}(y)$, which is given by:

$$e_{t+1}(y) = (1-\delta)e_{t+}(y) \tag{3.3}$$

Matches after the search stage survive to the next period's search stage if they avoid the exogenous separation shock at the end of period t. The expression in equation 3.3 can be converted to a density by dividing through by the size of the labor force in period $t+1$, which returns:

$$\hat{e}_{t+1}(y) = \left(\frac{1-\delta}{1+\lambda}\right)\hat{e}_{t+}(y)$$

where:

$$\hat{e}_{t+}(y) = \hat{e}_t(y)\left(1-\phi p(\theta_t)\int_{m_1(y)}\frac{\hat{v}_t(\tilde{y})}{\hat{v}_t}d\tilde{y})\right) + \hat{u}_t p(\theta_t)\frac{\hat{v}_t(y)}{\hat{v}_t}\mathbb{I}\{y\in m_1(U)\}$$
$$+\int_{\mathbb{Y}_0}\hat{e}_t(y_0)\phi p(\theta_t)\frac{\hat{v}_t(y)}{\hat{v}_t}\mathbb{I}\{y\in m_1(y_0)\}dy_0$$

With the density of matches across firms defined the notion of aggregate output in the model can be introduced.

Aggregate Output

In this subsection, I define aggregate output in the model. To account for changes in the size of the labor force, I use output per worker as the measure of aggregate output in the model. Let $\hat{Y}$ denote output per worker, which is defined as:

$$\hat{Y} = \int_{\mathbb{Y}}\hat{e}(y)f(y)dy \tag{3.4}$$

where $\hat{e}(y)$ is the share of the labor force that is employed at firm y and $f(y)$ is the output of firm y when matched with a worker.

3.2.4 Bellman Equations

In this section, I characterize the payoffs to each agent.[9]

Let U be the value of unemployment to a worker. In the current period the worker receives UI benefit b, and then searches for a job that would begin the following period. Unemployed workers are able to match with firms as described above, but the assumption that firms make take it or leave it offers to unemployed workers, makes it so that an unemployed worker receives no immediate gain when matching with a firm, which generates the following value to being unemployed:

$$U = b + \beta U \tag{3.5}$$

Let $W(y, U)$ be the value of being an employed worker at firm y, whose outside option is unemployment. In the current period the worker receives a wage $w(y, U)$ and then faces the exogenous separation shock at the end of the period. If the worker is hit by the separation shock then they become an unemployed worker in the following period.[10] If the worker does not exogenously separate, then they receive the continuation value of the match $W(y, U)$, and engage in on the job search for a new employment match. With probability $\phi p(\theta)$ the worker meets a firm $\tilde{y}$ while searching. If the firm is in the worker's matching set, $\tilde{y} \in m_1(y)$, then the worker switches firms and obtains all of the surplus from their match with their prior firm y. Alternatively if the firm is in the worker's renegotiation set $\tilde{y} \in m_2(y, U)$, then the worker remains employed at firm y but uses their meeting with firm $\tilde{y}$ to increase their compensation from firm y, which gives the worker a gain of $S(\tilde{y})$. The value to the worker of the match is given by:[11]

$$\begin{aligned} W(y, U) = {} & w(y, U) + \beta\delta U + \beta(1-\delta)W(y, U) \\ & + \beta(1-\delta)\phi p(\theta) \int_{m_1(y)} S(y) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} \\ & + \beta(1-\delta)\phi p(\theta) \int_{m_2(y,U)} S(\tilde{y}) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} \end{aligned} \tag{3.6}$$

Let $J(y, U)$ be the value of being a type y firm who is in a match with a worker who was

[9]The derivation of the Bellman equations is presented in Appendix C.5.

[10]Note that when an individual is hit by the separation shock in period t, but finds a job in the search stage in period $t+1$, the continuation value to the worker remains U given the assumption that unemployed workers having zero bargaining power.

[11]Note the Bellman equations for a worker whose outside option is another firm is presented in Appendix C.2.

hired out of unemployment. When a worker matches with a type y firm, they produce $f(y)$, and the firm pays the worker $w(y, U)$. If at the end of the period the match is hit by the exogenous separation shock, then the match dissolves. If the firm's match is not exogenously separated then the firm receives the continuation value of the match $J(y, U)$. With probability $\phi p(\theta)$ the worker meets another firm $\tilde{y}$ while searching. If the worker meets a firm in their matching set $\tilde{y} \in m_1(y)$, then the worker leaves the firm, and the firm loses all of the surplus from the match. If the worker meets a firm in their renegotiation set $\tilde{y} \in m_2(y, y_0)$, then the firm maintains their relationship with the worker but loses $S(\tilde{y})$ in match surplus, which they transfer to the worker to keep the worker employed at the firm. The value to the firm of the match is given by:

$$\begin{aligned} J(y, U) &= f(y) - w(y, U) + \beta(1-\delta)J(y, U) \\ &- \beta(1-\delta)\phi p(\theta)\int_{m_1(y)} S(y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\ &- \beta(1-\delta)\phi p(\theta)\int_{m_2(y,U)} S(\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \end{aligned} \tag{3.7}$$

With the payoffs to unemployed workers, employed workers and firms defined, the match surplus can be defined.

3.2.5 Match Surplus

In this section, I present a Proposition which defines the surplus of a match between a worker and firm.

Proposition 1. *Using the bargaining procedure defined in Section 3.2.2 the match surplus between a worker and firm is independent of the labor force growth rate and is given by:*

$$S(y) = \frac{f(y) - b}{1 - \beta(1-\delta)}$$

Proof. See Appendix C.1.1. □

The surplus of a match is the gain in market resources of a match $f(y) - b$ discounted for the expected duration that an individual will be employed. As the gain in market resources of a match as well as the expected duration of an individual's employment spell are not influenced by the labor force growth rate, match surplus is independent of the labor force growth rate. In Section 3.3 I will extend the model include heterogeneous workers and will again find that match surplus is independent of the rate of labor force growth.

3.2.6 Vacancy Posting

In this section, I define the value to firms of posting a vacancy and derive the condition which determines the quantity as well as density of vacancies posted in equilibrium.

A firm that is posting a vacancy, posts the vacancy and searches for a worker to start production with. With probability $q(\theta)$ the firm meets a worker, and conditional on meeting a worker with probability $\frac{\hat{u}}{\hat{s}}$, the firm meets an unemployed worker. If the firm meets an unemployed worker, the firm hires the worker and receives the full surplus of the match, $S(y)$. Conversely, with probability $\frac{\phi\hat{e}}{\hat{s}}$, the firm meets an employed worker. If the worker is employed at a firm $\tilde{y}$ that firm y is able to poach the worker from ($\tilde{y} \in m_F(y)$), then firm y promises the worker the entire match surplus from their prior firm $\tilde{y}$, and keeps the remaining match surplus $S(y) - S(\tilde{y})$. If the firm does not match with a worker the firm receives nothing. The Bellman equation for a firm with a vacancy that has *met* a worker is given by:

$$V(y) = \left[\frac{\hat{u}}{\hat{s}}S(y) + \frac{\phi\hat{e}}{\hat{s}}\int_{m_F(y)} \left(S(y) - S(y_0)\right)\frac{\hat{e}(y_0)}{\hat{e}}dy_0\right]$$

Firm's post vacancies to equate the marginal cost of posting a vacancy to the expected benefit of posting a vacancy, which requires:

$$c^{'}(\hat{v}(y)) = q(\theta)V(y)$$

I set the vacancy cost as in Lise and Robin (2017) to be $c(\hat{v}(y)) = \frac{\kappa\hat{v}(y)^{1+c_1}}{1+c_1}$.[12] This sets the firm's free entry condition to be:

$$\kappa\hat{v}(y)^{c_1} = q(\theta)V(y) \tag{3.8}$$

Using a Cobb-Douglas matching function $M(\hat{s},\hat{v}) = A\hat{s}^{\alpha}\hat{v}^{1-\alpha}$, $q(\theta) = \frac{A\hat{s}^{\alpha}\hat{v}^{1-\alpha}}{\hat{v}} = A\hat{s}^{\alpha}\hat{v}^{-\alpha} = A\theta^{-\alpha}$, the vacancy posting condition can be rearranged to return the density of vacancies across firm types:

$$\hat{v}(y) = \left[\frac{A\theta^{-\alpha}V(y)}{\kappa}\right]^{\frac{1}{c_1}} \tag{3.9}$$

Inverting the distribution of vacancies across firms, and integrating across all firm types returns the following expression for the match tightness:

$$\theta = \left(\int_{\mathbb{Y}} \frac{1}{\hat{s}}\left[\frac{AV(y)}{\kappa}\right]dy\right)^{\frac{c_1}{c_1+\alpha}} \tag{3.10}$$

[12]The assumption that firms pay a cost to post vacancies relative to the size of the labor force is made for tractability.

With the distribution of vacancies across firms and match tightness the definition of equilibrium can be introduced.

3.2.7 Equilibrium and Match Surplus

In this subsection, I define competitive equilibrium in the steady state of the economy presented above.

For a given labor force growth rate λ, a recursive competitive equilibrium for this economy is a set of Bellman equations $\{U, W(y, y_0), V(y), J(y, y_0)\}$, densities $\{\hat{e}(y), \hat{v}(y), \hat{u}\}$, a labor market tightness θ, and wage $w(y, y_0)$ such that:

1. Given θ, $w(y, y_0)$, $\{\hat{e}(y), \hat{v}(y), \hat{u}\}$, the Bellman equations $\{U, W(y, y_0), V(y), J(y, y_0)\}$ characterize optimal behavior for workers and firms.

2. Given θ, $w(y, y_0)$, and the Bellman equations $\{U, W(y, y_0), V(y), J(y, y_0)\}$, the densities $\{\hat{e}(y), \hat{v}(y), \hat{u}\}$ are stationary.

3. Given θ, the densities $\{\hat{e}(y), \hat{v}(y), \hat{u}\}$ and the Bellman equations $\{U, W(y, y_0), V(y), J(y, y_0)\}$, the wage $w(y, y_0)$ satisfies the bargaining procedure.

4. The free entry condition (equation 3.8) is satisfied for all firms $y \in \mathbb{Y}$.

With equilibrium in the model defined, I next perform a comparative statics exercise to examine how changes in the labor force growth rate impact the value of posting a vacancy and hiring.

3.2.8 Labor Force Growth & Probability of Workers Meeting a Firm

In this section, I show that across steady states of the economy as the labor force growth rate decreases, the probability that a worker meets a firm decreases. Driving the result is that as the labor force growth rate decreases, the value to a firm of posting a vacancy decreases.

Using the expression for the steady state unemployment rate from equation 3.2, the value of posting a vacancy in the steady state of the economy is given by:

$$\begin{aligned} V(y) = &\left(\frac{\delta+\lambda}{\delta+\lambda+\phi p(\theta)(1-\delta)}\right) S(y) \\ &+ \left(\frac{\phi p(\theta)(1-\delta)}{\delta+\lambda+\phi p(\theta)(1-\delta)}\right) \int_{m_F(y)} \left(S(y)-S(y_0)\right) \frac{\hat{e}(y_0)}{\hat{e}} dy_0 \end{aligned} \tag{3.11}$$

From the expression for the value of posting a vacancy in equation 3.11 the following proposition is immediate.

Proposition 2. *Holding labor market tightness θ fixed, as the labor force growth rate λ decreases, the value to a firm of posting a vacancy $V(y)$ decreases, i.e.* $\frac{\partial V(y)}{\partial \lambda} > 0$.

Proof. See Appendix C.1.2. □

The intuition for Proposition 2 is that firms prefer to hire unemployed workers rather than to poach a worker from another firm. When a firm hires an unemployed worker they are able to keep all of the match surplus, while when a firm hires an employed worker they must use some of the match surplus to entice the worker to leave their prior firm. From equation 3.11, if labor market tightness θ is held fixed, as the labor force growth rate decreases, the share of individuals searching for a job that are unemployed ($\frac{\delta+\lambda}{\delta+\lambda+\phi p(\theta)(1-\delta)}$) decreases. Hence, as the labor force growth rate decreases, conditional on meeting a worker, firms become more likely to meet an employed worker, who leaves the firm with a smaller amount of surplus, which decreases the value to a firm of posting a vacancy.[13] From this proposition, the following corollary is immediate.

Corollary. *If $\phi = 1$, then as the labor force growth rate decreases, the probability a firm meets a worker $q(\theta)$ increases, and the probability a worker meets a firm $p(\theta)$ decreases, i.e.* $\frac{\partial q(\theta)}{\partial \lambda} < 0$ *and* $\frac{\partial p(\theta)}{\partial \lambda} > 0$.

Proof. See Appendix C.1.3. □

Equation 3.10 links the value of posting a vacancy $V(y)$ to the equilibrium value of market tightness θ. With the assumption that the relative search intensity of the employed is the same as the unemployed ($\phi = 1$), equation 3.10 gives that market tightness is an increasing function of the value of posting a vacancy.[14] Then following from Proposition 2, since the value of posting a vacancy decreases as the labor force growth rate decreases, the equilibrium value of market tightness must decrease as well. With a decline in market tightness there are fewer vacancies for each searching worker, and the probability that a worker meets a firm while searching in the labor market declines. I refer to this channel where a change in the labor force growth rate impacts the probability that a worker meets a firm as the *meeting channel.*

Considering the U.S. labor market since the 1970s, Proposition 2 indicates that the decline in the labor force growth rate has decreased the value of posting a vacancy, and labor market tightness θ. A decline in labor market tightness decreases the probability that an unemployed worker matches with a firm and that an employed worker is able to switch firms. Through on the job search workers move to firms where they are more productive.

[13] Recall that match surplus $S(y)$ is independent of the labor force growth rate.

[14] In the calibrated model, I will calibrate the parameter ϕ, and find that for the calibrated parameter of ϕ, the above corollary holds numerically.

Hence, the decline in labor force growth may lower aggregate output by decreasing workers' ability to move to firms where they are more productive. In the next section, I calibrate the model to be consistent with the U.S. labor market, and conduct an experiment of feeding into the model the observed path of the labor force growth rate and estimate the impact on the allocation of workers across firms as well as aggregate output.

3.3 Quantitative Model and Estimation

In this section, I introduce heterogeneous workers into the model from Section 3.2, and allow worker's human capital to evolve over their working careers. Including worker heterogeneity enriches the model to measure the degree to which the allocation of workers across firms is impacted by changes in the labor force growth rate. I then discuss the estimation of the model, and calibrate the model to be consistent with the U.S. labor market between 2012 and 2016.

3.3.1 Quantitative Extension

Before estimating the model, I extend the model of Section 3.2 along several dimensions. First, I allow workers to be heterogeneous in their human capital (or productivity). With heterogeneous workers and firms, each worker has a firm where they are most productive, which allows the model to examine if changes in the labor force growth rate impact the degree to which workers are able to sort to the firms where they are most productive. Workers entering the labor market draw their productivity from a distribution $G(x)$ over a grid of productivity levels $\{x_1, x_2, ..., x_N\}$, and a worker's human capital evolves over their working careers as in Ljungqvist and Sargent (1998). In particular, during *employment spells* a worker with human capital x, sees their human capital evolve according to:

$$x^{'} = \begin{cases} \min\{x+1, x_N\} & \text{w/ prob } p_H \\ x & \text{w/ prob } 1-p_H \end{cases} \tag{3.12}$$

while during *unemployment* spells their human capital (x) evolves according to:

$$x^{''} = \begin{cases} \max\{x-1, x_1\} & \text{w/ prob } p_L \\ x & \text{w/ prob } 1-p_L \end{cases} \tag{3.13}$$

where x_1 and x_N are the minimum and maximum values of worker productivity, respectively. Finally, to additionally capture the life-cycle dynamics that workers face in the labor market, each period workers exit the model with probability ζ.

This process for human capital allows the model to capture that labor force entrants do not necessarily have the same productivity level as more experienced workers, but have their productivity evolve over their careers in the labor market. The process for human capital highlights another channel where changes in the labor force growth rate can influence the labor market. When the labor force growth rate is lower, the labor market will have a larger share of "older" workers who, on average tend to be more experienced give the human capital process characterized above. Additionally, through on the job search, workers move to firms where they are more productive, i.e. workers become better sorted with greater labor market experience. Hence, as the composition of the labor market shifts to a greater share of "older" workers, from a decrease in labor force growth, the labor market becomes better sorted, which increases output. I refer to this channel where changes in the labor force growth rate impacts the distribution workers across of productivity levels and the sorting of workers across firms by adjusting the composition of workers in the labor market as the *labor composition channel.*

The bargaining procedure as well as the matching process described in Section 3.2.2 extend naturally to the setting with heterogeneous workers. A worker's wage is now a function of their human capital, the firm they are currently working at as well as their outside option. Similarly, the matching sets for workers and firms now take into account the productivity of both the worker and firm as well as the worker's outside option.

Finally, I additionally allow for the rate of labor force growth to change from one period to the next. This addition to the model allows for solving the transition path of the model economy using the realized path of labor force growth rates over the past 40 years

Proposition 1, which stated that the match surplus between a worker and firm did not depend upon the worker's outside option and the labor force growth rate extends to the environment with heterogeneous workers. As changes in the labor force growth rates are the only aggregate shocks in the model, I can thus write the match surplus as being independent of time. In the environment with heterogeneous workers and where workers are subject to shocks to their human capital, match surplus is given by:

$$\begin{aligned} S(x,y) = f(x,y) - b(x) + \beta(1-\zeta)(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}S(x^{'},y)\right] \\ -\beta(1-\zeta)(1-\delta)\mathbb{E}_{x''}\left[U(x^{''})\right] + \beta(1-\zeta)(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \end{aligned} \tag{3.14}$$

where the value to being an unemployed worker $U(x)$ is given by:

$$U(x) = b(x) + \beta(1-\zeta)\mathbb{E}_{x''}\left[U(x^{''})\right] \tag{3.15}$$

Observe from equation 3.14 and 3.15 that the match surplus is independent of the distribution of unemployed workers across types as well as the rate of labor force growth.[15] This feature of the model allows for the tractable estimation of the transition path of the change in the labor force growth rate experienced by the U.S. labor market since the 1970s. In particular, we can determine the initial allocation of workers across firms by solving equations 3.14 and 3.15 as well as the laws of motion for workers and vacancy creation (Appendices C.3.3 and C.3.6, respectively). From this initial steady state, we can calibrate the model to be consistent with the US labor market. Then solving the transition path simply requires feeding the path of labor force growth rates through the laws of motion.
A full description of the quantitative model is located in Appendix C.3.

3.3.2 Calibration

In this subsection, I discuss the calibration of the model. Some parameters are assigned using estimates from the literature, while others will be calibrated to match moments from the U.S. labor market between 2012 and 2016. First, I discuss the assigned parameters, and then the calibrated parameters.

Assigned Parameters

The model is estimated at a monthly frequency. Between 2012 and 2016, the trend component of the labor force growth rate averaged 0.67 percent per year. Given the monthly timing of the model, this implies a period growth rate of $\lambda = 5.54 \times 10^{-4}$. Assuming an annual interest rate of 4 percent requires setting the discount factor $\beta = 0.99674$. Workers have, on average, a 30-year working career, implying a per-period exit probability of 2.8×10^{-3}.
I use a second-order Taylor series in worker and firm productivity for the production function, and use the coefficient estimates from Lise and Robin (2017):[16]

$$f(x, y) = p_1 + p_2 x + p_3 y + p_4 x^2 + p_5 y^2 + p_6 xy$$

The parameters from Lise and Robin (2017) result in a production function that exhibits the following three properties: (1) production is increasing in the worker's productivity

[15] Note in the expectation operator of equation 3.14 the term $\{S(x^{'}, y) > 0\}$ is to indicate that match surplus must remain positive in the next period if it is to add to the match surplus today. With the shocks to human capital, it is possible that a match that currently has positive surplus will turn negative after the shock to the worker's human capital. When the match surplus turns negative the match ends, and is considered an endogenous separation. For more details see Appendix C.3.

[16] Note the results are virtually identical using the CES production function estimated by Abowd et al. (2014) using matched employee-employer data from the LEHD.

holding a firm's productivity fixed, (2) production is non-monotone in the firm's productivity holding a worker's productivity fixed, and (3) there is positive complementarity between worker and firm productivity.

When a worker is not matched with a firm they receive unemployment insurance (UI) benefits. The UI benefit is set as a share of market production:

$$b(x) = \bar{b} \times f(x, y^*(x))$$

where $y^*(x) = \text{argmax } f(x, y)$ and the share parameter $\bar{b}$, which governs the generosity of the UI benefit, is set to 0.70 as in Lise and Robin (2017).

Meetings between searching individuals and vacancies occur according to a Cobb-Douglas function:

$$m(\hat{s}, \hat{v}) = A\hat{s}^{\alpha}\hat{v}^{1-\alpha} \tag{3.16}$$

Following Petrongolo and Pissarides (2001), I set the elasticity of the matching function to 0.5. The efficiency of the meeting function A, will be a calibrated parameter of the model and is discussed in Section 3.3.2.

I estimate the model on 30 evenly spaced grid points between 0 and 1 for worker and firm productivity. Values for the assigned parameters are shown in the top panel of Table 3.1.

Calibrated Parameters

In this section, I discuss the calibration of the remaining model parameters. These parameters are calibrated using simulated method of moments, which uses a set of moments that are informative for the model's parameters and minimizes the distance between the model's estimates of the moments and the data equivalents. Below I discuss the moments which are used to calibrate each parameter, and provide a heuristic identification argument to justify the moment choices. Appendix C.4 contains details on each of the moments used in the calibration.

The efficiency of the meeting function A governs the propensity that workers and firms meet one another while searching, and is calibrated to match the probability than an unemployed worker becomes employed (the UE transition rate). The probability an employed worker becomes unemployed, the EU transition rate, is monotonically increasing in the exogenous separation rate δ. The relative search intensity of employed workers ϕ is calibrated to target the share of workers who switch firms in a given month, i.e. the job to job transition rate. I assume a strictly convex cost of posting vacancies for each firm y with $c(\hat{v}(y)) = \frac{\kappa\hat{v}(y)^{1+c_1}}{1+c_1}$, and following Sahin et al. (2014) I set $c_1 = 1$. The scale parameter in the cost of posting a vacancy (κ) alters the number of vacancies posted in equilibrium and is calibrated to match the unemployment rate.

The remaining model parameters are calibrated using workers' earnings.[17] To calibrate moments based on workers' earnings, I rank workers based on their earnings by placing them into percentiles, which I refer to as *earnings rankings*.[18] To estimate the probability that a worker's human capital increases while employed p_H, I target the average increase in a worker's earnings ranking associated with an increase in age. With a higher value of p_H workers have more frequent increases in their human capital. As increases in human capital are associated with an increase in earnings, a higher value of p_H increases the average gain in a worker's earnings ranking over time. I estimate the average increase in a worker's earnings ranking associated with an increase in age using the following regression of age on earnings ranking for a cross-section of agents in period t:

$$R_{i,t} = \alpha + \beta_{age} Age_{i,t} + \epsilon_{i,t} \tag{3.17}$$

In equation 3.17, $R_{i,t}$ denotes the earnings ranking of individual i in year t, and $Age_{i,t}$ denotes the age of individual i in year t. The coefficient β_{age} estimates the average increase in earnings ranking associated with an increase in age. Using data from the CPS, I estimate an average increase in earnings ranking with a 1-year increase in age of 0.426. This indicates on average, every two and half years an individual moves up one-spot in the earnings rankings.

To estimate the probability that a worker's productivity decreases while unemployed p_L, I examine the decline in earnings rankings around displacement episodes. Using the the Displaced Workers Supplement from the CPS, I identify individuals with three or more years of tenure who are subsequently displaced from their job. I estimate that three-years after displacement these individuals move, on average, 6.86 spots lower in the earnings rankings relative to prior to displacement. On average, these individuals' earnings are 13.2 percent lower three years after job loss relative to before displacement.

Finally, I use an approach similar to Huckfeldt (2014) in calibrating the distribution of productivity types for new labor force entrants. The distribution of types $G(x)$ is assumed to follow a log-normal distribution with mean μ_e, and standard deviation σ_e. The mean of the distribution is calibrated to match the ratio of the earnings ranking for workers who have

[17] In the model there is no distinction between wages and earnings because there is no notion of hours. All workers in the model can be thought of as working full-time. To be consistent with this notion I only use full-time workers when calibrating parameters using earnings. For this reason, the terminology of "wages" and "earnings" will be used interchangeably in discussing the calibration.

[18] I use wage ranks rather than the wage level since with unemployed workers having zero bargaining power there are cases where workers are paid a negative wage. This occurs when a worker matches at a highly productive firm that will be able to pay the worker a high wage in the future, once the worker has a stronger outside option. To obtain these high wage payments in the future, workers are willing to effectively pay to work at these firms in the current period.

been in the labor market for five or more years over the earnings ranking of workers who have been in the labor market for less than five years. I refer to this ratio as the *experience premium*. A lower mean to the entrant distribution increases the degree to which workers can increase their productivity over time, and raises the experience premium. I estimate an experience premium of 1.48 using data from the CPS. The standard deviation of the entrant productivity distribution is calibrated to match the standard deviation of earnings rankings among workers with less than five years of labor market experience.[19] Using the CPS, I estimate the standard deviation of earnings rankings among individuals with less than five years of labor market experience to be 25.94.

3.3.3 Estimation Results: 2012-2016 Steady State

In this section, I present the model's estimates of the 2012-2016 steady state.

The bottom panel of Table 3.1 reports the parameter estimates from the calibration exercise. Table 3.2 displays the targeted data moments and their corresponding estimates from the calibrated model. Overall, the model provides a decent fit to the data.

Critical to the model's estimate of the impact of a change in the labor force growth rate on the labor market is the productivity distribution of labor force entrants $G(x)$. The dashed line in Figure 3.3 displays the distribution of labor productivity that labor force entrants draw from. The figure shows that the productivity distribution of labor force entrants is skewed to the right with the majority of labor force entrants being low productivity workers. Hence, as the labor force growth rate changes this alters the inflow of relatively low productivity workers into the labor market.

Labor force entrants enter the labor market as low productivity workers, but over time are able to increase their human capital by remaining employed. The parameter estimate for p_H, which governs the acquisition of human capital during employment, shows the process for increasing human capital is slow moving. With a monthly probability of increasing human capital of 0.6 percent, it takes an employed worker, on average, over 14 years to have an increase in their human capital. Hence, it takes labor force entrants years of experience to increase their productivity. The solid line in Figure 3.3 shows the distribution of all workers (employed and unemployed) across productivity levels, and shows how over time workers transition to higher productivity levels.

[19]Note the ranking of earnings is done across all workers regardless of their labor market experience. I then only consider individuals with less than five years of experience and estimate the standard deviation of their earnings rankings.

3.3.4 Model Validation: Non-Targeted Moments

In the above section, I calibrated the model to be consistent with aggregate statistics on the labor market from 2012-2016. In this section, I present the model's estimates for the distribution of earnings rankings as well as the the average path of earnings rankings by years of labor market experience. These moments were not targeted in the calibration of the model, and provide a validation of the model's estimation of the distribution of labor force entrants as well as the evolution of human capital over an individual's working life.

The left panel of Figure 3.4 shows the kernel density of earnings rankings for individuals with less than 5 years of labor market experience as predicted by the model along with the data counterpart. The figure shows that the model is able to accurately capture the distribution of earnings ranking among young workers. The figure also shows that the majority of individuals with less than five years of labor market experience have earnings in the bottom third of the earnings rankings. As worker productivity and earnings are closely related this supports the outcome of the calibration that labor force entrants are on average lower productivity workers.

The right panel of Figure 3.4 shows the average earnings ranking by years of labor market experience. The figure shows that the model is able to capture the general path of earnings rankings over the working life cycle, where individuals move up the earnings ranking quickly at the start of their career and then at a slower rate later in their career.

The results of this section show that the human capital process used in the model is able to generate patterns of earnings dynamics that are consistent with the data. In particular the model is able to generate a distribution of earnings among young workers and generate a path of earnings over a worker's career that is consistent with the data. In the following section, I use the model as a laboratory to conduct an experiment where I vary the rate of labor force growth and examine the implications for the allocation of workers across firms and aggregate output.

3.4 Impact of Changes in the Labor Force Growth Rate

In this section, I estimate the impact of the decline in the labor force growth rate on the labor market by feeding into the calibrated model the path of the labor force growth rate from 1975 to 2016.[20] The results of the transition experiment show that the decline in labor force growth has decreased vacancy creation, the job to job transition rate, and UE transitions. However these declines in vacancy creation, and worker reallocation (job to job and UE transitions) are small relative to the observed declines in the data. Despite the

[20] Comparing steady states across these two time periods gives similar results to solving the transition path.

decline in worker reallocation, due to the decline in labor force growth, output per worker *increases*. The increase in output per worker occurs as firms match on average with more experienced and productive workers as well as by improved sorting of workers across firms.

3.4.1 Transition Path

In this section, I solve the transition path of the economy using the observed path of the labor force growth rate from 1975 to 2016. In particular, I start from the steady state of the economy estimated at the 2012-2016 rate of labor force growth, and then feed into the model the trend labor force growth rate shown in Figure 3.1.[21] While this exercise is effectively solving the transition path "going backwards in time," I will discuss the results in terms of the decline in the labor force growth rate from 1975 to 2016. Solving the transition path requires updating the distribution of workers across firms, unemployed workers across productivity levels, as well as solving for the distribution of vacancies, and the labor market tightness that equates the value of posting a vacancy to the cost of posting an additional vacancy for each firm.[22] Figure 3.5 shows the impact of changes in the labor force growth rate on unemployment, vacancies, and worker flows from solving the transition path of the economy. In all panels of Figure 3.5, the time series are indexed so that the value from the year 1975 is equal to 100.

Panel (a) of Figure 3.5 shows the model's estimate of the unemployment rate as the labor force growth rate declines. The model predicts that due to the decline in labor force growth the unemployment rate declines by approximately 8%. As the unemployment rate declines, the pool of potential hires for firms shifts towards more expensive employed workers that must be poached away from another firm. With hiring becoming more expensive firms reduce the number of posted vacancies. Panel (b) of Figure 3.5 displays the model's estimate of the vacancy rate along the transition path. As the labor force growth rate declines, the rate of vacancy posting declines by nearly 2.5%. The decline in the vacancy posting makes it more difficult for both employed and unemployed workers to match with a firm while searching in the labor market.[23] Panel (c) of Figure 3.5 shows the model's estimate of the job to job transition rate since 1975. The figure shows that the model predicts as labor force growth declines, the rate at which workers switch jobs declines by nearly 4.5%. Similarly, as the rate of labor force growth declines, the probability than an unemployed worker gets hired declines by approximately 0.5%. These results indicate that the decline in labor force

[21] In solving the transition path, I use the annual trend labor force growth rate for each month within a year.

[22] Recall that match surplus is independent of the labor force growth rate. Thus to perform the transition path experiment I can take the match surplus from solving the initial steady state of the model, and simply update the distributions as the labor force growth rate evolves.

[23] Labor market tightness (θ_t), which controls the probability a worker meets a firm, declines along the transition path.

growth has led to a reduction in vacancy posting as well as hiring.

Over the past forty years there has been a steady decline in the rate at which workers are hired and switch jobs (e.g. Hyatt and Spletzer (2013), Davis and Haltiwanger (2014), and Molloy et al. (2016)). Qualitatively, the patterns presented in the Figure 3.5 are consistent with the declines in hiring for employed and unemployed workers, and implicate declining labor force growth as a potential cause to these declines. In Table 3.3 I compare the size of the declines in the unemployment rate, vacancy creation, and worker flows that have been observed in the data (Column (1)) as well as predicted by solving the transition path of the model given the decline in labor force growth (Column (2)). The table shows that the model accurately predicts the size of the decline in the unemployment rate between 1975 and 2016. However, the observed decline in labor force growth generates declines in vacancy creation and hiring that are small relative to the data. In particular, based on the observed decline in labor force growth, the model predicts job to job transitions decline by nearly 4.5%, while in the data job to job transition have declined by over 36%. Although small relative to the data, the results of the transition path experiment demonstrate that as the labor force growth rate decreases there is less reallocation of workers across firms. This decline in worker flows has the ability to influence the allocation of workers across firms as well as aggregate output, which I examine next.

Figure 3.6 shows the results of the transition experiment for aggregate output as well as for measures of the allocation of workers across firms. Despite the modest change in worker flows, the decline in labor force growth does have an impact on output per worker. Panel (a) Figure 3.6 shows output per worker *increases* by over 4.5 percent along the transition path as the labor force growth rate declines from 1975 to 2016.

There are two forces which generate an increase in output per worker along the transition path despite the fact that there is lower worker reallocation across firms. First, recall that the distribution of labor force entrants is skewed towards lower productivity workers (dashed line in Figure 3.3). Thus, as the labor force growth rate decreases, the share of lower productivity workers in the economy decreases. Panel (b) of Figure 3.6 displays the average productivity of workers at each firm in 2016 (solid line) as well as in 1975 (dashed lined). The figure shows that in 2016 when labor force growth is lower, firms match on average with more productive workers, which increases output.

Second, as the labor force growth rate declines the labor force has a larger share of older workers who tend to be better sorted across firms. In the model, workers spend their first several years making frequent job to job transitions as they move to firms where they are more productive, similar to the "job shopping phase" in Bagger et al. (2014). Panel (c) of Figure 3.6 shows that the correlation between worker and firm productivity increases as workers have greater experience in the labor market, which reflects better sorting of workers across firms. Panel (d) shows that for the aggregate economy as the labor force growth rate declines, the correlation of worker and firm productivity increases, i.e. sorting is improved. The improved sorting of workers across firms also increasing aggregate output.

These results suggests that for output per worker, with a lower labor force growth rate the cost of workers being less able to switch firms is offset by the effects of having a smaller share of low productivity workers and the improved sorting of workers across firms. In the next subsection, I further explore the labor composition channel in explaining the increase in output per worker as the labor force growth rate declines.

3.4.2 Transition Path: Fixed Worker Types

In this section, I repeat the transition path experiment but hold the distribution of worker productivity levels (types) fixed to disentangle the effects of improved sorting and a shifting distribution of workers across productivity levels that arise as the labor force growth rate declines. This experiment serves as a decomposition of the labor composition channel, which is the channel that generated an increase in output per worker along the transition path of lower labor force growth.

In this exercise, I set the distribution of productivity levels that labor force entrants draw from to be the equilibrium distribution of workers across productivity levels from the baseline estimation of the model in Section 3.3.3.[24] The non-calibrated parameters of the model remain fixed (top panel of Table 3.1), and I re-calibrate the model to be consistent with the U.S. labor market from 2012-2016 under the assumption that worker productivity is fixed indefinitely. Table 3.4 shows the values of the re-calibrated parameters as well as the model fit. With these parameters, I repeat the transition path experiment of feeding in the trend labor force growth rate from 1975 to 2016.

Figure 3.7 presents the results of this transition path experiment for unemployment, vacancies and labor market flows. The results of the experiment show that the decline in labor force growth decreases the unemployment rate, vacancy rate, job to job transition rate, as well as the UE transition rate. As in the baseline transition experiment, the decline in vacancies, job to job transitions, and UE transitions are small relative to the observed declines over this period (Column (3) of Table 3.3). Additionally, the path of the unemployment rate, vacancy rate, job to job transition rate, and UE transition rate with a fixed type distribution largely mirrors the respective paths when the distribution of worker types evolves over a working career (as in Figure 3.5). This indicates that shifts in the distribution of workers across productivity levels (types) arising from changes in the labor force

[24]The distribution of workers across productivity levels is given by the solid line in Figure 3.3. The results are virtually identical if I set the entrant distribution to the calibrated distribution of worker types from Lise and Robin (2017) and assume worker's productivity is fixed.

growth rate does not play a significant role in shaping the rate of worker reallocation or vacancy creation along the transition path.

While the impact of declining labor force growth on labor market flows is largely the same with the distribution of worker productivity held fixed, the implications for output per worker differ. Panel (a) of Figure 3.8 shows that output per worker increases by approximately 1.5 percent as the labor force growth rate decreases. The increase in output per worker occurs as workers are better sorted across firms (Panel (b) of Figure 3.8). However, the increase in output per worker with fixed worker types is approximately 1/3 of the size of the increase compared to the increase in output per worker when a workers type (productivity) evolves over their working career as in the baseline model. This results indicates that only 1/3 of the increase in output per worker from the baseline model is due to the improved sorting over workers across firms. The remaining increase in output per worker from the decline in labor force growth is due to the shifting of the distribution of workers toward higher productivity workers.

3.5 Conclusion

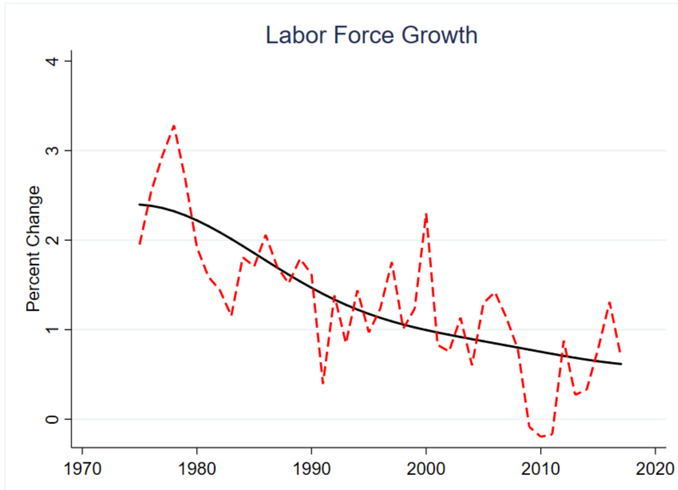
The rate at which workers enter the labor market has declined significantly since the 1970s. Prior research has shown that this demographic transition has been associated with changes in the rate of new businesses formation as well as the unemployment rate. In this paper, I examine how the decline in the labor force growth rate has influenced the allocation of workers across firms and aggregate output.

In answering this question, I make two contributions. First, I integrate labor force growth into the labor sorting model of Lise and Robin (2017) and demonstrate theoretically that declining labor force growth leads to a decline in hiring due to reduced vacancy creation by firms. Second, I quantitatively evaluate this theory using the decline in the labor force growth rate over the past 40 years. I find that the decline in the labor force growth rate has lead to lower vacancy creation, which has reduced the degree that workers switch firms and are hired out of unemployment. Despite the decline in worker flows and vacancy creation, output per worker is over 4.5 percent higher. With lower labor force growth, the supply of workers shifts towards more experienced workers who on average are more productive and better sorted across firms. The shift towards more productive and better sorted workers increases output per worker.

Finally, the results of this paper are informative for the literature that explores the "declining dynamism" of the U.S. economy (e.g. Decker et al. (2013), Hyatt and Spletzer (2013), Davis and Haltiwanger (2014), and Molloy et al. (2016)). This literature has documented that there has been a steady decline in businesses formation, hiring and job switching, but has yet to fully uncover the cause of these declines (see discussion in Molloy et al. (2016)). Te results of the transition path exercise shows that the changes in the job to job transition rate, UE transition rate, and vacancy rate are qualitatively consistent with the observed trends in the data, but are significantly smaller in magnitude than the changes observed in the data. These results indicate that the decline in labor force growth has played only a minor role in the declining dynamism of the U.S. economy.

Figures and Tables

Figure 3.1

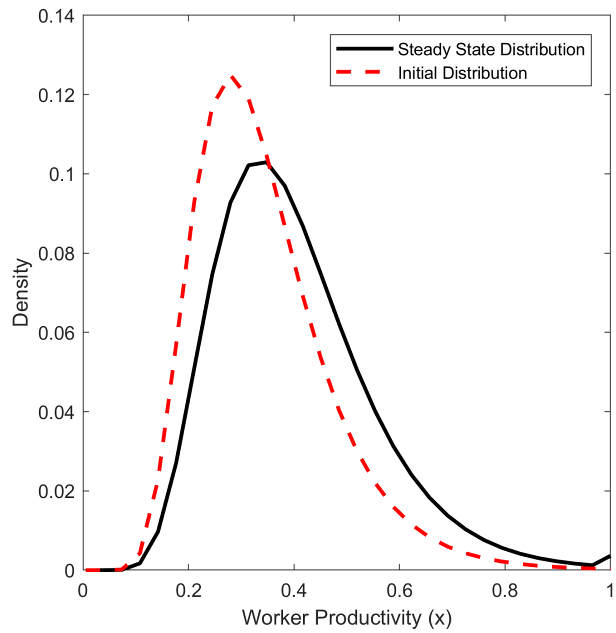


Note: Figure shows the labor force growth rate. The solid line is the trend labor force growth rate, where the trend is estimated using the Christiano and Fitzgerald (2003) band pass filter with a minimum period of 2 years and a maximum period of 30 years. The dashed line is the annual labor force growth rate. Data on the labor force growth rate is from the Current Population Survey (CPS).

Figure 3.2: Labor Market Flows and Vacancy Creation

Notes: Panel (a) shows the unemployment rate. Panel (b) shows the vacancy rate, which is the ratio of vacancies to the the labor force. Panel (c) shows the job to job transition rate, which is the monthly probability an employed worker switches firms. Panel (d) shows the monthly unemployment to employment (UE) transition rate, which is the monthly probability an unemployed worker becomes employed. The solid line is the trend component of the time series, where the trend is estimated using the Christiano and Fitzgerald (2003) band pass filter with a minimum period of 2 years and a maximum period of 30 years. The solid line represents the unfiltered time series. See Appendix C.4 for details on the construction of the Job to Job Transition Rate and the UE transition Rate. Data on the vacancy rate is from Barnichon (2010), and the unemployment rate is from the Current Population Survey (CPS).

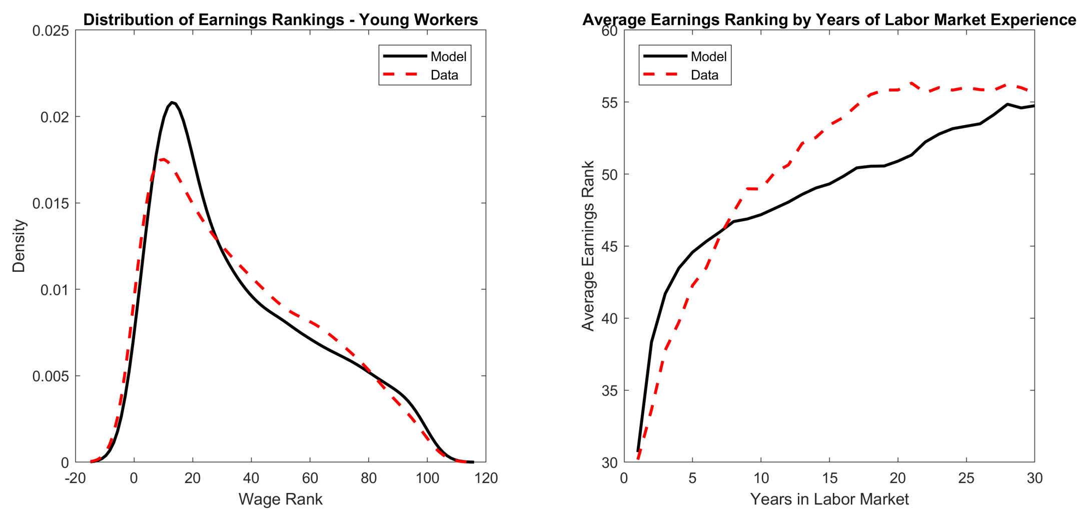
Figure 3.3: Productivity Distribution of Workers



Notes: The dashed line shows the productivity distribution for labor force entrants $G(x)$. The solid line displays the distribution of all workers, both employed and unemployed, across productivity levels.

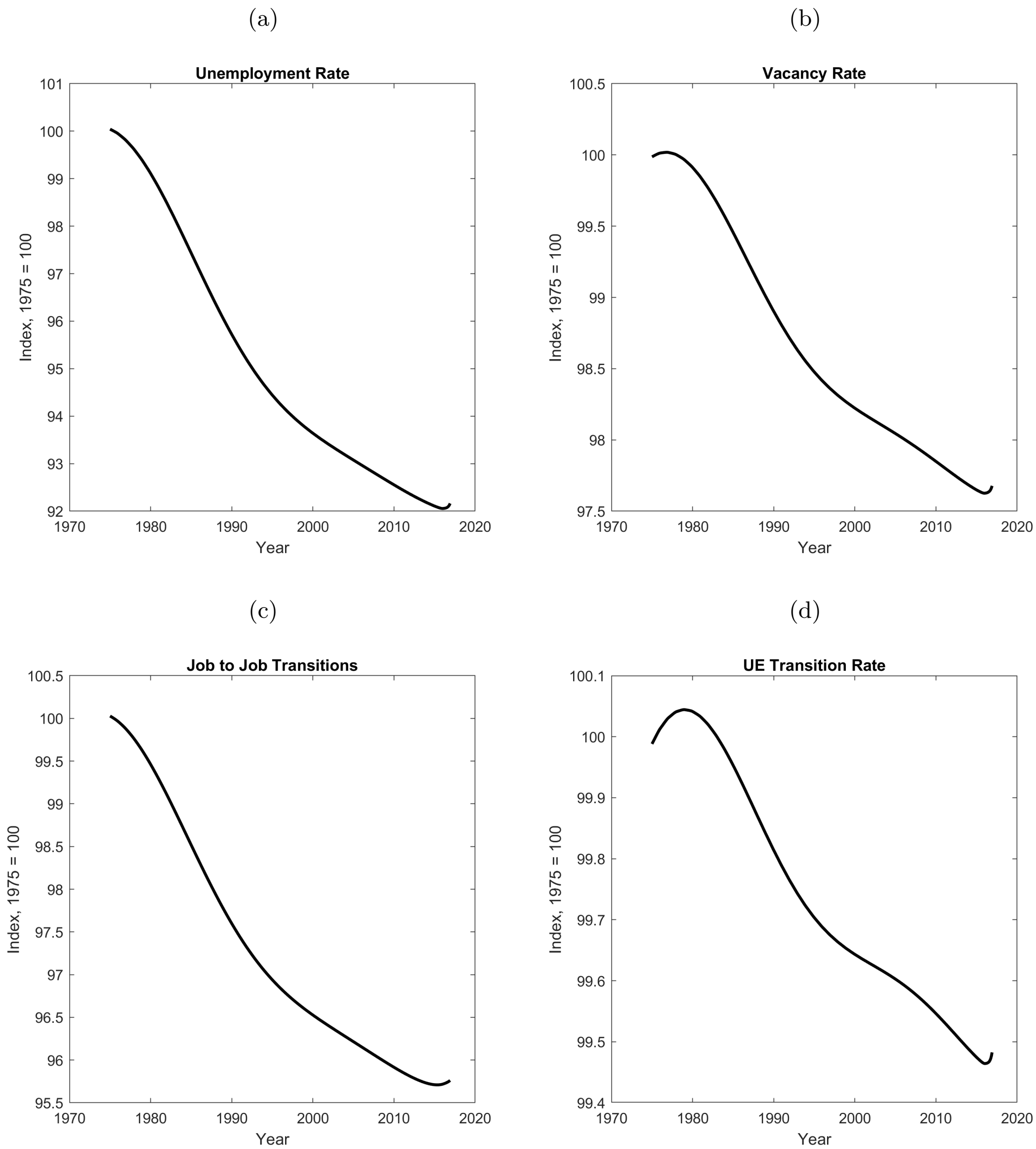
Figure 3.4: Non-Targeted Moments

(a) (b)



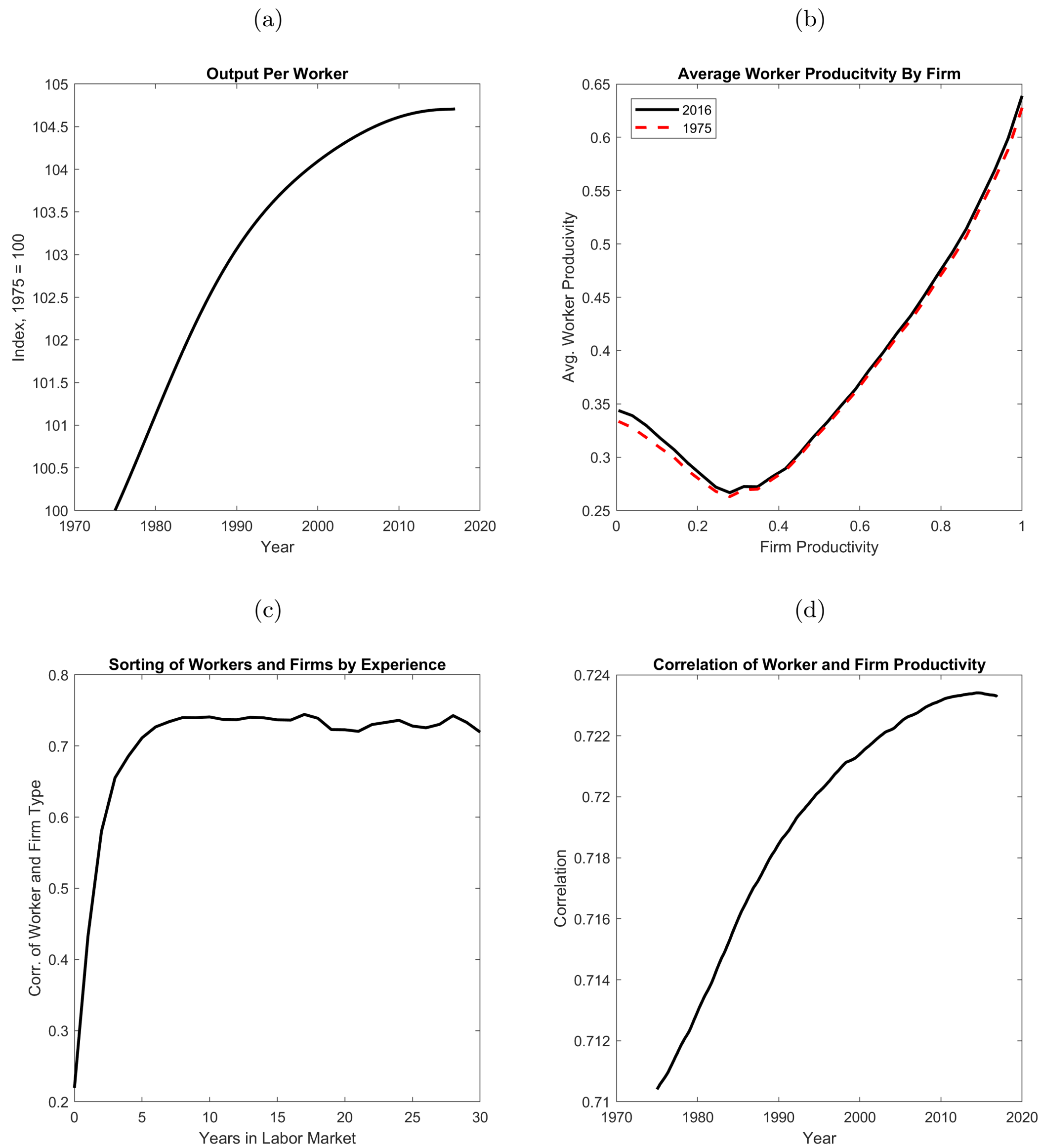
Notes: Panel (a) shows the kernel density of worker earnings ranks among individuals who have been in the labor market for less than five years. Panel (b) shows the average earnings rank by years in the labor market. In each figure, the solid line is the model estimate, and the dashed line the data estimate from the Current Population Survey (CPS).

Figure 3.5: Unemployment, Vacancies, and Labor Market Flows



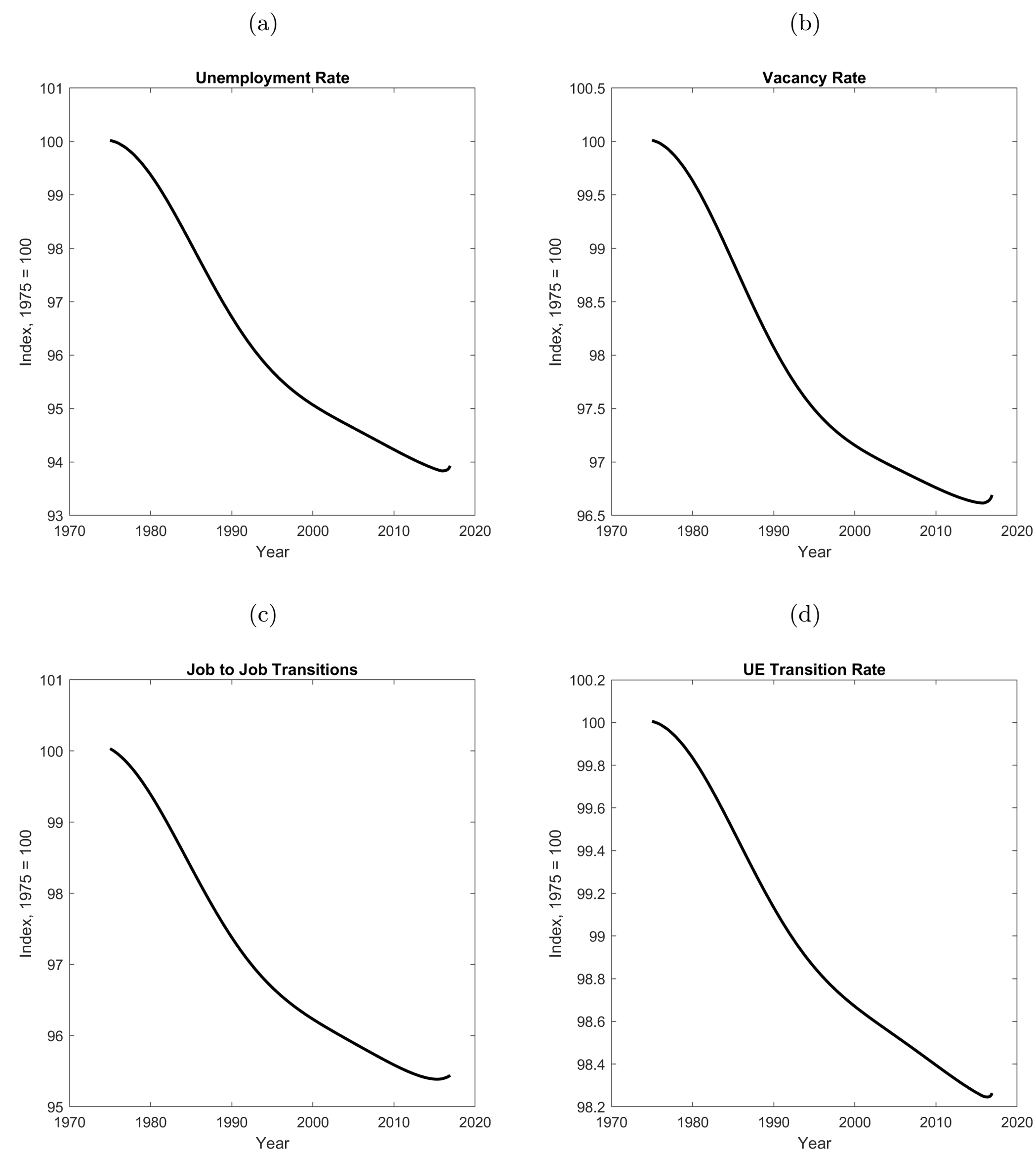
Notes: Results are from solving the transition path, which feeds the path of labor force growth rates from 1975 to the 2016 into the baseline model. In each figure the solid line is the model estimate from solving the transition path. Panel (a) shows unemployment rate. Panel (b) shows the vacancy rate, which is aggregate vacancies over the size of the labor force. Panel (c) is the job to job transition rate, which is the monthly probability that an employed worker switches firms from one month to the next. Panel (d) is the unemployment to employment (UE) transition rate, which is the monthly probability an unemployed worker becomes employed. In all figures, the time series are indexed so that the value from the year 1975 is equal to 100.

Figure 3.6: Aggregate Output and the Allocation of Workers Across Firms



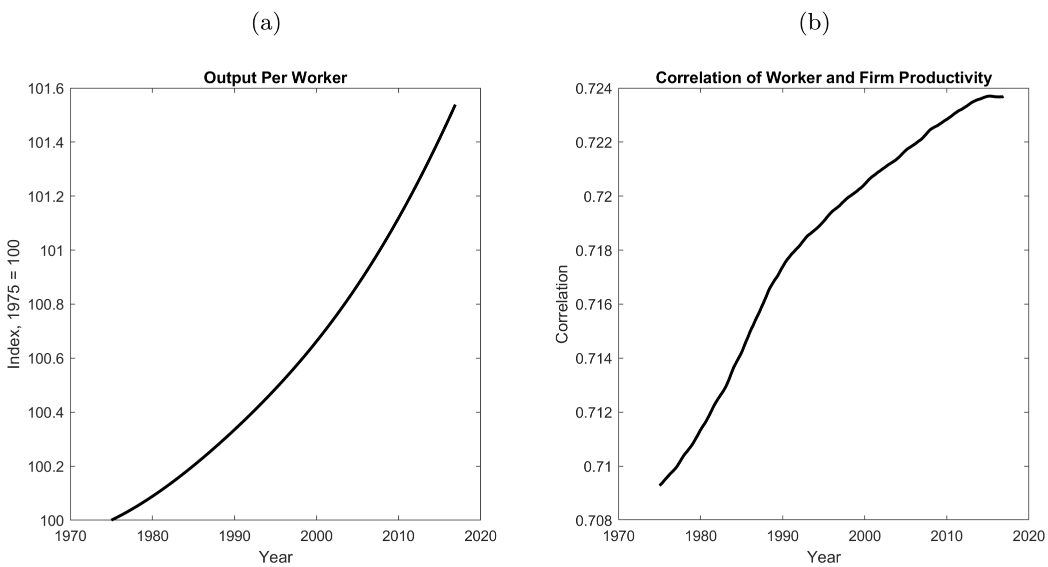
Notes: Results are from solving the transition path, which feeds the path of the labor force growth rate from 1975 to 2016 into the baseline model. Panel (a) shows output per worker. Panel (b) shows average worker productivity for each firm. Panel (c) shows the correlation of worker and firm productivity by labor market experience from the 2012-2016 steady state of the model. Panel (d) shows the correlation of worker and firm productivity along the transition path.

Figure 3.7: Unemployment, Vacancies, and Labor Market Flows with Fixed Worker Types



Notes: Results are from solving the transition path, which feeds the path of labor force growth rates from 1975 to 2016 into the model where a worker's type is fixed indefinitely. In each figure the solid line is the model estimate from solving the transition path. Panel (a) shows unemployment rate. Panel (b) shows the vacancy rate, which is aggregate vacancies over the size of the labor force. Panel (c) is the job to job transition rate, which is the monthly probability that an employed worker switches firms from one month to the next. Panel (d) is the unemployment to employment (UE) transition rate, which is the monthly probability an unemployed worker becomes employed. In all figures, the time series are indexed so that the value from the year 1975 is equal to 100.

Figure 3.8: Aggregate Output and the Allocation of Workers Across Firms w/ Fixed Worker Types



Notes: Results are from solving the transition path, which feeds the path of labor force growth rates from 1975 to 2016 into the model where a worker's type is fixed indefinitely. Panel (a) shows output per worker, and Panel (b) shows the correlation of worker and firm productivity.

Table 3.1: Model Parameters

	Non-Estimated		
Parameter	Description	Value	Source
λ	Labor force growth rate	5.41×10^{-4}	Ann. growth rate 0.667 percent
β	Discount factor	0.99674	Ann. interest rate 4 percent
ζ	Workers exiting probability	2.8×10^{-3}	30 year working career
$\bar{b}$	UI benefit generosity	0.70	Lise and Robin (2017)
α	Meeting function elasticity	0.5	Petrongolo and Pissarides 2001
c_1	Vacancy posting elasticity	1	Sahin et al. 2014
p_1	Production function parameter	0.003	Lise and Robin (2017)
p_2	Production function parameter	2.053	Lise and Robin (2017)
p_3	Production function parameter	−0.140	Lise and Robin (2017)
p_4	Production function parameter	8.035	Lise and Robin (2017)
p_5	Production function parameter	−1.907	Lise and Robin (2017)
p_6	Production function parameter	6.597	Lise and Robin (2017)
	Jointly Estimated		
Parameter	Description	Value	Source
A	Meeting efficiency	0.103	CPS
δ	Exogenous separation rate	0.011	CPS
ϕ	Relative search intensity	0.414	CPS
κ	Entry cost	4.344	CPS
p_L	Prob. worker type dec.	1.275×10^{-4}	CPS
p_H	Prob. worker type inc.	0.006	CPS
μ_E	Mean entrant worker type	−1.140	CPS
σ_E	Std. dev. entrant worker type	0.367	CPS

Table 3.2: Model Estimates

Parameter	Parameter Estimate	Target	Model	Data	Source
A	0.103	UE transition rate	23.17%	23.26%	CPS 2012-2016
δ	0.011	EU transition rate	1.15%	1.28%	CPS 2012-2016
ϕ	0.414	Job to job trans. rate	1.86%	1.69%	CPS 2012-2016
κ	4.344	Unemployment rate	5.97%	6.16%	CPS 2012-2016
p_L	1.275×10^{-4}	Earnings loss of unemp.	10.38	6.86	CPS 2012-2016
p_H	0.006	Earnings gain with age	0.425	0.426	CPS 2012-2016
μ_E	-1.140	Experience premium	1.53	1.48	CPS 2012-2016
σ_E	0.367	Std. dev. of young worker earnings ranking	26.27	25.94	CPS 2012-2016

Table 3.3: Changes in Unemployment, Vacancies, and Worker Flows 1975-2016

	(1) Data	(2) Baseline Model	(3) Fixed Worker Types Model
Unemployment Rate	-7.99%	-7.92%	-6.17%
Vacancy Rate	-19.24%	-2.36%	-3.37%
Job to Job Transition Rate	-36.06%	-4.26%	-4.62%
UE Transition Rate	-15.56%	-0.53%	-1.76%

Notes: The table shows the percent change in the unemployment rate, vacancy rate, job to job transition rate, and UE transition rate between 1975 and 2016 as observed in the data (Column (1)), solving the transition path of the baseline model (Column (2)), as well as the model with fixed worker types (Column (3)). See Appendix C.4 for details on the construction of the Job to Job Transition Rate and the UE transition Rate. Data on the vacancy rate is from Barnichon (2010), and the unemployment rate is from the Current Population Survey (CPS)..

Table 3.4: Model Estimates: Fixed Worker Types

Parameter	Parameter Estimate	Target	Model	Data	Source
A	0.216	UE transition rate	23.34%	23.26%	CPS
ϕ	0.337	Job to job transition rate	1.69%	1.69%	CPS
κ	61.995	Unemployment rate	6.45%	6.16%	CPS
δ	0.0128	EU transition rate	1.28%	1.28%	CPS

Notes: Data are the average values from 2012-2016. See Appendix C.4 for details on the construction of the data moments.

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Appendix A

Appendix to Chapter 1

A.1 Burning Glass Data

In this Appendix, we benchmark the Burning Glass data against other sources of data on vacancy posting (JOLTS, HWOL) and employment (OES).

A.1.1 Time Series of Aggregate Vacancy Posting

In this section, we compare the time series of aggregate vacancies from Burning Glass to other measures of the aggregate vacancy posting from the Job Openings and Labor Force Turnover Survey (JOLTS) as well as the Help Wanted Online Survey (HWOL).

Comparison to JOLTS

First we compare the aggregate time series of vacancies posted in the Burning Glass database relative to the time series produced from JOLTS.[1] Note, however, that Burning Glass and JOLTS differ in the universe of vacancies that they wish to capture. Burning Glass specifically aims to measure *new* vacancy postings, i.e. the same posting appears only in the first month that it is recorded. JOLTS measures all active job postings, i.e. the same posting can appear in two or more consecutive months. Additionally, Burning Glass only records vacancies which are posted online, while JOLTS records all job openings that firms are actively trying to fill, which includes online job postings as well as offline job postings such as advertising in newspapers or posting helped wanted signs.

Panel (a) of Figure A.1 presents time series of aggregate vacancies from Burning Glass as well as from JOLTS. The Burning Glass time series is created from taking the sum of all vacancies recorded in each month. From JOLTS we use the non seasonally adjusted

[1] JOLTS is a monthly survey of approximately 16,000 establishments, and records the number of hires, separations, and job openings at the sampled firms and uses these estimates to create aggregate time series for the U.S. For more information on the JOLTS see: https://www.bls.gov/jlt/#news

vacancies among all non-farm establishments. To ease the comparison of the two series, we present the two time series as an index where January 2016 is set to 100. Overall the time series of vacancies as measured by Burning Glass closely follows the time series from JOLTS.[2] Commonly the Burning Glass estimate of aggregate vacancies is below the estimate from JOLTS, which likely reflects the difference in the set of vacancies that each series is designed to capture.

Comparison to HWOL

Next we compare the aggregate time series of vacancies posted in the Burning Glass database relative to the Helped Wanted Online (HWOL) time series produced by The Conference Board.[3] Similar to Burning Glass, the HWOL index records new vacancy postings. The HWOL index counts a job posting as "new ad" if it is an unduplicated ad which did not appear in the previous reference period, and is the first month in which the ad appears. While the HWOL series is intended to cover a similar set of vacancies as Burning Glass its ability to capture the universe of vacancies posted online has recently come under question. Cajner and Ratner (2016) note that the HWOL series has diverged from JOLTS since the early to mid 2010s, and is likely due to a change in share of vacancies posted on Craigslist due to Craigslist starting to charge firms to post vacancies. Panel (b) of Figure A.1 shows the time series of Burning Glass vacancies against the HWOL time series. The figure shows that Burning Glass and HWOL are picking up a different trend in aggregate vacancy posting over the pas several years. The similarity between the Burning Glass time series and the one from JOLTS suggests that the Burning Glass database is not having the same difficulty in measuring trends in aggregate vacancy posting.

A.1.2 Industry Distribution

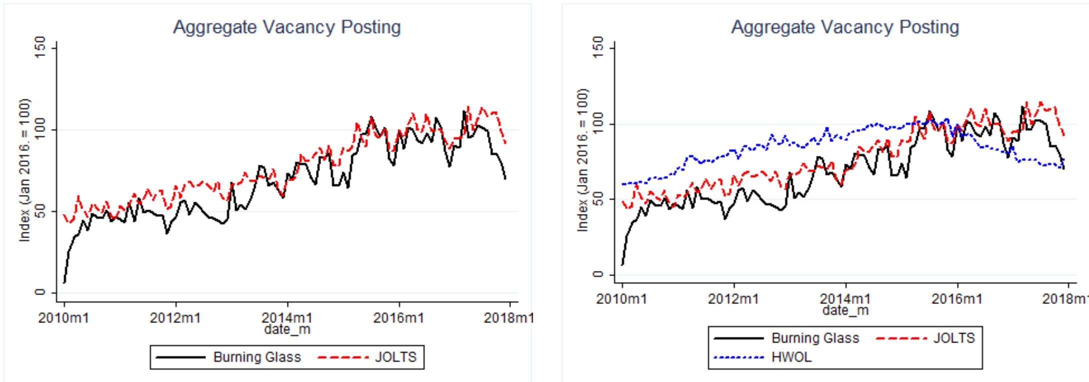
In this section, we compare the distribution of vacancy posting by industry in the Burning Glass database to the distribution recorded in JOLTS. For this comparison industries are recorded using 2-digit NAICS codes. Figure A.2 plots the distribution of vacancies from Burning Glass across industries as well as the distribution of vacancies from JOLTS. The figure shows that the distribution of vacancies by industry in the Burning Glass database

[2] The correlation between the two time series is 0.914.

[3] The HWOL program is targeted to cover the full universe of all online advertised vacancies which are posted directly on Internet job boards. The HWOL program uses data collected from over 16,000 online job-board sources including corporate job boards. Each year new job-board sources are added as they emerge while some existing sources may be dropped if it is determined that they primarily spider their ads from other job boards. See https://www.conference-board.org/data/helpwantedonline.cfm for more information.

Figure A.1: Aggregate Vacancy Posting

(a) Comparison to JOLTS (b) Comparison to HWOL



Notes: The figure shows an index of aggregate vacancy posting where January 2016 is equal to 100. Panel (a) compares the time series of vacancies from Burning Glass (solid black line) against the time series of vacancies in JOLTS (dashed red line). Panel (b) contains the Burning Glass and JOLTS sereis from panel (b), and includes the time series of new vacancy advertisements measured by Conference Board's the Help Wanted Online (HWOL) index. The JOLTS series is total non-farm vacancies that are not seasonally adjusted. Source: Burning Glass Technologies, Job Openings and Labor Force Turnover Survey (JOLTS), and the Conference Board's Help Wanted Online (HWOL).

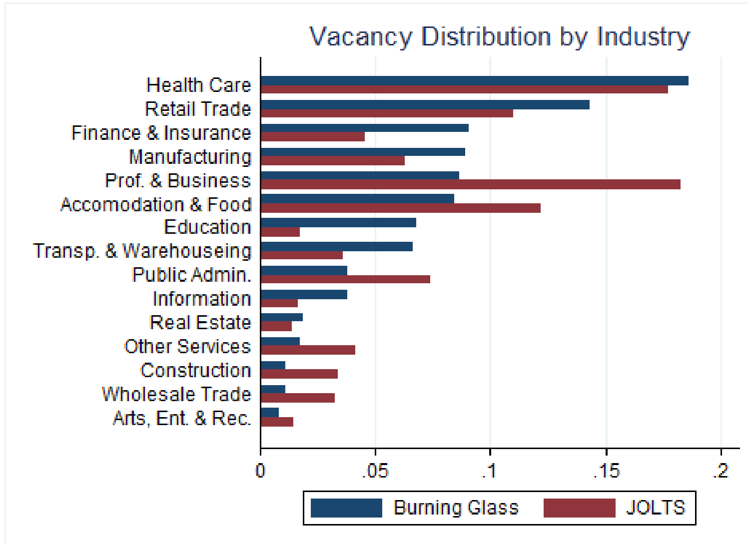
largely resembles the distribution from JOLTS. Burning Glass is over represented in retail trade, finance and insurance, as well as education. Burning Glass is under represented relative to JOLTS in professional and business services, accommodation and food services, as well as public administration. However, most of the differences in vacancy share by industry are small in magnitude.

A.1.3 Occupation Distribution

In this section, we analyze the distribution of vacancies by occupation. To our knowledge there is not another source of detailed data on vacancy posting by occupation. For this reason we compare the the distribution of vacancies posted in Burning Glass to measures of the stock of employment by occupation. In these comparison we measure occupation using 2-digit SOC codes.

To measure the stock of employment by occupation we use data from Occupational Employment Statistics (OES). Figure A.3 presents the distribution of vacancies from Burning Glass across occupations along with the distribution of employment from the OES. Burning Glass is over represented in sales, management, healthcare practitioners and computer and mathematical occupation. The Burning Glass data is under represented in office and

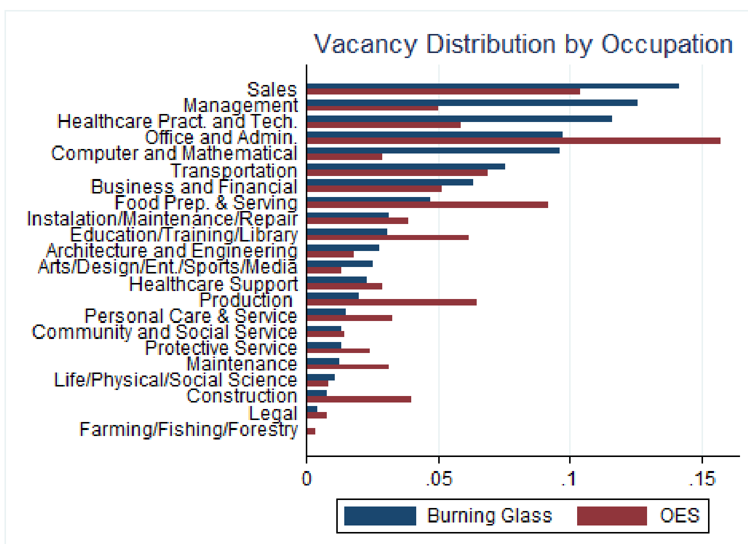
Figure A.2: Industry Distribution of Vacancy Postings



Notes: The figure shows distribution of vacancies posted by industry where industry is measured using a 2-digit NAICS code. Panel (a) compares the distribution of vacancies in the entire Burning Glass database (red bars) against the distribution from JOLTS (blue bars). Source: Burning Glass Technologies and Job Openings and Labor Force Turnover Survey (JOLTS).

administrative occupations, food preparation and serving, production and construction.

Figure A.3: Occupation Distribution of Vacancy Postings



Notes: The figure shows distribution of vacancies posted by occupation where occupation is measured using a 2-digit SOC code. Source: Burning Glass Technologies and Occupational Employment Statistics (OES).

A.2 Sample Comparisons

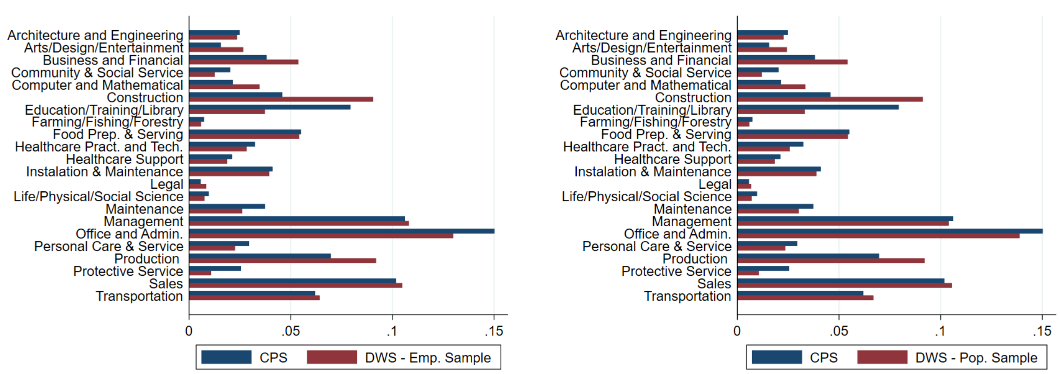
In this Appendix, we compare the distribution of occupation among displaced workers and non-displaced workers.

A.2.1 Comparing the DWS to the Monthly CPS

In this Appendix, we compare the distribution of occupations for individuals in the DWS to non-displaced individuals in the monthly CPS. In particular, we compare the distribution of occupations from which individuals were displaced from as recorded in the DWS. We compare this distribution of occupations among displaced workers, to the distribution of occupations from non-displaced workers in the same monthly CPS files. Panel (a) of Figure A.4 presents the distribution of workers across 2-digit occupations from our employment sample of the DWS, against the distribution of non-displaced workers. The figure shows that the distribution of occupations in the DWS is largely similar to the distribution in the CPS. The notable exception being that the DWS has a larger share of construction workers and smaller share of individuals working in education relative to the DWS. Panel (b) shows a similar pattern for our population sample from the DWS.

Figure A.4: Distribution of Workers Across Occupations: DWS & Monthly CPS

(a) Employment Sample (b) Population Sample



Notes: The figure shows distribution of workers across 2-digit occupations in the CPS displaced worker supplement (red bars), and non-displaced workers from the CPS. Panel (a) uses the employment sample from the DWS as defined in Section 1.2.1, while Panel (b) uses the population sample of the DWS as defined in Section 1.2.1.

A.3 Additional Results Empirics

A.3.1 Robustness Exercises

In this Appendix, we consider a series of robustness exercises for the empirical results presented in Section 1.2.3.

Alternative Years

In this Appendix, we present results where we measure the change in computer skill requirements over an alternative set of years (2012-2017). Table A.1 presents estimation results of equation 1.1 where we use the change in the share of vacancies listing a computer or software requirement between 2012 and 2017. The results presented in Table A.1 show that individuals displaced from occupations undergoing a greater increase in computer and software requirements (between 2012 and 2017) experience larger earnings losses (Column (1)), are more likely to switch occupations (Column (2)), are more likely to move to an occupation with lower computer and software requirements than their original occupation (Column (4)), but do not have longer unemployment spells (Column (3)). The results presented in Table A.1 are nearly identical to the results where we use the change in computer and software requirements between 2010 and 2017 as our measure of technological change.

Table A.1: Impact of Technological Change on Outcomes of Displaced Workers: Alternative Years

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Log Unemp. Duration	(4) Switch Occ. Lower (d)
Chg. Computer Req. (2012-2017)	-0.877***	0.621**	0.375	1.191***
	(0.259)	(0.249)	(0.677)	(0.251)
Observations	4,672	4,672	4,672	4,672
R-squared	0.264	0.015	0.077	0.121
	Emp. Sample	Emp. Sample	Emp. Sample	Emp. Sample
Controls	Yes	Yes	Yes	Yes

Notes: The table shows regression results from the estimation of equation 1.1. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In column (3) we remove the control variable for the log of unemployment duration, and in column (4) we add as a control the share of vacancies listing a computer or software requirement in 2010 in the occupation the individual was displaced from. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Alternative Measure of Technological Change

In this Appendix, we consider an alternative approach to measuring technological change. Let $r_{o,t}$ denote the share of all skills listed for an occupation that are classified as a computer or software skill.[4] We then measure technological change by analyzing the change in the share of skills listed for an occupation that are classified as a computer or software skill. Let $\Delta r_{o,t} = r_{o,2017} - r_{o,2010}$ denote the change in the share of skills listed for an occupation o that are classified as a computer or software skill between the years 2010 and 2017. We then estimate the following regression on our sample of displaced workers:

$$Y_{i,o,t} = \alpha + \beta \Delta r_{o,t} + \Gamma X_{i,o,t} + \epsilon_{i,o,t} \tag{A.1}$$

Table A.2 contains the estimation results from equation A.1. Column (1) of Table A.2 shows that under the alternative measure of technological change we continue to find that individuals displaced from occupations with larger increases in computer and software requirements experience larger declines in earnings. Column (2) shows that there is a positive correlation between larger increases in computer and software requirements and the propensity to switch occupations, however the relationship is not statistically significant. Column (3) shows that increases in computer and software requirements are not associated with longer unemployment spells. Finally, column (4) shows that increases in computer and software requirements are associated with displaced workers having a greater probability of moving to an occupation with a lower level of computer and software requirements. These results are consistent with our baseline results presented in Section 1.2.3 which showed that increases in computer and software requirements are associated with larger declines in earnings, and that the mechanism works through moving to occupations with lower computer and software requirements.

Measuring Technological Change in O*NET

In this Appendix, we consider an alternative measure of technological change, where our measure of technological change is derived from O*NET. We show that our baseline results are robust to measuring technological change using data available in O*NET.

Our baseline analysis uses the change in the share of vacancies in an occupation that list computer and software skills as a requirement for the position. In this Appendix, we use data from O*NET as an alternative measure of technological change. O*NET contains information on the skills and knowledge required in different occupations, where

[4] In the baseline analysis, we consider the share of vacancies that list a computer or software skill.

Table A.2: Alternative Measure of Computer and Software Requirements

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Log Unemp. Duration	(4) Switch Occ. Lower (d)
Chg. Computer Req.	-1.051**	0.481	-0.107	3.736***
	(0.518)	(0.551)	(1.390)	(0.604)
Observations	4,672	4,672	4,672	4,672
R-squared	0.262	0.014	0.077	0.068
	Emp. Sample	Emp. Sample	Emp. Sample	Emp. Sample
Controls	Yes	Yes	Yes	Yes

Notes: The table shows regression results from the estimation of equation A.1. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In column (3) we remove the control variable for the log of unemployment duration, and in column (4) we add as a control the share of skills in an occupation that are classified as a computer or software skill in 2010 in the occupation the individual was displaced from. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

the information is obtained by surveying individuals currently working in the occupation as well as occupational experts. In this Appendix, we use the O*NET measure of the level of knowledge needed in computers and electronics for a given occupation.[5] This variable records the level of the skill needed for an occupation with a range from 1-7, with higher values denoting a greater value of skills required. O*NET provides information on occupations at the 7-digit SOC code level, and to arrive at the level of computer knowledge at the four-digit SOC code level we average the variable within a 4-digit occupation. We additionally record for each 4-digit occupation, the share of the reports for that occupation that were conducted by an occupational expert, and the average year the occupation was updated.

The O*NET database is published each year, but in each publication approximately 100 occupations are updated. To measure how computer requirements have changed over time we compare the level of computer skills recorded in the August 2018 vintage of O*NET (Version 23, which contains data collected from 2011-2017), to the February 2011 vintage of O*NET (Version 15.1, which contains data collected from 2005-2010). We measure the change in the level of computer knowledge needed in an occupation across these two

[5] The variable we use is O*NET code 2.C.3.a.

vintages of the O*NET database.[6] To account for any differences in reporting standards across the two vintages of the O*NET, we studentize each variable within its vintage of O*NET before taking the difference across vintages.[7]

Let $\Delta Comp^{ONET}_{i,o,t}$ denote the change in the level of computer knowledge required in occupation o between the two vintages of O*NET data for an individual i displaced from that occupation, who is in the DWS in year t. Let $X_{i,t}$ denote a series of control variables that include the age of the displaced worker, the log duration of their unemployment spell after layoff, tenure prior to layoff, years of educational attainment, a series of dummy variables for the DWS survey year, the year of displacement, an indicator for working full-time prior to displacement and an indicator for working full-time at the time of the DWS survey as well as the year the occupation was updated in each vintage of O*NET for both vintages, as well as the share of reports in O*NET conducted by an occupational expert for that occupation in each O*NET vintage. The specification we use is of the form:

$$Y_{i,o,t} = \alpha + \beta \Delta Comp^{ONET}_{i,o,t} + \Gamma X_{i,o,t} + \epsilon_{i,o,t} \tag{A.2}$$

Table A.3 contains the estimation results of estimating equation A.2. Column (1) of Table A.3 shows that an increase in the level of computer knowledge in an occupation as reported in O*NET leads to a significant decline in earnings following displacement. Column (2) of Table A.3 shows that an increase in the level of computer knowledge in an occupation as reported in O*NET leads to a significant increase in the probability that an individual switches occupations following displacement. Column (3) of Table A.3 shows an increase in computer knowledge is associated with shorter unemployment spells.[8] Finally, column (4) of Table A.3 shows that increases in computer knowledge are associated with a greater probability of moving to an occupation with a lower level of computer knowledge. Table A.3 present results consistent with our baseline analysis that workers who are displaced from occupations undergoing larger changes in computer requirements (as measured using O*NET) experience larger declines in earnings, with the decline in earnings being driven by occupation switching and moving to occupations with lower computer and software requirements.

[6] Version 15.1 was chosen as the comparison group to Version 23 since it was the most recent version of O*NET where all occupations had been updated.

[7] In practice, studentizing the variables does not impact the results.

[8] Comparing a worker displaced at the 75th percentile of the change in computer knowledge relative to the 25th percentile has an unemployment spell that is approximately 0.83 weeks shorter.

Table A.3: Measuring Technological Change using O*NET

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Log Unemp. Duration	(4) Switch Occ. Lower (d)
Chg. Computer Req. (O*NET)	-0.0798***	0.0568**	-0.161**	0.112***
	(0.0282)	(0.0287)	(0.0692)	(0.0271)
Observations	4,672	4,672	4,672	4,672
R-squared	0.264	0.025	0.081	0.082
	Emp. Sample	Emp. Sample	Emp. Sample	Emp. Sample
Controls O*NET	Yes	Yes	Yes	Yes

Notes: The table shows regression results from the estimation of equation A.2. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In column (3) we remove the control variable for the log of unemployment duration, and in column (4) we add as a control the share of skills in an occupation that are classified as a computer or software skill in 2010 in the occupation the individual was displaced from. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Alternative Time Period (1982-2000)

In this Appendix, we consider an earlier time period to examine the impact of technological change on the outcomes of displaced workers. We use data on skill requirements from newspaper vacancy postings collected by Atalay et al. (2018b) to measure technological change between 1982 and 2000 at the occupation level.[9] We then consider displaced workers from the DWS, who were displaced between 1982 and 2000, and estimate how technological change impacts their earnings after job loss. We find results consistent with our baseline estimates, that workers displaced from occupations undergoing a greater degree of technological change experience a larger decline in earnings after job loss.

Data Overview

In this subsection, we discuss the data we use to consider the impact of technological change on the outcomes of displaced workers from 1982 to 2000.

Atalay et al. (2018b) collect the text from job vacancies advertised in the *New York Times*, *Wall Street Journal*, and *Boston Globe* from 1940 through 2000. From the raw text they identify the skills listed in each vacancy posting as well as the occupation for the vacancy. Atalay et al. (2018b) create and report many measures of the task content included in the newspaper vacancies. We use their measure of computer and software requirements, which counts per 1000 words of text, the number of words that contain the keywords: "computer," "software," or "spreadsheets." To measure technological change at the occupation level, we measure the change in the share of words which list a computer or software skill between 1982 and 2000 by occupation. For this exercise, we use the occupation classification from Autor and Dorn (2013).[10]

The data on displaced workers comes from the Displaced Workers Supplement (DWS) to the CPS. We use the 1984-2000 waves of the DWS, which identify workers who were displaced between 1982 and 2000. To restrict our sample to workers who lose their job due to reasons that are exogenous to their characteristics, we focus on workers who are displaced, and list the reason of their displacement as being either (1) their company or plant shutting

[9] We thank the authors for generously making their data available online. The data and programs are available at: https://occupationdata.github.io/.

[10] Autor and Dorn (2013) create time consistent occupation codes, which classify 336 distinct occupations. In our baseline analysis we used 4-digit SOC codes (2010 version), which specify 108 distinct occupations. For the 1982-2000 period, the DWS reports occupations using 1990 Census codes. Atalay et al. (2018b) report their skill measures by occupation using 2000 Census codes and 2010 SOC codes. We use the crosswalks created by Autor and Dorn (2013) for their measure of occupations to the 1990, and 2000 versions of the Census occupation codes to link the skill measures of Atalay et al. (2018b) to occupations recorded in the DWS. We are in the process of creating a crosswalk from the 1990 Census occupation codes to the 2010 SOC codes which would allow us to do the analysis of this Appendix at the 4-digit SOC code level. Preliminary results from our 1990 Census to 2010 SOC crosswalk are similar to the results presented here.

down, (2) their shift or position being eliminated, or (3) having insufficient work.[11] We additionally drop individuals who report that they expect to be recalled to their prior job. Using these workers who we identify as being displaced, we create two samples as in our baseline estimation:

1. **Employed sample:** Our first sample includes all individuals who are employed both at the time of the DWS and prior to displacement. We additionally require that individuals have non top-coded earnings both prior to displacement and after displacement.[12] This results in a sample of 19,885 individuals. We use this sample to measure the earnings loss around displacement as well as the propensity to switch occupations by degree of technological change in their original occupation.

2. **Population sample:** Our second sample includes all individuals who were identified as displaced in the DWS with non-top coded earnings prior to displacement.[13] This results in a sample of 29,667 individuals. We use this sample to examine whether individuals who are displaced from occupations that experienced a greater amount of technological change were less likely to regain employment after job loss.

Table A.4 presents summary statistics for these samples.

In the next section, with this sample of displaced workers and the measure computer and software requirements from Atalay et al. (2018b), we estimate the impact of technological change on the outcomes displaced workers for the years 1982 to 2000.

Empirical Approach and Results

In this section, we review our empirical approach and present results on the impact of changes in technology on the outcomes of displaced workers.

Let $Y_{i,o,t}$ denote the outcome variable of interest for individual i, who was displaced in occupation o and is in the DWS in year t (such as the change in log real earnings following displacement or an indicator variable for switching occupations following displacement). Let Δz_o denote the change in the share of words listing computer or software requirements for occupation o between the years 1982 and 2000. Let $X_{i,t}$ denote a vector of controls, which includes the age of the displaced worker, tenure prior to layoff, and years of educational

[11]This restriction removes individuals who are displaced due to a seasonal job ending, their self-operated business failing, or listing "other" as the reason for there displacement. These restrictions also align with the types of displacements considered in our baseline sample.

[12]Some individuals report being employed but also report zero earnings. To be in the sample, we require that an individual have real weekly earnings greater than $100 (in 2012 dollars) both prior to displacement and after displacement. Our results are robust to different values of this minimum earnings threshold.

[13]We impose the non-top coded earnings condition to maintain consistency with our employed sample. We additionally require that an individual have weekly real earnings greater than $100 (in 2012 dollars) prior to displacement. Our results are robust to this minimum earnings threshold.

Table A.4: Summary Statistics

	(1) Employed Sample	(2) Population Sample
Chg. Computer Req.	0.029	0.29
Share Vacancies w/ Computer or Software Req. (2010)	0.09	0.09
Weekly Real Earnings (Displaced Job)	787.94	770.84
Weekly Real Earnings (Current Job)	710.86	-
Years Since Displacement	2.30	2.14
Switch Occ. (d)	0.67	-
Age	36.52	36.83
Years of Education	13.31	13.13
Observations	19,885	29,667

Notes: See Section A.3.1 for sample selection criteria for employed and population samples. The change in computer requirements, and the share of vacancies listing a computer or software requirement are measured in the occupation from which the worker was displaced for the employed and population samples. For the non-displaced sample these variables are based on the worker's current occupation. Weekly earnings are measured in 2012 dollars. Occupation switching is measured between the occupation from which individuals were displaced and their current occupation, where occupation is measured using a four-digit SOC code. The symbol (d) denotes a dummy variable.

attainment, as well as a series of dummy variables including the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey.[14] The specification we use is of the form

$$Y_{i,o,t} = \alpha + \beta \Delta z_o + \Gamma X_{i,o,t} + \epsilon_{i,o,t}. \tag{A.3}$$

The coefficient of interest is β, which gives the change in the outcome variable $Y_{i,o,t}$ of a 100 percentage point increase in computer and software requirements in the occupation from which an individual was displaced. If $\beta < 0$, then we have evidence that an increase in computer and software requirements is associated with a decrease in the variable of interest. Table A.5 presents the results of estimating equation A.3. Column (1) present the impact of changes in computer and software requirements on earnings after displacement. The negative coefficient on the change in computer and software requirements indicates that increases in computer and software requirements in the occupation from which an individual was displaced is associated with a larger decline in earnings. Column (2) presents the impact of changes in computer and software requirements on the probability that an

[14]Note that when the outcome variable of interest is employment at the time of the DWS, we drop control variables that contain employment information at the time of the survey (i.e., the dummy variable for working full-time at the time of the DWS). In our baseline analysis we control for the duration of an individuals unemployment spell. As commented in Farber (2017), the DWS provides consistently reported measured of unemployment duration for the time periods 1988-1992 and 1996-2018. For this reason we omit the length of an unemployment spell from the analysis in this Appendix.

individual switches occupations after job loss. The positive coefficient indicates that increases in computer and software requirements are associated with a greater probability of switching occupations after job loss. Potentially, these individuals are switching occupations because they no longer have the skills to work in their prior occupation. We examine this hypothesis by identifying when an individual switches occupations and moves to an occupation with a lower level of computer and software requirements relative to their original occupation.[15] Column (3) shows the impact of changes in computer and software requirements on the probability of moving to an occupation with lower computer and software requirements relative to the individuals original occupation. The positive coefficient on changes in computer and software requirements indicates that workers whose occupation are undergoing a larger increase in computer and software requirements are more likely to move to occupations with a lower level of requirements. Finally, we examine the impact of changes in computer and software requirements on the probability of being employed following displacement. Column (4) presents the impact of changes in computer and software requirements on the probability of being employed after job loss. The coefficient is close to zero and not statistically significant, indicating that changes in computer and software requirements are not associated with a lower probability of being employed after job loss.

Table A.5: Impact of Technological Change on Outcomes of Displaced Workers

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Switch Occ. Lower (d)	(4) Emp. (d)
Chg. Computer Req.	-0.205***	0.316***	2.705***	-0.0299
	(0.0543)	(0.0487)	(0.0457)	(0.0340)
Observations	19,885	19,885	19,885	29,667
R-squared	0.192	0.031	0.242	0.125
	Emp. Sample	Emp. Sample	Emp. Sample	Pop. Sample
Controls	Yes	Yes	Yes	Yes

Notes: This table shows regression results from the estimation of equation A.3. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section A.3.1 for sample selection criteria, and sample definitions. Controls include the age of the displaced worker, tenure prior to layoff, and years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In column (3) we remove the control variable for the log of unemployment duration, and in column (4) we remove the control variables for unemployment duration and full-time employment after displacement. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

The results of this Appendix provide further support that technological change contributes

[15] We use computer and software requirements from the year 2000 to determine if an individual moves to an occupation with lower computer and software requirements relative to their original occupation.

to the decline in earnings following job loss, and works through occupation switching.

A.3.2 Additional Alternative Explanations

In this Appendix we consider a series for alternative explanations for the results presented in Section 1.2.3.

Routine/Non-Routine Occupations

In this Appendix, we consider the distinction between routine and non-routine occupations. The job polarization literature (see for instance Autor and Dorn (2013), and Jaimovich and Siu (2012)) has emphasized that a driver of job polarization is individuals moving from routine occupations to lower paying non-routine occupations (typically in the service sector). Additionally, in a recent paper Restrepo (2015) discusses the decline in routine cognitive employment as a cause of structural unemployment during and after the Great Recession. In this Appendix, we show that the mechanism in this paper is distinct from the prior literature on job polarization and routine/non-routine employment by introducing two separate controls for an occupation being routine, and showing that our results are robust to considering individuals only displaced from non-routine occupations.

Our first measure of routine vs. non-routine occupation comes from the classifications of Jaimovich and Siu (2012), who classify occupations as routine vs. non-routine based on their judgment of the skill content of the tasks performed in each occupation. Let $Routine_{i,o,t}$ be a dummy variable equal to one if individual i was displaced from an occupation o that is classified as routine in Jaimovich and Siu (2012), and is in the DWS in year t. The specification we use is of the form:

$$Y_{i,o,t} = \alpha + \beta \mathit{\Delta} z_o + \lambda Routine_{i,o,t} + \mathit{\Gamma} X_{i,o,t} + \epsilon_{i,o,t} \tag{A.4}$$

The coefficient of interest is β which gives the change in the outcome variable $Y_{i,o,t}$ of a 1-percentage point change in computer skill requirements of the occupation from which an individual was displaced, while controls for whether or not the individual was displaced from a routine occupation.

Table A.6 presents the estimation results of equation A.4. Column (1) of Table A.6 presents an estimate of the change in computer skill requirements on earnings for displaced workers controlling for whether an occupation is routine. Controlling for whether or not an occupation is routine does not alter our observation that individuals displaced from occupations that undergo a larger increase in computer skill requirements suffer a larger decline in earnings following layoff. Column (2) of Table A.6 present the estimation results from equation A.4 where the dependent variable is a dummy variable for switching occupations.

The coefficient on routine in Column (2) reveals that individuals displaced from a routine occupation are nearly 8 percentage points more likely to switch occupations following job loss. However, accounting for whether an occupation is classified as routine vs. non-routine does not alter our empirical results that a greater increase in computer skill requirements for an occupation increases the probability that a worker displaced from that occupation will switch occupations following displacement. Column (3) of Table A.6 present the estimation results where the dependent variable is the log duration of the individuals unemployment spell after displacement. The results indicate that changes in computer skill requirements do not impact the duration of unemployment following displacement. Finally column (4) of Table Table A.6 presents the estimation results where the dependent variable is if a worker moves to an occupation with lower computer and software requirements. We find that accounting for whether or not an occupation is routine/non-routine does not alter our result that workers who lose their job in occupations experiencing larger changes in computer and software requirements are more likely to move to occupations with lower computer and software requirements. In sum, these results indicate that our results are robust to controlling for whether an occupation is classified as routine vs. non-routine.

We next consider an alternative measure of whether an occupation is routine vs. non-routine, and which classifies specifies whether an occupation is routine-cognitive versus routine-manual. Acemoglu and Autor (2011) use data from O*NET to create continuous measures of the degree to which an occupation is routine manual and routine cognitive.[16] Let $Routine^{cog}_{i,o,t}$ be a dummy variable if individual i was displaced from an occupation o that is in the top quintile of the Acemoglu and Autor (2011) index for routine cognitive occupations, and is in the DWS in year t. Define $Routine^{man.}_{i,o,t}$ analogously for an individual displaced from a routine manual occupation.[17] The specification we use is of the form:

$$Y_{i,o,t} = \alpha + \beta \Delta z_o + \lambda^{cog} Routine^{cog.}_{i,o,t} + \lambda^{man.} Routine^{man.}_{i,o,t} + \Gamma X_{i,o,t} + \epsilon_{i,o,t} \tag{A.5}$$

Table A.6 presents the estimation results of equation A.5. The coefficient estimates of columns (5)-(8) show that controlling for whether the occupation that an individual is

[16]Acemoglu and Autor (2011) create their routine manual index by summing studentized versions of the following three attributes: (1) Controlling Machines and Processes [4.A.3.a.3]; (2) "Spend Time Making Repetitive Motions [4.C.2.d.1.i], and (3) Pace Determined by Speed of Equipment [4.C.3.d.3], and then restudentizing the sum. Their routine cognitive index is created by summing studentized versions of the following three attributes: (1) Importance of Being Exact or Accurate [4.C.3.b.4], (2) Importance of Repeating Same Tasks [4.C.3.b.7]. and (3) (reverse-scaled) Structured vs. Unstructed Work [4.C.3.b.8], and restudentizing the sum. Acemoglu and Autor (2011) index is measured at the 6-digit SOC code, to arrive at 4-digit soc codes we take an OES-employment weighted average across the 6-digit occupations that make up a 4-digit occupation.

[17]We follow Hershbein and Kahn (2018) in using the top quintile of the Acemoglu and Autor (2011) to define routine cognitive and routine manual occupations. We find similar results using the continuous measures of routine cognitive and routine manual occupations.

displaced from is routine cognitive or routine manual does not alter our empirical results that individuals displaced from an occupation undergoing a greater change in computer skill requirements experience greater earnings losses, are more likely to switch occupations, are more likely to move to an occupation with lower computer and software requirements, while having the same unemployment duration.

As a final check on the role of routine vs. non-routine occupations in driving our results, we estimate equation 1.1 using only individuals displaced from a non-routine occupation as classified by Jaimovich and Siu (2012). Table A.7 presents the results of estimating equation 1.1 with the sample of individuals displaced from non-routine occupations. The results show that among individuals displaced from non-routine occupations, those who are displaced from an occupation undergoing a greater increase in computer skill requirements experience larger earnings losses, and are more likely to switch occupations. These results are consistent with our baseline results, and further emphasize that the mechanism driving our results is distinct from prior work on routine vs. non-routine occupations.

Table A.6: Impact of Technological Change on Outcomes of Displaced Workers Accounting for Routine Occupations

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Log Unemp. Dur.	(4) Switch Occ. Lower (d)	(5) Chg. Log Real Earnings	(6) Switch Occ. (d)	(7) Log Unemp. Dur.	(8) Switch Occ. Lower (d)
Chg. Computer Req.	-0.633***	0.674***	0.869	1.522***	-0.597***	0.595***	0.668	1.440***
	(0.227)	(0.204)	(0.540)	(0.201)	(0.229)	(0.206)	(0.538)	(0.201)
Routine Occ. (d)	-0.0428**	0.0768***	0.0767*	0.100***				
	(0.0166)	(0.0174)	(0.0449)	(0.0171)				
Routine Man. Occ. (d)					-0.00296	-0.0105	-0.0728	0.0295
					(0.0209)	(0.0195)	(0.0576)	(0.0186)
Routine Cog. Occ. (d)					0.00918	-0.0110	0.150***	-0.0169
					(0.0172)	(0.0194)	(0.0489)	(0.0229)
Observations	4,672	4,672	4,672	4,672	4,672	4,672	4,672	4,672
R-squared	0.264	0.021	0.078	0.134	0.263	0.016	0.081	0.125
	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows regression results from the estimation of equation A.4 (columns (1)-(4)), and equation A.5 (columns (5)-(8)). Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. The variable Routine Occ. is a dummy variable that is equal to one for occupations which are classified as routine by Jaimovich and Siu (2012). The variable Routine Man. (Cog.) Occ. is a dummy variable indicating that an occupation is the top quintile of the Acemoglu and Autor (2011) index of routine manual (cognitive) occupations. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In columns (3) and (7) we remove the control variable for the log of unemployment duration, and in columns (4) and (8) we add as a control the share of skills in an occupation that are classified as a computer or software skill in 2010 in the occupation the individual was displaced from. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A.7: Regression Results for Non-Routine Occupation

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Log Unemp. Duration	(4) Switch Occ. Lower (d)
Chg. Computer Req.	-0.598**	1.160***	1.160	2.152***
	(0.298)	(0.293)	(0.754)	(0.254)
Observations	2,293	2,293	2,293	2,293
R-squared	0.254	0.019	0.079	0.132
	Emp. Sample	Emp. Sample	Emp. Sample	Emp. Sample
	Non-Routine	Non-Routine	Non-Routine	Non-Routine
Controls	Yes	Yes	Yes	Yes

Notes: The table shows regression results from the estimation of equation 1.1 where we restrict the sample to individuals displaced from non-routine occuapations. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. The variable Routine Occ. is a dummy variable that is equal to one for occupations which are classified as routine by Jaimovich and Siu (2012). Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In column (3) we remove the control variable for the log of unemployment duration, and in column (4) we add as a control the share of skills in an occupation that are classified as a computer or software skill in 2010 in the occupation the individual was displaced from. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Manufacturing Employment

In this appendix, we consider the degree to which our results are driven by individuals who are displaced from manufacturing.

We first control for whether or not an individual was displaced from the manufacturing industry. Columns (1)-(4) of Table A.8 include a dummy variable for whether not an individual is displaced from a manufacturing industry. Controlling for whether or not an individual was displaced from manufacturing does not change our baseline result, that individuals displaced from occupations undergoing a greater change in computer and software requirements: (1) experience larger earnings losses; (2) are more likely to switch occupations; (4) are more likely to move to an occupation with lower computer and software requirements, and (4) have unemployment spells of the same duration. Columns (5)-(8) of Table A.8 restrict the sample to individuals who are displaced from non-manufacturing industries. These results are qualitatively identical to our baseline results, and emphasize that our results are not driven by the trend of declining manufacturing employment.

Table A.8: Regression Results: Controlling for Manufacturing

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Log Unemp. Dur.	(4) Switch Occ. Lower (d)	(5) Chg. Log Real Earnings	(6) Switch Occ. (d)	(7) Log Unemp. Dur.	(8) Switch Occ. Lower (d)
Chg. Computer Req.	-0.596***	0.616***	0.813	1.975***	-0.588**	0.764***	0.757	1.572***
	(0.228)	(0.204)	(0.535)	(0.183)	(0.252)	(0.225)	(0.628)	(0.223)
Manufacturing (d)	-0.0230	0.0894***	0.0987*	0.0972***				
	(0.0212)	(0.0238)	(0.0592)	(0.0259)				
Observations	4,672	4,672	4,672	4,672	3,975	3,975	3,975	3,975
R-squared	0.263	0.020	0.078	0.045	0.261	0.020	0.071	0.129
	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp. Non. Manu.	Emp. Samp. Non. Manu.	Emp. Samp. Non. Manu.	Emp. Samp. Non. Manu.
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Clustered standard errors are in parentheses where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. In columns (3) and (7) we remove the control variable for the log of unemployment duration, and in columns (4) and (8) we add as a control the share of skills in an occupation that are classified as a computer or software skill in 2010 in the occupation the individual was displaced from. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Changes in Other Skill Requirements

In this Appendix, we examine how changes in other skill requirements (e.g., Cognitive, Social and Manual) impact the outcomes of displaced workers. We find that increases in cognitive skills are associated with larger earnings losses for displaced workers, while increases in social and manual skills do not impact the earnings of displaced workers. We then find that once we account for changes in computer and software requirements, increases in cognitive requirements are no longer associated with larger earnings losses for displaced workers.

We measure changes in cognitive, social, and manual skill requirements using the skill requirements reported in the Burning Glass database.[18] We use a series of keywords for each skill type to identify if a vacancy lists a given type of skill. Table A.9 presents the keywords that we use for each skill type.[19] Burning Glass also reports if an education or experience requirements is listed for a vacancy, and if one is listed the value of the education or experience requirement. As in Hershbein and Kahn (2018) we separately identify vacancies that list either an education or experience requirement. Let $z^j_{o,t}$ denote the share of vacancies in occupation o listing skill $j \in \{cognitive, manual, social, edu, exp\}$ in year t. Let $\Delta z^j_o = z^j_{o,2017} - z^j_{o,2010}$ denote the change in the share of vacancies listing skill j in occupation o between the years 2010 and 2017. The variable Δz^j_o is our measure of the change in skill type j in occupation o.

Table A.9: Keywords for Identifying Different Skills

Skill Type	Keywords
Cognitive	*Research, Analy, Decision, Solving, Math, Statistic, or Thinking*
Social	*Communication, Teamwork, Collaboration, Negotiation, or Presentation*
Manual	*Physical, or Lifting*

Notes: Table presents the keywords used to identify if a vacancy lists a given type of skill. The keywords for Cognitive skills comes from Hershbein and Kahn (2018). The keywords for Social skills comes from Deming and Kahn (2018).

With the measure Δz^j_o, we measure the impact of the change in skill j on the outcome of workers displaced from occupation o by estimating the following regression:

$$\Delta ln(Earn_{i,o,t}) = \alpha + \beta^j \Delta z^j_o + \Gamma X_{i,t} + \epsilon_{i,o,t} \quad \text{(A.6)}$$

The coefficient of interest is β^j, which reports how changes in skill j are associated with

[18] Recent work by Deming (2017) has documented a rising importance of social skills in the labor market. Work by Deming and Kahn (2018) show that social and cognitive skills are associated with higher wages.

[19] The keywords for cognitive skills comes from Hershbein and Kahn (2018). The keywords for social skills comes from Deming and Kahn (2018).

the change in earnings for displaced workers. If $\beta^j < 0$, then we have evidence that increases in skill j are associated with larger declines in earnings for displaced workers. Table A.10 presents the results of estimating equation A.6. Column (1) presents the results for changes in computer and software requirements. As presented in Section 1.2.3 increases in computer and software requirements are associated with larger declines in earnings for displaced workers. Column (2) presents the results for changes in cognitive requirements. The negative and statistically significant coefficient indicates that workers who loose their jobs in occupations undergoing larger increases in cognitive requirements have larger declines in earnings. Column (3) presents results for changes in social skills. The coefficient estimate is negative, but is not statistically significant, indicating that changes in social skill requirements are not associated with changes in earnings for displaced workers. In column (4), we find a similar result for changes in manual skills not being associated with changes in earnings for displaced workers. Finally, in columns (5) and (6) we examine the impact of changes in education and experience requirements and find that they do not impact the earnings of displaced workers. The results of Table A.10 suggest that changes in computer and software requirements as well as cognitive skills impact the size of earnings losses for displaced workers.

We next run a series of regressions where we include the change in computer and software requirements as well as the change in skill j for $j \in \{cognitive, manual, social, edu, exp\}$. Table A.11 presents the estimation results. Column (2) of Table A.11 presents results from the regressions where we analyze both the change in computer and software skills as well as the change in cognitive skills. Once we control for changes in computer and software skills, changes in cognitive skills no longer impact the earnings of displaced workers. In columns (3)-(6) of Table A.10 we control for changes in social, manual, experience, and education requirements respectively, and in each case controlling for these changes in skill requirements do not impact our baseline result that workers displaced from occupations undergoing larger increases in computer and software requirements experience larger declines in earnings.

Table A.10: Impact of Changes in Other Skill Requirements on Outcomes of Displaced Workers

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Chg. Log Earnings					
Skill Type	Computer	Cognitive	Social	Manual	Education	Experience
Chg. Skill Req.	-0.591***	-0.572**	-0.188	0.112	0.195	-0.0757
	(0.228)	(0.252)	(0.173)	(0.171)	(0.155)	(0.119)
Observations	4,672	4,672	4,672	4,672	4,672	4,672
R-squared	0.263	0.262	0.261	0.261	0.262	0.261
	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the results of estimating equation A.6. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A.11: Impact of Changes in Other Skill Requirements on Outcomes of Displaced Workers

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Chg. Log Real Earnings					
Chg. Computer Req.	-0.591***	-0.519**	-0.580**	-0.587**	-0.655***	-0.682***
	(0.228)	(0.234)	(0.243)	(0.229)	(0.244)	(0.226)
Chg. Cognitive Req.		-0.416				
		(0.259)				
Chg. Social Req.			-0.0303			
			(0.186)			
Chg. Manual Req.				0.0937		
				(0.173)		
Chg. Exp. Req.					0.0931	
					(0.126)	
Chg. Edu Req.						0.315**
						(0.153)
Observations	4,672	4,672	4,672	4,672	4,672	4,672
R-squared	0.263	0.264	0.263	0.263	0.263	0.264
	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.	Emp. Samp.
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the results of estimating equation A.6. Clustered standard errors are in parentheses, where the clustering is performed at the state and year of job loss. See Section 1.2.1 for sample selection criteria, and sample definitions. Controls include the the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, years of educational attainment, as well as a series of dummy variables for the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A.4 Additional Model Details

In this Appendix, we present additional details of the model. We first present the value functions for experienced workers, as well as firms that are matched with an experienced worker. We then prove that the model equilibrium is Block Recursive.

A.4.1 Bellman Equation for Unemployed Experienced Worker

In this subsection, we present the Bellman equation for an experienced unemployed worker. Let $U_t^E(a, h, k)$ denote the value of being an age t unemployed worker who is experienced in occupation k, with assets a and human capital h. In the current period the unemployed worker makes their consumption and savings decision, as well as their retraining decision. At the start of the next period, the unemployed worker becomes inexperienced in their current occupation with probability λ_N. After learning if they remain experienced in occupation k, the unemployed worker chooses which occupation to apply for a job in, and chooses the occupation with the highest continuation value. Note that if the worker is experienced in occupation k, they search a job in the experienced labor market for occupation k, and in the inexperienced labor market for all other occupations $\tilde{k} \in \mathcal{K}/\{k\}$. The value to an experienced unemployed worker is,

$$U_t^E(h, a, k) = \max_{a' \geq 0, R \in \{0,1\}} u(c) - R\psi + \beta \mathbb{E}\Big[(1-\lambda_N)\hat{U}_{t+1}^E(h', a', k) + \lambda_N \hat{U}_{t+1}^N(h', a', 0)\Big] \quad \forall t \leq T$$

$$U_{T+1}^E(h, a, k) = 0$$

where $\hat{U}_{t+1}^E(h', a', k)$ denotes the expected value of search for an experienced unemployed worker in the labor market, and is given by,

$$\begin{aligned}\hat{U}_{t+1}^E(h', a', k) = \max\Big\{ & p(\theta_{t+1}^E(h', a', k))W_{t+1}^E(h', a', \bar{z}, k) + \Big(1 - p(\theta_{t+1}^E(h', a', k))\Big) U_{t+1}^E(h', a', k), \\ & \max_{\tilde{k} \in \mathcal{K}/\{k\}} p(\theta_{t+1}^N(h', a', \tilde{k}))W_{t+1}^N(h', a', \bar{z}, \tilde{k}) + \Big(1 - p(\theta_{t+1}^N(h', a', \tilde{k}))\Big) U_{t+1}^E(h', a', k) \Big\}\end{aligned}$$

subject to the budget constraint,

$$c + \frac{a'}{1+r} + R(1-s)\kappa_R \leq b + a + d$$

and the law of motion for a worker's human capital, which is indexed by employment status U and their retraining decision $R \in \{0, 1\}$,

$$h' = H(h, U, R)$$

A.4.2 Bellman Equation for Employed Experienced Worker

In this subsection, we present the Bellman equation for an experienced employed worker. Let $W_t^E(h, a, z, k)$ denote the value of being an experienced worker with human capital h

and assets a, who is employed with a firm in occupation k that uses technology $z \leq \bar{z}$. The worker makes their consumption and savings choice, and receives utility from consumption. At the start of the next period, shocks to human capital and match technology are realized, and the worker becomes unemployed with probability δ. Workers who become unemployed immediately search in the labor market. In the labor market, agent's search across occupations, each of which is using the newest vintage of technology $\bar{z}$. Since the worker is experienced in occupation k, they search for a job in the experienced market for occupation k, and in the inexperienced market for all other occupations $\tilde{k} \in \mathcal{K}/\{k\}$. The continuation value of the worker is,

$$W_t^E(h, a, z, k) = \max_{a' \geq 0} u(c) + \beta \mathbb{E}\left[\delta \hat{U}_{t+1}^E(h', a', k) + (1-\delta)\hat{W}_{t+1}^E(h', a', z', k)\right] \quad \forall t \leq T$$

$$W_{T+1}^E(h, a, z, k) = 0$$

where $\hat{W}_{t+1}^E(h', a', z', k)$ denotes the value of on-the-job search for a worker who is experienced in occupation k, and is given by,

$$\begin{aligned}\hat{W}_{t+1}^E(h', a', z', k) = \max\Big\{ & p(\theta_{t+1}^E(h', a', k))W_{t+1}^E(h', a', \bar{z}, k) + \Big(1 - p(\theta_{t+1}^E(h', a', k))\Big) W_{t+1}^E(h', a', z', k), \\ & \max_{\tilde{k} \in \mathcal{K}/\{k\}} p(\theta_{t+1}^N(h', a', \tilde{k}))W_{t+1}^N(h', a', \bar{z}, \tilde{k}) + \Big(1 - p(\theta_{t+1}^N(h', a', \tilde{k}))\Big) W_{k,t+1}^E(h', a', z', k)\Big\}\end{aligned}$$

subject to the budget constraint,

$$c + \frac{a'}{1+r} \leq (1-\tau)\omega f(c_k z, h, E) + a$$

and the laws of motion for worker's human capital, and the firm's technology,

$$h' = H(h, W) \quad z' = Z(z)$$

A.4.3 Bellman Equation for Firm Matched with Experienced Worker

In this subsection, we present the Bellman equation for a firm that is matched with an experienced worker. Let $J_t^E(h, a, z, k)$ denote the value to a firm in occupation k of being matched with an experienced worker with human capital h, assets a and using technology $z \leq \bar{z}$. In the current period, the firm produces and makes wage payments. In the next period, the match can expire due to an exogenous separation, or the worker leaving due to on-the-job search. If the match continues, the firm continues to receive the benefits of the match. The value to the firm is given by:

$$J_t^E(h,a,z,k) = (1-\omega)f^E(c_k z, h, E) \\ + \frac{1-\delta}{1+r}\mathbb{E}\left[\left(1 - p(\theta_{t+1}^{e(\hat{k})}(h', a'(y), \hat{k}(y')))\right) J_{t+1}^E(h', a'(y), z', k)\right] \quad \forall t \leq T$$

$$J_{T+1}^N(h,a,z,k) = 0$$

where $p(\theta_{t+1}^{e(\hat{k})}(h', a'(y), \hat{k}(y')))$ is the probability that the worker matches with another firm in their optimal occupation choice $\hat{k}$ via on-the-job search, and leaves their current match.

A.4.4 Block Recursive Equilibrium

In this subsection, we prove that the model's equilibrium is Block Recursive (e.g., Menzio and Shi (2011)), i.e. the distribution of workers across states does not impact individual or firms decisions problems, and hence the equilibrium prices.

Suppose that the tax rate τ is given, and that the government's budget constraint is not required to hold. Then the individual, and firm problems can be solved independently of the distribution of individuals across states Ω. In solving the model we iterate on τ to balance the governments budget constraint both in the steady state of the model as well as when solving the transition path (in which case we iterate on a sequence of tax rates). The Block Recursive nature of the model is critical in being able to tractably solve the transition path to the optimal policy for unemployed workers. We formally define and proof the Block Recursive nature of the model below.

Proposition 3. *Suppose τ is given and the government budget does not need to balance. Assume that the utility function meets standard conditions ($u' > 0, u'' < 0, \lim_{c\to\infty} u'(c) = 0$ and u is invertible), the matching function is invertible and constant returns to scale, and there is bounded support for the choice set of occupations $k \in \mathcal{K} \equiv [\underline{k}, \bar{k}]$, then a Block Recursive Equilibrium exists.*

Proof. The proof is performed using backward induction. Let $t = T$ and consider an unemployed individual which is inexperienced for the sake of brevity (the proof follows in an identical manner for employed households, as well individuals who are experienced in an occupation). Since the individuals' continuation value is zero for $T+1$ onward, the individual's dynamic programming problem does not depend upon the aggregate distribution across states.

In the terminal period T, agents set their asset choice to zero (i.e. $a_T'(h,a,0) = 0$) and choose to not retrain ($R_T(h,a,0) = 0$), which gives the following continuation values for the terminal period:

$$U_T^N(h, a, 0) = u\left(b + a + d\right)$$

Hence, the value to an unemployed (inexperienced) household, does not depend upon the aggregate distribution.

In the labor market, the firm's value function is independent of the aggregate distribution as well, and is given by,

$$J_T^x(h, a, z) = f(c_k z, h, x) - w_T^x(h, z, k)$$

when the firm is matched with a worker with experience $x \in \{E, N\}$. Given this value to the firm of a match, the labor market tightness will also be independent of the aggregate distribution, and is given by,[20]

$$\theta_T^x(h, a, k) = p_f^{-1}\left(\frac{\kappa}{J_T^x(h, a, \bar{z}, k)}\right)$$

An unemployed inexperienced individual at age $T-1$ makes a labor market search choice over occupations $k \in \mathcal{K}$ to solve:

$$\max_k p(\theta_T^N(h, a, k))W_T^N(h, a, \bar{z}, k) + \left(1 - p(\theta_T^N(h, a, k))\right) U_T^N(h, a, 0)$$

As long as k is within a bounded interval the extreme value theorem guarantees at least one solution to this problem. The same holds for experienced unemployed individuals as well as employed individuals. Since τ is given the distribution of workers across states does not impact individual's decision problems.

Stepping back from $t = T-1, ..., 1$, and repeating the above procedure completes the proof. □

A.5 Solution Algorithm

In this Appendix, we present the algorithm for solving the model presented in Section 1.3. Solving the model proceeds in the following steps:

1. **Taxes:** Guess τ.

2. **Firms Bellman:** Compute the value to a firm of being in a match in the terminal

[20]Recall vacancies are only posted for the latest vintage of technology $\bar{z}$.

period $J_T^x(h, a, \bar{z})$ at the value of the frontier technology.[21] Using the value of a firm in the terminal period, invert the free entry condition to obtain labor market tightness $\theta_T^x(h, a, k)$.

3. **Individual Consumption Savings Problem:** Solve the individuals consumption, savings, and retraining choice problem in the terminal problem.

4. **Individual's Job Search:** Use the estimate of $\theta_T(\omega, h)$ to solve the individual's job search problem.

5. **Repeat for ages** $T-1$, $T-2, ..., 1$.

6. **Budget Balance:** Simulate a mass of individuals and check that the government's budget constraint is satisfied. Update guess of τ until the government budget is balanced.[22]

A.6 Calibration Details

In this Appendix we provide additional details on the calibration of the model that was presented in Section 1.4. We additionally discuss the calibration of the model without technology growth that was used in the policy experiment of Section 1.5.1.

A.6.1 Calibration of Technology Parameters

In this section, we provide additional details on the calibration of the technology intensity parameters of the model ($\{c_k\}$). Calibrating the technology intensity parameters proceeds in two steps: (1) assigning 4-digit occupation to one of 10 occupation groups, and (2) measuring earnings across the 10 occupation groups. Using estimates of earnings across the 10 occupation groups we calibrate the parameters ($\{c_k\}$).

Fist, we partition the distribution of occupations (in the data) into $K = 10$ groups based on the share of vacancies listing a computer or software requirement in 2010. The groups are formed by evenly spacing grid points in terms of the share of vacancies listing a computer or software requirement in 2010. Table A.12 contains the grid points that are in each group. Let $k \in \mathcal{K} = \{1, 2, .., 10\}$ denote an occupation group, and let o denote an occupation at the four-digit SOC code level.

Second, we measure earnings across the occupation groups k. Let $e_{i,o,t}$ be the real earnings of individual i working in occupation o in period t, let $z_{o,2010}$ denote the share of vacancies

[21] Not we measure the value at the frontier technology because all matches are formed at the frontier technology in an occupation.

[22] In the simulation to check the government's budget balance we simulate 125,000 individuals for 260 periods, 10 times, burning the first 120 periods. We report averages over the 5 simulations.

Table A.12: Occupation Groups and Cutoffs

Occupation Group (k)	Min. CPU Req.	Min. CPU Req.
1	0	0.075
2	0.075	0.125
3	0.125	0.175
4	0.175	0.225
5	0.225	0.275
6	0.275	0.325
7	0.325	0.375
8	0.375	0.425
9	0.425	0.475
10	0.475	–

Notes: Table shows the cutoffs used to form the 10 occupation groups in the data. 4-digit occupations are placed into one of the 10 occupation groups based on the share of vacancies listing a computer or software requirement in 2010.

listing a computer or software requirement in occupation o in the year 2010, and let γ_t denote a set of year dummy variables. We estimate the following regression of computer and software requirements on earnings using data from the CPS:[23]

$$e_{i,o,t} = \alpha + \beta z_{o,2010} + \gamma_t + \epsilon_{i,o,t} \tag{A.7}$$

Using the coefficients from the estimation of equation A.7, we compute the predicted earnings for each individual. Let $\hat{e}_{i,o,t}$ denote the predicted earnings for individual i working in occupation o in year t. From these predicted values we estimate average predicted earnings for each occupation group $k \in \mathcal{K}$, which is denoted by $\bar{e}_k$, and estimated using:

$$\bar{e}_k = \sum_{o \in k} \hat{e}_{i,o,t} \quad \forall k \in \mathcal{K}$$

We use the set of smoothed earnings $\bar{e}_k$ to govern the technology parameters in the model. We calibrate the technology intensity of the first occupation (c_1) to match the ratio of smoothed earnings in the first occupation to average earnings among all workers. We calibrate the remaining technology parameters ($\{c_k\}_{k=2}^{k=10}$) to match the ratio of smoothed earnings in occupation k relative to the first occupation ($\frac{\bar{e}_k}{\bar{e}_1}$). Table A.13 contains the parameter estimates of the technology intensity parameters as well as their model fit.

[23] In estimating equation A.7 we use the outgoing rotation groups of the monthly CPS survey between 2010 and 2017. Earnings are measured as real weekly earnings. To ensure a minimum degree of labor force attachment, we remove individuals with real weekly earnings below $100.

Table A.13: Calibration of Technology Intensity Parameters

Var.	Value	Target	Model	Data	Source
c_1	0.561	Ratio of Occ. Earnings / Avg. Earnings	0.762	0.797	CPS
c_2	0.581	Relative Earnings 2nd Occupation	1.044	1.045	CPS
c_3	0.608	Relative Earnings 3rd Occupation	1.115	1.112	CPS
c_4	0.646	Relative Earnings 4th Occupation	1.167	1.177	CPS
c_5	0.675	Relative Earnings 5th Occupation	1.225	1.235	CPS
c_6	0.708	Relative Earnings 6th Occupation	1.285	1.297	CPS
c_7	0.740	Relative Earnings 7th Occupation	1.347	1.359	CPS
c_8	0.763	Relative Earnings 8th Occupation	1.392	1.404	CPS
c_9	0.807	Relative Earnings 9th Occupation	1.482	1.487	CPS
c_{10}	0.890	Relative Earnings 10th Occupation	1.640	1.645	CPS

Notes: Table shows parameter estimate for the technology intensity parameters, as well as the model fit. Relative earnings for the k-th occupation is defined as the ratio of earning in the k-th occupation relative to earnings in the first occupation.

A.6.2 Calibration of Model With Constant Technology

In this section, we discuss the calibration of the model with constant technology ($g = 0\%$). In calibrating the model with constant technology, there are some parameters we hold fixed at their values from the baseline estimation while others are recalibrated. In particular, we keep the technology intensity parameters $\{c_k\}_{k=1}^{k=10}$ fixed at their values from the baseline estimation. In the model with constant technology individuals are significantly less likely to switch occupations following displacement (under 5% without technological change vs. nearly 55% with technological change). The parameter λ_N which governs the probability that an experienced worker looses their experience while unemployed disciplines the share of individuals who switch occupations in the baseline estimation of the model. Given the low rate of occupation switching in the model with constant technology, we keep the parameter λ_N at its value of the baseline estimation of the model. Finally, technological change impacts the distribution of workers general human capital in the model. To make the distribution of human capital consistent across estimations of the model in the model without technological change individuals draw their human capital from the stationary distribution of human capital from the baseline version of the model where retraining has been turned off. We use the estimation of the model with retraining removed to capture how initial human capital should be distributed. The remaining parameters are calibrated as in the baseline estimation of the model. Table A.14 presents the results of this estimation exercise.

Table A.14: Calibration With Constant Technology

Var.	Value	Target	Model	Data	Source
b	0.207	Transfer to Income Loss	43.7%	41.2%	PSID
κ	1.085	Unemployment Rate	6.9%	6.8%	BLS
κ_R	0.024	Retraining Cost / Avg. Earnings	4.8%	5.1%	KR
ψ	0.303	Retraining Rate	15.7%	16.6%	JLS
λ_R	0.156	Earnings Gain from Retraining	3.63%	2.25%	JLS
β	0.989	P75 Net Liquid Assets to Income	20.9%	21.1%	SCF
d	0.075	Consumption After Displacement	91.9%	93.8%	PSID

Notes: Table shows parameter estimate from calibrating the model with constant technology ($g =$ 0%).

A.7 Welfare Calculation

In this section, we describe our process for performing the welfare calculation. We first discuss the welfare calculation for the steady state experiment, and then discuss the welfare calculation for the transition path experiment.

A.7.1 Steady State Welfare Calculation

Let $(\{c_t^j, R_t^j\}_{t=1}^{t_{max}})$ be the consumption, and retraining policy functions for an individual j over their lifetime under the baseline policy (i.e. public insurance transfer and subsidy to retraining tuition costs) for unemployed workers. Let $(\{\tilde{c}_t^j, \tilde{R}_t^j\}_{t=1}^{t_{max}})$ be the consumption, and retaining policy functions for an individual j under an alternative policy for unemployed workers. We will perform welfare calculations by estimating the share of lifetime consumption an individual would be willing to forgo (or must receive) to leave the baseline economy and move to an economy with an alternative policy for unemployed workers. Formally, we estimate the scaling factor for consumption λ_j that makes individual j indifferent between living under either policy:

$$\sum_{t=1}^{T} \beta^t \left(\frac{\left(\lambda_j c_t^j\right)^{1-\sigma} - 1}{1-\sigma} - \psi R_t^j \right) = \sum_{t=1}^{T} \beta^t \left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma} - 1}{1-\sigma} - \psi \tilde{R}_t^j \right) \tag{A.8}$$

Solving equation (B.3) for λ_j returns:

$$\lambda_j = \left[\frac{\sum_{t=1}^{T} \beta^t \left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma}}{1-\sigma} - \left(\psi \tilde{R}_t^j - \psi R_t^j\right) \right)}{\sum_{t=1}^{T} \beta^t \left(\frac{\left(c_t^j\right)^{1-\sigma}}{1-\sigma} \right)} \right]^{\frac{1}{1-\sigma}} \tag{A.9}$$

We use the model to simulate a large mass of individuals under a series of alternative policies for unemployed workers. Let N denote the number of individuals that we simulate, and let P be the set of public insurance policies that we consider. For each simulated individual and policy $p \in P$, we estimate $\lambda_{j,p}$, the scaling factor for consumption that makes the individual indifferent between living under the alternative policy for unemployed workers and the baseline policy. To convert the units of the scaling term $\lambda_{j,p}$ into the percentage of lifetime consumption the individual would be willing to forgo (or must receive), hereafter referred to as lifetime consumption equivalents and denoted $\tilde{\lambda}_{j,p}$, we perform the following transformation:

$$\tilde{\lambda}_{j,p} = 100(\lambda_{j,p} - 1)$$

Let $\{\{\tilde{\lambda}_{j,p}\}_{j=1}^{N}\}_{p=1}^{P}$ denote the set of lifetime consumption equivalents from the simulation of alternative policies for unemployed workers. From the distribution of lifetime consumption equivalents, we measure the utilitarian welfare effect and median welfare effect for each policy $p \in P$. The utilitarian welfare effect for an alternative policy $p \in P$, which is denoted $Welfare_U(p)$, is measured as:

$$Welfare_U(p) = \frac{1}{N}\sum_{j=1}^{N}\tilde{\lambda}_{j,p}$$

The optimal policy under the utilitarian welfare effect is the policy $p^* \in P$ that maximizes the utilitarian welfare effect $Welfare_U(p)$.

A.7.2 Transition Path Welfare Calculation

In the transition path experiment, we perform welfare calculations by estimating the share of *remaining* lifetime consumption an individual would be willing to forgo (or must receive) to leave the baseline economy and move to an economy where there is an unexpected and permanent policy change. Let $(\{c_t^j, R_t^j\}_{t=1}^{t_{max}})$ be the consumption, and retraining policy functions for an individual j over their lifetime under the baseline policy (public insurance transfers and subsidy for retraining) for unemployed workers. Let $(\{\tilde{c}_t^j, \tilde{R}_t^j\}_{t=1}^{t_{max}})$ be the consumption, and retraining policy functions for an individual j under an alternative policy for unemployed workers. Assume that for individual j, the policy change occurs at age $\hat{t}_j$. Note that because the policy change is unexpected, individual j makes identical consumption, default, and credit search decisions for the first $\hat{t}_j - 1$ periods of their life. Thus to measure the welfare effects of the policy change, we only consider an individuals behavior in the remaining $T - \hat{t}$ periods of their life.[24] Formally, we estimate the scaling factor for consumption η_j that makes individual j indifferent between living the remaining periods of their life under either public insurance policy:

$$\sum_{t=\hat{t}_j}^{T} \beta^t \left(\frac{\left(\eta_j c_t^j\right)^{1-\sigma} - 1}{1-\sigma} - \psi R_t^j \right) = \sum_{t=\hat{t}_j}^{T} \beta^t \left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma} - 1}{1-\sigma} - \psi \tilde{R}_t^j \right) \tag{A.10}$$

Solving equation (B.5) for η_j returns:

$$\eta_j = \left[\frac{\sum_{t=\hat{t}_j}^{T} \beta^t \left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma}}{1-\sigma} - \left(\psi \tilde{R}_t^j - \psi R_t^j \right) \right)}{\sum_{t=\hat{t}_j}^{T} \beta^t \left(\frac{\left(c_t^j\right)^{1-\sigma}}{1-\sigma} \right)} \right]^{\frac{1}{1-\sigma}} \tag{A.11}$$

To convert the units of the scaling term η_j into the percentage of remaining lifetime consumption the individual would be willing to forgo (or must receive), hereafter referred to as remaining lifetime consumption equivalents and denoted $\tilde{\eta}_j$, we perform the following transformation:

$$\tilde{\eta}_j = 100(\eta_j - 1)$$

As we discuss in greater detail in Section B.7, we simulate a large mass of individuals and unexpectedly increase public insurance transfers to the unemployed as well as the retraining subsidy. Let N denote the number of simulated individuals who are alive at the time of the policy transition. We track the consumption and retraining behavior of individuals, and estimate the share of remaining lifetime consumption that makes each agent indifferent between the policy transition and no policy transition. Let $\{\tilde{\eta}_j\}_{j=1}^{N}$ denote the set of lifetime consumption equivalents from the simulation of the transition experiment. The utilitarian welfare effect of the transition experiment, which is denoted $Welfare_T$, is measured as:

$$Welfare_T = \frac{1}{N} \sum_{j=1}^{N} \tilde{\eta}_j$$

A.8 Transition Path Experiment

In this appendix, we discuss the details of the transition path experiment presented in Section 1.5.2. Solving the transition path of the policy change is tractable in this environment since the model is Block Recursive (e.g., Menzio and Shi (2011)), conditional on τ (see Appendix A.4.4). The Block Recursive nature of the model means that (conditional on a

[24] Note we also only consider the welfare of individuals who are alive at the time of the policy transition.

path of taxes, τ), the distribution of agents across states does not alter equilibrium prices, which in this environment are the market tightness functions. Only through the path of taxes (τ), do individuals' policy functions as well as prices depend on the distribution of agents across states. Given a path of taxes, we solve the individual's problem and simulate a mass of individuals along the transition path. We then compute the government budget balance and iterate on the path of taxes until the government budget constraint holds at each point along the transition path.

Let $\mathit{\Omega} = (b, s, \tau)$ denote the aggregate policy state, where b is the public insurance to the unemployed, s is the retraining subsidy and τ is the tax rate. In the transition path experiment, the aggregate policy state $\mathit{\Omega}$ follows the transition matrix in equation (B.7), with corresponding values for (b, s, τ) in Table B.8. The realizations of the Markov chain are such that the economy transitions from the interim stage to the new steady state after 20 quarters. Individuals rationally understand the law of motion for $\mathit{\Omega}$, and all equilibrium prices depend on $\mathit{\Omega}$. For example, an unemployed individual takes $\mathit{\Omega}$ and the Markov transition matrix for $\mathit{\Omega}$ as given, where the expectation operator now realizes the aggregate policy shocks:

$$U_t^N(h, a, 0; \mathit{\Omega}) = \max_{a^{'} \geq 0, R \in \{0,1\}} u(c) - R\psi + \beta \mathbb{E}\left[\hat{U}_{t+1}^N(h^{'}, a^{'}, 0; \mathit{\Omega}^{`})\right] \quad \forall t \leq T$$

$$U_{T+1}^N(h, a, 0; \mathit{\Omega}) = 0$$

where $\hat{U}_{t+1}^N(h^{'}, a^{'}, 0; \mathit{\Omega}^{`})$,

$$\begin{aligned}\hat{U}_{t+1}^N(h^{'}, a^{'}, 0; \mathit{\Omega}^{`}) = \max_{k \in \mathcal{K}} \, & p(\theta_{t+1}^N(h^{'}, a^{'}, k; \mathit{\Omega}^{`})) W_{t+1}^N(h^{'}, a^{'}, \bar{z}, k; \mathit{\Omega}^{`}) \\ & + \left(1 - p(\theta_{t+1}^N(h^{'}, a^{'}, k; \mathit{\Omega}^{`}))\right) U_{t+1}^N(h^{'}, a^{'}, 0; \mathit{\Omega}^{`})\end{aligned}$$

subject to the budget constraint,

$$c + \frac{a^{'}}{1+r} + R(1-s)\kappa_R \leq b + a + d$$

and the transition matrix for the aggregate state $\mathit{\Omega}$ ((B.7)), and the law of motion for human capital.

Table A.15: Transfers and Taxes Along Transition Path

	Transfer (b)	Replacement Rate	Retraining Subsidy	Tax Rate (τ)
Initial Steady State	0.202	41.1%	0%	3.15%
1st Year After Policy Change	0.247	50.3%	30%	4.07%
2nd Year After Policy Change	0.247	50.3%	30%	4.12%
3rd Year After Policy Change	0.247	50.3%	30%	4.11%
4th Year After Policy Change	0.247	50.3%	30%	4.05%
5th Year After Policy Change	0.247	50.3%	30%	4.03%
New Steady State	0.247	50.3%	30%	3.78%

$$P_{\Omega} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.75 & 0.25 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.75 & 0.25 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.75 & 0.25 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{A.12}$$

The transition path experiment begins in the steady state of the baseline economy with a 41.1% replacement rate to the unemployed, and a 0% retraining subsidy. An unexpected and permanent increase in the generosity of public insurance to the unemployed and the retraining subsidy then occurs, which increases the replacement rate to 50.3% and the retraining subsidy to 30%. For the government budget to balance the tax rate is increased as well. In each of the first five-years after the policy change, the tax rate adjusts to balance the government's budget constraint. In all remaining years after the policy change, the tax rate from the steady state of the economy with a 50.3% replacement rate and 30% retraining subsidy balances the government's budget constraint. Along the transition path individuals have rational expectations for the path of the tax rate and the public insurance policy.

To perform the transition path experiment we simulate 125,000 individuals for 380 periods, 20 times, burning the first 130 periods. We report averages over the 20 simulations. The path of the aggregate policy state in the simulation is such that we are in the initial steady state for 260 periods (including the burn), then we are in the "1st Year After Policy Change" state for 4-quarters where the values for the aggregate policy state parameters are given in Table B.8. For each year after the policy change Y where $Y \in \{2, 3, 4, 5\}$, we are in the "Y Years After Policy Change" state for 4-quarters where the values for the aggregate policy

state parameters are given in Table B.8. Finally, the aggregate policy state is in the "New Steady State" for the final 100 periods of the simulation.
Solving the transition path of the economy proceeds in the following steps:

1. **Taxes** Guess a sequence of taxes $\tau = [\tau_o, \tau_1, \tau_2, \tau_3, \tau_4, \tau_5, \tau_{new}]$ where τ_o is the tax rate in the initial steady state, τ_Y is the tax rate Y years after the policy change, and τ_{new} is the tax rate in the new steady state following the transition.

2. **Model Estimation** Solve the model following the steps presented in Appendix A.5 using the taxes guessed in Step 1, the transfers to unemployed workers and retraining subsidy from Table B.8, and the transition matrix for the aggregate policy state given by equation B.7.

3. **Simulation and Budget Balance**: Simulate a mass of individuals, perform the policy transition and check the government's budget constraint in each of the 7 aggregate policy states. Iterate until the government's budget is balanced in each aggregate policy state.

A.9 Model Extensions

In this Appendix, we present the Bellman equations that govern the behavior of agents in various extensions to the baseline model. We first consider a version of the model where agents search for jobs across occupations and wage piece-rates. We then consider a version of the model where the unemployment insurance benefit component of public insurance transfers is subject to expire.

A.9.1 Model with Search over Wages and Occupations

In this Appendix, we present a version of the model where workers search for jobs across occupations *and* wage piece-rates. In the subsequent sections, we present the Bellman equations that govern the behavior of agents in the model where they search over both occupations and piece-rates as well as the calibration and model fit.

Bellman Equations

In this section, we present the Bellman equations for the model with search over wage piece-rates. We present the Bellman equations for inexperienced workers. The Bellman equations for experienced workers follow naturally.

Unemployed Inexperienced Worker. Let $U_t^N(h,a,0)$ denote the value of being an inexperienced, unemployed worker of age t, with assets a and human capital h. The unemployed worker makes their consumption and savings decision, as well as their retraining decision. Upon entering the retraining program, the worker pays cost $(1-s)\kappa_R$ and has their human capital updated from h to $h+\Delta_R$ with probability λ_R. Those who retrain incur a utility penalty of ψ, which can be thought of as lost leisure due to enrolling in the retraining program. At the start of the next period after shocks to human capital are realized, the unemployed worker searches for a job in the inexperienced labor market by searching across the set of occupations and wage piece-rates, and applying for a job with the highest continuation value. The value to an inexperienced unemployed worker is

$$U_t^N(h,a,0) = \max_{a^{'}\geq 0, R\in\{0,1\}} u(c) - R\psi + \beta\mathbb{E}\left[\hat{U}_{t+1}^N(h^{'},a^{'},0)\right] \quad \forall t \leq T$$

$$U_{T+1}^N(h,a,0) = 0,$$

where $\hat{U}_{t+1}^N(h^{'},a^{'},0)$ denotes the expected value of search for an inexperienced unemployed worker, which is given by

$$\hat{U}_{t+1}^N(h^{'},a^{'},0) = \max_{\omega,k\in\mathcal{K}} p(\theta_{t+1}^N(h^{'},a^{'},k,\omega))W_{t+1}^N(h^{'},a^{'},\bar{z},k,\omega) + \left(1-p(\theta_{t+1}^N(h^{'},a^{'},k,\omega))\right)U_{t+1}^N(h^{'},a^{'},0),$$

subject to the budget constraint,

$$c + \frac{a^{'}}{1+r} + R(1-s)\kappa_R \leq b + a + d,$$

and the law of motion for a worker's human capital, which is indexed by employment status U and their retraining decision $R\in\{0,1\}$,

$$h^{'} = H(h,U,R).$$

Experienced unemployed workers face a problem similar to that of inexperienced unemployed workers. The main difference is that experienced unemployed workers search in the experienced labor market for a job in their own occupation and in the inexperienced market for jobs in all other occupations.

Employed Inexperienced Worker. Let $W_t^N(h,a,z,k,\omega)$ denote the value of being an inexperienced worker with human capital h and assets a, who is employed at a firm in occupation k that uses technology $z \leq \bar{z}$, and receives share ω of the match output as a wage. The agent makes their consumption and savings choice, and receives utility from consumption. At the start of the next period, shocks to human capital and match technology are realized, and the worker becomes unemployed with probability δ. Workers who become unemployed are immediately allowed to search in the labor market. If the worker is not hit by the separation shock δ, then the worker becomes experienced in occupation k with probability λ_E. After the experience shock is revealed, the worker engages in on-the-job search where they search over occupations and wage piece-rates. If the worker becomes experienced, then they search for a job in their own occupation in the experienced labor market and search for a job in all other occupations in the inexperienced labor market. If the worker did not become experienced, then they search in the inexperienced labor market for all occupations. The continuation value of the inexperienced employed worker is

$$\begin{aligned} W_t^N(h,a,z,k,\omega) = \max_{a' \geq 0} u(c) + \beta \mathbb{E} \Big[& \delta \hat{U}_{t+1}^N(h', a', k) \\ & + (1-\delta) \Big(\lambda_E \hat{W}_{k,t+1}^E(h', a', z', k, \omega) + (1-\lambda_E) \hat{W}_{t+1}^N(h', a', z', k, \omega) \Big) \Big] \quad \forall t \leq T \end{aligned}$$

$$W_{T+1}^N(h,a,z,k,\omega) = 0,$$

where $\hat{W}_{t+1}^N(h', a', z', k, \omega)$ denotes the value of on-the-job search for an inexperienced employed worker from occupation k with wage piece-rate ω, and is given by

$$\begin{aligned} \hat{W}_{t+1}^N(h', a', z', k, \omega) = & \max_{\tilde{\omega}, \tilde{k} \in \mathcal{K}} p(\theta_{t+1}^N(h', a', \tilde{k}, \tilde{\omega})) W_{t+1}^N(h', a', \bar{z}, \tilde{k}, \tilde{\omega}) \\ & + \Big(1 - p(\theta_{t+1}^N(h', a', \tilde{k}, \tilde{\omega}))\Big) W_{t+1}^N(h', a', z', k, \omega), \end{aligned}$$

and $\hat{W}_{t+1}^E(h', a', z', k, \omega)$ denotes the value of on-the-job search for a worker who is experienced in occupation k with wage piece-rate ω, and is given by

$$\begin{aligned} \hat{W}_{t+1}^E(h', a', z', k, \omega) = \max \Big\{ & \max_{\tilde{\omega}} p(\theta_{t+1}^E(h', a', k, \tilde{\omega})) W_{t+1}^E(h', a', \bar{z}, k, \tilde{\omega}) + (1 - p(\cdot))\, W_{t+1}^E(h', a', z', k, \omega), \\ & \max_{\tilde{\omega}, \tilde{k} \in \mathcal{K}/\{k\}} p(\theta_{t+1}^N(h', a', \tilde{k}, \tilde{\omega})) W_{t+1}^N(h', a', \bar{z}, \tilde{k}, \tilde{\omega}) + (1 - p(\cdot))\, W_{k,t+1}^E(h', a', z', k, \omega) \Big\}, \end{aligned}$$

subject to the budget constraint,

$$c + \frac{a'}{1+r} \leq (1-\tau)\omega f(c_k z, h, N) + a,$$

and the laws of motion for worker's human capital, and the firm's technology,

$$h' = H(h, W), \quad z' = Z(z).$$

Experienced employed workers face a problem similar to that of inexperienced employed workers.

Firm Matched with Inexperienced Worker. Let $J_t^N(h,a,z,k,\omega)$ denote the value to a firm in occupation k of being matched with an age t inexperienced worker with human capital h, assets a, wage piece-rate ω and using technology $z \leq \bar{z}$. In the current period, the firm produces and makes wage payments. At the start of the period, shocks to the worker's human capital and technology within the match are realized, and with probability δ the match ends exogenously. If the match avoids the separation shock, then the worker becomes experienced with probability λ_E and searches in the labor market.

If the worker does not match with another job via on-the-job search, then the match continues and the firm continues to receive the benefits of the match. The probability that the worker leaves the firm via on-the-job search depends on their asset choice in the current period as well as where the worker searches for a new match in the next period. Let $y = (t, h, a, z, x, k, \omega)$ denote the state of the individual that the firm is matched with in the current period, and let $a^{'}(y)$ denote the agents asset choice. Let $y^{'} = (t+1, h^{'}, a^{'}(y), z^{'}, x^{'}, k, \omega)$ denote the agent's state in the next period when making their decision about which occupation to search for a job in (i.e., after shocks to human capital, match technology, and experience are realized). Let $\hat{k}(y^{'})$ denote the occupation where the worker searches for a job, and let $\hat{\omega}(y^{'})$ denote the wage piece-rate where the worker searches for a job. With probability $p(\theta_{t+1}^{x(\hat{k})}(h^{'}, a^{'}(y), \hat{k}(y^{'}), \hat{\omega}(y^{'})))$ the worker matches with another job via on-the-job search.[25] The value to the firm is given by

$$\begin{aligned} J_t^N(h,a,z,k,\omega) &= (1-\omega) f(c_k z, h, N) \\ &+ \frac{1-\delta}{1+r}\mathbb{E}\left[(1-\lambda_E)\left(1-p(\theta_{t+1}^N(h^{'},a^{'}(y),\hat{k}(y^{'}),\hat{\omega}(y^{'})))\right) J_{t+1}^N(h^{'},a^{'}(y),z^{'},k,\omega)\right] \\ &+ \frac{1-\delta}{1+r}\mathbb{E}\left[\lambda_E\left(1-p(\theta_{t+1}^{x(\hat{k})}(h^{'},a^{'}(y),\hat{k}(y^{'}),\hat{\omega}(y^{'})))\right) J_{t+1}^E(h^{'},a^{'}(y),z^{'},k,\omega)\right] \quad \forall t \leq T \end{aligned}$$

$$J_{T+1}^N(h,a,z,k,\omega) = 0,$$

and the laws of motion for worker's human capital and the firm's technology,

$$h^{'} = H(h, W), \quad z^{'} = Z(z).$$

Firms matched with experienced workers face a similar problem as firms matched with inexperienced workers.

Vacancies. Potential firms enter the market and post vacancies to hire an age t worker with experience $x \in \{E, N\}$, human capital h, and assets a for occupation k at wage piece-rate ω subject to the free-entry condition

$$\kappa \geq p_f(\theta_t^x(h,a,k,\omega)) J_t^x(h,a,\bar{z},k,\omega) \;\text{ for } x \in \{E, N\},$$

[25] Note that when the worker becomes experienced, their choice of which occupation to search for a new job in determines whether they search in the experienced market (i.e., if they choose to search in their current occupation k) or the inexperienced market (i.e., if they choose to search in any other occupation $\tilde{k} \in \mathcal{K}/\{k\}$). For this reason, we denote the market the agent searches in as $x(\hat{k})$.

where $p_f(\theta_t^x(h,a,k,\omega))$ is the matching rate for firms in occupation k paying wage piece-rate ω with an age t worker with skills h, assets a, and experience $x \in \{E, N\}$. The free-entry condition binds for all submarkets such that $\theta_t^x(h,a,k,\omega) > 0$.

Calibration

In this section, we discuss the calibration of the model where workers search across occupations and wage piece-rates. Using the same moments as in the baseline model and keeping all non-calibrated moments the same as their baseline values, we recalibrate the model where agents search across wage piece-rates.[26] Table A.16 presents the model fit.

Table A.16: Model Calibration

Var.	Value	Target	Model	Data	Source
b	0.272	Transfer to Income Loss	40.3%	41.2%	PSID
κ	0.230	Unemployment Rate	4.6%	6.8%	BLS
κ_R	0.034	Retraining Cost / Avg. Earnings	5.2%	5.1%	KR
ψ	0.673	Retraining Rate	17.6%	16.6%	JLS
λ_R	0.576	Earnings Gain from Retraining	1.94%	2.25%	JLS
λ_N	0.679	Share Switching Occ. After Layoff	56.4%	63.4%	CPS
λ_H	0.172	Share Emp. in Highest Tech Occ.	17.2%	15.6%	CPS
c_1	0.561	Ratio of Occ. Earnings / Avg. Earnings	0.770	0.797	CPS
β	0.983	P75 Net Liquid Assets to Income	22.0%	21.1%	SCF
d	0.125	Consumption After Displacement	91.0%	93.8%	PSID

A.9.2 Model with Benefit Expiration

In this Appendix, we consider an extension of the model where we allow unemployment insurance benefits to expire. As in Mitman and Rabinovich (2015) individuals become *ineligible* for unemployment insurance benefits stochastically for tractability.[27] Let λ_I denote the probability that an individual becomes ineligible for unemployment insurance benefits. Standard unemployment benefits expire after 26 weeks, and given the quarterly timing of the model we set $\lambda_I = 0.5$. When an individual becomes ineligible for unemployment insurance benefits they receive a transfer $b_I = \vartheta b$, where $\vartheta < 1$ reflects the non-UI share of the transfer. From the estimates of Nakajima (2012) we set $\vartheta = 0.5$. In this subsection below, we present the Bellman equations that govern the model with benefit expiration.

[26] We additionally keep the technology intensity parameters $\{c_k\}_{k=1}^{10}$ fixed at their values from the baseline estimation.

[27] Using stochastic unemployment benefit expiration allows us to avoid keeping an individuals unemployment duration as a state variable.

Bellman Equations

In this section, we present the Bellman equations for the model with benefit expiration. We present the Bellman equations for inexperienced workers. The Bellman equations for experienced workers follow naturally. The Bellman equation for an inexperienced employed worker is identical to as in Section 1.3.

Unemployed Workers Eligible for UI Benefits. Let $U_t^N(h,a,0)$ denote the value of being an inexperienced unemployed worker that is eligible for unemployment insurance benefits, with general human capital h and assets a. This value is given by,

$$
\begin{aligned}
U_t^N(h,a,0) = &\max_{a^{'}\geq 0, R\in\{0,1\}} u(c) - R\psi \\
&+ \beta\mathbb{E}\left[(1-\lambda_I)\hat{U}_{t+1}^N(h^{'},a^{'},0) + \lambda_I \hat{I}_{t+1}^N(h^{'},a^{'},0)\right] \quad \forall t \leq T
\end{aligned}
$$

$$
U_{T+1}^N(h,a,0) = 0,
$$

where $\hat{U}_{t+1}^N(h^{'},a^{'},0)$ denotes the expected value of search for an inexperienced unemployed worker, which is given by

$$
\begin{aligned}
\hat{U}_{t+1}^N(h^{'},a^{'},0) = &\max_{k\in\mathcal{K}} p(\theta_{t+1}^N(h^{'},a^{'},k))W_{t+1}^N(h^{'},a^{'},\bar{z},k) \\
&+ \left(1 - p(\theta_{t+1}^N(h^{'},a^{'},k))\right) U_{t+1}^N(h^{'},a^{'},0),
\end{aligned}
$$

and $\hat{I}_{t+1}^N(h^{'},a^{'},0)$ denotes the expected value of search for an inexperienced unemployed worker who is *ineligible* for unemployment insurance benefits, which is given by

$$
\hat{I}_{t+1}^N(h^{'},a^{'},0) = \max_{k\in\mathcal{K}} p(\theta_{t+1}^N(h^{'},a^{'},k))W_{t+1}^N(h^{'},a^{'},\bar{z},k) + \left(1 - p(\theta_{t+1}^N(h^{'},a^{'},k))\right) I_{t+1}^N(h^{'},a^{'},0)
$$

subject to the budget constraint,

$$
c + \frac{a^{'}}{1+r} + R(1-s)\kappa_R \leq b + a + d,
$$

and the law of motion for a worker's human capital, which is indexed by employment status U and their retraining decision $R \in \{0,1\}$,

$$
h^{'} = H(h,U,R).
$$

Unemployed Workers Ineligible for UI Benefits. Let $I_t^N(h,a,0)$ denote the value of being an inexperienced unemployed worker that is *ineligible* for unemployment insurance benefits, with general human capital h and assets a. This value is given by,

$$I_t^N(h,a,0) = \max_{a^{'} \geq 0, R \in \{0,1\}} u(c) - R\psi + \beta \mathbb{E}\left[\hat{I}_{t+1}^N(h^{'},a^{'},0)\right] \quad \forall t \leq T$$

$$I_{T+1}^N(h,a,0) = 0,$$

where $\hat{I}_{t+1}^N(h^{'},a^{'},0)$ denotes the expected value of search for an inexperienced unemployed worker who is *ineligible* for unemployment insurance benefits, which is given by

$$\begin{aligned}\hat{I}_{t+1}^N(h^{'},a^{'},0) = \max_{k \in \mathcal{K}} & \; p(\theta_{t+1}^N(h^{'},a^{'},k))W_{t+1}^N(h^{'},a^{'},\bar{z},k) \\ & + \left(1 - p(\theta_{t+1}^N(h^{'},a^{'},k))\right) I_{t+1}^N(h^{'},a^{'},0),\end{aligned}$$

subject to the budget constraint,

$$c + \frac{a^{'}}{1+r} + R(1-s)\kappa_R \leq b_I + a + d,$$

and the law of motion for a worker's human capital, which is indexed by employment status U and their retraining decision $R \in \{0,1\}$,

$$h^{'} = H(h, I, R).$$

Appendix B

Appendix to Chapter 2

B.1 Data Appendix

B.1.1 Identifying Mass Layoffs

To identify mass layoffs, we combine data from the Longitudinal Business Dynamics (LBD) database on establishment exits with the LEHD. In each state, employers are assigned a State Employment Identification Number (SEIN) in the LEHD database. This is our unit of analysis for mass layoffs. We define a mass layoff to occur when an SEIN with at least 25 employees reduces its employment by 30% or more within a quarter and continues operations, or exits in the LEHD with a contemporaneous plant exit in the LBD. In California, we do not have LBD establishment exit information, however. To ensure that the there was actually a mass layoff, we then verify that fewer than 80% of laid-off workers move to any other single SEIN using the Successor Predecessor File (SPF). This allows us to remove mergers, firm name-changes, and spin-offs from our sample.

B.2 Robustness

In this appendix, we provide various robustness checks on our primary results. We include summary statistics for additional measures of consumer credit. We also present additional results for the average response of credit variables following job loss, and estimates of the response of borrowing to unemployment as measured in the SCF.

B.2.1 Summary Statistics: Additional Credit Measures

Table B.1 provides summary statistics on the panel sample for additional measures of credit access and usage. The table shows that the treatment and control groups are very similar in their use of bank cards as well as their limits and unused limits to income in the year prior to mass layoff. The table also shows that individuals in the treatment and control groups are similar in their amount of total outstanding credit as well as credit limit in the year prior to layoff.

Table B.1: Summary Statistics: Bank Cards and Total Credit

Panel Sample (Year Prior to Mass Layoff)		
	(1) Treatment	(2) Control
Bank Card Balance	\$5,641	\$6,103
Bank Card Limit	\$16,660	\$18,020
Unused Bank Card Limit to Income	0.30	0.28
Total Balance	\$116,900	\$125,500
Total Limit	\$143,300	\$154,200
Observations (Rounded to 000s)	31000	30000

Note: Sample selection criteria in Section 2.2.2. Credit balances and limits are in 2008 dollars. Unused bank card credit limit to income is winsorized at the 1-percent level at the top and bottom of the distribution.

B.2.2 Additional Average Response Results

In this section, we estimate the average response of additional credit variables to job loss. First, we examine estimates of credit access as well as usage (Table B.2), and then examine the impact on measures of default (Table B.3). The coefficients in Tables B.2 and B.3 correspond to $(\beta_{-4}, \beta_{-3}, ..., \beta_4, \beta_5)$ in equation (2.1), and are interpreted as the difference in the outcome variable between displaced and nondisplaced individuals. Figure B.1 plots the coefficient estimates from Tables B.2 and B.3 along with 95 percent confidence intervals for bank card limits and balances, as well as 60 day delinquencies and bankruptcy flags.

Credit Access and Usage

Table B.2 documents the average response of additional measures of credit access and usage following job loss. Column (1) of Table B.2 and Panel (a) of Figure B.1 shows the difference in bank card limits for displaced and nondisplaced individuals around a mass layoff event. The figure shows that displaced and nondisplaced individuals do not have significantly different bank card limits prior to job loss; however in the years following displacement, displaced individuals have bank card limits which are significantly lower than nondisplaced individuals. While statistically significant, the size of the difference in bank card limits between displaced and nondisplaced individuals never exceeds \$1200 and is economically small relative to the size of limits that individuals have prior to job loss (over \$16.5k for individuals in the treatment group).

Column (2) of Table B.2 and Panel (b) of Figure B.1 displays the difference in bank card balances for displaced and nondisplaced individuals around a mass layoff event. The figure shows that displaced and nondisplaced individuals do not have significantly different bank card balances in the years prior to job loss and for the first several years following job loss. Two years after job loss, the difference in bank card balances between displaced and nondisplaced individuals is only $282, which, while statistically significant, is not economically significant, especially relative to the size of earnings losses, which two years after layoff remain over $9k.

Columns (3) and (4) show that there are similar results for total credit limits and balances around job loss. The magnitude of the decline in total credit balances is larger and statistically significant, however, column (5) shows the decline in total credit balances following job loss is driven almost entirely by declining mortgage balances.

Column (6) of Table B.2 shows the difference in the probability to take out a new home equity line of credit for displaced and nondisplaced individuals around a mass layoff event. One year after job loss, the probability a displaced individuals takes out a new home equity line is 0.379 percentage points less than a nondisplaced individual. In all other years, there is no significant difference between the probability of taking out a new home equity line for displaced and nondisplaced individuals.

Measures of Default

Table B.3 documents the average response of additional measures of default activity following job loss.

Column (1) of Table B.3 and Panel (c) of Figure B.1 shows the difference in the probability of having a 30 day delinquency within the past year between displaced and nondisplaced individuals. The figure shows that individuals begin to default on their outstanding debt balances following job loss. One year after displacement, the probability that a displaced individual has a 30 day delinquency is nearly 3 percentage points higher than a nondisplaced individual.

Column (2) of Table B.3 and Panel (d) of Figure B.1 shows the difference in the probability of having a bankruptcy flag between displaced and nondisplaced individuals. The figure shows that following job loss there is a steady increase in the probability that an individual has a bankruptcy flag on their credit report.

Column (3) of Table B.3 shows the difference in the probability of having a foreclosure within the past year between displaced and nondisplaced individuals. The coefficient estimates show that in the year following displacement, the probability an individual has a foreclosure increases by nearly 0.5 percentage points.

Column (4) of Table B.3 shows the difference in the probability of having a 60-day mortgage delinquency within the past year between displaced and nondisplaced individuals. The coefficient estimates show that in the year following displacement, the probability an individual has a sixty day mortgage delinquency increases by nearly 0.8 percentage points.

Table B.2: Average Response of Additional Credit Variables to Displacement: Credit Access and Usage

	(1) Bank Card Limit	(2) Bank Card Balance	(3) Total Credit Limit	(4) Total Credit Balance	(5) Mortgage Balance	(6) New Home Equity Line (d)
4 Years Before Displacement (d)	-85.24	41.51	440.2	629.2	756.4	-0.000220
	(123.6)	(70.73)	(1,040)	(982.4)	(914.7)	(0.00155)
3 Years Before Displacement (d)	-202.1	-4.864	-891.8	-622.0	-747.1	-1.20e-05
	(161.7)	(87.64)	(1,412)	(1,319)	(1,214)	(0.00164)
2 Years Before Displacement (d)	-301.0	-33.00	-2,015	-1,624	-1,968	0.000381
	(186.6)	(94.32)	(1,746)	(1,622)	(1,483)	(0.00169)
1 Year Before Displacement (d)	-244.7	4.168	-2,909	-2,211	-2,854	-8.66e-05
	(209.2)	(102.3)	(2,081)	(1,929)	(1,750)	(0.00182)
Year of Displacement (d)	-486.1**	-139.1	-7,670***	-6,488***	-6,111***	-0.000649
	(227.8)	(108.5)	(2,343)	(2,171)	(1,981)	(0.00190)
1 Year After Displacement (d)	-837.3***	-149.9	-14,710***	-12,590***	-11,280***	-0.00379**
	(242.0)	(114.6)	(2,576)	(2,385)	(2,178)	(0.00179)
2 Years After Displacement (d)	-966.1***	-282.6**	-13,440***	-11,230***	-10,100***	-6.11e-05
	(262.7)	(124.0)	(2,841)	(2,632)	(2,404)	(0.00199)
3 Years After Displacement (d)	-1,059***	-385.9***	-11,540***	-9,111***	-8,310***	0.00260
	(288.3)	(136.2)	(3,185)	(2,958)	(2,704)	(0.00225)
4 Years After Displacement (d)	-1,148***	-307.3**	-12,860***	-10,180***	-9,742***	0.000949
	(328.4)	(156.3)	(3,567)	(3,313)	(3,026)	(0.00241)
5 Years After Displacement (d)	-1,133***	-427.7**	-13,000***	-10,490***	-9,551***	0.00299
	(390.4)	(184.7)	(3,972)	(3,696)	(3,366)	(0.00268)
Individual Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Age and Wealth Controls	Y	Y	Y	Y	Y	Y
R-squared	0.012	0.006	0.081	0.074	0.072	0.007
Indiv-Yr Obs.	472000	472000	472000	472000	472000	472000
No. of Indiv	61000	61000	61000	61000	61000	61000

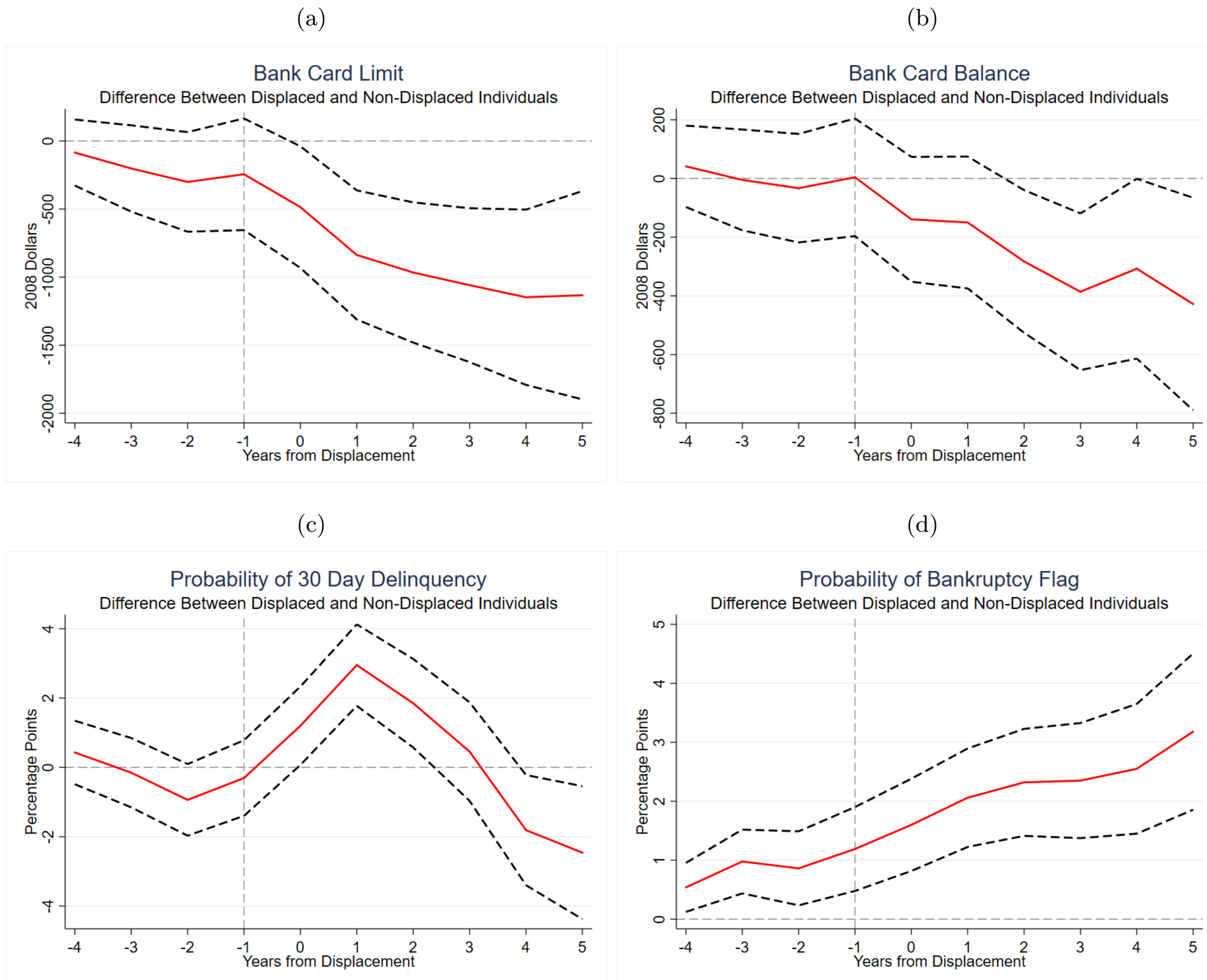
Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. The symbol (d) indicates a dummy variable. Bank card limit and balance are in 2008 dollars.*

Table B.3: Average Response of Additional Credit Variables to Displacement: Measures of Default

	(1) 30 Day Delinq. (d)	(2) Bankruptcy Flag (d)	(3) Foreclosure (d)	(4) 60 Day Mort. Delinq. (d)
4 Years Before Displacement (d)	0.00430	0.00539**	0.00114	-0.000562
	(0.00467)	(0.00212)	(0.000782)	(0.00164)
3 Years Before Displacement (d)	-0.00153	0.00978***	0.00104	0.00293
	(0.00510)	(0.00276)	(0.000786)	(0.00186)
2 Years Before Displacement (d)	-0.00938*	0.00862***	0.00110	-0.000114
	(0.00527)	(0.00320)	(0.000822)	(0.00196)
1 Year Before Displacement (d)	-0.00308	0.0119***	0.00154*	0.00128
	(0.00556)	(0.00363)	(0.000895)	(0.00215)
Year of Displacement (d)	0.0120**	0.0160***	0.00247**	0.00405*
	(0.00577)	(0.00399)	(0.000966)	(0.00227)
1 Year After Displacement (d)	0.0295***	0.0206***	0.00468***	0.00792***
	(0.00600)	(0.00426)	(0.00103)	(0.00243)
2 Years After Displacement (d)	0.0185***	0.0232***	0.00347***	0.00172
	(0.00651)	(0.00463)	(0.00106)	(0.00260)
3 Years After Displacement (d)	0.00455	0.0235***	0.00287**	0.000879
	(0.00725)	(0.00498)	(0.00121)	(0.00287)
4 Years After Displacement (d)	-0.0181**	0.0255***	0.00172	-0.00396
	(0.00811)	(0.00561)	(0.00136)	(0.00328)
5 Years After Displacement (d)	-0.0246**	0.0318***	0.000127	-0.00762*
	(0.00979)	(0.00676)	(0.00159)	(0.00414)
Individual Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Age and Wealth Controls	Y	Y	Y	Y
R-squared	0.008	0.020	0.003	0.006
Indiv-Yr Obs.	472000	472000	472000	472000
No. of Indiv	61000	61000	61000	61000

Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. The symbol (d) indicates a dummy variable. Bank card limit and balance are in 2008 dollars.*

Figure B.1: Additional Average Response Results



Notes: Figure presents estimates of the effect of job loss on credit market variables and measures of default and delinquency. Solid line is the difference in the outcome variable between displaced and nondisplaced individuals. Dashed line represents a 95 percent confidence interval. Figures present coefficient estimates from Tables B.2 and B.3.

B.2.3 Heterogeneous Response to Earnings Changes

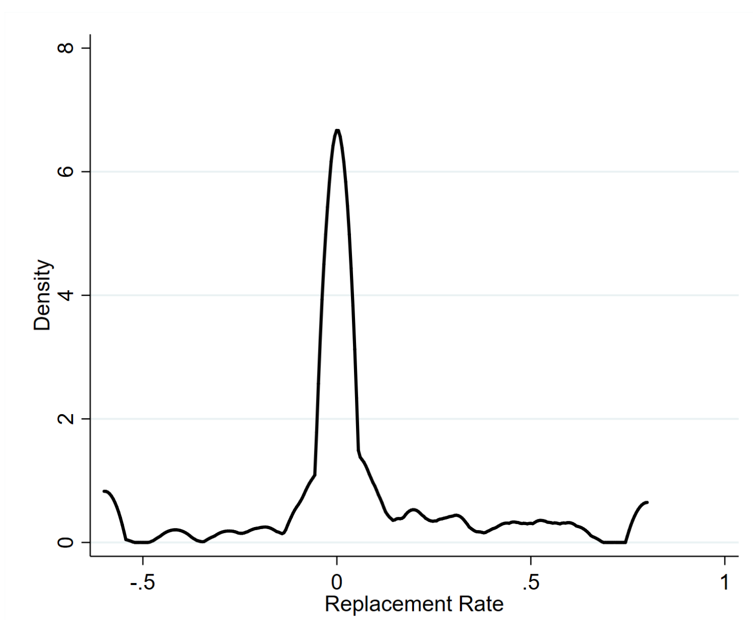
In this Appendix we present the estimation results of equation (2.4) for: (1) changes in revolving credit balances (Table B.4); (2) 60 day delinquencies (Table B.5); (3) debt chargeoffs (Table B.6); and (4) derogatory public flags (Table B.7). These results underlie the graphs presented in Figure 2.5.

B.2.4 SCF Evidence

In this section we present results from the publicly available SCF and show that they are consistent with the results from our LEHD/TransUnion sample.

In Figure B.2, we present the credit replacement rate of the unemployed as measured in the SCF. To estimate the credit replacement rate in the SCF, we exploit the panel nature of the SCF between 2007 and 2009. In the SCF, we identify an individual to be unemployed in a given wave if they are either unemployed at the time of the survey or have had an unemployment spell of longer than 4 weeks within the past year. We measure the replacement rate and share of individuals deleveraging among household heads and their spouses who were not identified as unemployed in the 2007 wave, but were identified as unemployed in the 2009 wave and had an earnings loss between the 2007 and 2009 waves. Among these individuals, we estimate the change in non-mortgage debt over the change in income in order to measure the replacement rate. Figure B.2 reveals a similar pattern on the borrowing activity of the unemployed as our LEHD/TransUnion sample (Figure 2.3).

Figure B.2: Credit Replacement Rate of Unemployed from SCF



Notes: Figure presents the credit replacement rate using the 2007-2009 waves of the SCF.

Table B.4: Earnings Losses and Change in Revolving Credit Balances by Credit Score

	2 Yr. Chg. Revolving Bal.	2 Yr. Chg. Revolving Bal.	2 Yr. Chg. Revolving Bal.
2 Yr. Chg. Earnings	-0.0304***	0.0330**	0.0210
	(0.00853)	(0.0135)	(0.0145)
2 Yr. Chg. Earnings x CS Quin 2		0.00454	0.00595
		(0.0209)	(0.0209)
2 Yr. Chg. Earnings x CS Quin 3		-0.0299	-0.0303
		(0.0234)	(0.0235)
2 Yr. Chg. Earnings x CS Quin 4		-0.0515**	-0.0517**
		(0.0241)	(0.0241)
2 Yr. Chg. Earnings x CS Quin 5		-0.0737***	-0.0749***
		(0.0222)	(0.0223)
Constant	324.6	-627.7**	-4,587**
	(246.3)	(305.0)	(1,991)
Credit Score Quin 2 (d)		-359.7	-321.1
		(504.3)	(507.9)
Credit Score Quin 3 (d)		-335.3	-220.1
		(595.6)	(596.9)
Credit Score Quin 4 (d)		3,220***	3,369***
		(704.6)	(699.9)
Credit Score Quin 5 (d)		6,365***	6,618***
		(754.6)	(749.5)
Year Fixed Effects	N	N	Y
Age and Wealth Controls	N	N	Y
R-Square	0.001	0.031	0.034
No of Indiv.	19000	19000	19000
P-Value Chg Earn Quin 2		0.0197	0.113
P-Value Chg Earn Quin 3		0.870	0.632
P-Value Chg Earn Quin 4		0.347	0.139
P-Value Chg Earn Quin 5		0.0209	0.00403

Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. *The 2-year change in real annual earnings, and 2-year change in real revolving balances are measured comparing the year after displacement relative to the year prior to displacement, are both winsorized at the top and bottom at the 1 percent level, and are measured in 2008 dollars. Credit Score Quin k refers to credit score quintile k, where credit score quintiles are based upon an individuals TransUnion bankruptcy score in the year prior to displacement. The symbol (d) indicates a dummy variable. Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. P-Value 2-Year Chg Earn Quin k refers to the p-value for the sum of the coefficients 2-Year Chg. Earn and 2-Year Chg. Earn x Credit Score Quin k.*

Table B.5: Earnings Losses and 60 Day Delinquency by Credit Score In Year After Mass Layoff

	(1) 60 Day Delinq (d)	(2) 60 Day Delinq (d)	(3) 60 Day Delinq (d)
	(Year After Mass Layoff)		
2 Yr. Chg. Earnings	8.57e-07***	-6.54e-07*	-1.23e-06***
	(1.33e-07)	(3.78e-07)	(3.90e-07)
2 Yr. Chg. Earnings x CS Quin 2 (d)		-2.21e-08	-2.22e-08
		(5.45e-07)	(5.45e-07)
2 Yr.Chg. Earnings x CS Quin 3 (d)		9.57e-07*	9.67e-07*
		(4.96e-07)	(4.96e-07)
2 Yr. Chg. Earnings x CS Quin 4 (d)		7.70e-07*	8.11e-07*
		(4.53e-07)	(4.53e-07)
2 Yr. Chg. Earnings x CS Quin 5 (d)		9.88e-07**	1.03e-06**
		(4.24e-07)	(4.25e-07)
Constant	0.419***	0.526***	0.486***
	(0.00557)	(0.0129)	(0.0540)
Credit Score Quin 2 (d)		-0.0302	-0.0320*
		(0.0185)	(0.0185)
Credit Score Quin 3 (d)		-0.0835***	-0.0822***
		(0.0179)	(0.0179)
Credit Score Quin 4 (d)		-0.241***	-0.236***
		(0.0170)	(0.0170)
Credit Score Quin 5 (d)		-0.309***	-0.301***
		(0.0163)	(0.0164)
Year FE	N	N	Y
Age and Wealth Controls	N	N	Y
R-Square	0.002	0.074	0.078
No of Indiv.	19000	19000	19000
P-Value 2-Year Chg Earn Quin 2		0.0862	0.00190
P-Value 2-Year Chg Earn Quin 3		0.354	0.432
P-Value 2-Year Chg Earn Quin 4		0.646	0.116
P-Value 2-Year Chg Earn Quin 5		0.0851	0.325

Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *The 2-year change in real annual earnings measures the change in earnings from the year after mass layoff relative to the year before mass layoff and is winsorized at the top and bottom at the 1 percent level. Earnings are measured in 2008 dollars. The dependent variable 60-day delinquency is measured in the year after displacement. Credit Score Quin k refers to credit score quintile k, where credit score quintiles are based upon an individuals TransUnion bankruptcy score in the year prior to displacement. The symbol (d) indicates a dummy variable. Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. P-Value 2-Year Chg Earn Quin k refers to the p-value for the sum of the coefficients 2-Year Chg. Earn and 2-Year Chg. Earn x Credit Score Quin k.*

Table B.6: Earnings Losses and Debt Chargeoff by Credit Score In Year After Mass Layoff

	(1) Debt Chargeoff (d)	(2) Debt Chargeoff (d)	(3) Debt Chargeoff (d)
	(Year After Mass Layoff)		
2 Yr. Chg. Earnings	3.88e-07***	-3.62e-07	-7.36e-07**
	(9.88e-08)	(3.42e-07)	(3.46e-07)
2 Yr. Chg. Earnings x CS Quin 2 (d)		-3.15e-09	-2.31e-08
		(4.71e-07)	(4.69e-07)
2 Yr.Chg. Earnings x CS Quin 3 (d)		2.85e-07	2.85e-07
		(4.20e-07)	(4.17e-07)
2 Yr. Chg. Earnings x CS Quin 4 (d)		3.75e-07	4.32e-07
		(3.78e-07)	(3.76e-07)
2 Yr. Chg. Earnings x CS Quin 5 (d)		3.09e-07	3.84e-07
		(3.59e-07)	(3.57e-07)
Constant	0.179***	0.249***	0.319***
	(0.00428)	(0.0117)	(0.0432)
Credit Score Quin 2 (d)		-0.0133	-0.0154
		(0.0159)	(0.0159)
Credit Score Quin 3 (d)		-0.0629***	-0.0625***
		(0.0151)	(0.0150)
Credit Score Quin 4 (d)		-0.150***	-0.146***
		(0.0137)	(0.0137)
Credit Score Quin 5 (d)		-0.195***	-0.189***
		(0.0129)	(0.0130)
Year FE	N	N	Y
Age and Wealth Controls	N	N	Y
R-Square	0.001	0.046	0.050
No of Indiv.	19000	19000	19000
P-Value 2-Year Chg Earn Quin 2		0.278	0.0263
P-Value 2-Year Chg Earn Quin 3		0.756	0.0767
P-Value 2-Year Chg Earn Quin 4		0.941	0.0893
P-Value 2-Year Chg Earn Quin 5		0.631	0.00478

Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. *The 2-year change in real annual earnings measures the change in earnings from the year after mass layoff relative to the year before mass layoff and is winsorized at the top and bottom at the 1 percent level. Earnings are measured in 2008 dollars. The dependent variable debt chargeoff is measured in the year after displacement. Credit Score Quin k refers to credit score quintile k, where credit score quintiles are based upon an individuals TransUnion bankruptcy score in the year prior to displacement. The symbol (d) indicates a dummy variable. Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. P-Value 2-Year Chg Earn Quin k refers to the p-value for the sum of the coefficients 2-Year Chg. Earn and 2-Year Chg. Earn x Credit Score Quin k.*

Table B.7: Earnings Losses and Derogatory Flag by Credit Score In Year After Mass Layoff

	Derogatory Flag (d)	Derogatory Flag (d)	Derogatory Flag (d)
	(Year after Mass Layoff)		
2 Year Chg. Earnings	-1.03e-07	-5.60e-07**	-6.13e-07**
	(6.86e-08)	(2.75e-07)	(2.77e-07)
2 Year Chg. Earnings x CS Quin 2		1.84e-07	1.84e-07
		(3.52e-07)	(3.51e-07)
2 Year Chg. Earnings x CS Quin 3		7.85e-08	7.12e-08
		(3.30e-07)	(3.30e-07)
2 Year Chg. Earnings x CS Quin 4		3.57e-07	3.66e-07
		(2.98e-07)	(2.99e-07)
2 Year Chg. Earnings x CS Quin 5		4.04e-07	4.08e-07
		(2.85e-07)	(2.86e-07)
Constant	0.0572***	0.0940***	0.0444*
	(0.00270)	(0.00864)	(0.0260)
Credit Score Quin 2 (d)		-0.0270**	-0.0269**
		(0.0111)	(0.0110)
Credit Score Quin 3 (d)		-0.0410***	-0.0405***
		(0.0106)	(0.0106)
Credit Score Quin 4 (d)		-0.0654***	-0.0641***
		(0.00982)	(0.00982)
Credit Score Quin 5 (d)		-0.0829***	-0.0810***
		(0.00920)	(0.00921)
Year Fixed Effects	N	N	Y
Age and Wealth Controls	N	N	Y
R-Square	0.000	0.020	0.021
No of Indiv.	19000	19000	19000
P-Value Chg Earn Quin 2		0.0941	0.0592
P-Value Chg Earn Quin 3		0.00830	0.00360
P-Value Chg Earn Quin 4		0.0978	0.0528
P-Value Chg Earn Quin 5		0.0441	0.0191

Notes: Clustered SE in parenthesis, where the clustering is performed at the level of the firm where the worker was displaced. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *The 2-year change in real annual earnings measures the change in earnings from the year after mass layoff relative to the year before mass layoff and is winsorized at the top and bottom at the 1 percent level. Earnings are measured in 2008 dollars. The dependent variable derogatory public flag is measured in the year after displacement. Credit Score Quin k refers to credit score quintile k, where credit score quintiles are based upon an individuals TransUnion bankruptcy score in the year prior to displacement. The symbol (d) indicates a dummy variable. Age and wealth controls include a quadratic in age, and deciles for lagged cumulative earnings. P-Value 2-Year Chg Earn Quin k refers to the p-value for the sum of the coefficients 2-Year Chg. Earn and 2-Year Chg. Earn x Credit Score Quin k.*

B.3 Employed Value Functions

In this appendix we present the value functions for employed individuals, as well as lenders who are matched with an employed individual.

B.3.1 Bellman Equations for Employed Individuals

In this appendix, we present the Bellman equations for an employed agent.

Every period employed individuals without a credit contract, decide whether or not to search for a credit contract:

$$
\begin{aligned}
W_{i,t}^{S}(\omega, b, \vec{h}; 0, 0) &= \max\left\{-\kappa_S + W_{i,t}^{A}(\omega, b, \vec{h}; 0, 0),\ W_{i,t}^{N}(\omega, b, \vec{h}; 0, 0)\right\} \quad \forall t \leq T \\
W_{i,T+1}^{S}(\omega, b, \vec{h}; 0, 0) &= 0
\end{aligned}
$$

where:

$$
\begin{aligned}
W_{i,t}^{A}(\omega, b, \vec{h}; 0, 0) = \max_{(\underline{b}, r)\in\underline{\mathcal{B}}\times\mathcal{R}} & p^c(\theta_{i,t}^{c,W}(\omega, b, \vec{h}; \underline{b}, r))W_{i,t}^{C}(\omega, b, \vec{h}; \underline{b}, r) \\
& + \left(1 - p^c(\theta_{i,t}^{c,W}(\omega, b, \vec{h}; \underline{b}, r))\right) W_{i,t}^{N}(\omega, b, \vec{h}; 0, 0)
\end{aligned}
$$

After the asset market closes, the agent makes their consumption and savings decisions. For an agent that did not not receive a credit contract, their consumption and savings problem is constrained in that the agent is not allowed to borrow. At the start of the next period with probability δ the agent looses their job, and is immediately able to search for a job.[1] The value function summarizing the payoffs of an employed agent without credit access is

$$
\begin{aligned}
W_{i,t}^{N}(\omega, b, \vec{h}; 0, 0) = \max_{b' \geq 0} & \ u(c) \\
& + \beta_i \mathbb{E}\Big[(1-\delta)W_{i,t+1}^{S}(\omega, b', \vec{h}'; 0, 0) + \delta\Big(\max_{\tilde{\omega}} p(\theta_{t+1}(\tilde{\omega}, \vec{h}'))W_{i,t+1}^{S}(\tilde{\omega}, b', \vec{h}'; 0, 0) \\
& \quad + (1 - p(\theta_{t+1}(\tilde{\omega}, \vec{h}')))U_{i,t+1}^{S}(b', \vec{h}'; 0, 0)\Big)\Big] \quad \forall t \leq T
\end{aligned}
$$

$$
W_{i,T+1}^{N}(\omega, b, \vec{h}; 0, 0) = 0
$$

subject to the budget constraint,

$$
c + q(b', 0)b' \leq (1-\tau)\omega f(\vec{h}) + b
$$

[1] Given the model period is 1 quarter we must allow individuals to search immediately in order for the model to match labor flows in the data.

and law of motion for employed individuals' human capital,

$$\vec{h}' = H(\vec{h}, W) \tag{B.1}$$

As before, the bond price is given by: $q(b', r) = \mathbb{I}\{b' < 0\}\frac{1}{1+r} + \mathbb{I}\{b' \geq 0\}\frac{1}{1+r_f}$.
For an agent with a credit contract, their consumption and savings problem is constrained by their borrowing limit $\underline{b}$. At the start of the next period with probability δ the agent loses their job, and is immediately able to search for a job. The value function summarizing the payoffs of an employed agent with credit access is

$$\begin{aligned} W^C_{i,t}(\omega, b, \vec{h}; \underline{b}, r) = &\max_{b' \geq \underline{b}} u(c) \\ &+ \beta_i \mathbb{E}\Big[(1-\delta)W^D_{i,t+1}(\omega, b', \vec{h}'; \underline{b}, r) + \delta\Big(\max_{\tilde{\omega}} p(\theta_{t+1}(\tilde{\omega}, \vec{h}'))W^D_{i,t+1}(\tilde{\omega}, b', \vec{h}'; \underline{b}, r) \\ &+ \Big(1 - p(\theta_{t+1}(\tilde{\omega}, \vec{h}'))\Big) U^D_{i,t+1}(b', \vec{h}'; \underline{b}, r)\Big)\Big] \quad \forall t \leq T \end{aligned}$$

$$W^C_{i,T+1}(\omega, b, \vec{h}; 0, 0) = 0$$

subject to the budget constraint,

$$c + q(b', r)b' \leq (1-\tau)\omega f(\vec{h}) + b$$

and the law of motion for human capital (equation (B.1)). After the labor market closes, the agent observes if their credit match has been exogenously ended. With probability δ_C the agent looses their credit market access. After the realization of the credit separation shock the agent decides whether or not to default. The default decision and the resulting continuation value for an unemployed worker is given by

$$\begin{aligned} W^D_{i,t+1}(\omega, b', \vec{h}'; \underline{b}, r) = &\delta_C \max\{W^N_{i,t+1}(\omega, 0, \vec{h}'; 0, 0) - \psi_D(b'),\ W^N_{i,t+1}(\omega, b', \vec{h}'; 0, 0)\} \\ &+ (1-\delta_C)\max\{W^N_{i,t+1}(\omega, 0, \vec{h}'; 0, 0) - \psi_D(b'),\ W^C_{i,t+1}(\omega, b', \vec{h}'; \underline{b}, r)\} \end{aligned}$$

Let $D^{N,W}_{i,t+1}(\omega, b', \vec{h}'; \underline{b}, r)$ be an indicator function denoting an individual's default decision when they are employed and are hit by the credit separation shock, (i.e. $D^{N,W}_{i,t+1} = 1$ when the individual defaults and is equal to zero otherwise). Let $D^{C,W}_{i,t+1}(\omega, b', \vec{h}'; \underline{b}, r)$ be an indicator function denoting an individual's default decision when they are employed and are not hit by the credit separation shock.

B.3.2 Bellman Equation for Lender Matched with Employed Worker

In this appendix, we present the Bellman equations for a lender in a match with an employed worker.

Let $\Pi^W_{i,t}$ denote the profits to a lender of being matched with a type i, age t, employed individual. The profits to the lender of offering a contract with borrowing limit $\underline{b}$, and interest rate r is

$$\begin{aligned}\Pi^W_{i,t}(\omega, b, \vec{h}; \underline{b}, r) &= \beta_{lf} b^{'}_{i,t}(\vec{x}) \left(\frac{(r_f - r)}{1+r} + \mathbb{E}\left[\delta_C \hat{D}^{N,W}_{i,t+1}(\vec{x}^{'}) + (1-\delta_C)\hat{D}^{C,W}_{i,t+1}(\vec{x}^{'})\right]\right) \times \mathbb{I}\{b^{'}_{i,t}(\vec{x}) < 0\} \\ &+ \beta_{lf}(1-\delta_C)\mathbb{E}\left[\left(1 - \hat{D}^{C,W}_{i,t+1}(\vec{x}^{'})\right) \hat{\Pi}^W_{i,t+1}(\vec{x}^{'})\right]\end{aligned}$$

At the end of the period an age t agent makes their consumption/savings decision $b^{'}_{i,t}$. If the individual is borrowing, $b^{'}_{i,t} < 0$, then in the next period the lender receives income from the difference between the interest rate r and the risk free rate r_f. However the lender faces default risk on the outstanding loan $b^{'}_{i,t}$. The default risk faced by the lender incorporates the probability of the credit separation shock, as well as shocks to human capital and probability that the borrower loses their job. When the worker exogenously separates from the firm, the worker immediately is able to search again. The default probability when hit by the credit shock is[2]

$$\begin{aligned}\hat{D}^{N,W}_{i,t+1}(\vec{x}^{'}) &= (1-\delta) D^{N,W}_{i,t+1}(\vec{x}^{'}) \\ &+ \delta \left[p\left(\theta_{t+1}(\hat{\omega}, \vec{h}^{'})\right) D^{N,W}_{i,t+1}(\hat{\omega}, b^{'}, \vec{h}^{'}; \underline{b}, r) + \left(1 - p\left(\theta_{t+1}(\hat{\omega}, \vec{h}^{'})\right)\right) D^{N,U}_{i,t+1}(b^{'}, \vec{h}^{'}; \underline{b}, r)\right]\end{aligned}$$

where $\hat{\omega}$ is the unemployed worker's choice for where to search for a job. If the agent does not default and the credit match is not hit by the credit separation shock, then the match between the lender and borrower continues to the next period. The profits to the lender in the next period are denoted by $\hat{\Pi}^W_{i,t+1}(\vec{x}^{'})$, and take into account the probability that the agent loses their job. The continuation profits to the lender are

$$\begin{aligned}\hat{\Pi}^W_{i,t+1}(\vec{x}^{'}) &= (1-\delta)\Pi^W_{i,t+1}(\omega, b^{'}, \vec{h}^{'}; \underline{b}, r) \\ &+ \delta \left[p\left(\theta_{t+1}(\hat{\omega}, \vec{h}^{'})\right) \Pi^W_{i,t+1}(\hat{\omega}, b^{'}, \vec{h}^{'}; \underline{b}, r) + \left(1 - p\left(\theta_{t+1}(\hat{\omega}, \vec{h}^{'})\right)\right) \Pi^U_{i,t+1}(b^{'}, \vec{h}^{'}; \underline{b}, r)\right]\end{aligned}$$

Lenders pay cost κ_C to enter the lending market. Free-entry in the lending market requires that the cost of entering the market is equal to the expected payout of entering the market:

$$\kappa_C \geq p^c_f\left(\theta^{c,W}_{i,t}(\omega, b, \vec{h}; \underline{b}, r)\right) \Pi^W_{i,t}(\omega, b, \vec{h}; \underline{b}, r) \tag{B.2}$$

Note that individuals who are searching for credit contracts are not currently able to borrow, hence the free entry condition (equation (B.2)) holds for $b \geq 0$.

[2]Note the default probability when an individual is not hit by the credit separation shock, denoted $\hat{D}^{C,W}_{i,t+1}(\vec{x}^{'})$, is defined analogously.

B.4 Equilibrium Definition

Let $\mu : \{e, a, i, \omega, b, \vec{h}, \underline{b}, r, t\} \to [0, 1]$ be the distribution of individuals across states. Let $\vec{x}$ summarize the state vector of a individual, where with a slight abuse of notation, $\vec{x} = (b, \vec{h}; \underline{b}, r)$ for the unemployed and $\vec{x} = (\omega, b, \vec{h}; \underline{b}, r)$ for the employed.

Definition. A recursive equilibrium in this economy is a set of individual policy functions for savings and borrowing $\{b^{'}_{i,e,t}(\vec{x})\}_{t=1}^{T}$, credit applications $\{S_{i,e,t}(\vec{x})\}_{t=1}^{T}$, bankruptcy $\{D^{a,e}_{i,t}(\vec{x})\}_{t=1}^{T}$, job search choice $\{\hat{\omega}_{i,t}(\vec{x})\}_{t=1}^{T}$, credit contract choice $\{(r, \underline{b})_{i,e,t}(\vec{x})\}_{t=1}^{T}$, labor market tightness function $\{\theta_t(\omega, \vec{h})\}_{t=1}^{T}$, credit market tightness function $\{\theta^{c,e}_{i,t}(\vec{x})\}_{t=1}^{T}$ for employed $e = W$ and unemployed $e = U$ individuals as well as patient $i = L$ and impatient $i = H$ individuals, a public insurance transfer to the unemployed z, a proportional tax rate τ, and a distribution of individuals across states μ:

i Households' decision rules are optimal.

ii The labor market tightness satisfies the free entry condition in the labor market (equation (2.11)).

iii The credit market tightnesses satisfy the free entry conditions for lenders entering into credit contracts with unemployed workers (equation 2.10) and employed workers (equation B.2).

iv The distribution of individuals across states μ is consistent with individual policy functions.

v The tax rate τ balances the government budget.

Suppose τ is given and the government budget constraint is not required to balance (i.e. equilibrium condition *v.* is not imposed). Then the individual, lender, and firm problems can be solved independently of the distribution of individuals across states μ (i.e. equilibrium conditions *i.* through *iii.* depend on the aggregate distribution of individuals across states only through τ). We will refer to this property of the model as *Block Recursivity.* Ultimately, the equilibrium tax rate τ depends on μ, but this intermediate form of Block Recursivity allows us to solve the transition path. We state this property formally below.

Proposition 4. *Suppose τ is given and the government budget does not need to balance (i.e. equilibrium condition v. is not imposed). Assume that the utility function meets standard conditions ($u^{'} > 0, u^{''} < 0, \lim_{c\to\infty} u^{'}(c) = 0$ and u is invertible), the labor and credit matching functions are invertible and constant returns to scale, and there are compact supports for the choice set of interest rates $r \in \mathcal{R} \equiv [\underline{r}, \bar{r}]$, borrowing limits $\underline{b} \in \underline{\mathcal{B}} \equiv [\underline{B}, 0]$, and the piece rate of wages $\omega \in [0, 1]$, then individual policy functions, the credit market* *tightness, and the labor market tightness do not depend on the distribution of individuals across states, μ.*

Proof. The proof is performed using backward induction. Let $t = T$ and consider an unemployed individual for the sake of brevity (the proof follows in an identical manner for employed individuals). Since the individuals' continuation value is zero for $T+1$ onward, the individual dynamic programming problem does not depend upon the aggregate distribution of individuals across states μ.

In the terminal age T, individuals set their asset choice to zero (i.e. $b'_{i,T}(b, \vec{h}; \underline{b}, r) = 0$), which gives the following continuation values for the terminal period:

$$U^a_{i,T}(b, h; \underline{b}, r) = u\left(z + g + b\right)$$

This holds for both unemployed individuals with credit access $a \in C$, and individuals without credit access $a \in N$. This does not depend on μ.

Individuals with credit access make a default decision in the terminal period, which does not depend upon the aggregate distribution μ,

$$\begin{aligned} U^D_{i,T}(b, \vec{h}; \underline{b}, r) = \delta_C \max\{&U^N_{i,T}(0, h; 0, 0) - \psi_D(b), U^N_{i,T}(b, h; 0, 0)\} \\ &+ (1 - \delta_C) \max\{U^N_{i,T}(0, h; 0, 0) - \psi_D(b), U^C_{i,T}(b, h; \underline{b}, r)\} \end{aligned}$$

Let $D^{a,U}_{i,T}(b, \vec{h}; b, r)$ denote the default policy of the individual. Since there is a utility penalty of defaulting, debt can be supported in equilibrium, and the default decision policy will not be trivially equal to one.

Lender's profits also do not depend upon the aggregate distribution μ. Lenders make zero profits in the terminal period since $b'_{i,T}(b, \vec{h}; \underline{b}, r) = 0$ for all states. This implies $\theta^{c,U}_{i,T}(b, \vec{h}; \underline{b}, r) = 0$, which does not depend upon the aggregate distribution μ. Given the credit finding rate is zero all individuals will choose not to search in the credit market, and we have $U^A_{i,T}(b, \vec{h}; 0, 0) = U^N_{i,T}(b, \vec{h}; 0, 0)$, and thus $U^S_{i,T}(b, \vec{h}; 0, 0) = U^N_{i,T}(b, \vec{h}; 0, 0)$. Hence, the payoffs to individuals who do not have a credit contract, and would be searching for one also does not depend upon the aggregate distribution μ.

In the labor market, the firm's value function is independent of the aggregate distribution μ as well, and is given by,

$$J_T(\omega, \vec{h}) = (1 - \omega) f(\vec{h})$$

Given this value to the firm of a match, the labor market tightness will also be independent of the aggregate distribution μ, and is given by,

$$\theta_T(\omega, \vec{h}) = p_f^{-1}\left(\frac{\kappa}{J_T(\omega, \vec{h})}\right)$$

An unemployed individual at age $T-1$ makes a labor market search choice over piece rates ω:

$$\max_{\tilde{\omega}} p(\theta_T(\tilde{\omega}, \vec{h}^{'}))W^a_{i,T}(\tilde{\omega}, b^{'}, \vec{h}^{'}; \underline{b}, r) + \left(1 - p(\theta_T(\tilde{\omega}, \vec{h}^{'}))\right) U^a_{i,T}(b^{'}, \vec{h}^{'}; \underline{b}, r)$$

As long as $\tilde{\omega}$ is chosen within a closed, bounded interval, the extreme value theorem guarantees at least one solution to this problem.
The same holds true for employed individuals since τ is given.
Working backwards from $t = T-1, ..., 1$, and repeating the above procedure completes the proof. □

B.5 Solution Algorithm

We solve the model using value function iteration on a discrete grid. Assets lie on the grid $[-1.1492, 3.5]$ with 56 grid points including the ends of the grid. The grid points are spaced symmetrically around zero using exponential spacing.[3] The grid contains 16 grid points below zero, a grid point at 0, and 39 grid points above zero.[4] We set the curvature parameter for the exponential spacing of the asset grid to $\frac{1}{1.25}$. Borrowing limits lie on the grid $[-1.1492, -0.0359]$ with 5 evenly spaced grid points including the end of the grid. We set the highest value of the borrowing limit grid to -0.0359 as it is the largest strictly negative grid point in asset grid. Annualized interest rates lie on the grid $[10.5\%, 22.5\%]$ with 15 grid points. The grid points are exponentially spaced with curvature parameter 1.5. Persistent human capital lies on the grid $[0.6, 1.2]$ with 7 evenly spaced grid points including the ends of the grid. The grid for transitory human capital is given by equation 2.13 where the step size is given by $\Delta_\epsilon(\tilde{h}^{'}) = 0.095\tilde{h}^{'}$ for persistent human capital $\tilde{h}^{'}$. The piece rate for wages lie on the grid $[0.60, 0.90]$ with 10 grid points including the ends of

[3]Let $y_{grid} = [y_1, y_2,, ..., y_N]$ be the desired exponential spaced grid with N grid points inclusive of the end points. Define $y_i = x_i^{1/c}$, where i denotes a point in the grid and c is referred to as the curvature parameter. Inverting the expression we have $x_i = y_i^c$. To create the exponentially spaced grid, we pick y_1 and y_N, as well as the curvature parameter c, and with these values calculate x_1 and x_N. We then define a linearly spaced grid with N points from x_1 to x_N. Then define the elements of y_{grid} by using $y_i = x_i^{1/c}$. When $c > 1$ points at the top of the grid are closer to one another than grid points at the bottom of the grid. When $c < 1$ grid points at the bottom of the grid are closer together than points at the top of the grid. When $c = 1$ the grid is evenly spaced.

[4]Recall the value of lowest value of the asset grid (and hence the number of grid points in the negative asset region) is a calibrated parameter of the model

the grid. The grid points are exponentially spaced with curvature parameter $c = 5$. In the simulation to check the government's budget balance we simulate 125,000 individuals for 260 periods, 10 times, burning the first 120 periods. We report averages over the 10 simulations.

Solving the model proceeds in the following steps:

1. **Taxes:** Guess τ.

2. **Firms Bellman:** Compute the value to a firm of being in a match in the terminal period $J_T(\omega, h)$. Using the value of a firm in the terminal period, invert the free entry condition to obtain labor market tightness $\theta_T(\omega, h)$.

3. **Individual Problem:** Solve the individual problem in the terminal period.

   (a) Compute the value to the individual of being in a credit match and not in a credit match for both employed and unemployed individuals, $W_{i,T}^C(\omega, b, \vec{h}; \underline{b}, r)$, $U_{i,T}^C(b, \vec{h}; \underline{b}, r)$ and $W_{i,T}^N(\omega, b, \vec{h}; 0, 0)$, $U_{i,T}^N(b, \vec{h}; 0, 0)$ respectively.

   (b) Solve the individual's default decisions, which returns the values $W_{i,T}^D(\omega, b, \vec{h}; \underline{b}, r)$ and $U_{i,T}^D(b, \vec{h}; \underline{b}, r)$.

4. **Lenders Bellman:** Compute the lender's Bellman equation in the terminal period, $\Pi_{i,T}^W(\omega, b, \vec{h}; \underline{b}, r)$ and $\Pi_{i,T}^U(b, \vec{h}; \underline{b}, r)$. Invert the free entry condition for lenders to obtain the credit market tightness for each credit contract $\theta_{i,T}^{c,W}(\omega, b, \vec{h}; \underline{b}, r)$ and $\theta_{i,T}^{c,U}(b, \vec{h}; \underline{b}, r)$.

5. **Individual Credit Search:** Use the credit market tightness functions $\theta_{i,T}^{c,e}(b, \vec{h}; \underline{b}, r)$ to find the values of $W_{i,T}^a(\omega, b, \vec{h}; 0, 0)$ and $U_{i,T}^a(b, \vec{h}; 0, 0)$. Using these value functions, compute each individual's policy function for searching for a credit contract $S_{i,T}^e(b, \vec{h}; 0, 0)$ as well as the value of $W_{i,T}^S(\omega, b, \vec{h}; 0, 0)$ and $U_{i,T}^S(b, \vec{h}; 0, 0)$.

6. **Individual's Job Search:** Use the estimate of $\theta_T(\omega, h)$ to solve the individual's job search problem.

7. **Repeat for ages** $T - 1$, $T - 2, ..., 1$.

8. **Budget Balance:** Simulate a mass of individuals and check that the government's budget constraint is satisfied. Update guess of τ until the government budget is balanced.

B.6 Welfare Calculation

In this section, we describe our process for performing the welfare calculation. We first discuss the welfare calculation for the steady state experiment, and then discuss the welfare calculation for the transition path experiment.

B.6.1 Steady State Welfare Calculation

Let $(\{c_t^j, D_t^j, S_t^j\}_{t=1}^{t_{max}})$ be the consumption, default, and credit search policy functions for an individual j over their lifetime under the baseline public insurance policy. Let $(\{\tilde{c}_t^j, \tilde{D}_t^j, \tilde{S}_t^j\}_{t=1}^{t_{max}})$ be the consumption, default, and credit search policy functions for an individual j under an alternative public insurance policy. We will perform welfare calculations by estimating the share of lifetime consumption an individual would be willing to forgo (or must receive) to leave the baseline economy and move to an economy with an alternative public insurance policy. Let $i(j)$ denote the individual's type. Formally, we estimate the scaling factor for consumption λ_j that makes individual j indifferent between living under either public insurance policy:[5]

$$\sum_{t=1}^{T} \beta_{i(j)}^t \left(\frac{\left(\lambda_j c_t^j\right)^{1-\sigma} - 1}{1-\sigma} - \psi_D(b_t^j) D_t^j - \kappa_S S_t^j \right) = \sum_{t=1}^{T} \beta_{i(j)}^t \left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma} - 1}{1-\sigma} - \psi_D(\tilde{b}_t^j) \tilde{D}_t^j - \kappa_S \tilde{S}_t^j \right) \tag{B.3}$$

Solving equation (B.3) for λ_j returns:

$$\lambda_j = \left[\frac{\sum_{t=1}^{T} \beta_{i(j)}^t \left(\frac{(\tilde{c}_t^j)^{1-\sigma}}{1-\sigma} - \left(\psi_D(\tilde{b}_t^j)\tilde{D}_t^j - \psi_D(b_t^j) D_t^j \right) - \left(\kappa_S \tilde{S}_t^j - \kappa_S S_t^j \right) \right)}{\sum_{t=1}^{T} \beta_{i(j)}^t \left(\frac{(c_t^j)^{1-\sigma}}{1-\sigma} \right)} \right]^{\frac{1}{1-\sigma}} \tag{B.4}$$

We use the model to simulate a large mass of individuals under a series of alternative public insurance policies. Let N denote the number of individuals that we simulate, and let P be the set of public insurance policies that we consider. For each simulated individual and policy $p \in P$, we estimate $\lambda_{j,p}$, the scaling factor for consumption that makes the individual indifferent between living under the alternative pubic insurance policy and the baseline policy. To convert the units of the scaling term $\lambda_{j,p}$ into the percentage of lifetime consumption the individual would be willing to forgo (or must receive), hereafter referred to as lifetime consumption equivalents and denoted $\tilde{\lambda}_{j,p}$, we perform the following transformation:

$$\tilde{\lambda}_{j,p} = 100(\lambda_{j,p} - 1)$$

[5] Note the discount factor is specific to the agent j, since individuals in our economy are heterogeneous in their discount factor.

Let $\{\{\tilde{\lambda}_{j,p}\}_{j=1}^{N}\}_{p=1}^{P}$ denote the set of lifetime consumption equivalents from the simulation of alternative public policies. From the distribution of lifetime consumption equivalents, we measure the utilitarian welfare effect and median welfare effect for each policy $p \in P$. The utilitarian welfare effect for an alternative policy $p \in P$, which is denoted $Welfare_U(p)$, is measured as:

$$Welfare_U(p) = \frac{1}{N}\sum_{j=1}^{N}\tilde{\lambda}_{j,p}$$

The optimal policy under the utilitarian welfare effect is the policy $p^* \in P$ that maximizes the utilitarian welfare effect $Welfare_U(p)$.

B.6.2 Transition Path Welfare Calculation

In the transition path experiment, we perform welfare calculations by estimating the share of *remaining* lifetime consumption an individual would be willing to forgo (or must receive) to leave the baseline economy and move to an economy where there is an unexpected and permanent policy change. Let $(\{c_t^j, D_t^j, S_t^j\}_{t=1}^{t_{max}})$ be the consumption, default, and credit search policy functions for an individual j over their lifetime under the baseline public insurance policy. Let $(\{\tilde{c}_t^j, \tilde{D}_t^j, \tilde{S}_t^j\}_{t=1}^{t_{max}})$ be the consumption, default, and credit search policy functions for an individual j under an alternative public insurance policy. Assume that for individual j, the policy change occurs at age $\hat{t}_j$. Note that because the policy change is unexpected, individual j makes identical consumption, default, and credit search decisions for the first $\hat{t}_j - 1$ periods of their life. Thus to measure the welfare effects of the policy, we only consider an individuals behavior in the remaining $T - \hat{t}$ periods of their life.[6] Let $i(j)$ denote the type of individual j. Formally, we estimate the scaling factor for consumption η_j that makes individual j indifferent between living the remaining periods of their life under either public insurance policy:

$$\sum_{t=\hat{t}_j}^{T}\beta_{i(j)}^{t}\left(\frac{\left(\eta_j c_t^j\right)^{1-\sigma}-1}{1-\sigma} - \psi_D(b_t^j)D_t^j - \kappa_S S_t^j\right) = \sum_{t=\hat{t}_j}^{T}\beta_{i(j)}^{t}\left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma}-1}{1-\sigma} - \psi_D(\tilde{b}_t^j)\tilde{D}_t^j - \kappa_S \tilde{S}_t^j\right) \tag{B.5}$$

Solving equation (B.5) for η_j returns:

$$\eta_j = \left[\frac{\sum_{t=\hat{t}_j}^{T}\beta_{i(j)}^{t}\left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma}}{1-\sigma} - \left(\psi_D(\tilde{b}_t^j)\tilde{D}_t^j - \psi_D(b_t^j)D_t^j\right) - \left(\kappa_S\tilde{S}_t^j - \kappa_S S_t^j\right)\right)}{\sum_{t=\hat{t}_j}^{T}\beta_{i(j)}^{t}\left(\frac{\left(c_t^j\right)^{1-\sigma}}{1-\sigma}\right)}\right]^{\frac{1}{1-\sigma}} \tag{B.6}$$

[6] Note we also only consider the welfare of individuals who are alive at the time of the policy transition.

To convert the units of the scaling term η_j into the percentage of remaining lifetime consumption the individual would be willing to forgo (or must receive), hereafter referred to as remaining lifetime consumption equivalents and denoted $\tilde{\eta}_j$, we perform the following transformation:

$$\tilde{\eta}_j = 100(\eta_j - 1)$$

As we discuss in greater detail in Section B.7, we simulate a large mass of individuals and unexpectedly lower the public insurance to the unemployed. Let N denote the number of simulated individuals who are alive at the time of the policy transition. We track the consumption, default, and credit search behavior of individuals, and estimate the share of remaining lifetime consumption that makes each agent indifferent between the policy transition and no policy transition. Let $\{\tilde{\eta}_j\}_{j=1}^{N}$ denote the set of lifetime consumption equivalents from the simulation of the transition experiment. The utilitarian welfare effect of the transition experiment, which is denoted $Welfare_T$, is measured as:

$$Welfare_T = \frac{1}{N}\sum_{j=1}^{N}\tilde{\eta}_j$$

B.7 Transition Path Experiment

In this appendix, we discuss the details of the transition path experiment presented in Section 2.5.3. The transition dynamics are very simple since the model is Block Recursive, conditional on τ (see Appendix B.4). Given a path of τ's, Block recursivity means that the distribution of agent's across states does not enter the equilibrium prices (in this setting, the prices are only the market tightnesses). In other words, only through the path of τ's do policy functions and prices depends on the distribution of individuals across states. Given a path of τ's, we solve the individual problem and simulate a mass of individuals along the transition path. We then compute the government budget balance and iterate on τ's until the government budget constraint holds at each point along the transition path.

Let $S = (z, \tau)$ denote the aggregate policy state, where z is the public insurance to the unemployed and τ is the tax rate. In the transition path experiment, the aggregate policy state S follows the transition matrix in equation (B.7), with corresponding values for (z, τ) in Table B.8. The realizations of the Markov chain are such that the economy transitions from the interim stage to the new steady state after 20 quarters, as shown in Panel (b) of Figure 2.11. Individuals rationally understand the law of motion for S, and all equilibrium prices depend on S. For example, an employed individual takes S and the Markov transition matrix for S as given, where the expectation operator now realizes the aggregate policy shocks:

$$
\begin{aligned}
W^C_{i,t}(\omega, b, \vec{h}; \underline{b}, r, S) = \max_{b' \geq \underline{b}} u(c) \\
+ \beta_i \mathbb{E}\Big[(1-\delta) W^D_{i,t+1}(\omega, b^{'}, \vec{h}^{'}; \underline{b}, r, S') + \delta \Big(\max_{\tilde{\omega}} p(\cdot) W^D_{i,t+1}(\tilde{\omega}, b^{'}, \vec{h}^{'}; \underline{b}, r, S') \\
+ (1 - p(\cdot))\, U^D_{i,t+1}(b^{'}, \vec{h}^{'}; \underline{b}, r, S')\Big)\Big] \quad \forall t \leq T
\end{aligned}
$$

$$W^C_{i,T+1}(\omega, b, \vec{h}; 0, 0, S') = 0$$

subject to the budget constraint,

$$c + q(b^{'}, r) b^{'} \leq (1-\tau)\omega f(\vec{h}) + b$$

and the transition matrix for the aggregate state S (B.7), and the law of motion for human capital (B.1).

Table B.8: Transfers and Taxes Along Transition Path

	Transfer (z)	Replacement Rate	Tax Rate (τ)
Initial Steady State	0.327	41.2%	2.12%
1st Year After Policy Change	0.307	38.3%	1.85%
2nd Year After Policy Change	0.307	38.3%	1.81%
3rd Year After Policy Change	0.307	38.3%	1.81%
4th Year After Policy Change	0.307	38.3%	1.80%
5th Year After Policy Change	0.307	38.3%	1.80%
New Steady State	0.307	38.3%	1.79%

$$P_S = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.75 & 0.25 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.75 & 0.25 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.75 & 0.25 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{B.7}$$

The transition path experiment begins in the steady state of the baseline economy with a 41.2% replacement rate to the unemployed. An unexpected and permanent decline in the generosity of public insurance to the unemployed then occurs, which lowers the replacement rate to 39.8%. For the government budget to balance the tax rate is lowered as well. In each of the first five-years after the policy change, the tax rate adjusts to balance the government's budget constraint. In all remaining years after the policy change, the tax rate from the steady state of the economy with a 39.8% replacement rate balances the government's budget constraint.[7] Along the transition path individuals have rational expectations for the path of the tax rate and the public insurance policy.

Estimation Details We solve the transition path on a discrete grid using value function iteration. The grid for assets, borrowing limits, persistent and transitory human capital, and wage piece rates are identical to the grids used in the baseline estimation of the model (see Appendix B.5 for details). To tractably estimate the transition path annualized interest rates lie on a grid from $[10.5\%, 22.5\%]$ with 7 grid points rather than 15 as in the baseline estimation of the model. The grid points are exponentially spaced with a curvature parameter of 1.5. In Table B.9 we show that steady state predictions of the model are virtually identical with 7 grid points for interest rates and 15 grid points for interest rates. The aggregate policy state contains both the transfer to unemployed workers z and the tax rate on labor income τ. The aggregate policy state has 7 grid points, and the values of the aggregate policy state are given in Table B.8. Individuals beliefs about the path of the aggregate state are given by the transition matrix in equation B.7.

To perform the transition path experiment we simulate 125,000 individuals for 380 periods, 20 times, burning the first 120 periods. We report averages over the 20 simulations. The path of the aggregate policy state in the simulation is such that we are in the initial steady state for 260 periods (including the burn), then we are in the "1st Year After Policy Change" state for 4-quarters where the values for the aggregate policy state parameters are given in Table B.8. For each year after the policy change K where $K \in \{2, 3, 4, 5\}$, we are in the "K Years After Policy Change" state for 4-quarters where the values for the aggregate policy state parameters are given in Table B.8. Finally, the aggregate policy state is in the "New Steady State" for the final 100 periods of the simulation.

Solving the transition path of the economy proceeds in the following steps:

1. **Taxes** Guess a sequence of taxes $\tau = [\tau_o, \tau_1, \tau_2, \tau_3, \tau_4, \tau_5, \tau_{new}]$ where τ_o is the tax rate in the initial steady state, τ_K is the tax rate K years after the policy change, and τ_{new} is the tax rate in the new steady state following the transition.

[7] The tax rate in the new steady state following the transition is 1.79%, while the tax rate in the new steady state in the welfare experiment presented in Section 2.5 is 1.77%. The discrepancy is due to a slight government deficit in years 6 through 9 following the introduction of the policy, which requires a higher tax rate in future periods. If we allowed the tax rate to adjust in years 6 through 9, and then have the economy enter into the new steady state the government budget would balance. However, adding additional years to the transition significantly expands the state-space of the problem. Due to computational requirements of allowing the transition to occur over a longer period of time, we impose that the transition period only last 5 years before entering the new steady state. Due to the fast convergence properties of this class of models, this restriction is effectively non-binding.

2. **Model Estimation** Solve the model following the steps presented in Appendix A.5 using the taxes guessed in Step 1, the transfers to unemployed workers from Table B.8, and the transition matrix for the aggregate policy state given by equation B.7.

3. **Simulation and Budget Balance**: Simulate a mass of individuals, perform the policy transition and check the government's budget constraint in each of the 7 aggregate policy states. Iterate until the government's budget is balanced in each aggregate policy state.

Table B.9: Comparison of Model Predictions

Moment	Model with 7 Interest Rates	Model with 15 Interest Rates
Transfer to Income Loss	41.2%	41.2%
Unemployment Rate	5.3%	5.3%
Credit Finding Rate	64.1%	64.1%
Share of Individuals w/ Credit Access	69.9%	69.9%
Bankruptcy Rate	0.141%	0.142%
Earnings Loss 5 Yr. After Layoff	6.5%	6.6%
Earnings Gain With Age	0.92%	0.92%
Share of Indiv. w/ 9.5% Wage Decline	8.6%	8.6%
Share of Indiv. w/ 9.5% Wage Increase	17.2%	17.2%
P75-P25 Earnings Ratio Among Young Workers	0.479	0.479
Consumption After Layoff	94.0%	94.0%
Unused Credit Limit to Income	23.6%	23.5%
P95 Real Credit Card Interest Rate	15.9%	16.0%
Share of Individuals w/ Net Liquid Assets to Income < 1%	31.6%	31.6%

Appendix C

Appendix to Chapter 3

C.1 Proofs

C.1.1 Proof of Proposition 1

Combining equations 3.5, 3.6, and 3.7 we have the following expression for the match surplus for a worker matched with firm y, where the worker's outside option is unemployment:

$$\begin{aligned}
S(y,U) &= W(y,U) - U + J(y,U) \\
&= f(y) - b - \beta U + \beta(1-\delta)J(y,U) + \beta\delta U + \beta(1-\delta)W(y,U) \\
&= f(y) - b + \beta(1-\delta)\left[J(y,U) + W(y,U) - U\right] \\
S(y,U) &= f(y) - b + \beta(1-\delta)S(y,U)
\end{aligned}$$

Observe that the expression does not depend upon the worker's outside option, hence we conclude that:

$$S(y) = f(y) - b + \beta(1-\delta)S(y)$$

Hence, the match surplus is given by:

$$S(y) = \frac{f(y) - b}{1 - \beta(1-\delta)} \tag{C.1}$$

This completes the proof that match surplus does not depend upon the worker's outside option or the labor force growth rate.

C.1.2 Proof of Proposition 2

Using the expression for the steady state unemployment rate from equation 3.2, the value of posting a vacancy is given by:

$$
\begin{aligned}
V(y) = &\left(\frac{\delta+\lambda}{\delta+\lambda+\phi p(\theta)(1-\delta)}\right) S(y) \\
&+ \left(\frac{\phi p(\theta)(1-\delta)}{\delta+\lambda+\phi p(\theta)(1-\delta)}\right) \int_{m_F(y)} \left(S(y) - S(\tilde{y})\right) \frac{\hat{e}(\tilde{y})}{\hat{e}} d\tilde{y}
\end{aligned}
$$

The following Lemma establishes that the firm receives greater surplus from hiring an unemployed worker compared to an employed worker.

Lemma. *For all firms $y \in \mathbb{Y}$, $S(y) > \int_{m_F(y)} (S(y) - S(\tilde{y})) \frac{\hat{e}(\tilde{y})}{\hat{e}} d\tilde{y}$.*

Proof. Let $y \in \mathbb{Y}$ be given. If $m_F(y)$ is the empty set, then the lemma is true since $S(y) > 0$ $\forall y$ by equation C.1.[1]

Suppose $m_F(y)$ is not empty. From the definition of the matching set for firms defined in Section 3.2.2, $S(y) > S(\tilde{y})$ $\forall \tilde{y} \in m_F(y)$. Since $S(\tilde{y}) > 0$ $\forall \tilde{y} \in m_F(y)$, we have $\forall \tilde{y} \in m_F(y)$:

$$
S(y) > (S(y) - S(\tilde{y}))
$$

By definition, $\forall \tilde{y} \in m_F(y)$, $\frac{\hat{e}(\tilde{y})}{\hat{e}} \in [0,1]$, and $\int_{m_F(y)} \frac{\hat{e}(\tilde{y})}{\hat{e}} d\tilde{y} \leq 1$. Thus,

$$
S(y) > \int_{m_F(y)} (S(y) - S(\tilde{y})) \frac{\hat{e}(\tilde{y})}{\hat{e}} d\tilde{y}
$$

□

Given the above Lemma, firms obtain more surplus from hiring an unemployed worker than from hiring employed workers. Thus, holding θ fixed, as λ decreases $\frac{\delta+\lambda}{\delta+\lambda+\phi p(\theta)(1-\delta)}$ decreases, while $\frac{\phi p(\theta)(1-\delta)}{\delta+\lambda+\phi p(\theta)(1-\delta)}$ increases, which decreases the value to firm y of posting a vacancy. This completes the proof that as the labor force growth rate decrease, the value to the firm of posting a vacancy decreases, holding all else fixed.

C.1.3 Proof of Corollary

Setting $\phi = 1$ in equation 3.10 returns:

$$
\begin{aligned}
\theta &= \left(\int_{\mathbb{Y}} \left(\frac{1}{\hat{u}+\hat{e}}\right) \left[\frac{AV(y)}{\kappa}\right] dy\right)^{\frac{c_1}{c_1+\alpha}} \\
&= \left(\int_{\mathbb{Y}} \left[\frac{AV(y)}{\kappa}\right] dy\right)^{\frac{c_1}{c_1+\alpha}}
\end{aligned}
$$

[1] Recall by assumption $f(y) > b$ $\forall y \in \mathbb{Y}$.

Then using Proposition 2 since $\frac{\partial V(y)}{\partial \lambda} > 0$, we have that $\frac{\partial \theta}{\partial \lambda} > 0$.[2] Then given the Cobb-Douglas matching technology we have:

$$\begin{aligned} q(\theta) &= \frac{A\hat{s}^{\alpha}\hat{v}^{1-\alpha}}{\hat{v}} = A\hat{s}^{\alpha}\hat{v}^{-\alpha} = A\theta^{-\alpha} \\ p(\theta) &= \frac{A\hat{s}^{\alpha}\hat{v}^{1-\alpha}}{\hat{s}} = A\hat{s}^{\alpha-1}\hat{v}^{1-\alpha} = A\theta^{1-\alpha} \end{aligned}$$

Then given that $\frac{\partial \theta}{\partial \lambda} > 0$, we have that $\frac{\partial q(\theta)}{\partial \lambda} < 0$ and $\frac{\partial p(\theta)}{\partial \lambda} > 0$. This completes the proof of the corollary.

C.2 Theoretical Model: Additional Elements

In this Appendix, I present additional elements to the theoretical model presented in Section 3.2.

C.2.1 Bellman Equations: Workers Outside Option is Another Firm

In this section, I present the Bellman equations for workers and firms when the worker's outside option is another firm.

First consider a worker employed by firm y whose outside option is another firm $y_0 \in \mathbb{Y}$. The worker receives wage payment $w(y, y_0)$ in the current period. In the following period the worker receives the continuation value of being unemployed regardless of whether they exogenously separate from the firm. If the worker does not exogenously separate then the worker receives their share of the match surplus, which given the workers outside option, is $S(y_0)$. The worker then searches in the labor market. With probability $\phi p(\theta)$ the worker meets a firm $\tilde{y}$ while searching. If the firm is in the workers matching set, $\tilde{y} \in m_1(y)$, then the worker switches firms and extracts the remaining surplus from firm y. Alternatively if the firm is in the workers renegotiation set $\tilde{y} \in m_2(y, y_0)$, then the worker remains employed at firm y but uses their meeting with firm $\tilde{y}$ to increase their compensation from firm y. Through renegotiating the worker gains $S(\tilde{y}) - S(y_0)$ of the match surplus. The Bellman equation characterizing the payoffs to the worker is given by:

[2] Note as is standard in the literature, I assume that $\alpha \in (0, 1)$, $c_1 \geq 0$, $\kappa > 0$, and $A > 0$. In the estimation of the model in Section 2, these conditions are all satisfied, and I find that numerically this corollary holds true.

$$
\begin{aligned}
W(y, y_0) = {} & w(y, y_0) + \beta U + \beta(1-\delta) S(y_0) \\
& + \beta(1-\delta)\phi p(\theta) \int_{m_1(y)} \left(S(y) - S(y_0)\right) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} \\
& + \beta(1-\delta)\phi p(\theta) \int_{m_2(y,y_0)} \left(S(\tilde{y}) - S(y_0)\right) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}
\end{aligned} \tag{C.2}
$$

A firm y that is matched with a worker whose outside option is y_0, produces output $f(y)$ and makes a wage payment $w(y, y_0)$ in the current period. If the match is hit by the exogenous separation shock δ, then the match ends and the firm is left with nothing. If the firm's match is not exogenously separated then the firm receives their share of the match surplus, which given the worker's outside option is $S(y) - S(y_0)$. With probability $\phi p(\theta)$ the worker meets another firm $\tilde{y}$ while searching. If the worker meets a firm in their matching set $\tilde{y} \in m_1(y)$, then the worker leaves the firm, and the firm looses their entire surplus from the match. If the worker meets a firm in their renegotiation set $\tilde{y} \in m_2(y, y_0)$, then the firm maintains their relationship with the worker but has to give up $S(\tilde{y}) - S(y_0)$ in match surplus to keep the worker at their firm. The Bellman equation characterizing the payoffs to the firm is given by:

$$
\begin{aligned}
J(y, y_0) = {} & f(y) - w(y, y_0) + \beta(1-\delta)\left(S(y) - S(y_0)\right) \\
& - \beta(1-\delta)\phi p(\theta) \int_{m_1(y)} \left(S(y) - S(y_0)\right) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} \\
& - \beta(1-\delta)\phi p(\theta) \int_{m_2(y,y_0)} \left(S(\tilde{y}) - S(y_0)\right) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}
\end{aligned} \tag{C.3}
$$

C.3 Quantitative Model

In this Appendix, I give a full model description of the quantitative model that is used in Section 3.3.

C.3.1 Model Ingredients

Workers are heterogeneous in their productivity denoted by $x \in \mathbb{X}$. Workers draw their type from a distribution $G(x)$ when they are born and enter into the labor market. The distribution $G(x)$ will be a calibrated feature of the model. Over the agents lifetime their human capital evolves as in Ljungqvist and Sargent (1998) (discussed in detail in Section C.3.2). Workers die in each period with probability ζ, where ζ is set so that worker's have, on average, a 30-year working career. For ease of notation I will use $\tilde{\beta} = \beta(1-\zeta)$ in the Bellman equations characterizing the payoffs to each agent in Section C.3.4.

At the beginning of each period idiosyncratic shocks to individuals human capital are realized. If the shocks to workers human capital make the surplus of a match negative then the worker and firm endogenously separate from one another. After endogenous separations, the labor force grows and labor force entrants arrive in the economy as unemployed workers. Firms observe the rate at which the labor force grows and decide how many vacancies to post. Workers and firms then search and match in the labor market. After the labor market closes, production and wage payments occur. The exogenous separation shock then occurs at the end of the period.

When a worker x and a firm y are matched with one another they produce $f(x, y)$. The bargaining procedure for wages presented in Section 3.2.2 extends naturally to the environment with heterogeneous workers. The matching process also extends naturally, with each worker having a set of firms they are willing to match and renegotiate with, and firms having a set of workers they are willing to hire.

C.3.2 Changes in Human Capital

A worker's type (or human capital) can increase while employed and decrease while unemployed as in Ljungqvist and Sargent (1998). In particular, during employment spells a worker with human capital x, sees their human capital evolve according to:

$$x^{'} = \begin{cases} \min\{x+1, x_N\} & \text{w/ prob } p_H \\ x & \text{w/ prob } 1 - p_H \end{cases} \tag{C.4}$$

while during unemployment spells, their human capital (x) evolves as follows:

$$x^{''} = \begin{cases} \max\{x-1, x_1\} & \text{w/ prob } p_L \\ x & \text{w/ prob } 1 - p_L \end{cases} \tag{C.5}$$

where x_1 and x_N are the minimum and maximum values of worker productivity, respectively.

When a worker continues an employment relationship with a firm their human capital can increase, which causes their wage to update. For a worker whose outside option is unemployment, they continue to have zero bargaining power and firms offer them their reservation value. Next consider a type $x-1$ worker who is employed at firm y, with outside option is $y_0 \in \mathbb{Y}$. Given the bargaining procedure firm y compensates the worker with $S(x-1, y_0)$, the surplus that the worker can generate with their outside option y_0.

When the worker's type updates to x, the firm adjusts their compensation to the worker to be $S(x, y_0)$, and the firm now receives $S(x, y) - S(x, y_0)$. Following the shocks to human capital, matches continue as long as the joint match surplus is positive.[3] This bargaining procedure assumes that workers and firms agree ex-ante that the firm will respond to changes in the worker's human capital using the worker's outside option at the time the match is formed.

C.3.3 Densities

In this section, I derive recursive expressions for the density of matches, unemployed workers, and vacancies.

Density of Matches

In this subsection, I define a recursive expression for the density of matches across workers and firms. In levels, let $e_t(x, y)$ be the number of matches between worker x and firm y going into the search stage in period t. Let $e_{t+}(x, y)$ be the number of matches between worker x and firm y after the search stage in period t, which is given by:

$$\begin{aligned} e_{t+}(x,y) = e_t(x,y)&\left(1 - \phi p(\theta_t) \int_{m_1(x,y)} \frac{v_t(\tilde{y})}{v_t} d\tilde{y}\right) \\ &+ u_t(x) p(\theta_t) \frac{v_t(y)}{v_t} \mathbb{I}\{y \in m_1(x, U)\} \\ &+ \int_{\mathbb{Y}_0} e_t(x, y_0) \phi p(\theta_t) \frac{v_t(y)}{v_t} \mathbb{I}\{y \in m_1(x, y_0)\} dy_0 \end{aligned}$$

Matches after the search stage in period t can be classified into three mutually exclusive groups: (1) workers who were employed by firm y going into the search stage today and did not match with another firm, (2) workers who entered the search stage today as unemployed workers and matched with firm y, and (3) workers who entered the search stage in period t employed at firm y_0, and matched with firm y.

Using matches after the search stage from period t, we can obtain the distribution of matches going into the search stage in period $t + 1$, denoted $e_{t+1}(x, y)$, which is given by:

$$e_{t+1}(x,y) = (1-\zeta)\left[(1-\delta)(1-p_H)e_{t+}(x,y) + (1-\delta)e_{t+}(x-1,y)p_H \mathbb{I}\{S(x,y) > 0\}\right] \tag{C.6}$$

Matches going into the search stage of the next period can be classified into two groups: (1) matches between that survive the exogenous separation shock as well as the shock to

[3] This process where the wage adjusts following the shock to a worker's human capital is similar to the updating of wages following shocks to firm productivity or beliefs about match quality in Borovickov (2016).

the workers human capital, and (2) matches between a type $x-1$ worker and a type y firm where the worker is hit by the human capital shock. Additionally, all workers must avoid the death shock at the end of the period.

The expression in equation C.6 can be converted to a density by dividing through by the size of the labor force in period $t+1$, which returns:

$$\hat{e}_{t+1}(x,y) = \frac{(1-\delta)(1-\zeta)}{1+\lambda_{t+1}} \left[(1-p_H)\hat{e}_{t+}(x,y) + \hat{e}_{t+}(x-1,y)p_H \mathbb{I}\{S(x,y)>0\}\right]$$

where:

$$\begin{aligned} \hat{e}_{t+}(x,y) = \hat{e}_t(x,y) & \left(1 - \phi p(\theta_t) \int_{m_1(x,y)} \frac{\hat{v}_t(\tilde{y})}{\hat{v}_t} d\tilde{y})\right) \\ & + \hat{u}_t(x) p(\theta_t) \frac{\hat{v}_t(y)}{\hat{v}_t} \mathbb{I}\{y \in m_1(x,U)\} \\ & + \int_{\mathbb{Y}_0} \hat{e}_t(x,y_0) \phi p(\theta_t) \frac{\hat{v}_t(y)}{\hat{v}_t} \mathbb{I}\{y \in m_1(x,y_0)\} dy_0 \end{aligned}$$

Density of Unemployed Workers

In this subsection, I define a recursive expression for the density of unemployed workers across worker types. As above, I first derive a recursive expression in levels, and then divide the expression through by the size of the labor force to arrive at the stationary density of unemployed workers.

To arrive at a recursive expression, for the distribution of unemployed workers going into the search stage, I first write the distribution of unemployed workers *after* the search stage as a function of the distribution of vacancies and unemployed workers *going into* the search stage. The distribution of unemployed workers after the search stage in period t, denoted $u_{t+}(x)$ is:

$$u_{t+}(x) = u_t(x) \left[1 - p(\theta_t) \int_{m_1(x,U)} \frac{v_t(\tilde{y})}{v_t} d\tilde{y}\right]$$

A worker who enters the search stage of the model as unemployed remains unemployed after the search stage if they do not meet a firm that is in their matching set.

The distribution of unemployed workers going into the search stage of the following period, denoted $u_{t+1}(x)$, is then given by:

$$
\begin{aligned}
u_{t+1}(x) = (1-\zeta) & \left[u_{t+}(x)(1-p_L) + \int_{\mathbb{Y}} \delta e_{t+}(x,\tilde{y})(1-p_L)d\tilde{y}\right] \\
&+ (1-\zeta)\left[\int_{\mathbb{Y}} (1-\delta)\, e_{t+}(x-1,\tilde{y})p_H \mathbb{I}\{S(x,\tilde{y})<0\}d\tilde{y}\right] \\
&+ (1-\zeta)\left[u_{t+}(x+1)p_L + \int_{\mathbb{Y}} \delta e_{t+}(x+1,\tilde{y})p_L d\tilde{y}\right] \\
&+ G(x)\left[\lambda_{t+1}+\zeta\right] l_t
\end{aligned}
$$

Workers entering the search stage of the model as unemployed workers in the *following* period can be classified into 6 mutually exclusive groups: (1) workers who were unemployed after the search stage and did not get hit by the human capital shock or death shock, (2) workers who were exogenously separated from their firm after the search stage and who did not get hit by the human capital shock or death shock, (3) workers who were employed after the exogenous separation shock but had their human capital updated, endogenously separated from their firm and were not hit by the death shock, (4) type $x+1$ unemployed worker who had their human capital decline and where not hit by the death shock, (5) type $x+1$ employed worker who were hit by the exogenous separation shock, were hit by the human capital shock but were not hit by the death shock, (6) new labor force entrants.
The above distributions are converted to densities by dividing through by the size of the labor force in period $t+1$, which returns:

$$
\begin{aligned}
\hat{u}_{t+1}(x)(1+\lambda_{t+1}) = (1-\zeta) & \left[\hat{u}_{t+}(x)(1-p_L) + \int_{\mathbb{Y}} \delta \hat{e}_{t+}(x,\tilde{y})(1-p_L)d\tilde{y}\right] \\
&+ (1-\zeta)\left[\int_{\mathbb{Y}} (1-\delta)\, \hat{e}_{t+}(x-1,\tilde{y})p_H \mathbb{I}\{S(x,\tilde{y})<0\}d\tilde{y}\right] \\
&+ (1-\zeta)\left[\hat{u}_{t+}(x+1)p_L + \int_{\mathbb{Y}} \delta \hat{e}_{t+}(x+1,\tilde{y})p_L d\tilde{y}\right] \\
&+ G(x)\left(\lambda_{t+1}+\zeta\right)
\end{aligned}
$$

where:

$$
\hat{u}_{t+}(x) = \hat{u}_t(x)\left[1 - p(\theta_t)\int_{m_1(x,U)} \frac{\hat{v}_t(\tilde{y})}{\hat{v}_t} d\tilde{y}\right]
$$

Aggregate Output

In this subsection, I define aggregate output in the quantitative model. To account for population growth, I consider output per worker which is defined as:

$$Y_t = \int_{\mathbb{X}} \int_{\mathbb{Y}} \hat{e}_t(x, y) f(x, y) dx dy$$

where $\hat{e}_t(x, y)$ is the share of the labor force that is a worker with productivity x that is employed at firm y, and $f(x, y)$ is output of type x worker matched with a type y firm.

C.3.4 Bellman Equations

In this Appendix, I present the steady state Bellman equations of the quantitative model.[4] Note to solve the transition path we simply need the steady state match surplus function as well as the value of unemployment in addition to the laws of motion. The steady state Bellman equations presented below are used to recover wages, which are used in the calibration of the initial steady state.

Let $U(x)$ be the value of unemployment to a type x worker at time t. In the current period the worker receives UI benefit b, and then searches for a job. Unemployed workers are able to match with firms as described above, but the assumption that firms make take it or leave it offers to unemployed workers, makes it so that an unemployed worker receives no immediate gain when matching with a firm. Additionally, the unemployed worker faces the potential to have their human capital decline during their unemployment spell. This generates the following value to being an unemployed worker:

$$U(x) = b(x) + \tilde{\beta} \mathbb{E}_{x''} \left[U(x'') \right] \tag{C.7}$$

Let $W(x, y, U)$ be the value of being an employed type x worker at firm y, whose outside option is unemployment. In the current period the worker receives a wage $w(x, y, U)$. At the end of the period if the worker exogenously separates from the firm they receive the continuation value of being unemployed, and are subject to having their human capital decline. If the worker does not exogenously separate then their human capital is subject to increase at the beginning of the next period as in equation C.4. If the surplus of the match becomes negative, then the worker becomes unemployed. However if the match surplus remains positive following the shock to human capital, the match continues and the worker receives the continuation value of the match and engages in on the job search. With probability $\phi p(\theta)$ the worker meets a firm $\tilde{y}$ while searching. If the firm is in the worker's matching set, $\tilde{y} \in m_1(x', y)$, then the worker switches firms and obtains all of

[4]These Bellman equations are derived in Appendix C.5.

the surplus from their match with their prior firm y. Alternatively if the firm is in the worker's renegotiation set $\tilde{y} \in m_2(x^{'}, y, U)$, then the worker remains employed at firm y but uses their meeting with firm $\tilde{y}$ to increase their compensation from firm y, which gives the worker a gain of $S(x^{'}, \tilde{y})$. The value to the worker of the match is given by:

$$\begin{aligned} W(x, y, U) = w(x, y, U) &+ \tilde{\beta}\delta \mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) \leq 0\}U(x^{'})\right] \\ &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}W(x^{'}, y, U)\right] \\ &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{m_1(x', y)} S(x^{'}, y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\ &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{m_2(x', y, U)} S(x^{'}, \tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \end{aligned} \tag{C.8}$$

Let $J(x, y, U)$ be the value a type y firm who is in a match with a type x worker whose outside option is unemployment. When a type x worker matches with a type y firm, they produce $f(x, y)$, and the firm pays the worker $w(x, y, U)$. At the end of the period, if the match is hit by the exogenous separation shock, then the match dissolves. If the firm's match is not exogenously separated, then the worker's human capital is subject to increase at the start of the next period as in equation C.4. If the surplus of the match becomes negative following the shock to the worker's human capital then the match dissolves, and the firm receives a continuation value of zero. However, if the match persists then the firm receives the continuation value of the match $J(x^{'}, y, U)$ and the worker engages in on the job search. With probability $\phi p(\theta)$ the worker meets another firm $\tilde{y}$ while searching. If the worker meets a firm in their matching set $\tilde{y} \in m_1(x^{'}, y)$, then the worker leaves the firm, and the firm looses all of the surplus from the match. If the worker meets a firm in their renegotiation set $\tilde{y} \in m_2(y, y_0)$, then the firm maintains their relationship with the worker but loses $S(x^{'}, \tilde{y})$ in match surplus, which they transfer to the worker to keep the worker employed at the firm. The value to the firm of this match is given by:

$$\begin{aligned} J(x, y, U) = f(x, y) - w(x, y, U) &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}J(x^{'}, y, U)\right] \\ &- \tilde{\beta}(1-\delta)\phi p(\theta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\int_{m_1(x', U)} S(x^{'}, y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\ &- \tilde{\beta}\phi p(\theta)(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\int_{m_2(x', y, U)} S(x, \tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \end{aligned} \tag{C.9}$$

C.3.5 Match Surplus

From the Bellman equations presented in equations C.7, C.8, and C.9 the match surplus can be easily derived. Match surplus is given by:

$$\begin{aligned} S(x,y) &= W(x,y,U) - U(x) + J(x,y,U) \\ &= f(x,y) - b(x) - \tilde{\beta}(1-\delta)\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y) \leq 0\}U(x^{'})\right] \\ &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y) > 0\}W(x^{'},y,U)\right] \\ &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y) > 0\}J(x^{'},y,U)\right] \end{aligned}$$

Adding and subtracting $\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y) > 0\}U(x^{'})\right]$ from the RHS of the above expression returns:

$$\begin{aligned} S(x,y) = f(x,y) &- b(x) - \tilde{\beta}(1-\delta)\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\ &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y) > 0\}W(x^{'},y,U)\right] \\ &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y) > 0\}J(x^{'},y,U)\right] \\ &- \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y) > 0\}U(x^{'})\right] \end{aligned}$$

Finally, using the definition of the match surplus allows the above expression to be simplified to:

$$\begin{aligned} S(x,y) = f(x,y) &- b(x) - \tilde{\beta}(1-\delta)\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\ &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y) > 0\}S(x^{'},y)\right] \end{aligned}$$

C.3.6 Vacancy Posting

The number of job postings created by a type y firm is determined by equating the marginal cost of posting a vacancy to the expected benefit to the firm of posting a vacancy:

$$c^{'}(\hat{v}_t(y)) = q(\theta_t)V_t(y) \tag{C.10}$$

where $V_t(y)$ denotes the expected value of posting a vacancy for a type y firm is given by (conditional on meeting a worker):

$$V_t(y) = \left[\frac{\hat{u}_t}{\hat{s}_t}\int_{m_F(y,U)} S(x^{'},y)\frac{\hat{u}_t(x^{'})}{\hat{u}_t}dx^{'} + \frac{\phi\hat{e}_t}{\hat{s}_t}\int_{\mathbb{Y}}\int_{m_F(y,y_0)}\Big(S(x^{'},y) - S(x^{'},y_0)\Big)\frac{\hat{e}_t(x^{'},y_0)}{\hat{e}_t}dx^{'}dy_0\right]$$

If they meet an unemployed worker in their matching set they obtain the value of the match. Similarly, if they meet an employed worker in their matching set they receive the value of the match.

C.3.7 Equilibrium

In this section, we define a a steady state equilibrium for the quantitative model. For a given labor force growth rate λ, a recursive competitive equilibrium for this economy is a set of Bellman equations $\{U(x), W(x,y,y_0), V(y), J(x,y,y_0)\}$, densities $\{\hat{e}(x,y), \hat{v}(y), \hat{u}(x)\}$, a labor market tightness θ, and wage $w(x,y,y_0)$ such that:

1. Given θ, $w(x,y,y_0)$, and the densities $\{\hat{e}(x,y), \hat{v}(y), \hat{u}(x)\}$, the Bellman equations $\{U(x), W(x,y,y_0), V(y), J(x,y,y_0)\}$ characterize optimal behavior for workers and firms.

2. Given θ, $w(x,y,y_0)$, and the Bellman equations $\{U(x), W(x,y,y_0), V(y), J(x,y,y_0)\}$, the densities $\{\hat{e}(x,y), \hat{v}(y), \hat{u}(x)\}$ are stationary.

3. Given θ, the densities $\{\hat{e}(x,y), \hat{v}(y), \hat{u}(x)\}$ and the Bellman equations $\{U(x), W(x,y,y_0), V(y), J(x,y,y_0)\}$, the wage $w(x,y,y_0)$ satisfies the bargaining procedure.

4. The vacancy posting condition (equation C.10) is satisfied for all firms $y \in \mathbb{Y}$.

C.4 Data Appendix

In this Appendix, I discuss the measurement of the data moments used for calibrating the model in Section 3.3.2.

C.4.1 Labor Market Flows

In this subsection, I discuss how the labor market flows (the UE, EU, and job to job transition rates) that are used in the calibration of the model are measured. I then discuss how the time series are filtered to recover the trend component of each series, which are the values to which the model is calibrated.

UE and EU Transition Rates

The UE transition rate is the share of unemployed individuals in month t, who are employed in the following month. The EU transition rate is the share of employed individuals in month t, who are unemployed in the following month. For 1990-2016, I use the estimates of the UE and EU transition rates derived from the CPS and published as the part of the Employment

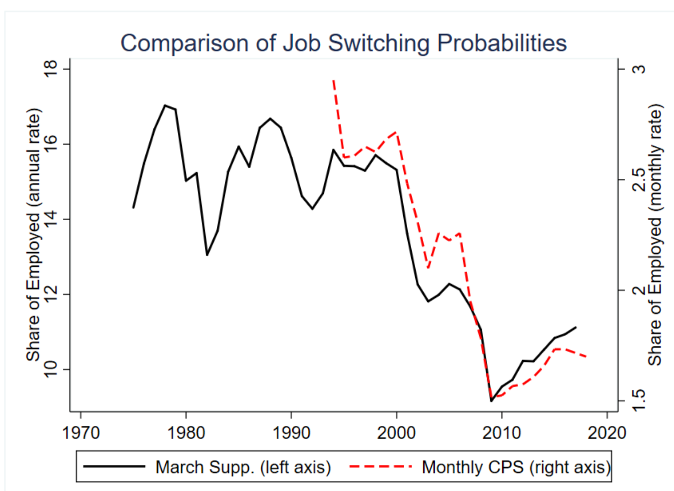
Situation Report. Data between 1976 and 1990 were constructed by Robert Shimer. For additional details see Shimer (2012). The data for unemployment to employment transitions from June 1967 through December 1975 were tabulated by Joe Ritter and made available by Hoyt Bleakley.

Job to Job Transition Rate

I measure the probability that an employed individual switches jobs from one month to the next using the CPS and the methodology of Fallick and Fleischman (2004). The approach of Fallick and Fleischman (2004) can only be used following the CPS redesign in 1994. For data prior to 1994, I use the March Supplement to the CPS survey. In the March Supplement, respondents are asked the number of employers they had in the prior year, and are specifically asked to not report multiple jobs held at the same time. As in Molloy et al. (2016), I measure the share of employed individuals who report having more than one employer in the prior year.

Figure C.1 plots the annual average of the monthly job switching probability along with the measure from the March Supplement. The figure shows that the estimates of the job switching probability across the two surveys are highly correlated. To arrive at a single time series, I take the annual average of the monthly job switching probability and "back-cast" on the annual series from the March Supplement. This process generates the time series for the job switching probability displayed in Panel (a) of Figure 3.2.

Figure C.1: Job Switching Probability: Comparison of Monthly CPS and March Supplement



Note: Figure shows the different measures of the job switching rate. The black solid line is an annual measure of job switching based off of the March Supplement to the CPS. The red dashed line is a yearly average of monthly job switching probabilties from the CPS survey.

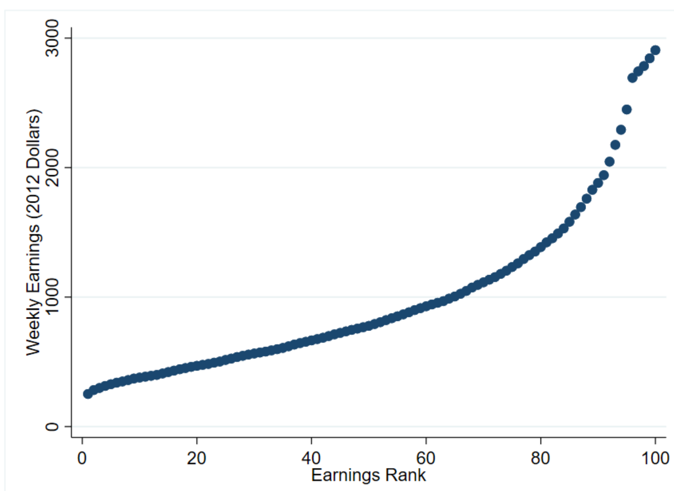
Trend Components of Labor Market Flows

In the calibration, we calibrate the model to match the average value of the trend component of the time series from 2012 through 2016. The trend components of each time series (the UE, EU, and job to job transition rates, as well as the unemployment rate) is estimated using the Christiano and Fitzgerald (2003) band pass filter with a minimum period of 2 years and a maximum period of 30 years, where the filter is estimated over the time period 1976-2016.

C.4.2 Earnings Ranking of Workers

As discussed in Section 3.3.2, I calibrate moments based on worker's earnings by using a ranking of worker's earnings. Using the microdata to the CPS from 2012-2016, I estimate the cutoffs needed to rank workers based on their earnings. For comparability to the model, I only consider full time workers. To additionally focus on workers with attachment to the labor force, I only use workers whose real weekly earnings would generate an annual income of $\$10K$ (measured in 2012 dollars). Figure C.2 presents the earnings cutoffs that define the earnings rankings used in this paper.

Figure C.2: Cutoff for Rankings of Real Earnings 2012-2016



Note: Figure the cutoffs for the earnings rankings that are used in calibrating the model. Weekly earnings are measured in 2012 dollars as recorded in the 2012-2016 monthly CPS samples.

C.4.3 Earnings Gain with Increase in Age

I calibrate the probability that an individual's human capital increases by targeting the average increase in an individual's earnings ranking associated with an increase in age. I estimate the average increase in earnings ranking associated with age by estimating the following regression using data from the CPS from 2012-2016:

$$R_{i,t} = \alpha + \beta_{age} Age_{i,t} + \gamma X_{i,t} + \epsilon$$

where $R_{i,t}$ is an individuals earnings ranking, $Age_{i,t}$ is the age of the individual, and $X_{i,t}$ is a vector of controls for individual i in year t. I use the same sampling restrictions as above and only consider individuals who report working full time and have real weekly earnings that are consistent with making at least $\$10K$ annually. Table C.1 contains the estimation results. The coefficient estimate on age in Column (1) of Table C.1 indicates that on average every two and a half years an individual climbs a rank in the earnings rankings.

Table C.1: Earnings Rank Gain Associated with Increase in Age

	1	2
VARIABLES	Earnings Rank	Earnings Rank
Age	0.4266***	0.4594***
	(0.0028)	(0.0029)
Education Dummies	Yes	Yes
Industry Dummies	Yes	No
R-squared	0.376	0.277
Observations	590,862	590,862

*Note: Robust standard errors in parenthesis. *** p¡0.01, ** p¡0.05, * p¡0.1 See Appendix C.4.2 for a the details of how the earnings rankings are constructed.*

C.4.4 Earnings Losses of Unemployed Workers

I calibrate the probability that an individual's human capital decreases while unemployed by targeting the decline in an individual's earnings rank around job loss. Using the the Displaced Workers Supplement from the CPS, I identify individuals with three or more years of tenure who are subsequently displaced from their job. I estimate the change in an individual's earnings ranking three years after job loss relative to prior to job loss. For compatibility to the model, I only consider individuals who are classified as full time workers prior to displacement as well as three years after displacement. We additionally require that an individual have weekly earnings that are consistent with a $10K$ annual salary both prior to displacement as well as after displacement. I pool displacements reported in the 2012-2018 waves of the Displaced Workers Supplement and consider workers displaced between 2012 and 2016. On average, a displaced worker's earnings ranking declines by 6.86 spots, and on average has an 13.17 percent decline in earnings.

C.4.5 Experience Premium and Variance of Earnings Rankings

I use a similar strategy as Huckfeldt (2014) in calibrating the distribution of labor market entrants. The distribution of labor market entrants is assumed to follow a log normal distribution. The mean of the distribution is calibrated to match the ratio of the average earnings ranking for individuals with five or more years of experience to the average earnings ranking of individuals with less than five years of labor market experience, which is referred to as the *experience premium*. The variance of the distribution is calibrated to match the standard deviation of earnings ranking among individuals with less than 5 years of labor market experience.

I estimate an individuals labor market experience by taking an individuals age and subtracting their years of education plus 6. That is for an individual i in year t, I estimate an individuals labor market experience using:

$$Exp_{i,t} = Age_{i,t} - (Edu_{i,t} + 6)$$

As above, I restrict the sample to individuals who are full time workers making at least $\$10K$ annually in 2012 dollars. Using data from 2012 through 2016, I estimate an experience premium of 1.48, and a standard deviation of earnings ranking among individuals with less than 5 years of experience of 25.94.

C.5 Derivations

In this appendix, I derive the Bellman equations which are a function of match surplus and are used in the computation of the model.

C.5.1 Bellman Equations with Homogeneous Workers

In this Appendix, I derive the Bellman equations presented in Section 3.2.4 when workers are homogeneous.

Unemployed Bellman

In the current period, the agent receives the unemployment insurance benefit b. The unemployed worker then searches for a job in the next period. With probability $p(\theta)$, the unemployed worker meets a firm in which case the worker receives the continuation value of being match with the worker. If the worker does not meet a firm, the worker continues as an unemployed worker. The Bellman equations characterizing the payoffs being an unemployed worker are given by:

$$
\begin{aligned}
U &= b + \beta \left[p(\theta) \int W(\tilde{y}, U) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} + \left(1 - p(\theta) \int \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}\right) U \right] \\
&= b + \beta \left[p(\theta) \int \left(W(\tilde{y}, U) - U\right) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} + U \right]
\end{aligned}
$$

From the bargaining procedure, unemployed workers extract no surplus when hired out of unemployment, i.e. $W(\tilde{y}, U) - U = 0 \; \forall \tilde{y} \in \mathbb{Y}$, which simplifies the unemployed worker's Bellman equation to:

$$
U = b + \beta U
$$

Employed Bellman

In the current period, the the worker makes wage $w(y, U)$. At the end of the period, the exogenous separation shock arrives. If the match is hit by the separation shock then the worker becomes an unemployed worker in the next period. If the match continues following the separation shock the employed worker searches in the labor market. There are four outcomes for the worker while searching in the labor market: (1) the worker meets a firm in their *matching set* $\tilde{y} \in m_1(U)$, in which case the worker receives the continuation value $W(\tilde{y}, y)$, (2) the worker meets a firm in their *renegotiation set* $\tilde{y} \in m_2(y, U)$, in which case the worker receives the continuation value $W(\tilde{y}, y)$, (3) the worker meets a firm, but the firm is not in the worker's matching or renegotiation sets $\tilde{y} \in (m_1(U) \cup m_2(y, U))^C$, which causes the worker's continuation value to be $W(y, U)$, and (4) the worker does not meet a firm and receives continuation value $W(y, U)$. These payoffs are summarized in the following Bellman equation:

$$
\begin{aligned}
W(y, U) = w(y, U) &+ \beta \phi p(\theta) \left[\int_{m_1(y)} \left((1-\delta) W(\tilde{y}, y) + \delta U\right) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} \right] \\
&+ \beta \phi p(\theta) \left[\int_{m_2(y,U)} \left((1-\delta) W(y, \tilde{y}) + \delta U\right) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} \right] \\
&+ \beta \phi p(\theta) \left[\int_{(m_1(y) \cup m_2(y,U))^C} \left((1-\delta) W(y, U) + \delta U\right) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y} \right] \\
&+ \beta \left(1 - \phi p(\theta)\right) \left[(1-\delta) W(y, U) + \delta U\right]
\end{aligned}
$$

Rearranging the terms where the agent is hit by the δ-shock we have:

$$\begin{aligned}
W(y,U) = {} & w(y,U) + \beta\delta U + \beta\phi p(\theta)(1-\delta)\int_{m_1(y)} W(\tilde{y},y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
& + \beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} W(y,\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
& + \beta\phi p(\theta)(1-\delta)\int_{(m_1(y)\cup m_2(y,U))^C} W(y,U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
& + \beta\left(1-\phi p(\theta)\right)(1-\delta)W(y,U)
\end{aligned}$$

Adding and subtracting $\beta\phi p(\theta)(1-\delta)\int_{m_1(y)} W(y,U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}$ and $\beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} W(y,U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}$ to the above expression returns

$$\begin{aligned}
W(y,U) = {} & w(y,U) + \beta\delta U + \beta(1-\delta)W(y,U) \\
& + \beta\phi p(\theta)(1-\delta)\int_{m_1(y)} \left(W(\tilde{y},y) - W(y,U)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
& + \beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} \left(W(y,\tilde{y}) - W(y,U)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}
\end{aligned}$$

We can re-write the above expression as

$$\begin{aligned}
W(y,U) = {} & w(y,U) + \beta\delta U + \beta(1-\delta)W(y,U) \\
& + \beta\phi p(\theta)(1-\delta)\int_{m_1(y)} \left((W(\tilde{y},y) - U) - (W(y,U) - U)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
& + \beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} \left((W(y,\tilde{y}) - U) - (W(y,U) - U)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}
\end{aligned}$$

Exploiting the bargaining solution we have

$$\begin{aligned}
W(y,U) = {} & w(y,U) + \beta\delta U + \beta(1-\delta)W(y,U) \\
& + \beta\phi p(\theta)(1-\delta)\int_{m_1(y)} \left(W(\tilde{y},y) - U\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
& + \beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} \left(W(y,\tilde{y}) - U\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}
\end{aligned}$$

Then using the definition the bargaining and matching procedure we have:

$$
\begin{aligned}
W(y,U) &= w(y,U) + \beta\delta U + \beta(1-\delta)W(y,U) \\
&\quad + \beta\phi p(\theta)(1-\delta)\int_{m_1(y)} S(y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
&\quad + \beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} S(\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}
\end{aligned}
$$

Firm in a match with a worker

In the current period, the firm produces $f(y)$ and pays wage $w(y,U)$ to the worker. At the end of the period, the exogenous separation shock arrives. If the match is hit by the separation shock then the firm is left with nothing. If the match survives the separation shock then the employed worker searches in the labor market. There are four outcomes for the firm when the worker searches in the labor market: (1) the worker meets a firm in their *matching set* $\tilde{y} \in m_1(U)$, in which case the firm is left with nothing, (2) the worker meets a firm in their *renegotiation set* $\tilde{y} \in m_2(y,U)$, in which case the firm receives continuation value $J(y,\tilde{y})$, (3) the worker meets a firm, but the firm is not in the worker's matching or renegotiation sets $\tilde{y} \in (m_1(U) \cup m_2(y,U))^C$, in which case the continuation value for the firm is $J(y,U)$, and (4) the worker does not meet a firm and the firm receives the continuation value $J(y,U)$. These payoffs are summarized in the following Bellman equation:

$$
\begin{aligned}
J(y,U) = f(y) - w(y,U) &+ \beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} J(y,\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
&+ \beta\phi p(\theta)(1-\delta)\int_{(m_1(y)\cup m_2(y,U))^C} J(y,U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
&+ \beta\left(1-\phi p(\theta)\right)(1-\delta)J(y,U)
\end{aligned}
$$

Adding and subtracting $\beta\phi p(\theta)(1-\delta)\int_{m_1(y)} J(y,U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}$ and $\beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} J(y,U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}$ to the above expression returns:

$$
\begin{aligned}
J(y,U) = f(y) - w(y,U) &- \beta\phi p(\theta)(1-\delta)\int_{m_1(y)} \left(J(y,U)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
&+ \beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} \left(J(y,\tilde{y}) - J(y,U)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\
&+ \beta(1-\delta)J(y,U)
\end{aligned}
$$

From the bargaining solution we have that: $J(y,U) = S(y)$ and $J(y,\tilde{y}) = S(y) - S(\tilde{y})$, which simplifies the above expression to:

$$\begin{aligned} J(y,U) &= f(y) - w(y,U) + \beta(1-\delta)J(y,U) \\ &\quad - \beta\phi p(\theta)(1-\delta)\int_{m_1(y)} S(y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \\ &\quad - \beta\phi p(\theta)(1-\delta)\int_{m_2(y,U)} S(\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} \end{aligned}$$

C.5.2 Bellman Equations with Heterogeneous Workers

In this appendix I derive the Bellman equations for the steady state quantitative model where workers are heterogeneous in their productivity. For ease of notation define $\tilde{\beta} = \beta(1-\zeta)$.

Unemployed Bellman

In the current period, the agent receives the unemployment insurance benefit b. The unemployed worker then searches for a job in the next period. With probability $p(\theta)$, the unemployed worker meets a firm, and if the firm is the workers matching set, $\tilde{y} \in m_1(x^{''},U)$, then the worker receives the continuation value of being match with the worker. If the firm is not in the workers matching set, or the worker does not meet a firm, the worker continues as an unemployed worker. The Bellman equations characterizing the payoffs being an unemployed worker are given by:

$$\begin{aligned} U(x) &= b + \tilde{\beta}\mathbb{E}_{x''}\left[p(\theta)\int_{m_1(x'',U)} W(x^{''},\tilde{y},U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} + \left(1 - p(\theta)\int_{m_1(x'',U)}\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right)U(x^{''})\right] \\ &= b + \tilde{\beta}\mathbb{E}_{x''}\left[p(\theta)\int_{m_1(x'',U)}\left(W(x^{''},\tilde{y},U) - U(x^{''})\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y} + U(x^{''})\right] \end{aligned}$$

From the bargaining procedure, unemployed workers extract no surplus when hired out of unemployment, i.e. $W(x,\tilde{y},U) - U(x) = 0 \ \forall\tilde{y} \in \mathbb{Y}$ and $\forall x \in \mathbb{X}$, which simplifies the unemployed worker's Bellman equation to:

$$U(x) = b + \tilde{\beta}\mathbb{E}_{x''}\left[U(x^{''})\right]$$

Employed Bellman

In the current period, the the worker makes wage $w(x, y, U)$. At the end of the period, the exogenous separation shock arrives. If the match is hit by the separation shock then the worker becomes an unemployed worker in the next period. At the start of the period, the agents human capital is subject to a shock. Employed worker have their human capital increase with probability p_H, while unemployed workers have their human capital decrease with probability p_L. For an employed worker if the change in their human capital causes the surplus of their match with firm y to become negative then the match is destroyed and the worker becomes an unemployed worker. If the match surplus remains positive following the shock to human capital then the employed worker searches in the labor market. There are four outcomes for the worker while searching in the labor market: (1) The worker meets a firm in their *matching set* $\tilde{y} \in m_1(x^{'}, y)$, where $x^{'}$ is the worker's human capital after the human capital shock, in which case the worker receives the continuation value $W(x^{'}, \tilde{y}, y)$, (2) The worker meets a firm in their *renegotiation set* $\tilde{y} \in m_2(x^{'}, y, U)$, in which case the worker receives the continuation value $W(x^{'}, \tilde{y}, y)$, (3) The worker meets a firm, but the firm is not in the worker's matching or renegotiation sets $\tilde{y} \in \Big(m_1(x^{'}, y) \cup m_2(x^{'}, y, U)\Big)^C$, which causes the worker's continuation value to be $W(x^{'}, y, U)$, and (4) The worker does not meet a firm and receives continuation value $W(x^{'}, y, U)$. These payoffs are summarized in the following Bellman equation:

$$
\begin{aligned}
W(x, y, U) = w(x, y, U) &+ \tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) \leq 0\}U(x^{'})\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{m_1(x^{'}, y)} W(x^{'}, \tilde{y}, y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{m_2(x^{'}, y, U)} W(x^{'}, y, \tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{\left(m_1(x^{'}, y)\cup m_2(x^{'}, y, U)\right)^C} W(x^{'}, y, U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\left(1-\phi p(\theta)\right)W(x^{'}, y, U)\right]
\end{aligned}
\tag{C.11}
$$

Adding and subtracting $\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},U)}W(x^{'},y,U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]$ as well as $\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,U)}W(x^{'},y,U)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]$ to equation C.11 returns:

$$\begin{aligned} W(x,y,U) = {} & w(x,y,U)+\tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right]+\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)\leq 0\}U(x^{'})\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}W(x^{'},y,U)\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)}\left(W(x^{'},\tilde{y},y)-W(x^{'},y,U)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,U)}\left(W(x^{'},y,\tilde{y})-W(x^{'},y,U)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \end{aligned} \tag{C.12}$$

Adding and subtracting $\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)}U(x^{'})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]$ as well as $\beta(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y.U)}U(x^{'})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]$ to equation C.12 and using the bargaining solution which state that $W(x^{'},y,U)-U(x)=0\ \forall x\in\mathbb{X}$, we have:

$$\begin{aligned} W(x,y,U) = {} & w(x,y,U)+\tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right]+\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)\leq 0\}U(x^{'})\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}W(x^{'},y,U)\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)}\left(W(x^{'},\tilde{y},y)-U(x^{'})\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y.U)}\left(W(x^{'},y,\tilde{y})-U(x^{'})\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \end{aligned} \tag{C.13}$$

Finally, from the bargaining solution we have that $W(x^{'},\tilde{y},y)-U(x^{'})=S(x^{'},y)\ \forall x\in\mathbb{X}$, and $\forall y\in\mathbb{Y}$, which simplifies equation C.13 to:

$$\begin{aligned} W(x,y,U) = {} & w(x,y,U)+\tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right]+\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)\leq 0\}U(x^{'})\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}W(x^{'},y,U)\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)}S(x^{'},y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\ & +\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y.U)}S(x^{'},\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \end{aligned}$$

Firm in a match with a worker

In the current period, the firm produces $f(x,y)$ and pays wage $w(x,y,U)$ to the worker. At the end of the period, the exogenous separation shock arrives. If the match is hit by the separation shock then the firm is left with nothing. If the match survives the exogenous separation shock, then at the start of the next period, the agents human capital is subject to a shock. Employed workers have their human capital increase with probability p_H. If the change in the worker's human capital causes the surplus of the match with firm y to become negative then the match is destroyed, and the firm is left with nothing. If the match surplus remains positive following the shock to human capital then the employed worker searches in the labor market. There are four outcomes for the firm when the worker searches in the labor market: (1) The worker meets a firm in their *matching set* $\tilde{y} \in m_1(x^{'}, y)$, where $x^{'}$ is the worker's human capital after the human capital shock, in which case the firm is left with nothing, (2) The worker meets a firm in their *renegotiation set* $\tilde{y} \in m_2(x^{'}, y, U)$, in which case the firm receives continuation value $J(x, y, \tilde{y})$, (3) The worker meets a firm, but the firm is not in the worker's matching or renegotiation sets $\tilde{y} \in \Big(m_1(x^{'}, y) \cup m_2(x^{'}, y, U)\Big)^C$, in which case the continuation value for the firm is $J(x^{'}, y, U)$, and (4) The worker does not meet a firm and the firm receives the continuation value $J(x^{'}, y, U)$. These payoffs are summarized in the following Bellman equation:

$$\begin{aligned} J(x, y, U) &= f(x, y) - w(x, y, U) \\ &+ \tilde{\beta}\phi p(\theta)(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\} \int_{m_2(x^{'}, y, U)} J(x^{'}, y, \tilde{y}) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}\right] \\ &+ \tilde{\beta}\phi p(\theta)(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\} \int_{\left(m_1(x^{'}, y) \cup m_2(x^{'}, y, U)\right)^C} J(x^{'}, y, U) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}\right] \\ &+ \tilde{\beta}\left(1 - \phi p(\theta)\right)(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\} J(x^{'}, y, U)\right] \end{aligned} \tag{C.14}$$

Adding and subtracting $\tilde{\beta}(1-\delta)\phi p(\theta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\} \int_{m_1(x^{'}, y)} J(x^{'}, y, U) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}\right]$ as well as $\tilde{\beta}(1-\delta)\phi p(\theta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\} \int_{m_2(x^{'}, y . U)} J(x^{'}, y, U) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}\right]$ to equation C.14 returns:

$$\begin{aligned} J(x, y, U) = f(x, y) - w(x, y, U) &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\} J(x^{'}, y, U)\right] \\ &- \tilde{\beta}(1-\delta)\phi p(\theta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\} \int_{m_1(x^{'}, y)} J(x^{'}, y, U) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}\right] \\ &+ \tilde{\beta}\phi p(\theta)(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\} \int_{m_2(x^{'}, y, U)} \Big(J(x^{'}, y, \tilde{y}) - J(x^{'}, y, U)\Big) \frac{\hat{v}(\tilde{y})}{\hat{v}} d\tilde{y}\right] \end{aligned} \tag{C.15}$$

From the bargaining solution we have $J(x^{'}, y, U) = S(x^{'}, y)$, and $J(x^{'}, y, \tilde{y}) = S(x, y) - S(x, \tilde{y})$, which allows equation C.15 to be rewritten as:

$$\begin{aligned}
J(x, y, U) = f(x, y) - w(x, y, U) + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}J(x^{'}, y, U)\right] \\
- \tilde{\beta}(1-\delta)\phi p(\theta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\int_{m_1(x', y)} S(x^{'}, y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
- \tilde{\beta}\phi p(\theta)(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\int_{m_2(x', y, U)} S(x, \tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}$$

C.5.3 Wage Equations

In this subsection, I derive expressions for the wage paid to workers. First, I derive an expression for the wage paid to a worker whose outside option is unemployment. I then derive an expression for the wage paid to a worker whose outside option is another firm.

Worker With Unemployment as Outside Option

Recall from equation C.8, the Bellman equation for a worker whose outside option is unemployment is given by:

$$\begin{aligned}
W(x, y, U) = w(x, y, U) + \tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) \leq 0\}U(x^{'})\right] \\
+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}W(x^{'}, y, U)\right] \\
+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{m_1(x', y)} S(x^{'}, y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{m_2(x', y, U)} S(x^{'}, \tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}$$

Subtracting $U(x)$ from both sides, and exploiting that given the bargaining solution $W(x, y, U) - U(x) = 0$ returns:

$$\begin{aligned}
0 = w(x, y, U) - U(x) + \tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) \leq 0\}U(x^{'})\right] \\
+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}W(x^{'}, y, U)\right] \\
+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{m_1(x', y)} S(x^{'}, y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'}, y) > 0\}\phi p(\theta)\int_{m_2(x', y, U)} S(x^{'}, \tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}$$

Adding and subtracting $\tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}U(x^{'})\right]$ from the right hand side of the above expression returns:

$$
\begin{aligned}
0 = w(x,y,U) - U(x) &+ \tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\Big(W(x^{'},y,U)-U(x^{'})\Big)\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)} S(x^{'},y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,U)} S(x^{'},\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}
$$

Exploiting the bargaining solution $W(x,y,U)-U(x)=0$ returns:

$$
\begin{aligned}
0 = w(x,y,U) - U(x) &+ \tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)} S(x^{'},y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,U)} S(x^{'},\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}
$$

Recall the Bellman equation for an unemployed worker is: $U(x)=b+\tilde{\beta}\mathbb{E}_{x''}\left[U(x^{''})\right]$, which allows the above expression to be simplified to:

$$
\begin{aligned}
0 = w(x,y,U) - b &- \tilde{\beta}(1-\delta)\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)} S(x^{'},y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,U)} S(x^{'},\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}
$$

Rearranging the equation to obtain an expression for wages returns:

$$
\begin{aligned}
w(x,y,U) = b &+ \tilde{\beta}(1-\delta)\mathbb{E}_{x''}\left[U(x^{''})\right] - \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\
&- \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)} S(x^{'},y)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&- \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,U)} S(x^{'},\tilde{y})\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}
$$

Worker With Another Firm as Outside Option

A worker whose outside option is another firm has the following Bellman equation:[5]

$$\begin{aligned}
W(x,y,y_0) = w(x,y,y_0) &+ \tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}S(x^{'},y_0)\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)}\left(S(x^{'},y)-S(x^{'},y_0)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,y_0)}\left(S(x^{'},\tilde{y})-S(x^{'},y_0)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}$$

Recall that from the bargaining solution $W(x,y,y_0) - U(x) = S(x,y_0)$. Then subtracting $U(x)$ from both sides of the above expression returns

$$\begin{aligned}
S(x,y_0) = w(x,y,y_0) - U(x) &+ \tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right] + \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}S(x^{'},y_0)\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)}\left(S(x^{'},y)-S(x^{'},y_0)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&+ \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,y_0)}\left(S(x^{'},\tilde{y})-S(x^{'},y_0)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}$$

Rearranging the above expressions returns the wage for a worker whose outside option is another firm:

$$\begin{aligned}
w(x,y,y_0) = S(x,y_0) + U(x) &- \tilde{\beta}\delta\mathbb{E}_{x''}\left[U(x^{''})\right] - \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[U(x^{'})\right] \\
&- \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}S(x^{'},y_0)\right] \\
&- \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_1(x^{'},y)}\left(S(x^{'},y)-S(x^{'},y_0)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right] \\
&- \tilde{\beta}(1-\delta)\mathbb{E}_{x'}\left[\{S(x^{'},y)>0\}\phi p(\theta)\int_{m_2(x^{'},y,y_0)}\left(S(x^{'},\tilde{y})-S(x^{'},y_0)\right)\frac{\hat{v}(\tilde{y})}{\hat{v}}d\tilde{y}\right]
\end{aligned}$$

[5] Note the derivation of this Bellman equation follows exactly as in Section C.5.2