Essays on Government Transfers and Labor Markets

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Dedication

To my parents and my wife. My accomplishments would not be possible without them.

Abstract

This dissertation consists of three chapters. In the first chapter, I document a small spousal earnings response to the job displacement of the family head. The response is even smaller in recessions when earnings losses are larger and additional insurance is most valuable. I investigate whether the small response is an outcome of crowding-out effects of existing government transfers. To accomplish this, I use an incomplete asset markets model with family labor supply and aggregate fluctuations whose predicted spousal labor supply elasticities with respect to transfers are in line with microeconomic estimates both in aggregate and across subpopulations. In this model, counterfactual experiments indeed show that generous transfers in recessions discourage spousal labor supply significantly after the head's job displacement. Then, I solve for optimal means-tested transfers paid to poor families and employment-tested transfers paid to the unemployed. Unlike the current policy that maintains generous transfers of both types in recessions, I find that the optimal policy features procyclical means-tested and countercyclical employment-tested transfers.
The second chapter (joint with Kurt See) studies the optimal design of unemployment insurance (UI) over the business cycle, paying particular attention to the effects of generous UI payments on firm vacancy creation. While UI provides insurance to jobless individuals, generous UI payment results in higher reservation wages, a corresponding reduction in firm vacancy creation, both of which lead to a decline in the job finding rate. Using a heterogeneous agent job search model, designed to consider the effects of UI on labor demand, we find that optimal UI policy should be countercyclical.
Finally, the third chapter (joint with Anmol Bhandari, Ellen McGrattan, and Kurt Gerrard See) examines the reliability of widely used surveys on U.S. businesses. We compare survey responses of business owners with administrative data and document large inconsistencies in business incomes, receipts, and the number of owners. We document problems due to nonrepresentative samples and measurement errors. Nonrepresentativeness is reflected in undersampling of owners with low incomes. Measurement errors arise because respondents do not refer to relevant documents and possibly because of framing issues. We conclude that predictions based on current survey data should be treated with caution.

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Chapter 1

Spousal Labor Supply Response to Job Displacement and Implications for Optimal Transfers

1.1 Introduction

Job displacement has large negative and long-lasting effects on individual labor earnings. These effects are more pronounced when the displacement happens in recessions. The impact of earnings losses on family consumption is mitigated through both public insurance and private insurance. Government transfers in the United States are more generous in recessions. At the same time, households also have access to self-insurance mechanisms, a crucial component of which is spousal labor supply adjustments in response to severe earnings loss within the household.[1] Importantly, the magnitude of spousal labor supply response to unexpected earnings fluctuations depends on the generosity of government transfers made available to these households. Thus, while generous transfers in recessions are thought to alleviate earnings losses in the event of a head's job loss, they may crowd out private insurance in the form of spousal labor supply and, in effect, leave households worse off because of a higher tax burden. Given the interaction of public and private insurance,

[1] For example, Blundell, Pistaferri, and Saporta-Eksten (2016) show that family labor supply provides sizeable consumption insurance against wage shocks within the family.

I ask the following questions: how much do government transfers affect the magnitude of the spousal labor supply response to the family head's job displacement over the business cycle? What is the optimal design of transfers over the business cycle when spousal labor supply is endogenous to policy?

To answer these questions, I first measure the impact of a family head's job displacement in both recessions and expansions on family labor earnings and spousal labor earnings, using data from the Panel Study of Income Dynamics (PSID).[2] Little is known about the change in family and spousal earnings upon the head's job displacement across recessions and expansions, but it has an important role in quantifying the magnitude of private insurance available to families over the business cycle under current public insurance programs. I address this gap by documenting two novel results. First, families enjoy some insurance from the presence of a second earner who was simultaneously employed with the head prior to his displacement. In particular, the decline in family labor earnings is around two-thirds of the decline in the head's labor earnings one year after the job displacement in recessions and expansions. Second, the change in spousal earnings in response to the head's displacement is small, especially after displacements that occur in recessions. Over 10 years after the head's displacement, the average change in spousal earnings relative to the spousal earnings of non-displaced head is only -0.8 percent in recessions and 8 percent in expansions. This result is particularly interesting because one might expect a stronger spousal earnings response during times when the head experiences larger earnings losses. Hence, this finding motivates an investigation of the potential reasons behind the small change in spousal earnings upon the head's displacement in recessions.

I argue that the small spousal earnings response in recessions is an outcome of crowding-out effects of existing government transfers, which feature more generous transfers in recessions relative to expansions (i.e., countercyclical). To investigate this, I use an incomplete asset markets model with family labor supply and aggregate fluctuations. In the model, employed individuals are subject to idiosyncratic job displacement risk, while unemployed individuals face the risk of a long duration without a job because of frictions in the labor market that prevent the formation of matches. Negative and persistent effects of unemployment on individual earnings are captured by human capital depreciation, as in Ljungqvist and

[2] Family labor earnings is defined as the sum of the head's and spouse's labor earnings.

Sargent (1998). The strength of the labor market frictions varies over the business cycle: job displacement rate increases, while job finding rates endogenously decrease in recessions since firms decrease vacancy posting when labor productivity is lower. Individuals can partially self-insure against idiosyncratic and aggregate risk through their spouse's labor market earnings, savings of their family in an incomplete asset market, and means-tested and employment-tested government transfers.[3]

The key contribution of this framework is to endogenize the labor supply decisions of both members of the household to changes in government transfer generosity over the business cycle. I show that when the model is calibrated to match the level and cyclicality of i) the head's earnings loss upon job displacement, ii) job finding rates, and iii) government transfers, it generates small changes in spousal earnings upon the head's displacement as I have documented in the data.

I quantify the crowding-out effects of existing government transfers on spousal earnings responses to the head's job displacement over the business cycle in a counterfactual experiment. When government transfers are designed to be less generous in recessions and more generous in expansions (i.e., procyclical), I find that spousal earnings increase significantly following the head's displacement in recessions but remain small in expansions. The procyclical policy leaves the marginal utility of consumption high after job loss in recessions and induces spouses to supplement family earnings by working. In expansions, earnings losses are relatively smaller and the marginal value of increasing spousal earnings is lower. Hence, during these times, spousal response to the head's displacement is small and inelastic to government transfer generosity. To ensure that the role of crowding-out effects of transfers in explaining the small spousal earnings response is not overstated in the model, I show that the model implied female labor supply elasticities are in line with empirical estimates. In particular, female participation elasticity with respect to net wages is 0.31 in the model and between $0.15 - 0.43$ in the data. Female earnings elasticity with respect to transfers is 0.37 in the model and 0.44 in the data. Furthermore, the female participation elasticity with respect to net wages in the model is decreasing in household income as in the

[3]The Supplemental Nutrition Assistance Program (SNAP), Earned Income Tax Credit (EITC), and Temporary Assistance for Needy Families (TANF), and Medicaid are examples of means-tested transfers, while Unemployment Insurance (UI) is an example of employment-tested transfers. These types of government transfers are typically available to families with frequently displaced members.

data. This corroborates why spousal labor supply is more elastic to transfers in recessions when the head's earnings loss is larger.

The results of this counterfactual experiment show that the incentive costs of transfers in the form of reduced spousal labor supply are larger in recessions and smaller in expansions. Since existing transfers are more generous in recessions, there may be potential welfare gains from changing the generosity of government transfers over the business cycle. Motivated by this observation, I study the optimal design of means-tested and employment-tested transfers over the business cycle. In my main optimal policy analysis, I restrict policy instruments to take the form of the means-tested transfer amount and the employment-tested transfer amount as linear functions of current aggregate labor productivity and a constant income tax used to balance the government's budget for any proposed government program.[4]

I find that the optimal policy features countercyclical employment-tested and procyclical means-tested transfers. Overall, however, total government transfers under the optimal policy are procyclical which is in contrast to the current policy that maintains generous transfers in recessions. Means-tested transfers are procyclical because lower transfers in recessions induce a large increase in spousal entry into the labor force upon a head's displacement. This is a direct implication of the high incentive costs of transfers during recessions. Employment-tested transfers are more generous in recessions because these benefits are smaller and short-term, and thus have relatively lower incentive costs on spousal labor supply. As a result, the provision of insurance is better accomplished through more generous employment-tested transfers in recessions when unemployment is higher.

In an economy in which the optimal policy is implemented, female labor force participation is 5 percentage points higher compared to an economy in which the current policy is implemented. Higher employment reduces the income tax required to finance a similar average level of government transfers.[5] Moreover, the economy under the optimal policy

[4]When solving for the optimal mix of means-tested and employment-tested transfers, I follow a large literature that uses calibrated models to study the optimal policy for a restricted class of policy instruments. See Hansen and Imrohoroğlu (1992), Acemoglu and Shimer (2000), Abdulkadiroğlu, Kuruşcu, and Şahin (2002), Wang and Williamson (2002), Krusell, Mukoyama, and Şahin (2010), and Koehne and Kuhn (2015).

[5]I will show in Section 1.5 that the optimal policy has similar levels of average transfers to the current policy.

is wealthier and has a lower fraction of families with non-positive liquid wealth. These differences in the macroeconomy result in a higher average consumption level and a slightly lower average consumption volatility. Overall, the optimal policy yields an ex-ante welfare gain of around 0.6 percent additional lifetime consumption compared with the current policy. Most of the welfare gains are enjoyed by wealth-poor families with an unskilled male who is married to a skilled female. It is precisely for this family that a spouse's participation in the labor force can bring higher levels of income to the family especially when a displacement of the head occurs.

To understand why accounting for the response of spouses in the presence of transfers is critical in determining the optimal policy, I modify the model such that spousal labor supply is exogenous to government policy. In particular, I keep female labor supply decisions unchanged even when government policy is varied. Abstracting from the incentive costs of transfers on spousal labor supply results in an optimal policy that is more generous on average than the optimal policy in the model with endogenous spousal labor supply. Furthermore, the optimal policy now features slightly countercyclical means-tested and employment-tested transfers because the optimal cyclicality of government transfers is driven largely by the cyclicality of insurance benefits, which is larger in recessions. This exercise shows that endogenizing the spousal labor supply response to changes in government policy is critical in determining both the optimal level and cyclicality of government transfers. As a result, policy makers should recognize that married households have an important source of self-insurance through adjustments in spousal labor supply, and generous payments to these households make them worse-off due to large crowd-out.

Related Literature This paper contributes to the literature that explores the role of female labor supply as an insurance mechanism against idiosyncratic earnings risk within the family. Importantly, Blundell, Pistaferri, and Saporta-Eksten (2016) find that female labor supply provides sizeable consumption insurance against wage shocks faced by the husband. Wu and Krueger (2018) show that a calibrated life-cycle two-earner household model with endogenous labor supply can match well these empirically estimated labor supply and consumption responses to wage shocks within the family.[6] In this paper, I condition the change in spousal earnings and hours in response to the head's job displacement to the aggregate state of the economy, rather than looking at an average spousal response. Empirically, I find small changes in spousal earnings and hours upon the head's job displacement in recessions. In expansions, spousal responses are positive and statistically significant, but only a few years after the head's displacement. I then explore the effects of more generous government transfers on the small changes in spousal earnings upon the head's displacement in recessions and study the optimal design of these transfers over the business cycle.

Another strand of literature studies the optimal design of transfer programs. It is possible to divide this large literature into two groups based on their modeling choices and welfare analysis. The first is a group of papers that study the optimal design of transfers using models with endogenous family labor supply but without aggregate fluctuations (Ortigueira and Siassi 2013, Haan and Prowse 2017, Mankart and Oikonomou 2017).[7] The second is a group of papers that study the optimal design of taxes or transfers in a model with aggregate fluctuations but without endogenous family labor supply as a private insurance mechanism (Mitman and Rabinovich 2015, Birinci and See 2017, McKay and Reis 2017, Bhandari, Evans, Golosov, and Sargent 2018, Kekre 2018, Landais, Michaillat, and Saez 2018).[8] This paper combines these two groups of studies because it analyzes the optimal

[6]Previously, Attanasio, Low, and Sanchez-Marcos (2005) also quantify the role of female labor supply response to earnings risk within the family. They also find that female participation rates increase when risk is larger. Guler, Guvenen, and Violante (2012) study joint search problem of household and show that higher wage offers received by spouses allow the family head to look for better employment opportunities. Furthermore, Rendon and Garcia-Perez (2018) study the change in job search decisions due to the employment risk of the other member and their wealth.

[7]Mankart and Oikonomou (2017) incorporate aggregate fluctuations into their baseline model to explain the acyclicality of labor force participation, which is their main focus. However, when they study the optimal design of UI program, they reduce the model into a stationary environment.

[8]Among these papers, my paper is closest to Birinci and See (2017). There, we emphasize the importance of incorporating endogenous changes in precautionary saving motives in response to changes in UI generosity over the business cycle using a directed search model with aggregate fluctuations and incomplete asset markets. Here, I extend our previous work by analyzing the role of endogenous spousal labor supply response to idiosyncratic and aggregate risk on the optimal mix of means-tested and employment-tested transfers over the business cycle.

level and cyclicality of means-tested and employment-tested transfers using a model with endogeneous family labor supply and aggregate fluctuations. I overcome the computational difficulties encountered in models of this nature through an application of segmented search across skill requirements of jobs, achieved by an extension of block recursivity (Menzio and Shi, 2010, 2011).[9] Relative to the first group of papers, I study the optimal cyclicality of transfers using a model with aggregate fluctuations and find that more than half of the welfare gains from the optimal policy are attributable to its cyclicality since insurance benefits net of incentive costs vary substantially over the cycle. Relative to the second group of papers, I show that endogenizing spousal labor supply changes the optimal level and cyclicality of means-tested transfers.

Finally, this paper contributes to two empirical literatures. The first literature studies the impact of job displacement on individual earnings (Jacobson, LaLonde, and Sullivan 1993, Ruhm 1991, Stevens 1997). More recently, Davis and Von Wachter (2011) estimate the earnings loss upon job displacement separately for recessions and expansions. In addition to individual earnings, I estimate the impact of a head's job displacement in recessions and expansions on family earnings and on spousal earnings and hours. This helps me to quantify the available spousal insurance to displaced individuals in recessions and expansions.[10] The second literature actually estimates the contemporaneous change in spousal earnings upon her husband's unemployment, otherwise known as the "added worker effect", without conditioning on the time of his unemployment (Heckman and MaCurdy 1980, 1982, Lundberg 1985, Cullen and Gruber 2000, Stephens 2002, Hendren 2017). Pruitt and Turner (2018) measure spousal earnings responses to earnings fluctuations of the household head in both recessions and expansions using Social Security Administration data but do not focus on measuring these responses to job displacements. Job displacement events are particularly relevant because their effects are large and long-lasting compared with temporary earnings fluctuations. My paper focuses on measuring the dynamic response of spousal earnings

[9] To the best of my knowledge, this paper is the first to extend the concept of a block recursive equilibrium in an endogeneous family labor supply model with aggregate fluctuations.

[10] Davis and Von Wachter (2011) also show that standard search and matching models fail to generate such large negative and long-lasting effects of job displacement on labor earnings. More recently, Jarosch (2015), Huckfeldt (2016), Krolikowski (2017), and Jung and Kuhn (2018) develop variants of such models that can endogenously generate these persistent effects of job displacement.

specifically in response to a head's job displacement and how this response varies over the business cycle. I then use these empirical findings in a structural model to understand the effects of government transfers on spousal earnings response to the head's displacement, and then study the optimal design of these transfers over the business cycle.[11]

This chapter is organized as follows. Section 1.2 presents the model. Section 1.3 documents the empirical findings about the impact of the head's displacement on family and spousal earnings, and explains the calibration strategy and the model's validation against untargeted data moments. Section 1.4 discusses the effects of transfer policies on spousal labor supply response to the head's displacement. Section 1.5 studies the optimal design of government transfers. In Section 1.6, I provide a list of extensions and robustness checks on the optimal policy analysis. Finally, Section 1.7 concludes.

1.2 Model

In this section, I develop a tractable job search model of families with incomplete asset markets and aggregate fluctuations. The key contribution of this framework is to endogenize labor supply decisions of both members of the household to changes in government transfers.

1.2.1 Environment

Setting

Time t is discrete and runs forever. The economy is populated by a large number of ex-ante identical households, and each household j consists of a male m and a female f individual

[11] A separate literature studies the effects of income taxation on i) the observed time series of married female labor force participation (Kaygusuz 2010), ii) participation of married women over their life cycle (Borella, De Nardi, and Yang 2018), and iii) international differences in married women's hours worked (Bick and Fuchs-Schundeln 2017). These papers conclude that reducing marginal tax rates for married households incude a sizeable increase on the labor supply of married women. Gayle and Shephard (2018) show that the optimal tax system for married couples is characterized by negative jointness, i.e. reducing marginal tax rates on the wife when the husband makes more money. My paper complements them as I show that a decline in the implicit tax rate of work during recessions encourage spousal labor supply upon a large permanent decline in household income.

i, i.e. $i \in \{m, f\} \; \forall j$.[12] At any point in time, a household can be in the labor force or retired. I model retirement as an exogenous event. In every period, both members of the household retire with probability ζ_R. Retired households die with probability ζ_D and they are replaced by new households entering into the labor force. Households discount future at rate β.

Households are heterogeneous in terms of their asset holdings a, human capital level of each member h_i, and employment status of each member l_i. An individual can be classified into one of the following employment statuses: employed E, unemployed individual who is eligible for employment-tested UI benefits U_b, unemployed individual who is ineligible for such benefits U_n, or retired R.

Households have access to incomplete asset markets where they can save or borrow up to a limit at an exogenous interest rate r. They make joint choices of savings and labor supply of the non-employed members. Preferences of a household are given by

$$U\left(c,\, l_m,\, l_f,\, s_m,\, s_f\right) = u\left(c\right) + \sum_i \eta_i \times \underbrace{\mathbf{1}\left(l_i \neq E,\ \text{and}\ s_i = 0\right)}_{\text{out of labor force}}$$

where $u\left(\cdot\right)$ is a strictly increasing and strictly concave utility function over household consumption level c that satisfies Inada conditions, $s_i \in \{0, 1\}$ is labor supply decision of individual i at the extensive margin, and η_i is the value of leisure.[13] Thus, the above functional form assumes that individuals only enjoy value of leisure if they do not look for jobs when unemployed.[14]

The aggregate state variables of the economy are summarized by $\mu = (z, \Gamma)$, where z is aggregate labor productivity, and Γ is the distribution of households across individual states.

[12]Throughout the chapter, I suppress the index j when it is clear that a variable is a household variable. Instead, I use the index i for individual variables to differentiate them from household variables.

[13]The only parameter that defines gender in this model is η_i. This implies that utility cost of work or search is different between male and female to capture the employment differences between them.

[14]In Section 1.6, I also analyze the effect of a utility function with non-separable consumption and leisure on my main results, following Blundell, Browning, and Meghir (1994) and Attanasio and Weber (1995).

Labor market

The labor market is segmented in human capital h, i.e. jobs are characterized by their human capital requirement level h. Vacant firms post job openings in specific human capital submarkets after paying a fixed cost κ of posting a vacancy. On the other side of the labor market, when unemployed individuals decide to participate into the labor market by exerting positive job search effort s_i, they look for jobs that are compatible with their own human capital level.

The labor market tightness of submarket h is defined as the ratio of vacancies v posted in the submarket to the number of unemployed individuals searching for a job within that submarket. It is denoted as $\theta\left(h;\,\mu\right) = \frac{v(h;\mu)}{u(h;\mu)}$. Let $M\left(v,u\right)$ be a constant returns to scale matching function that determines the number of matches in a submarket with number of unemployed u and number of vacancies v. Then, $p\left(h;\,\mu\right) = \frac{M(v(h;\mu),u(h;\mu))}{u(h;\mu)}$ is the job finding rate and $q\left(h;\,\mu\right) = \frac{M(v(h;\mu),u(h;\mu))}{v(h;\mu)}$ is the vacancy filling rate in submarket h when aggregate state is μ. The constant returns to scale assumption on the matching function guarantees that the equilibrium object θ suffices to determine job finding and vacancy filling rates since $p\left(\theta\right) = \frac{M(v,u)}{u} = M\left(\theta, 1\right)$ while $q\left(\theta\right) = \frac{M(v,u)}{v} = M\left(1, \frac{1}{\theta}\right)$.

Once matched, the firm-worker pair operates a constant returns to scale technology that converts one indivisible unit of labor into final consumption goods. The amount of production output is given by $g\left(h,\,z\right)$, where $g\left(\cdot\right)$ is strictly increasing function of both worker's human capital level h, and aggregate productivity z. Firm pays a wage $w\left(h,\,z\right)$ to the worker. I assume that the period output is shared between the firm and the worker. In particular, worker receives α share of the period output as wage, which implies that $w\left(h,\,z\right) = \alpha g\left(h,\,z\right)$.[15]

[15] This assumption is similar to Herkenhoff, Phillips, and Cohen-Cole (2017) and it serves for two purposes. First, when I analyze the role of government transfers in explaining the small changes in spousal earnings upon head's displacements in recessions, this assumption implies that varying the government policy does not affect equilibrium wages and thus firm vacancy posting decisions, leaving the labor demand same across policies. This allows me to better isolate the effect of transfers on labor supply. Second reason is tractability. This is because if unemployed also choose the wage submarket when looking for jobs, I would then need to keep track of wage levels of employed members of the household as additional state variables. I refrain doing this in the baseline model, but, in Section 1.6, I extend the baseline model to endogenize wage choices of the unemployed into a directed search model, and analyze the effects of this assumption on my main results.

The firm-worker pair continues to operate until the match exogenously dissolves with probability $\delta(h, z)$ or the worker retires with probability ζ_R. $\delta(\cdot)$ is a decreasing function of both h and z.

Human capital dynamics

Human capital of an individual h lies in an equispaced grid $\mathcal{H} \equiv \{h_L, ..., h_H\}$. All newborn individuals begin with the lowest skill level. Employed and unemployed individuals experience stochastic accumulation or depreciation of skills as in Ljungqvist and Sargent (1998). For an unemployed individual with human capital level h, human capital evolves as follows:

$$h' = \begin{cases} h & \text{with probability} \quad 1 - \pi^U \\ h - \Delta^U(z) & \text{with probability} \quad \pi^U. \end{cases}$$

Similarly, for an employed individual with human capital level h, human capital evolves as follows:

$$h' = \begin{cases} h + \Delta^E & \text{with probability} \quad \pi^E \\ h & \text{with probability} \quad 1 - \pi^E. \end{cases}$$

The only extra assumption in this process when compared to the one in Ljungqvist and Sargent (1998) is that I allow Δ^U to vary over the business cycle z. This assumption helps the model to generate cyclical difference in the magnitude of individual earnings drop upon job displacement, as documented by Davis and von Wachter (2011).[16]

Government transfers

Government runs three transfer programs: means-tested transfers, employment-tested transfers, and retirement transfers. Employment-tested and means-tested transfers are paid to only eligible households in the labor force, while only retired households receive

[16]In principle, the model generates larger earnings losses upon displacements in recessions relative to displacements in expansions due to endogenously lower job finding rates in recessions. However, this alone is insufficient to generate the observed difference in magnitude. Hence, the extra assumption on larger human capital loss when unemployed in recessions is needed. Moreover, this assumption is in fact reasonable, given that most of the human capital is indeed occupation specific (Kambourov and Manovskii 2009), and finding a job within the same occupation is much more difficult in recessions (Huckfeldt 2016).

retirement transfers. The time-invariant amount of retirement transfers paid to the retired households is given by b_R.

Eligibility for the means-tested transfers is determined at the household level. A household is eligible for the means-tested transfers if the amount of household assets a is lower than an asset threshold $\underline{a}$, and the amount of household labor income y (which is the summation of the labor income of male and female) is lower than an income threshold $\underline{y}$. Both $\underline{a}$ and $\underline{y}$ are policy instruments of the government. Eligibility for means-tested transfers never expires as long as the income and assets tests are satisfied. The amount of means-tested transfers may also vary over the business cycle, and it is given as follows:[17]

$$\phi\left(z;\, a,\, y\right) = \begin{cases} \phi\left(z\right) & \text{if} \quad y < \underline{y},\, a < \underline{a} \\ 0 & \text{otherwise.} \end{cases}$$

Eligibility for the employment-tested transfers is determined at the individual level. An individual may be eligible U_b or ineligible U_n for employment-tested transfers upon job displacement, and the eligible individual only starts receiving these transfers if he/she actively searches for a job, i.e. $s_i > 0$.[18] Employment-tested transfers stochastically expire at rate e, as in Fredriksson and Holmlund (2001), Albrecht and Vroman (2005), Faig and Zhang (2012), and Mitman and Rabinovich (2015). This assumption simplifies the solution of the model because I do not need to carry the unemployment duration as another state variable for the eligible unemployed. The generosity of employment-tested transfers b and the expiration rate e may vary over the business cycle. Hence, the amount of employment-tested transfers is given as follows:

$$b\left(z;\, l_i,\, s_i\right) = \begin{cases} b\left(z\right) & \text{if} \quad l_i = U_b,\, s_i > 0 \\ 0 & \text{otherwise.} \end{cases}$$

[17] I restrict the policy instruments to depend on the aggregate state of the economy μ only through the current aggregate productivity z and not through the distribution of individuals across states Γ. This restriction allows my model to retain the block recursitivity, which I will explain in Section 1.2.4.

[18] Here, I assume that government can observe the search behavior of the unemployed. In the U.S., UI offices may verify job search activities of UI recipients by asking them to fill a form about name, location, and contact information of the employer that recipients have recently contacted. In Section 1.6, I remove the assumption that search effort is observable to the government and check the implications on my main results.

To finance these programs, government levies a flat income tax τ applied to labor income, employment-tested transfers, and retirement transfers.[19] The government balances the following budget constaint in expectation:[20]

$$\sum_{t=0}^{\infty}\left(\frac{1}{1+r}\right)^{t}\times\Bigg[\sum_{i}\mathbf{1}_{\{l_{it}=E\}}w_{it}\tau-\sum_{i}\mathbf{1}_{\{l_{it}=U_b,\,s_{it}>0\}}b_t\left(1-\tau\right) \\ -\sum_{j}\mathbf{1}_{\left\{y_{jt}<\underline{y},\,a_{jt}<\underline{a}\right\}}\phi_t-\sum_{j}\mathbf{1}_{\{l_{jt}=R\}}b_R\left(1-\tau\right)\Bigg]=0 \tag{1.1}$$

where the terms in the bracket respectively are total income tax revenues generated from employed individuals, net employment-tested transfers paid to eligible unemployed individuals with positive search effort, total means-tested transfers paid to eligible households, and net retirement transfers paid to retired households.

Timing

Every single period t is divided into three stages. In the first stage, ζ_R fraction of households in the labor force retires, and ζ_D fraction of retired households dies and they are replaced with new households entering into the labor force. Then, aggregate productivity z realizes. The period productivity level z completely determines i) the government policy of generosity of employment-tested transfers $b\left(z\right)$, its expiration rate $e\left(z\right)\in\left[0,1\right]$, and the generosity of means-tested transfers $\phi\left(z\right)$, ii) the exogenous job separation rate $\delta\left(h,\,z\right)\in\left[0,1\right]$ in each submarket h. This implies that $\delta\left(h,\,z\right)$ fraction of those who were employed in $t-1$ in each submarket h loses their jobs and must spend at least one period being unemployed. Among those who lose their job, $e\left(z\right)$ fraction become ineligible for employment-tested transfers.

Search and matching in the labor market occurs in the second stage. Vacant firms decide the human capital submarket in which to post a vacancy, while the unemployed individuals look

[19]According to the U.S. tax policy, social security and UI benefits are subject to income tax, while means-tested transfers are mostly non-taxable. Moreover, in Section 1.6, I also analyze the effects of progressive taxation on the main results.

[20]This assumption is motivated by the fact that according to the current transfer system in the United States, states are allowed to borrow from a federal fund. For example, states may borrow from federal UI trust fund when they meet certain federal requirements, and thus they are allowed to run budget deficits during some periods.

for a job in a submarket that is compatible their own human capital level. Then, $p(h, z)$ fraction of unemployed individuals searching for a job in submarket h finds a job. Human capital stochastically evolves based on labor market outcomes. Finally, the third stage is the production and consumption stage. Each firm-worker pair produces $g(h, z)$ units of consumption goods. Wages are paid to workers, employment-tested transfers are paid to eligible unemployed individuals, means-tested transfers are paid to eligible households, and retirement income is paid to retired households. Each household then makes their joint saving/borrowing decision. Prior to time $t+1$, households in the labor force jointly decide whether its unemployed members will supply labor in the labor market stage of time $t+1$ where the forgone utility of leisure for the member with positive labor supply is incurred at time t.

1.2.2 Household problem

A household's state vector consists of the net asset level $a \in \mathcal{A} \equiv [a_L, a_H] \subseteq \mathbb{R}$, the current employment status of each member $l_i \in \{E, U_b, U_n, R\}$, and the current human capital level of each member $h_i \in \mathcal{H} \equiv \{h_L, ..., h_H\}$.

The aggregate state is denoted by $\mu = (z, \Gamma)$, where $z \in \mathcal{Z} \subseteq \mathbb{R}_+$ denotes the current aggregate productivity and $\Gamma : \{E, U_b, U_n, R\} \times \{E, U_b, U_n, R\} \times \mathcal{A} \times \mathcal{H} \times \mathcal{H} \to [0, 1]$ denotes the distribution of agents across employment statuses, asset level, and human capital levels. The law of motion for the aggregate states is given by $\Gamma' = \Lambda(\mu, z')$ and $z' \sim \Phi(z' \mid z)$.

Among the households in the labor force, there are nine distinct types of households in terms of the employment statuses of their members, given that individual employment status for the individuals in the labor force can take three different values, i.e. $l_i \in \{E, U_b, U_n\}$. Thus, there are nine different value functions for such households. In the main text, I will lay out the recursive problem of three types of households: i) one member is employed, the other is eligible unemployed, ii) both members are eligible unemployed, and iii) both members are employed. I will then discuss the changes for the problems of other types of households. Finally, I will show the recursive problem of the retired households.

Let $V^{l_m l_f}$ denote the value function of household with male's employment status of l_m and female's employment status of l_f after search and matching has occurred, i.e. the value at the start of third stage of a period. Let $\mathbf{h} \equiv (h_m,\, h_f)$ and $\mathbf{l} \equiv (l_m,\, l_f)$ be the human capital and employment state vectors of the household. To simplify the notation further in the recursive formulations below, let $\delta_i \equiv \delta\,(h_i,\, z)$ and $p_i \equiv p\,(h_i,\, z)$ be the job displacement rate and job finding rate of individual $i \in \{m,\, f\}$, and δ_i' and p_i' denote the respective probabilities in the next period. Finally, let $\lambda_b = 1 - e\,(z)$ be the probability that eligibility for employment-tested benefits does not expire, and $\lambda_n = e\,(z)$ be the expiration probability. Similarly, λ_b' and λ_n' denote the respective probabilities in the next period.

Employed - unemployed household

First, consider a household in which the male is employed and the female is eligible unemployed. The recursive problem of this household is given as follows:[21]

$$
\begin{aligned}
V^{EU_b}\,(a,\, \mathbf{h};\, \mu) \;\; = & \max_{a' \geq a_L,\, s_f \in \{0,1\}} \quad u\,(c) + \eta_f\,(1 - s_f) \\
& + \;\; \beta \Big[(1 - \zeta_R)\, \mathbb{E}_{\mathbf{l}', \mathbf{h}', \mu'} \Big[V^{l'}\left(a',\, \mathbf{h}';\, \mu'\right) \Big| s_f, \mathbf{l}, \mathbf{h}, \mu \Big] + \zeta_R V^R\left(a'\right) \Big] \qquad (1.2)
\end{aligned}
$$

subject to

$$
\begin{aligned}
& c + a' \leq (1 + r)\, a + y + \phi\,(z;\, a,\, y) + b\,(z;\, U_b,\, s_f)\,(1 - \tau) \\
& y = w\,(h_m,\, z)\,(1 - \tau) \\
& \Gamma' = \Lambda\left(\mu,\, z'\right) \quad \text{and} \quad z' \sim \Phi\left(z' \,|\, z\right).
\end{aligned}
$$

In the current period, the household decides savings and female labor force participation, given that she is the non-employed member of the household. If the household stays in the labor force with probability $1 - \zeta_R$, the household takes expectation over the transition of employment statuses, human capital levels of both members, and the aggregate states, conditional on current employment statuses, human capital levels of both members, and the job search decision for the female. If the household retires with probability ζ_R, then the only relevant state variable is assets a. The household receives employment-tested transfers only if eligible female searches for a job in the current period. Given that male is only employed member of the household, total labor income of the household y is equal to his net wage.

[21] The problem of the symmetric household is identical to this household's problem with the change of indices for m and f.

For the household in which male is employed but female is ineligible unemployed, the above problem is the same except that she does not receive employment-tested transfers even if she searchers for a job. This captures the fact that according to current UI policy in the United States, the unemployed receive UI benefits only for a certain number of weeks - which varies over the business cycle - and once that threshold is reached, the unemployed cannot continue to collect UI benefits.

It is also insightful to discuss the expectation over the transition of employment statuses of this household, which I lay out below:[22]

$$\begin{aligned}
\mathbb{E}_{\mathbf{l}',\mathbf{h}',\mu'}\left[V^{l'}\left(a',\mathbf{h}';\mu'\right)\Big|s_f,\mathbf{l},\mathbf{h},\mu\right] = \mathbb{E}_{\mathbf{h}',\mu'}\Bigg[& s_f\left(1-\delta_m'\right)p_f'V^{EE}\left(a',\mathbf{h}';\mu'\right) \\
& + s_f\left(1-\delta_m'\right)\left(1-p_f'\right)\sum_{k\in\{b,n\}}\lambda_k'V^{EU_k}\left(a',\mathbf{h}';\mu'\right) \\
& + s_f\delta_m'p_f'\sum_k\lambda_k'V^{U_kE}\left(a',\mathbf{h}';\mu'\right) \\
& + s_f\delta_m'\left(1-p_f'\right)\sum_{k,d\in\{b,n\}}\lambda_k'\lambda_d'V^{U_kU_d}\left(a',\mathbf{h}';\mu'\right) \\
& + \left(1-s_f\right)\left(1-\delta_m'\right)\sum_k\lambda_k'V^{EU_k}\left(a',\mathbf{h}';\mu'\right) \\
& + \left(1-s_f\right)\delta_m'\sum_{k,d\in\{b,n\}}\lambda_k'\lambda_d'V^{U_kU_d}\left(a',\mathbf{h}';\mu'\right)\Bigg)\Bigg|\mathbf{h},\mu\Bigg].
\end{aligned}$$

The first two lines in the right hand side is the case when she searches for a job in the current period and he keeps his current job. In this case, if she finds the job, the household will be an employed - employed household, otherwise the household will continue to be an employed - unemployed household but she may retain or lose eligibility for employment-tested transfers. The third and fourth lines describes the case when she searches for a job and he loses his current employment. Then, if she finds a job, the household will be an unemployed - employed household where the male may or may not be eligible for

[22]Expectations over human capital levels and aggregate states are relatively simpler and are already discussed in the previous sections.

employment-tested transfers.[23] If she cannot find a job, then both members of the household will be unemployed, and they will both face eligibility risk for the employment-tested transfers. The fifth line is the case when she does not search for a job and continue to be unemployed with or without eligibility, and he keeps his current job. Finally, the last line shows the case when she does not search for a job and he loses his job. In this case, again, both members of the household will be unemployed, and they will both face eligibility risk for the employment-tested transfers.

For the household in which male is employed but female is ineligible unemployed, the above expectation is the same except that she stays ineligible for employment-tested transfers if she does not find a job.[24]

Unemployed - unemployed household

Second, consider a household in which both male and female are eligible unemployed. The recursive problem of this household is given as follows:

$$\begin{aligned} V^{U_bU_b}\left(a,\mathbf{h};\mu\right) &= \max_{a'\geq a_L,\, s_m,s_f\in\{0,1\}} u\left(c\right) \\ &+ \sum_{i\in\{m,f\}} \eta_i\left(1-s_i\right) + \beta\left(1-\zeta_R\right)\mathbb{E}_{\mathbf{l}',\mathbf{h}',\mu'}\left[V^{l'}\left(a',\mathbf{h}';\mu'\right)\Big| s_m,s_f,\mathbf{l},\mathbf{h},\mu\right] \\ \text{subject to} & \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (1.3) \\ & c+a'\leq\left(1+r\right)a+\phi\left(z;a,0\right)+\Big[b\left(z;U_b,s_m\right)+b\left(z;U_b,s_f\right)\Big]\left(1-\tau\right) \\ & \Gamma'=\Lambda\left(\mu,\,z'\right) \quad \text{and} \quad z'\sim\Phi\left(z'\,|\,z\right). \end{aligned}$$

Given that both members of the household are now unemployed, the household chooses labor supply of both members. Moreover, both members enjoy leisure if they do not look for a job, in which case they do not receive employment-tested transfers even if they are both eligible. In the current period, the household does not have any labor income.

[23] According to the current UI policy in the United States, not all workers transitioning into unemployment qualify for UI benefits. In particular, individuals do not qualify for benefits if they voluntarily quit their job or if they do not meet requirements for wages earned or time worked during an established period of time referred to as the base period.

[24] This captures the fact that according to current UI policy in the United States, the unemployed individuals receive UI benefits only for a certain number of weeks - which varies over the business cycle - and once that threshold is reached, the unemployed cannot continue to collect UI benefits.

Similarly, for the household in which any unemployed member is ineligible unemployed, the above problem is the same except that this member does not receive employment-tested transfers even if he/she searchers for a job.
The expectation term in the right hand side of Equation (1.3) is similar to the one I discussed in Equation (1.2) except that employment statuses of both members in the next period are determined by their labor supply decisions and job finding rates. In Appendix A.1, I lay out and discuss the expectation over the transition of employment statuses of this household.

Employed - employed household

Next, consider a household in which both male and female are employed. The recursive problem of this household is given as follows:

$$
\begin{aligned}
V^{EE}(a, \mathbf{h}; \mu) \quad &= \quad \max_{a' \geq a_L} \quad u(c) + \beta(1-\zeta_R)\,\mathbb{E}_{\mathbf{l}', \mathbf{h}', \mu'}\left[V^{l'}\left(a', \mathbf{h}'; \mu'\right) \Big| \mathbf{l}, \mathbf{h}, \mu\right] \\
\text{subject to} & \\
& c + a' \leq (1+r)\,a + y + \phi(z;\, a,\, y) \\
& y = \Big[w(h_m,\, z) + w(h_f,\, z)\Big](1-\tau) \\
& \Gamma' = \Lambda\left(\mu,\, z'\right) \quad \text{and} \quad z' \sim \Phi\left(z' \,|\, z\right).
\end{aligned}
\tag{1.4}
$$

The employed - employed household chooses only consumption vs savings given that there is no on-the-job-search in the baseline model. Individuals of this household are not eligible for employment-tested transfers. Total labor earnings of the household is equal to the sum of net wages of male and female.
The expectation term in the right hand side of Equation (1.4) is similar to the one I discussed in Equation (1.2) except that employment statuses of both members in the next period are determined only by their job separation rates. In Appendix A.1, I lay out and discuss the expectation over the transition of employment statuses of this household.

Retired household

Finally, I discuss the problem of retired households. Here, I assume that both members of the households retire at the same time and the household receives a time-invariant retirement transfers b_R upon retirement. In every period, retired households die with probability ζ_D and they are replaced with new households entering into the labor force. I also assume that retired members of the households do not enjoy leisure. Given that the retired household is not allowed to re-enter into the labor market and that the retirement households receive time-invariant transfers, the state variables of such households reduce to only their asset holdings a.[25]

Let V^R be the value of a retired household. The recursive problem of this household is given as follows:

$$\begin{aligned} V^R(a) &= \max_{a' \geq a_L} \quad u(c) + \beta(1-\zeta_D) V^R(a') \\ \text{subject to} & \\ & c + a' \leq (1+r)a + b_R \end{aligned} \tag{1.5}$$

1.2.3 Firm problem

First, consider a firm that is matched with a worker in submarket h when the aggregate state is μ. The pair operates under a constant returns to scale technology and produces $g(h, z)$ units of output, and the worker is paid a wage of $w(h, z)$. With some probability $\delta(h, z)$ the match dissolves, and the worker retires with probability ζ_R. Let $J(h; \mu)$ be the value of a matched firm in submarket h when the aggregate state is μ. The recursive problem of this firm is given as follows:

$$\begin{aligned} J(h;\mu) &= g(h,z) - w(h,z) + \frac{1}{1+r}(1-\zeta_R)\mathbb{E}_{h',\mu'}\left[\left(1-\delta(h',z')\right)J(h';\mu')\,\middle|\,h,\mu\right] \\ \text{subject to} & \\ & \Gamma' = \Lambda(\mu, z') \quad \text{and} \quad z' \sim \Phi(z' \mid z). \end{aligned} \tag{1.6}$$

Meanwhile, the value of a vacant firm that posts a vacancy in submarket h under aggregate state μ is given by

$$V(h;\mu) = -\kappa + q(\theta(h;\mu))J(h;\mu) \tag{1.7}$$

where κ is a fixed cost of posting a vacancy that is financed by risk-neutral foreign entrepreneurs who own the firms.

[25] Relaxing the assumptions about leisure or transfer payments to retired households has only small quantitative effects on the baseline calibration of the model.

When vacant firms decide the submarket in which to post a vacancy to maximize profits, they face the trade-off between the probability of filling a vacancy and the level of surplus from a possible match. This is because if a firm posts a vacancy in a high human capital submarket, then the firm's surplus from the match in that submarket will be higher given that the period output net of wages is increasing in h and job displacement rate $\delta(\cdot)$ is decreasing in h. However, the probability of filling the vacancy is lower in high human capital submarkets given that few unemployed individuals are able to visit such submarket to search for a job.

The free entry condition implies that profits are just enough to cover the cost of filling a vacancy in expectation. As a result, the owner of the firm makes zero profits in expectation. Thus, $V(h;\,\mu) = 0$ for any submarket h such that $\theta(h;\,\mu) > 0$. Then, imposing the free entry condition to Equation (2.5) yields the equilibrium market tightness:

$$\theta(h;\,\mu) = \begin{cases} q^{-1}\left(\frac{\kappa}{J(h;\,\mu)}\right) & \text{if} \quad h \in \mathcal{H}(\mu) \\ 0 & \text{otherwise.} \end{cases} \tag{1.8}$$

The equilibrium market tightness contains all the relevant information needed by households to evaluate the job finding probabilities at each submarket.

1.2.4 Equilibrium

Definition of the Recursive Equilibrium: Given government transfer policies $\left\{b(z), e(z), \phi(z), \underline{a}, \underline{y}, b_R, \tau\right\}_{z\in\mathcal{Z}}$, a recursive equilibrium is a list of household policy functions for assets $\left\{a'^{l_m l_f}(a,\,\mathbf{h},\,\mu)\right\}_{l_m,\,l_f\in\{E,\,U_b,\,U_n,\,R\}}$ and labor supply of unemployed members of the household $\left\{s_i(a,\,\mathbf{h},\,\mu)\right\}_{i\in\{m,\,f\}}$, a labor market tightness function $\theta(h;\,\mu)$, and an aggregate law of motion $\mu' = (z',\,\Gamma')$ such that

1. Given government policy, shock processes, and the aggregate law of motion, the household's policy functions solve their respective dynamic programming problems (1.2), (1.3), (1.4), and similar problems for other types of households.

2. The labor market tightness is consistent with the free entry condition (2.6).

3. The government budget constraint (2.7) is satisfied.

4. The law of motion of the aggregate state is consistent with household policy functions.

Notice that in order to solve the recursive equilibrium defined above, one must keep track of an infinite dimensional object Γ in the state space, making the solution of the model infeasible. To address this issue, I utilize the structure of the model and use the notion of block recursive equilibrium (BRE) developed by Menzio and Shi (2010, 2011).

Definition of the Block Recursive Equilibrium (BRE): A BRE for this economy is an equilibrium in which the value functions, policy functions, and labor market tightness depend on the aggregate state of the economy μ, only through the aggregate productivity z, and not through the aggregate distribution of agents across states Γ.

The model presented here is block recursive. Notice that the only payoff relevant individual state variable of the unemployed for the firm is the human capital level h of the unemployed because h determines the level of output, wage, and separation risk of the match. Thus, given that the segmented labor market allows unemployed to self-select into a specific submarket in searching for a job that is compatible with their own human capital level, once the firm is inside this submarket, it does not need to know the entire distribution of unemployed across the domain of the state space. Moreover, firms are indifferent across human capital submarkets when they are posting a job opening because of the trade-off between vacancy filling rate and their surplus from a match, and the free entry condition for firms guarantees the entry of firms until the profits are run down to zero. Finally, the constant returns to scale feature of the matching function implies that the relative ratio of vacancies to number of unemployed visiting each submarket, i.e. the market tightness, matters for agents when they make their own decisions. These features, together with the assumption that government policy instruments are functions of aggregate productivity z, allows the model to admit block recursivity. In Appendix A.4, I provide a proof for the existence of BRE for an extended version of the baseline model with endogeneous wages, which also shows that the baseline model is also block recursive. Appendix A.5 provides a computational algorithm for solving BRE.

The block recursivity of the model is very useful because it allows me to solve the model numerically without keeping track of the aggregate distribution of agents across states Γ. This becomes especially important when I solve for the optimal government transfers, which requires solving the equilibrium and finding the tax rate that balances the government budget over a long simulation period for each set of policy instruments.

1.3 Calibration and Validation

I calibrate the stochastic steady state of the model to match key labor market moments pre-Great Recession. Besides these, I also calibrate the model to match three particularly important moments: the level and cyclicality of i) head's earnings drop upon job loss, ii) government transfers, and iii) job finding rates. It is important to match the depth and cyclicality of heads' earnings losses because it determines how critical the role of both public and private insurance when a displacement in the family occurs. Likewise, matching the average generosity of government transfers and how it varies over the business cycle allows me to correctly quantify the insurance benefits of increasing or decreasing transfers as well as its incentive costs on family labor supply. Finally, the model must also match well how job finding rates vary over the cycle since this directly affects the strength of private insurance mechanisms through family employment. Since job finding rates are low in recessions, spouses may find it difficult to find a job and may thus not be able to provide adequate insurance to the family.

Next, I validate the calibrated model against the change in family earnings and spousal earnings upon head's job displacements in recessions and in expansions, consumption drop upon job displacement, marginal propensity to consume (MPC) level and cyclicality, asset-to-income distribution, and correlation between head and spouse displacements.

Among these data moments, I emphasize the effect of head's job displacement on head's own earnings, family earnings, and spousal earnings, as these turn out to be key in understanding the effects of transfers on spousal labor supply as well as in correctly quantifying the insurance benefits and incentive costs of these transfers. Thus, I will now measure these moments from the data. The magnitude of head's own earnings loss upon displacements will be a calibration input, while the effects of head's displacement on family and spouse earnings will be validation inputs.

1.3.1 Earnings loss upon job displacement over the business cycle

Data and methodology

In this section, I use data from Panel Study of Income Dynamics (PSID) between 1968-2015 to study the changes in head earnings and hours, spouse earnings and hours, and family earnings upon a family head's job displacement over the business cycle. For this analysis, I restrict the sample to families in which both the husband and the wife are between ages of 20 and 60 who are not in the Latino sample. I drop families with only one year of observation and those above the 99th percentile of family labor income distribution.[26] I create variables for involuntary job displacement using a question that asks the reason for losing the previous job to individuals who are either without a job or have been employed in their current job for less than a year. Following the literature, I define an involuntary job loss as a separation due to firm closure, layoff or firing.[27] This way, I only consider unexpected separations so that I can eliminate cases in which family were informed about the separation and spouses were already searching for a job. The resulting unbalanced sample of families contains 86,541 observations on 9,383 families with 1,204 of them experiencing at least one displacement in a recession, and 2,269 of them experiencing at least one displacement in an expansion. The family head of 674 families have at least one displacement event both in recessions and expansions. In this sample, there are 1,573 displacements in recessions, and 3,517 displacements in expansions. Appendix A.2 provides more details about the data and sample selection.

Table 1.1 compares the characteristics of families in which the head is never displaced whenever family is surveyed with characteristics of families in which the head of the family is displaced at least once. Couples of the families in which the head experiences a job displacement are slightly younger and less educated than families in which the head is never displaced. On average, displaced heads and their spouses work relatively lower hours than never displaced heads and their spouses even in the year prior to displacement.

To study the effects of head's job displacement on his individual earnings and hours, spousal

[26] Appendix A.2 discusses that main results of this section are robust to alternative sample selections.

[27] The latter category includes workers who report that they have been fired, which is typically not considered as an exogenous job displacement event. However, Boisjoly, Duncan, and Smeeding (1994) report that only 16% of the workers in the layoff or fired category have indeed been fired.

earnings and hours, and family earnings, I adopt the regression specification in Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997) given as follows:[28]

$$y_{it} = \beta X_{it} + \sum_{k \geq -2}^{10} \psi_k D_{it}^k + \alpha_i + \gamma_t + \epsilon_{it} \tag{1.9}$$

The outcome variable y_{it} include the real annual labor earnings of the head, spouse, and the family (defined as the sum of head and spouse labor earnings), as well as the head's and spouse's annual working hours.[29] The variable X_{it} is a vector of time-varying family characteristics, including a quadratic term of the head's experience, a quadratic term of spouse's experience, the number of children, and the number of young children with age less than 6. α_i captures time invariant unobserved error component associated with family i, and γ_t is an error component common to all families in the sample at year t. The vector of dummy variables D_{it}^k indicate a job displacement of the head in a future, current, or previous year. For example, $D_{it}^3 = 1$ if the individual i is displaced at time $t-3$, and zero otherwise. I estimate the impact a head's job displacement on individual and spousal earnings and hours as well as family earnings in the two years preceding job loss ($k = -2, -1$), in the year of job loss ($k = 0$), and in every year until 10 years after job loss ($k = 1, 2, ..., 10$). Thus, ψ_k captures the effect of job displacement on outcome variables in families whose head were displaced k years prior/after (treatment group) relative to families whose head has never been displaced (control group). Thus, individuals in the control group would have $D_{it}^k = 0$ for all years t. In all of the results below, the relative change of an outcome variable means the change in the outcome variable of the treatment group relative to the change in the outcome variable of the control group.[30]

In order to measure the differential effects of job displacements in recessions and in expansions on outcome variables, I group displacements into those that occurred in recessions and those that occured in expansions using NBER business cycle definitions. This means that when a displacement occurs in a recession year t, the individual is considered to be

[28]Based on the definition of the head in the PSID, family head is almost always male. In my sample, only 49 observations have female head among 86, 541 observations.

[29]Labor earnings include wages and salaries, bonuses, overtime, tips, commissions, professional practice or trade, market gardening, miscellaneous labor income, and extra job income.

[30]Individuals who experience an unemployment spell because of reasons other than displacement (such as quits) are part of the control group.

part of the treatment group that is displaced in recessions. I then estimate the regression Equation (1.9) for i) a treatment group where the head is displaced only in recessions and a control group where the head is never displaced, and ii) a treatment group where the head is displaced only in expansions and a control group where the head is never displaced. The regressions are estimated with fixed effects and robust standard errors clustered at the family level. In the following figures I report estimated ψ_k as a percent of the pre-displacement mean value of the outcome variable.

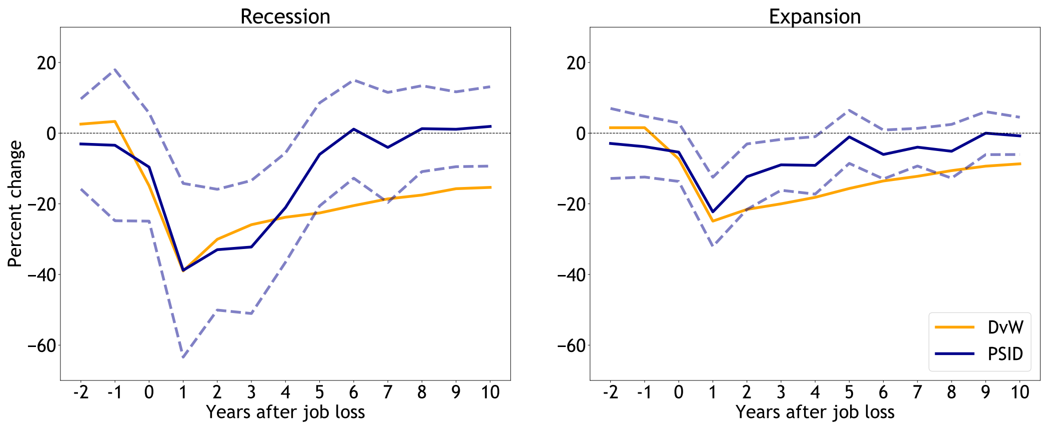
Head earnings

Figure 1.1 shows the change in relative labor earnings of the family head upon job displacement in recessions and expansions. The solid blue line shows the estimated coefficeints $\{\psi_k\}_{k=-2}^{10}$ as a percent of pre-displacement mean labor earnings of displaced heads, and the dashed light blue line shows the 90 percent confidence interval. I compare these results that I obtain from the PSID to the estimates of Davis and von Wachter (2011) who use Social Security Administration (SSA) data between 1974-2008.[31] I find that the magnitude of the average drop in head's relative labor earnings is larger when the head is displaced in recessions. In the year following the job displacement, the relative earnings drop by 39 percent in recessions and only 22 percent in expansions.[32] These results are consistent with the findings of Davis and von Wachter (2011) as they also document larger earnings losses upon displacements that occur in recessions (39 percent) than in expansions (25 percent). Furthermore, I find that these earnings losses upon job displacement over the business

[31] My econometric model is slightly different than the model that Davis and von Wachter (2011) use. In their analysis, they regress equation (1.9) for every year, obtain δ_k for each of these years, and then report the average values of δ_k across these years. Given that my sample size is smaller in PSID, I follow the baseline specification applied by Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997) who also use PSID. However, I still compare my results to Davis and von Wachter (2011) results because they provide the only empirical baseline for cyclicality of the magnitude of earnings drop upon job displacement.

[32] This finding is similar to results in the previous literature that estimates the earnings loss upon job displacement without conditioning the timing of displacement. Jacobson, LaLonde, and Sullivan (1993) find 25 percent, Stevens (1997) finds 30 percent, Stephens (2002) finds 30 percent, and Huckfeldt (2016) finds 32.5 percent drop in individual earnings upon displacement using annual data from PSID (until 1997 survey). Moreover, Saporta-Eksten (2014) shows that relative hourly wages of laid-off workers drops by around 30 percent in the year following job loss.

Figure 1.1: Relative labor earnings of family head upon job displacement



Note: This figure plots the changes in relative labor earnings of the family head upon his job displacement in recessions (left panel) and expansions (right panel). I estimate the changes in relative labor earnings from a distributed lag-recession model using PSID. The solid blue line shows the point estimates and the dashed light blue line shows the 90 percent confidence interval. I compare these results to the estimates of Davis and von Wachter (2011) given by the orange line.

cycle are persistent. Labor earnings of the head recover after 5 years upon displacements in recessions and expansions. A notable difference between my results and Davis and von Wachter (2011) is that, according to my results, the persistence of earnings losses is not as prolonged as their findings wherein individual earnings do not recover even 10 after years following displacements in recessions and expansions. This difference is partly because my sample is restricted to married or cohabiting households. The labor earnings of married men is typically larger than single men, given that they have higher education levels on average.

Figure A.1 in Appendix A.2 measures the effect of a head's job displacement over the business cycle on his annual hours. I find that hours recover relatively quickly. Moreover, results suggest that both the cyclical gap in earnings loss upon displacements over the business cycle and the persistence of earnings losses are largely explained by a drop in wages rather than a drop in hours.

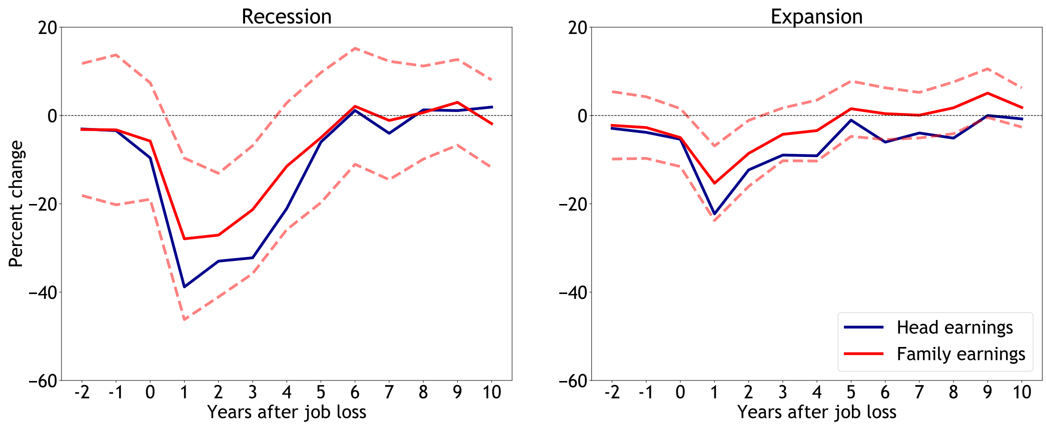
Family earnings and spousal earnings

The main focus of this section of the paper is to measure the effects of a head's job displacement in recessions and expansions on family earnings (defined as the sum of head and spouse labor earnings), and spousal earnings and hours. Figure 1.2 shows the change in relative labor earnings of the family upon job displacement of the family head in recessions and expansions, and compares it to the changes in relative head earnings as obtained above. I will highlight three results. First, I find that family earnings drop by 28 percent when the head's displacement occurs in recessions and by 15 percent when it occurs in expansions in the year following displacement. This implies that families enjoy some insurance from the presence of a second earner who was simultaneously employed with the head prior to his displacement. Having the spouse retain employment results in family earnings dropping by one-third less than individual earnings.[33] Second, the initial cyclical gap of family earnings loss upon head's job displacement between recessions and expansions ($28 - 15 = 13$ pp) is not very different from the initial cyclical gap of heads earnings loss ($39 - 22 = 17$ pp). Finally, the statistical significance of the coefficients based on the 90th percent confidence intervals plotted as blue dashed-lines in Figure 1.2 suggests that family earnings recovers 4 years after displacements in recessions (1 year earlier than head's earnings recovery), and 3 years after displacements in expansions (2 year earlier than head's earnings recovery). However, it is important to notice from the figure that the slopes of the recovery of head's earnings and family earnings look similar to each other. This hints us that earlier recoveries of family earnings are mostly due to a smaller initial drop coming from already working spouses rather than behavioral responses of, say, non-employed spouses who may enter the labor force to increase earnings.

The small behavioral response of spouses is confirmed by Figure 1.3 which shows the change in relative spousal earnings upon the head's displacement in recessions and in expansions. I find that the relative spousal earnings upon the head's displacement in recessions fluctuates around 0 and that these behavioral responses are always insignificant across years after the head's displacement in recessions. Moreover, the mean of the post displacement coefficients is only -0.8 percent for displacements in recessions. Hence, the

[33]The presence of a second-earner reduces the initial earnings loss by $100 \times ((39 - 28)/39) = 28$ percent in recessions and $100 \times ((22 - 15)/22) = 32$ percent in expansions.

Figure 1.2: Relative labor earnings of the head and family upon job displacement



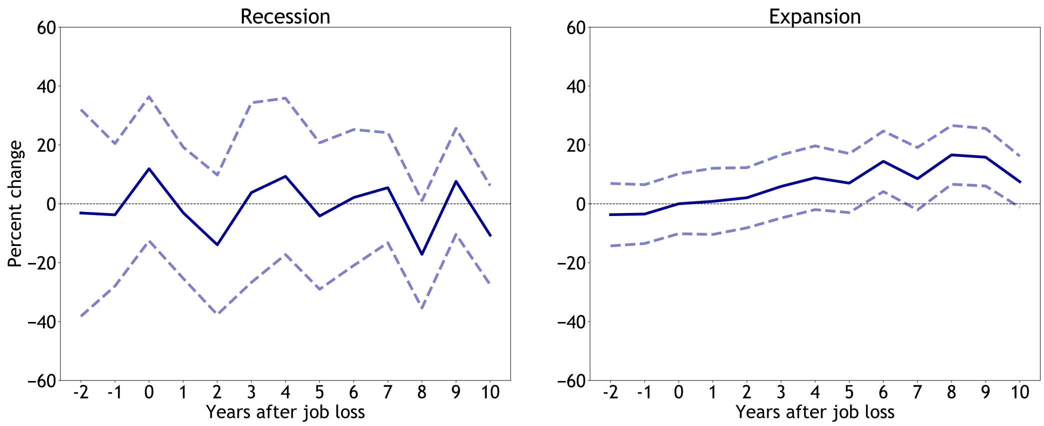
Note: This figure plots the changes in relative labor earnings of the head (blue line) and relative labor earnings of the family (red line) - defined as the sum of head and spouse labor earnings - upon head's job displacement in recessions (left panel) and expansions (right panel). The dashed light blue line shows the 90 percent confidence interval for family earnings. I estimate the changes in relative labor earnings of the head and the family from a distributed lag-recession model using PSID.

insignificance of the post displacement coefficients is not only explained by larger error bands around the point estimates in the recession regression due to a comparably smaller sample size, but also because of the small average behavioral spousal response to head's displacement in recessions. On the other hand, in expansions, there is a slight positive trend in spousal earnings upon head's displacement, but coefficients are also insignificant until year 6. Similarly, the mean of the post displacement coefficients is 8 percent in expansions. Furthermore, the p-values of a statistical test on joint significance of post displacement coefficients allow us to reject the hypothesis that they are jointly significant ($p = 0.35$ in recession and $p = 0.11$ in expansion).[34]

Figure A.2 in Appendix A.2 measures the effect of the head's job displacement over the business cycle on annual spouse hours. I also find that the change in spousal hours upon the head's displacement in recessions is very small in recessions, with a mean post displacement coefficient of only -0.1 percent. On the other hand, spousal hours in expansions becomes

[34] Small initial response of relative hours both in recessions and expansions is consistent with previous "added worker effect" literature that studies the contemporaneous change in spousal hours upon husband's unemployment (Heckman and MaCurdy 1980, 1982, Cullen and Gruber 2000).

Figure 1.3: Relative labor earnings of the spouse upon job displacement



Note: This figure plots the changes in relative labor earnings of the spouse upon family head's job displacement in recessions (left panel) and expansions. I estimate the changes in relative spousal labor earnings from a distributed lag-recession model using PSID. The solid blue line shows the point estimates and the dashed light blue line shows the 90 percent confidence interval.

significantly positive 3 years after the head's displacement and later increases by up to 15 percent. The mean of post displacement coefficients in expansions is 10.1 percent and the p-value of joint significance test is $p = 0.02$.

As a result, I find no evidence for significantly positive spousal earnings and hours response to head's displacements in recessions, during when the drop in head's earnings is much larger. On the other hand, spousal earnings and hours response to a head's displacement in expansions are small during the early years following displacement, and if anything, they become significantly positive at least 3 years after the displacement with a later increase by as much as 15 percent.

In Appendix A.2, I discuss that these results are robust to many different sample selections, including using combinations of alternative PSID samples (SRC, SEO, Immigrant, Latino), using alternative age limits, incorporating singles, keeping outliers of the labor income distribution, or keeping families when the head is displaced both in recessions and expansions in the treatment group.

Summary of empirical results

It is useful to summarize important empirical findings of this section, all of which except the first one are novel contributions to the literature. First, I find that there are large negative and persistent effects of head's displacement on his own labor earnings and that the magnitude of the earnings loss is larger when the displacement occurs in recessions, as in Davis and von Wachter (2011). Second, the mere presence of a second earner already mitigates close to one-third of the head's earnings losses upon job displacements both in recessions and in expansions. Third, there is no evidence for significantly positive spousal earnings and hours response to head's displacements in recessions, during when the drop in head's earnings is much larger. On the other hand, spousal earnings and hours response to head's displacement in expansions becomes significantly positive at least 3 years after the displacement with a later increase by as much as 15 percent.

The last empirical result is particularly interesting because one could expect a stronger spousal earnings and hours response during times when the head experiences larger earnings losses. Hence, it motivates an investigation of potential reasons behind the small change in spousal earnings upon head's displacement in recessions. In the next section, I am going to calibrate the model to match the first empirical result above. Then, I am going to use the second and the third empirical findings to validate my model against. Next, using the model, I will investigate the role of countercyclical generosity of current government transfers on small labor earnings response to head's displacement in recessions.

1.3.2 Calibration

Functional forms

The model period is set to be a quarter. Utility function over consumption is $u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma}$ with risk aversion parameter σ. The labor market matching function is $M(v, u) = \frac{uv}{[u^\gamma + v^\gamma]^{1/\gamma}}$ as in den Haan, Ramey, and Watson (2000). This functional form implies that job finding rate $p(\theta) = \theta(1+\theta^\gamma)^{-1/\gamma}$ and vacancy filling rate $q(\theta) = (1+\theta^\gamma)^{-1/\gamma}$ are between 0 and 1.

As in Shimer (2005), I use a process for the job displacement rate that depends on labor productivity, which is extended to incorporate that displacement rates across jobs with various skill levels may be different: $\delta(h, z) = \bar{\delta} \times \exp\left(\omega_z^{\delta} \times (z - \bar{z})\right) \times \exp\left(\omega_h^{\delta} \times \left(h - \bar{h}\right)\right)$, where $\bar{\delta}$ is mean of the displacement rate over time, ω_z^{δ} captures the volatility of job displacement rate over time, and ω_h^{δ} captures the variation of job displacement rate across skills, and $\bar{z}$ and $\bar{h}$ are average labor productivity and human capital levels respectively. In general, these separation shocks can be interpreted as idiosyncratic match quality shocks that drive down the productivity of a match to a low enough level so that the match endogenously finds it optimal to dissolve, as in Lise and Robin (2017). Finally, production function is set to be $g(h, z) = hz$.

The generosity of means-tested transfers ϕ and employment-tested transfers b vary with aggregate state. I set $\phi(z) = \bar{\phi} - \omega_{\phi}(z - \bar{z})$ and $b(z) = \bar{b} - \omega_b(z - \bar{z})$. This implies that if, for example, $\omega_{\phi} > 0$, then means-tested policy is countercyclical.

The logarithm of the aggregate labor productivity z_t follows an AR(1) process:

$$\ln z_{t+1} = \rho \ln z_t + \sigma_{\epsilon}\epsilon_{t+1}$$

where $0 \leq \rho < 1$, $\sigma_{\epsilon} > 0$, and ϵ are independent and identically distributed standard normal random variables. I take z_t as the average seasonally adjusted quarterly real output per person in the non-farm business sector, which is constructed by the Bureau of Labor Statistics (BLS). The data for the time period 1948:I-2007:IV is logged and HP filtered to obtain deviations from trend.[35] In the model, I use five grid points for the process and set $\bar{z} = 1$. Estimation of this process yields $\rho = 0.7612$ and $\sigma_{\epsilon} = 0.0086$.

External calibration

Having specified functional forms and the law of motion of the productivity process, I now calibrate several parameters outside of the model. Table 1.2 summarizes these parameters and their values.

I choose a coefficient of relative risk aversion $\sigma = 2$. I set the value of leisure for male to be 0, implying that males are always searching for the job. Hence, changes in government

[35] I choose to exclude Great Recession period from this data due to the increase in the value of this measure of productivity, since the reconciliation of this is beyond the scope of my paper. Standard deviations of quarterly time series are computed as log deviations from an HP-trend with parameter 1600. For standard deviations of annual times series, I use the same object with parameter 100.

transfers do not affect the search behavior of the household's primary earner in the model. [36]

Next, I set $r = 0.005$, which generates an annual return on assets of around 2 percent. I set ζ_R to 0.00625, which implies 40 years of average working lifetime, and ζ_D to 0.01666, which implies 15 years of retirement.

I use data from National Income and Product Account (NIPA) tables and calculate the ratio of total wages and salaries to GDP between 1948-2007. I find that the average ratio across these years is 0.477. I then set worker's share of output α to this value.

I use 20 equally-spaced grid points for human capital, $h \in \{h_L, ..., h_H\}$. I set $h_L = 0.2$ and $h_H = 1.8$. I assume that the human capital increases by one step with probability π^E when employed. This implies $\Delta^E = 0.084$. Moreover, I set the probability of human capital depreciation when unemployed π^U to be 0.75.[37]

I also calibrate the asset and income thresholds $\underline{a}$ and $\underline{y}$ for means-tested transfers as well as the benefit expiration rate $e(\cdot)$ for employment-tested transfers outside of the model. In the baseline calibration, I consider three means-tested transfers: Supplemental Nutrition Assistance Program (SNAP), Earned Income Tax Credit (EITC), and Temporary Assistance for Needy Families (TANF).[38]

Asset threshold of eligibility for SNAP has been \$2000 between 1997 and 2007 according to the program reports published by U.S. Department of Agriculture.[39] Asset threshold

[36]The average labor force participation rate of married men is 92 percent, implying that η_m would be small if any. Moreover, this assumption allows me to focus on the effects of government transfers on spousal labor supply.

[37]Ljungqvist and Sargent (1998) set $\pi^U = 0.2$ in the calibration of their model, where the model period is taken to be 2 weeks. For a quarterly calibration (i.e. around 6 period long unemployment spell), this implies that the probability of experiencing human capital loss is around 0.75.

[38]Another quantitatively large means-tested transfer paid to households in the working age population is Medicaid. However, I do not incorporate insurance provided by Medicaid transfers into the calibration of the means-tested transfer policy instruments given that the baseline model does not incorporate extra eligibility risk such as health status or presence of a young children rules. In Section 1.6, I incorporate Medicare to the calibration of total-means tested transfers in an extension of baseline model with these eligibility risks, and study the effects of it on the main conclusions of this paper.

[39]These reports are titled "Characteristics of Supplemental Nutrition Assistance Program Households" and published for every fiscal year since 1997. Reports are available at https://www.fns.usda.gov/ops/supplemental-nutrition-assistance-program-snap-research.

of eligibility for EITC was \$2350 in 1995 and \$2900 in 2007 according to the program reports published by U.S. Internal Revenue Service (IRS).[40] Finally, in 2007, while the asset limit for TANF eligibility varied across different states, most of states applied \$2000 as the asset limit according to the program report published by U.S. Department of Health and Human Services.[41] In order to convert these values into model units, I calculate the ratio of the weighted-average of these asset limit values in the data to quarterly minimum labor earnings.[42] I find that this is around 0.73 in the data. Then, I set $\underline{a}$ in the model so that the ratio of asset limit $\underline{a}$ to quarterly minimum labor earnings, $\alpha h_L z_L$, in the model is the same as its counterpart in the data.[43] As a result, I set $\underline{a}$ to be 0.068.

Using the same program reports, I first calculate the weighted-average of income limits for these three programs in 2007. I find that the average gross quarterly income limit is around \$7000. Similarly, I calculate the ratio this value to the same quarterly minimum labor earnings in the data, and find that this ratio is around 2.58. Then, I set $\underline{y}$ in the model so that the ratio of income limit $\underline{y}$ to quarterly minimum labor earnings in the model is the same as its counterpart in the data. As a result, I set $\underline{y}$ to be 0.24.

Finally, the average duration of UI payments is around 26 weeks (i.e. 2 quarters), while this duration is typically extended during recessions. For example, during the Great Recession, UI payment duration was extended up to 99 weeks (i.e. 7.6 quarters). Hence, I set expiration rate of employment-tested transfers to be 0.5 (i.e. 1/2) when the labor productivity is greater or equal to its mean, and set it to be 0.13 (i.e. 1/7.6) when the labor productivity is at its lowest level.[44]

[40] These reports are available at https://www.irs.gov/pub/irs-prior.

[41] This report is available at https://www.acf.hhs.gov/sites/default/files/opre/wel_rules07.pdf

[42] Between 2000 and 2006, the federal minimum hourly wage was \$5.15, and in 2007, it was \$5.85. For these years, I calculate the total quarterly minimum labor earnings as min hourly wage $\times$ 40 hours/week $\times$ 13 weeks/quarter. Next, I divide the average of asset limit to the average of quarterly minimum labor earnings in the data.

[43] Notice that the quarterly minimum labor earnings in the model is invariant to policy changes. This allows me to calibrate both $\underline{a}$ and $\underline{y}$ outside of the model.

[44] Specifically, the grid for e is set to be $[1/(99/13), 1/(75/13), 1/(26/13), 1/(26/13), 1/(26/13)]$, where 75 weeks reflect the intermediary extensions of UI transfers.

Internal calibration

I jointly estimate the remaining fifteen parameters using the model to match the moments of the U.S. economy. Table 1.3 summarizes the results of this estimation.

I choose two paremeters, the discount factor β and borrowing limit a_L, to match two data moments of the asset-to-income distribution from Survey of Consumer Finances (SCF) 2007: the fraction of households with non-positive liquid wealth, and the median ratio of credit limit to quarterly labor income. Section 1.3.3 and Appendix A.2 provide the details of calculating these moments from the data.

Utility value of leisure for female η_f controls the level of opportunity cost of searching for a job for female. I choose η_f to match the female labor force participation rate (LFPR) relative to male LFPR in the data. I use monthly data from Current Population Survey (CPS) 2000-2007 to compute the average LFPR of males and females separately for a sample of married or cohabiting couples of ages between 20 and 60, i.e. a similar sample to the PSID sample used in Section 1.3.1. I find that the average LFPR is 71 percent for female and 92 for male, which implies a relative female LFPR of 77 percent.

The next five parameters are calibrated to discipline five labor market moments of the model. I obtain the average unemployment rate from quarterly data provided by the BLS between 1948 and 2007, and choose the cost of posting a vacancy κ to match the same level in the model.[45] Next, I target the volatility of job finding rate in the data by choosing the elasticity of matching function γ. I use quarterly data from CPS between 1948 - 2007 and compute standard deviation as log deviations from an HP-trend with parameter 1600.[46] Finally, I use three parameters $\bar{\delta}$, ω_z^δ, and ω_h^δ of the job displacement process in the model to match three moments in the data: the average job displacement rate, its volatility over time, and its variation across the earnings distribution.[47] According

[45] I use the data provided by FRED - Federal Reserve Economic Data from the Federal Reserve Bank of St. Louis, which is constructed from the BLS data.

[46] Job finding rate data was constructed by Robert Shimer. For additional details, please see Shimer (2012). The data from June 1967 and December 1975 were tabulated by Joe Ritter and made available by Hoyt Bleakley.

[47] The model-implied Beveridge curve, which plots the relationship between unemployment and vacancies, exhibits a negative slope as in the data. This is because when labor productivity declines, firms cut back on vacancies, which translates to lower job finding rates and higher unemployment. Moreover, the rise in separation shocks further amplifies the increase in unemployment. As a result, unemployment and vacancies

to the Job Openings and Labor Turnover Survey (JOLTS) data between 2008 and 2018, average quarterly total separation rate is around 9 percent of total employment, and that an average of 38 percent of all separations are due to layoff or discharge. This implies a quarterly average job displacement rate of 3.4 percent.[48] I find a standard deviation of job displacement rate as 0.06. Finally, I calculate the ratio of median predisplacement labor earnings of displaced household heads (i.e. labor earnings one year prior to displacement) to median labor earnings of never displaced heads using the PSID data under the sample created in Section 1.3.1. I find that this ratio in the data is 76 percent, which implies that displacement risk is relatively higher for the lower paying jobs. In the model, ω_h^δ controls the heterogeneity in job displacement risk across jobs with different human capital, and as a result different wages given that skill level directly affects wages in the model. Hence, I choose ω_h^δ to match the same earnings ratio in the model.

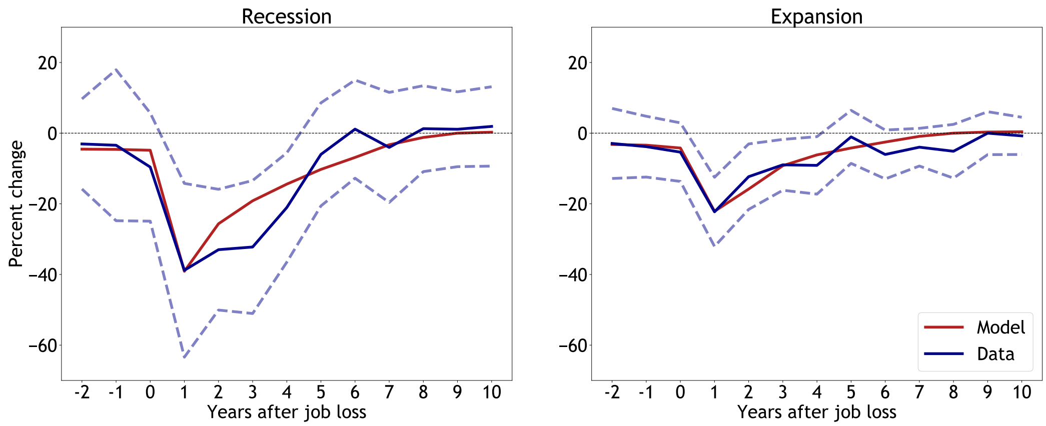
I choose two parameters of the human capital process to discipline the cyclicality of the initial drop in head earnings upon job loss, and the labor earnings distribution across employed individuals. Recall that, in the model, the magnitude of the decline in human capital Δ^U varies across displacements that occur in recessions and expansions, so that the model is constructed to generate the cyclicality of the initial drop in head earnings upon job loss. I set $\Delta^U = 0.59$ for relaziations of z that are lower than its mean value $\bar{z}$, and $\Delta^U = 0.34$ for realizations of z that are greater than or equal to $\bar{z}$.[49] Figure 1.4 compares

move in the opposite direction.

[48]This value is larger than estimates based on annual data. Davis and von Wachter (2011) report annual job displacement rate of around 4 percent using SSA data, which is accordance with job displacement rates reported by Stevens (1997) using the PSID data and Farber (1997) using the Displaced Worker Supplement. However, these estimates are likely to be underestimated of the true dusplacement probabilities because of recall bias (Topel 1991).

[49]Notice that these values of Δ^U are quite large. Given that the human capital levels are in between 0.2 and 1.8, a drop of 0.59 implies that when a worker with a mean human capital level of $\bar{h} = 1$ loses his job in a recession, he would lose 60 percent of his skill with probability π^U in the quarter following displacement. However, it is well known in this literature that generating large and persistent earnings losses upon job displacement with a more reasonable calibration of the human capital process is quite unsuccessful. Hence, for example, Huckfeldt (2016) use a model of two different types of occupations (skill-intensive and skill-neutral) with a more reasonable parametrization of the human capital process to explain the cyclicality of earnings loss. In this paper, I do not aim to endogenously generate the cyclicality of earnings loss, but rather take this as a calibration target and anaylze its effects on spousal behavior. Moreover, one could

Figure 1.4: Relative labor earnings of the head upon job displacement: Model vs data



Note: This figure plots the changes in relative labor earnings of the family head upon his job displacement in recessions (left panel) and expansions (right panel) both in the model and in the data. I estimate the changes in relative labor earnings from a distributed lag-recession model using PSID. The solid blue line shows the point estimates and the dashed light blue line shows the 90 percent confidence interval. I compare these results to the estimates obtained from the same regression using the model simulated data, which is aggregated up to yearly period. Earnings drop one year after displacements both in recessions and expansions are targeted in the model calibration.

head's earnings loss upon his job displacement in recessions and in expansions between the model and the data, where the latter was obtained in Section 1.3.1. While the model generates the same magnitude of earnings losses one year after displacements in recessions and expansions, as they are targeted in calibration, the recovery of head's earnings loss is slightly later in the model than in the data.

Next, the probability of human capital accumulation π^E controls the skill distribution, and thus labor earnings distribution in the model. For example, if π^E is very large, then workers would quickly accumulate their human capital, and resulting dispersion of labor earnings would be small. I calculate the ratio of 90th to 10th value of labor earnings distribution of employed individuals from the PSID 2007 survey as 7.6. I choose π^E to match the same ratio in the model.

Finally, I choose remaining five parameters of the model related to government transfers. I measure the average generosity of means-tested transfers by the ratio of total quarterly

interpret a relatively larger loss of human capital in recessions as "occupational displacement" similar to Huckfeldt (2016).

means-tested transfers per recipient individual to the minimum quarterly labor earnings using data from NIPA 1976 - 2007 and program reports.[50] The average ratio across these years in the data is 0.74. I choose the average level of means-tested transfers $\bar{\phi}$ so that this statistic in the model is the same as its data counterpart. Similarly, I calculate the average ratio of total quarterly UI transfers per unemployed individual to the minimum quarterly labor earnings using data on UI transfer amount from NIPA and data on total number of unemployed from BLS between 1948 - 2007, and find 0.36. Again, I choose the average level of employment-tested transfers $\bar{b}$ so that this statistic in the model is the same as its data counterpart. Using micro data from SIPP between 1996 and 2014, I find that, on average, around 35 percent of all means-tested transfers and 60 percent of total UI transfers are paid to married households. Also, married households constitute around 33 percent of all means-tested transfer recipients and 58 percent of all UI recipients. Finally, around 60 percent of all transfers received by the married households are means-tested transfers. I present detailed results in Appendix A.2.

Next, I measure the cyclicality of means-tested transfers by the standard deviation of total means-tested transfers per recipient individual. The standard deviation of this value across years in the data is 0.06. In the model, I choose ω_ϕ to generate the same value for the standard deviation of means-tested transfers per recipient individual.[51] Similarly, I measure the cyclicality of employment-tested transfers by the standard deviation of total UI transfers per unemployed individual. In the data, this value is 0.15, implying that UI transfers are much more cyclical than means-tested transfers. In the model, I set ω_b to match the same value for this statistic. Last, I choose retirement transfers b_R to match the average ratio of total social security payments to GDP between 1976 - 2007 in NIPA.[52]

[50]For each program, the program reports published by the government agencies provide information on the number of recipient individuals for each year. Using this data together with data from NIPA, I calculate the total transfer amount per recipient for each program at a given year and then sum these amounts to obtain the total means-tested transfer amount per recipient for that year. 1976 is the year that we observe positive transfer amounts paid under each of the three programs in NIPA. I divide annual amounts of total means-tested transfers per recipient by 4 to obtain the quarterly amounts. Then, I divide this amount by the minimum quarterly labor income to obtain the ratio of total quarterly means-tested transfers per recipient to minimum labor earnings in the data.

[51]Standard deviation of this annual time series is computed as log deviations from an HP-trend with

1.3.3 Validation

In this section, I will compare model outcomes with a list of important untargeted data moments. I will emphasize that the model endogenously generates reasonable changes in family earnings and spousal earnings upon head's displacement over the business cycle. This is important for two reasons. First, it later allows me to quantify the crowding-out effects of government transfers (incentive costs) on spousal earnings response to displacement by comparing the change in spousal earnings under counterfactual government policies. Second, it helps the model to correctly quantify the magnitude and cyclicality of available spousal insurance, which in turn determines the insurance benefits of government transfers over the business cycle. The other untargeted moments presented below are also related to either insurance benefits or incentive costs of government transfers, and thus relevant for optimal policy analysis.

Family and spouse earnings upon head's job displacement over the business cycle

Figure 1.5 compares the change in family earnings upon head's job displacement in recessions and in expansions between the model and the data. In the model, the magnitudes of drops in family earnings one year after head's displacements both in recessions and in expansions are slightly larger than their respective counterparts in the data. Moreover, family earnings in the model fully recover around 2 years later than full recovery of family earnings in the data both in recessions and in expansions.

Next, Figure 1.6 compares the change in spouse earnings upon head's job displacement in recessions and in expansions between the model and the data. In the model, changes in spousal earnings upon head's displacements both in recessions and expansions are limited as in the data. However, the model fails to capture the slight positive trend in the change in spousal earnings in expansions that we observe in the data. In recessions (expansions), the mean of the post displacement coefficients is 3.2 (5.2) percent in the model compared

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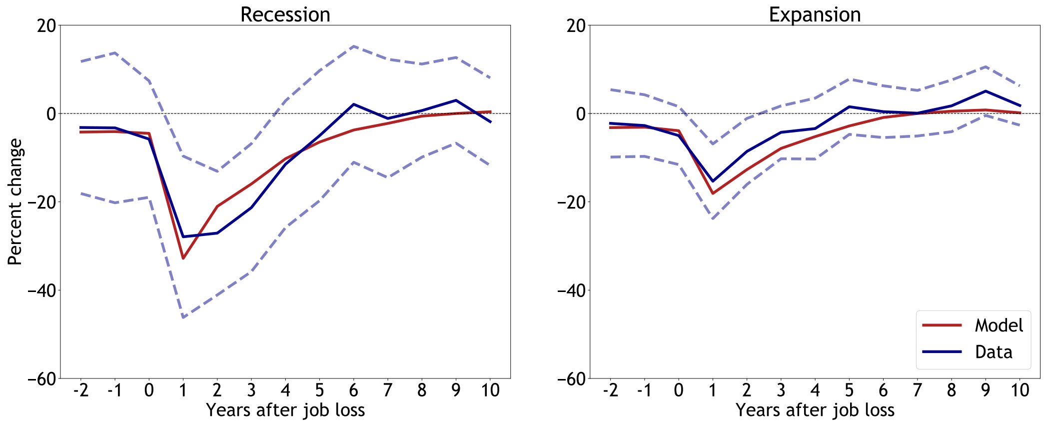
parameter 100.

[52] There is a large increase in social security transfers between 1948 - 1975, but this increase mostly disappeared since then. Given that I do not model any trend in social security transfers, I calculate the social security to GDP ratio starting from 1976 in the data.

Figure 1.5: Relative labor earnings of the family upon job displacement: Model vs data



Note: This figure plots the changes in relative labor earnings of the family upon head's job displacement in recessions (left panel) and expansions (right panel) both in the model and in the data. I estimate the changes in relative family earnings from a distributed lag-recession model using PSID. The solid blue line shows the point estimates and the dashed light blue line shows the 90 percent confidence interval. I compare these results to the estimates obtained from the same regression using the model simulated data, which is aggregated up to yearly period.

to -0.8 (8) percent in the data.

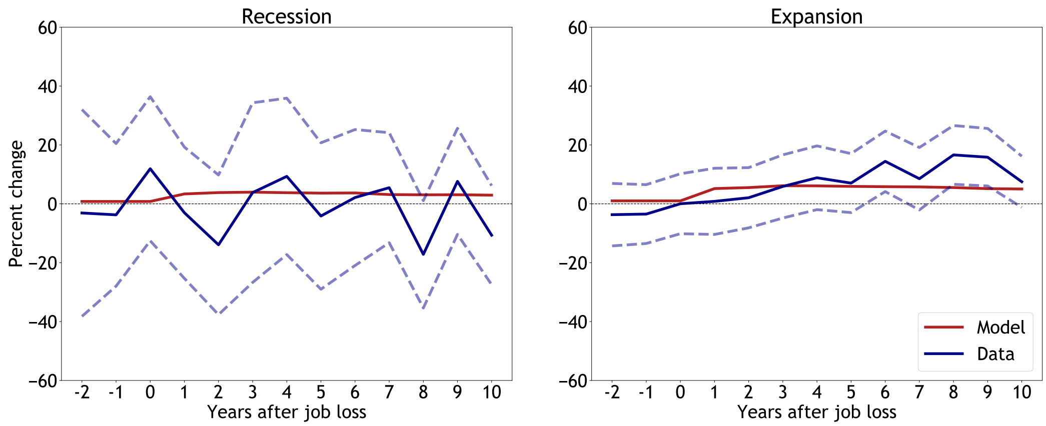
This comparison shows that when the model is calibrated to match level and cyclicality of i) head's earnings drop upon job loss, ii) government transfers, and iii) job finding rates and job separation rates, it is able to generate small change in spousal earnings upon head's displacement especially in recessions, as I have documented in the data.

Consumption upon job loss

I now compare the average drop in family consumption in the year following head's job displacement in the model and in the data. This is another way to assess the insurance benefits of transfers in the model. For example, if the magnitude of consumption drop is very low in the model, then the insurance benefits would be understated in the model.

Several papers in the literature estimated the average consumption drop upon job loss from various data sources. Gruber (1997) estimates a decline in food expenditure of 6.8 percent using the PSID for the period up to 1987. Saporta-Eksten (2014) uses cross-sectional variation in the PSID and measures an 8 percent decline in consumption expenditure

Figure 1.6: Relative labor earnings of the spouse upon job displacement: Model vs data



Note: This figure plots the changes in relative labor earnings of the spouse upon head's job displacement in recessions (left panel) and expansions (right panel) both in the model and in the data. I estimate the changes in relative spouse earnings from a distributed lag-recession model using PSID. The solid blue line shows the point estimates and the dashed light blue line shows the 90 percent confidence interval. I compare these results to the estimates obtained from the same regression using the model simulated data, which is aggregated up to yearly period.

in the year during which a job loss happens.[53] Stephens (2004) estimates the average decline in food expenditure upon job loss in the Health and Retirement Survey (HRS) and the PSID and finds that the decline is between 12 percent (PSID) and 15 percent (HRS). Browning and Crossley (2001) report a 14 percent decline using Canadian Out of Employment Panel (COEP) survey data. Chodorow-Reich and Karabarbounis (2016) conduct an analysis of the effects of job loss on consumption both in the PSID and the Consumer Expenditure Survey (CE) and find that the decline in total food expenditure is between 14 percent (PSID) and 21 percent (CE). Finally, Aguiar and Hurst (2005) measure a 19 percent decline in food expenditure among the unemployed using scanner data.
I estimate the consumption drop upon job displacement in the model using Equation (1.9). I find that family consumption drops on average by 14 percent in the year following head's displacement, which is in line with available empirical estimates discussed above.

[53]However, this estimate does not condition on the fraction of the year spent as unemployed. When we assume an average unemployment duration of 17 weeks, this would imply a decline in consumption of around 24 percent.

Marginal propensity to consume: average, cyclicality, and heterogeneity

Insurance benefits of transfers can directly be measured by the fraction of an unexpected transfer that families spend on consumption.

The empirical literature documents two aggregate marginal propensity to consume (MPC) data moments that I can use to validate the model. First, Parker, Souleles, Johnson, and McClelland (2013) measure that households, under different specifications, spend between 12 and 30 percent of unexpected tax rebates in the quarter that they are received. Second, Gross, Notowidigdo, and Wang (2016) measure the cyclicality of the MPC by exploiting the unexpected changes in credit card borrowing limits of previously bankrupt individuals and find that the MPC is countercyclical over the Great Recession. In particular, they show that the average semiannual MPC difference of borrowing-constrained individuals between 2008 and 2011 is 8 percent.

In the model, I compute the MPC of a family by calculating the fraction of an unexpected transfer, scaled such that it is equivalent to $500, that the family spends on consumption. This transfer can be interpreted as a one time unexpected deposit to family's bank account. As in Kaplan and Violante (2014), I implement a $500 rebate in order to ensure consistency with the above available empirical estimates.

Table 2.4 compares the average economy-wide quarterly MPC and the magnitude of MPC increase for borrowing-constrained families in recessions in the model to available empirical estimates discussed above.[54] The results show that the model generated average quarterly MPC lies in the middle of range of estimates provided by Parker, Souleles, Johnson, and McClelland (2013). However, the cyclicality of MPC for borrowing-constrained individuals is slightly larger in the model than in the data. This means that the insurance benefits in recessions would probably be slightly overestimated in the model.[55]

In order to quantitatively understand how MPCs differ across heterogeneous families in the economy, Table 1.5 presents the average quarterly MPC of different employment, wealth, and skill level of the head groups based on the stationary distribution of the economy.

[54] I group families with non-positive wealth as borrowing-constrained families. Then, I report the difference in average semiannual MPC for such families between when labor productivity is strictly below the mean and it is equal to or above the mean.

[55] Nevertheless, the optimal policy is less generous in recessions, implying that even if insurance benefits would be overestimated in recessions, incentive costs still exceed the insurance benefits in recessions.

Noticeably, wealth-poor families with unskilled head exhibit highest MPC given the absence of self-insurance through savings and low labor earnings of the head. On the other hand, wealth-rich families spend only 2 percent of the tax rebate on consumption regardless of the head's skill and employment status of their members.

Asset-to-income distribution

Wealth distribution of the economy is also relevant for both insurance benefits and incentive costs of transfers. Both insurance benefits and incentive costs are larger for wealth-poor families, implying that the model would overstate benefits and costs of transfers if the fraction of such families is much larger in the model than its data counterpart. For this reason, fraction of families with non-positive liquid wealth is taken as a calibration target in Table 1.3, while the percentiles of the distribution presented below are not targeted in the calibration.

To normalize wealth and better capture the level of self-insurance available to families, I compute asset-to-income ratio by dividing net liquid assets to quarterly family labor income both in the PSID 2015 and SCF 2007.[56] I use net liquid asset holdings as the primary measure of wealth because of its immediate availability as a means to smooth consumption in the event of job loss. The net liquid asset holdings of a family are calculated by adding transaction accounts (checking, saving, money market accounts) and tradable assets (mutual funds, certificates of deposits, stocks, bonds), and then deducting unsecured debt. Furthermore, countable assets for asset eligibility threshold of means-tested transfers often include vehicles across many states in the United States. For this reason, I incorporate vehicle equity to the liquid assets calculation. Appendix A.2 provides more details on the calculation of the liquid asset to quarterly labor income distributions from the PSID and SCF.

I compute the same distribution using the model simulated data and compare it to empirical estimates, as shown in Table 2.2. In the model, the median family holds net liquid wealth equivalent to 1.1 quarter of family labor earnings, while it is 1.2 quarter of family labor

[56]PSID collects information for the amount of credit card debt starting from 2011 survey. Since this information is needed to calculate net liquid wealth, we can only calculate the asset-to-income distribution after 2011. Here, I choose to present data from the latest survey.

earnings both in the PSID and the SCF. However, the model misses both the amount of wealth owned by richest and the dispersion of wealth among the rich families, given that 75th and 90th percentiles are much closer in the model than in the data.

Correlated spells of family members

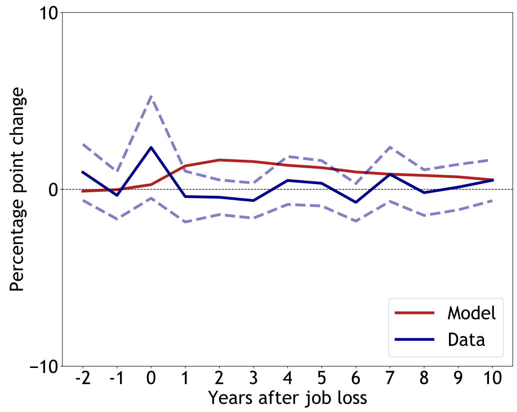
Finally, imagine that there are two types of families in which the head is displaced: i) the spouses are also displaced around the year of their husband's displacement and they also experience earnings losses, and ii) the spouses start working and contributing significantly to the family income. If this is the case, then these two opposite changes in spousal earnings among families with displaced heads may cancel out each other, and we would see small changes in spousal earnings on average. Moreover, if this is the case, the government policy should be targeted toward the former type of families.

In order to test whether this is the case, I estimate the same regression given in Equation (1.9) in which the outcome variable is now a dummy variable that takes a value of 1 if the spouse is also displaced, and 0 otherwise. Figure 1.7 compares the percentage point change in spousal displacement probability upon head's displacement both in the model and in the data. It shows that there is at most 2 percentage point increase in spousal displacement probability upon head's displacement in the data. The model successfully generates a similar pattern given that there is no such correlation of unemployment spells across family members present in it.

1.4 Effects of Transfers on Spousal Earnings Response

In this section, I will present two main results. First, I will implement a counterfactual experiment to discuss the role of more generous government transfers during recessions in explaining the small change of spousal earnings upon the head's displacement in recessions. Second, I will compare the model implied spousal labor supply elasticities to existing microeconomic estimates to provide external validation for the model's predictions from the counterfactual experiment.

Figure 1.7: Change in spousal displacement probability upon head's displacement: Model vs data



Note: This figure plots the changes relative displacement probability of spouses upon head's job displacement both in the model and in the data. I estimate the percentage point change in relative spousal displacement probability in the data from a distributed lag-recession model using PSID. The solid blue line shows the point estimates and the dashed light blue line shows the 90 percent confidence interval. I compare these results to the estimates obtained from the same regression using the model simulated data, which is aggregated up to yearly period.

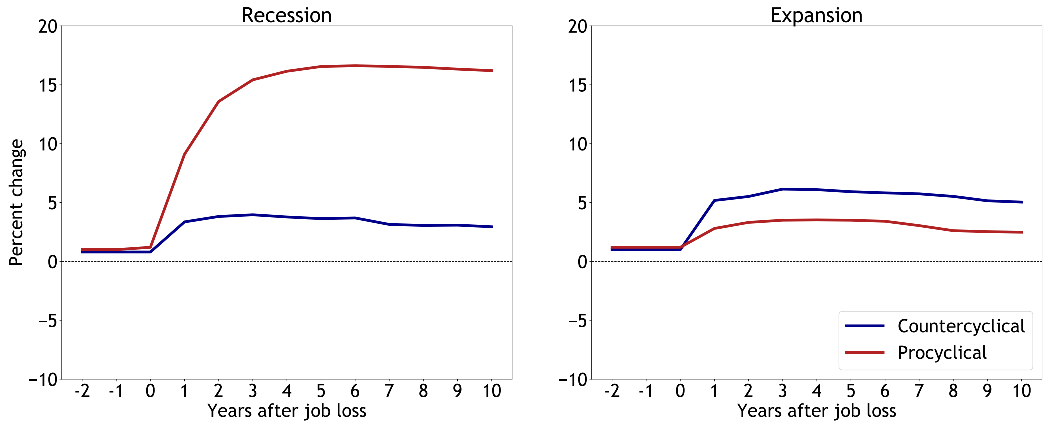
1.4.1 Counterfactual experiment

When the model is calibrated to match the level and cyclicality of i) head's earnings drop upon job loss, ii) government transfers, and iii) job finding rates and job separation rates, it is able to generate small changes in spousal earnings upon the head's displacement especially in recessions, as I have documented in the data.

I will now analyze the change in spousal earnings in response to head's displacement over the business cycle under alternative government policies. The calibrated model is designed to isolate the effect of varying transfers on spousal earnings. I do this in two steps. First, I normalize the value of leisure for male η_m as 0 to make male workers inelastic to changes in government policy. Second, I assume that the wage paid in each human capital submarket is a fraction of the period aggregate labor productivity. This implies that wages and firm vacancy posting decisions are invariant to government policy in the baseline model.[57] These two features of the model allow me to focus on changes in spousal earnings response to

[57]In Section 1.6, I explore the implications of allowing for endogenous wage choices by households to capture the effects of transfers on labor demand.

Figure 1.8: Relative labor earnings of the spouse upon job displacement under different policies



Note: This figure plots the changes in relative labor earnings of the spouse upon head's job displacement in recessions (left panel) and expansions (right panel) in the model under the countercyclical baseline policy and a procyclical policy, which later will be shown as the optimal policy. I estimate the changes in relative spouse earnings from a distributed lag-recession model using model simulated data, which is aggregated up to yearly period.

displacements under different government policies.

Figure 1.8 compares the change in spousal earnings upon the head's job displacement in recessions and in expansions in the model under the countercyclical baseline policy and a procyclical policy, which later will turn out to be the optimal policy. It shows that under the procyclical policy, relative spousal earnings increase by up to 15 percent in recessions, but remains below 5 percent in expansions. In particular, I find that the mean of the post-displacement coefficients in recessions is 14 percent under the procyclical policy as opposed to 3.2 percent under the current policy. For expansions, it is 2.9 percent under the procyclical policy and 5.2 percent under the current policy.

This result is driven by the fact that in recessions, the large earnings losses incurred by the head of the family are mitigated by generous transfers from government in the current policy. This lowers the marginal utility of consumption of the family and thus lowers spousal incentives to increase earnings during recessions. When transfers are less generous in recessions, a high marginal utility of consumption induces spouses to increase earnings to raise family consumption. In contrast, expansions are periods when earnings losses are small and the marginal utility of consumption is low regardless of the generosity of transfers.

As such, spousal response is small and inelastic to government transfer generosity.

1.4.2 Spousal labor supply elasticities: Data vs model

I now implement an external validation exercise to test whether the model implied spousal labor supply response to changes in government policies is reasonable. This is important because, for example, if the magnitude of this elasticity is much larger in the model than in the data, then the crowding-out effects of transfers would be overestimated in recessions, during when transfer generosity increases. As a result, the model would overstate the role of government transfers in explaining the small change of spousal earnings in response to the head's displacement in recessions. Furthermore, in the optimal policy analysis, the model would also overestimate the incentive costs of transfers, which would bias results toward less generous transfers.

The first panel of Table 1.7 compares female participation elasticity with respect to net wages in the data and in the model. Chetty, Guren, Manoli, and Weber (2012) summarize the magnitude of female participation elasticity estimates identified from permanent wage changes resulting from tax reforms across seven different studies.[58] They report female participation elasticity as the change in log employment rates divided by the change in log net-of-tax wages. Employment rate is typically defined as positive work hours in a year. The magnitude of these empirical estimates on the female participation elasticity with respect to net earnings lie between 0.15 and 0.43.

In order to calculate magnitude of the female participation elasticity with respect to net-of-tax wages in the model, I implement an unexpected and permanent decline in τ so that the average net wages of the employed in the model, i.e. $(1-\tau)\,\bar{w}$ where $\bar{w}$ is the average wage in the model prior to change in tax rate, increases by 10 percent. This way, the model generates permanent changes in wages resulting from an income tax reform, which is similar to the identification used in the microeconomic studies. I then calculate the model implied female participation elasticity with respect to net wages as the ratio of the change in log female employment rates to the change in log average wages of the employed.

[58] Chetty, Guren, Manoli, and Weber (2012) summarize results from nine different papers in total. However, two of these papers focus on men in their sample. Hence, I consider the remaining seven papers as my comparable benchmark.

I find that the magnitude of female participation elasticity with respect to net wages is 0.31 in the model, which lies in between the range of values found in the literature.

Moreover, it is possible to divide a subset of these empirical estimates summarized by Chetty, Guren, Manoli, and Weber (2012) into two groups based on the demographics and characteristics of their sample. On one hand, we can group estimates by Eissa and Liebman (1996), Meyer and Rosenbaum (2001), and Eissa and Hoynes (2004) as participation elasticities of female who are living in low income households. This is because these three studies focus on either married women living in low income households or single women receiving government transfers, both of which can be interpreted as spouses in low income households from the lens of my model. In these papers, the magnitude of female participation elasticities with respect to net-of-tax wages are 0.30, 0.43, and 0.27 respectively. On the other hand, Liebman and Saez (2006) estimate the participation elasticity of women who are married to high income men as 0.15. As a result, the participation elasticity is much larger for females living in low income households than in high income households.

This allows me to compare the heterogeneity of female participation elasticity across families with different income levels in the model with that of the data. I compute the magnitude of female participation elasticity with respect to net wages separately for women in low income households and high income households using the same calculations as before.[59] I find that the magnitudes of participation elasticities are 0.38 for spouses living in low income households and 0.21 for spouses living in high income households. Hence, the model also generates a quantitatively reasonable difference between the participation elasticities of females across different household income groups. However, the model overestimates the magnitude of the female participation elasticity for high income households. This is because as shown in Section 1.3, the model does not fully capture households in the right

[59] Eissa and Hoynes (2004) report the gross hourly wage of husband and wife as \$12.09 and \$7.56 in 1995 dollars respectively for their entire sample. This implies that the ratio of total gross hourly wage of the household (\$19.65) to the hourly minimum wage in 1995 (\$4.25) is equal to 4.62 in their sample. To discipline the model sample of low income households, I consider households whose total gross labor earnings are less than or equal to 4.62 times of the model's minimum wage as low income households. On the other hand, the data sample in Liebman and Saez (2006) that is used to calculate elasticities for high income families include heads whose earnings are above 75th percentile of earnings. Hence, in the model, I group households as high income households in the model if the head's gross wage is greater than or equal to 75th percentile of the wage distribution of the employed prior to the policy change.

tail of the asset and income distribution for whom these elasticities are very low.

The second panel of Table 1.7 compares female labor earnings elasticity with respect to transfers in the data and in the model. The goal here is to provide external evidence for the effect of transfer generosity on spousal labor supply response to the head's job displacement. In order to do so, I will compare the change in spousal earnings upon the head's job displacement for households living in either U.S. states providing the most generous transfer payments or states providing the least generous transfer payments. Using the PSID, I group the sample of households into these two groups and run the regression Equation (1.9) separately for spousal earnings and transfer receipts as dependent variables, also controlling for state fixed effects and state level employment rates to account for labor market differences.[60] As a result, I obtain post-displacement dollar amount changes of spousal earnings and transfer receipts of households upon the head's job displacement relative to non-displaced households separately for these two samples. Then, I calculate the ratio of the difference in log spousal earnings to the difference in log transfer receipts of displaced households between the sample in the most generous states and in the least generous states. I find that this ratio is 0.44, and I take this as the magnitude female labor earnings elasticity with respect to transfers in the data.[61]

I perform a similar exercise in the model by separately implementing a permanent 10 percent decline in i) average generosity of means-tested transfers $\bar{\phi}$, and ii) average generosity of employment-tested transfers $\bar{b}$. I find that female labor earnings elasticity with respect to $\bar{\phi}$ is 0.36 and with respect to $\bar{b}$ is 0.01. The combined elasticity of these transfers is

[60] U.S. states with most generous safety net programs are taken as Vermont, District of Columbia, North Dakota, Massachusetts, and Minnesota. U.S. states with the least generous safety net programs are taken as Alabama, South Carolina, Florida, Nevada, and Georgia. I have 421 displacements in the former sample and 647 displacements in the latter sample. Given this small sample size, it is unfortunately not possible to further divide these samples into displacements in recessions and in expansions, or displacements that occur in low income or high income families. One valid concern in this estimation is selection of households with frequently displaced heads into states with more generous transfers. I acknowledge this concern and view the estimates in this exercise as suggestive correlational evidence.

[61] This result implies a higher spousal labor supply response when government transfers are less generous. Similarly, Bredtmann, Otten, and Rulff (2017) use data from 28 European countries between 2004 and 2013, and document that spousal labor supply to their husband's unemployment is strongest in less generous welfare states (i.e. the Mediterranean, Central, and Eastern European countries), while it is weakest in more generous welfare states (i.e. the Continental European and Nordic countries).

close but lower than the elasticity of 0.44 in the data. Interestingly, in the model, most of the response is driven by changes in means-tested transfers while female earnings are inelastic to the generosity of employment-tested transfers. This is because eligibility for employment-tested transfers require job search and such transfers pay only low amounts for a short duration.

Finally, I calculate female labor earnings elasticity with respect to these two types of transfers separately for low income and high income households in the model. In particular, I find that the earnings elasticity with respect to $\bar{\phi}$ is 0.47 for females in low income households and 0.23 for females in high income households. In recessions, the head's job displacement causes a larger drop in the household income. For this reason, spousal labor supply is more responsive to changes in government transfers in recessions. Hence, reducing the generosity of transfers in recessions increases spousal earnings response to the head's displacement in recessions significantly, as shown in Figure 1.8.

1.5 Optimal Policy

The results in the previous section show that the incentive costs of transfers on spousal labor supply are larger in recessions and smaller in expansions. Since the existing transfers are more generous in recessions, it implies that there may be potential welfare gains from changing the generosity of government transfers over the business cycle. Motivated by this observation, in this section, I will study the optimal design of means-tested and employment-tested transfers over the business cycle.

1.5.1 Welfare calculation

The ex-ante welfare gains or losses of any proposed government policy is measured by answering the following question: how much additional lifetime consumption must be endowed to all families in an economy where the baseline countercyclical policy is being implemented so that average welfare will be equal to an economy where the proposed policy is implemented? This criterion evaluates whether an alternate policy will be welfare improving when compared the baseline countercyclical policy.

Let o denote the baseline (old) policy and n denote the new/proposed policy. Using a utilitarian social welfare function, I compute the additional percent lifetime consumption $\bar{x}$ that makes the average ex-ante welfare equal across these two economies using the following equation:

$$\begin{aligned}\int_j \left[E_0 \sum_{t=0}^{\infty} \beta^t U\left(c_{jt}^o\left(1+\bar{x}\right),\, l_{m,jt}^o,\, l_{f,jt}^o,\, s_{m,jt}^o,\, s_{f,jt}^o\right)\right] d\Gamma_{ss}\left(j\right) \\ = \int_j \left[E_0 \sum_{t=0}^{\infty} \beta^t U\left(c_{jt}^n,\, l_{m,jt}^n,\, l_{f,jt}^n,\, s_{m,jt}^n,\, s_{f,jt}^n\right)\right] d\Gamma_{ss}\left(j\right)\end{aligned} \tag{1.10}$$

subject to the government budget constraint given in Equation (2.7). Here, c_{jt}^k, $l_{i,jt}^k$, and $s_{i,jt}^k$ denote household consumption, employment status, and participation decision of individual $i \in \{m, f\}$ of family j at time t under government policy $k \in \{o, n\}$, and Γ_{ss} is the stationary distribution at the stochastic steady state of the economy.

The welfare exercise in Equation (2.15) can be interpreted as follows. Consider two countries populated by people with the same type-distribution under transfer policy o. The only difference between both countries is that the government of the first country continues to implement policy o, while the second introduces policy n unexpectedly and permanently.[62] The welfare effects of a proposed policy is measured by how much additional lifetime consumption $\bar{x}$ should the first government compensate a family who is behind the veil of ignorance (i.e., does not know initial type in the stationary distribution) in order to make the family indifferent between being part of one of these two countries? Thus, the best policy n that the second government can implement is the one that makes the first government pay the highest compensation $\bar{x}_{\max}$ to weakly attract this prospective citizen. This policy will be the optimal transfer policy.

In my main optimal policy analysis in this section, I restrict policy instruments to take the form of the means-tested transfer amount and employment-tested transfer amount as linear functions of current aggregate labor productivity. I set $\phi\left(z\right) = \bar{\phi} - \omega_{\phi}\left(z - \bar{z}\right)$ and $b\left(z\right) = \bar{b} - \omega_b\left(z - \bar{z}\right)$, where $\bar{z}$ is the average level of labor productivity z. This implies that if, for example, $\omega_{\phi} > 0$, then means-tested policy is countercyclical. Under this restriction of policy instruments, I search over five policy parameters $\left(\bar{\phi},\, \omega_{\phi},\, \bar{b},\, \omega_b,\, \tau\right)$ to solve for the

[62] Hence, the economy of the second country will transition to its new steady state under policy n. Thus, the welfare exercise already incorporates the welfare gains or losses from the transitional dynamics.

optimal transfer policy.[63]

1.5.2 Optimal policy in the baseline model

Table 1.8 compares per recipient transfer amount as a multiple of minimum wage in the model paid under the means-tested and employment-tested transfers in the current policy and the optimal policy. Separate comparisons are presented for when the aggregate labor productivity z is at its average level $\bar{z}$, and its minimum level, i.e. deep recession. Minimum wage in the model is exogeneous to changes in policy as discussed previously in Section 1.3. Thus, reporting transfer amounts as a multiple of minimum wage presents a useful interpretation.

The optimal level of transfers on average is determined by the tradeoff between insurance benefits vis-a-vis incentive costs. When labor productivity is at its average level, the optimal policy features a lower level of means-tested transfers and higher level of employment-tested transfers when compared to the current policy under the average labor productivity. This way, the optimal policy induces larger spousal labor force participation. Nevertheless, total transfers under the optimal policy is 2.58 times the minimum wage which is close to 2.48 under the current policy. This is because, given that the model well accounts for important sources of private insurance channels (e.g. assets and spousal earnings), there is little redistributive role of government transfers.

The optimal cyclicality is determined by how insurance benefits net of incentive costs vary over the business cycle. The most striking difference between the optimal policy and current policy is that optimal means-tested transfers provides less generous transfers in recessions (procyclical) while the current policy expands benefits (countercyclical). In recessions, optimal means-tested transfers reduce the amount paid per recipient household from 1.40 to 0.40 times the minimum wage, whereas current policy increases it from 1.61

[63]This means that for any values of $\left(\bar{\phi}^n,\, \omega_\phi^n,\, \bar{b}^n,\, \omega_b^n\right)$, I first solve for the income tax rate τ^n that balances the government budget in the long-run. Then, using these policy parameters, I numerically compute the welfare gains/losses relative to the baseline values of $\left(\bar{\phi}^b,\, \omega_\phi^b,\, \bar{b}^b,\, \omega_b^b,\, \tau^b\right)$, i.e. the baseline countercyclical policy, using Equation (2.15). Given any guess of $\bar{x}$, I can compute for both sides of this equation over the stationary distribution for any values of $\left(\bar{\phi}^n,\, \omega_\phi^n,\, \bar{b}^n,\, \omega_b^n,\, \tau^n\right)$. I then solve for the $\bar{x}$ that equates both sides of Equation (2.15). Finally, I select the policy that yields the highest welfare gain $\bar{x}_{max}$ as the optimal transfer policy.

to 1.90. Less generous transfers in recessions alleviates large incentive costs of public insurance on the labor supply of spouses and induce female participation as a response to a head's displacement due to a larger increase in marginal utility of consumption as a result of head's larger earnings losses upon his displacements in recessions. On the other hand, optimal employment-tested transfers is more generous in recessions (countercyclical) and is of comparable cyclicality with the current policy. In particular, the amount paid per eligible individual increases from 1.18 to 1.34 times the minimum wage under the optimal policy, while it increases from 0.86 to 1.04 under the current policy. The provision of insurance benefits in recessions is better accomplished through employment-tested transfers because these are small payments and more importantly, limited in duration. This dampens its crowding-out effects on the labor supply of family members. This is corroborated by results of Section 1.4.2, where I show that the magnitude of the elasticity of female labor supply elasticity with respect to changes in $\bar{b}$ is small. Overall, total government transfers under the optimal policy is procyclical, while it is countercyclical under the current policy. The optimal policy yields welfare gains equivalent to 0.61 percent additional lifetime consumption compared to the current policy. Roughly half of this welfare gains is attributable to optimizing over the average level of transfers, and the other half is attributable to optimizing over the cyclicality of transfers.[64]

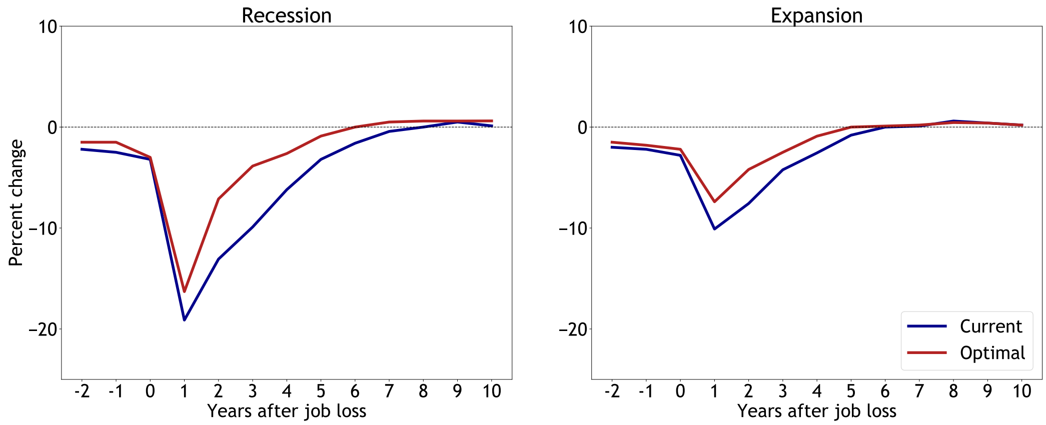
Understanding the reasons behind the optimality

In order to better understand the reasons behind the optimality of this policy, I will compare family outcomes and macroeconomic outcomes under the optimal and current policies.

Effects of optimal policy on family outcomes upon displacement As mentioned earlier in Section 1.4.2, Figure 1.8 compares the change in spousal earnings upon the

[64] Krusell, Mukoyama, Şahin, and Smith (2009) study the welfare effects of eliminating both aggregate risk and its impact on idiosyncratic risk when there is a correlation between these two shocks. Their study is an extension of Lucas (1987) into an incomplete asset markets model with heterogeneous households. They find that the welfare gains of eliminating the cycle and its effect on idiosyncratic risk are as much as 1 percent in consumption equivalents. Given that public and private insurance in my model can only partially smooth the effects of business cycles, welfare gains from the optimal policy are much lower than the upper bound provided by Krusell, Mukoyama, Şahin, and Smith (2009).

Figure 1.9: Relative consumption of the family upon job displacement: Current policy vs optimal policy



Note: This figure plots the changes in relative family consumption upon head's job displacement in recessions (left panel) and expansions (right panel) in the model under the countercyclical baseline (current) policy and the optimal policy. I estimate the changes in relative family consumption from a distributed lag-recession model using model simulated data, which is aggregated up to yearly period.

head's job displacement in recessions and expansions in the model under the countercyclical baseline (current) policy and a procyclical policy which was set to be what turned out to be the optimal policy. Thus, we know that the optimal policy induces a larger spousal labor supply response upon the head's job displacement in recessions, and it does not alter the magnitude of this response much in expansions due to reasons discussed earlier.

Next, I compare the change in family consumption upon the head's job displacement in recessions and expansions under the current policy and the optimal policy. It shows that families experience a smaller consumption drop upon the head's displacement both in recessions and in expansions under the optimal policy. Moreover, family consumption fully recovers 6 years after displacements in recessions, and 5 years after in expansions under the optimal policy, 2 years earlier in recessions and 1 year earlier in expansions. While the earlier recovery in recessions under the optimal policy is explained by a larger spousal labor earnings response, the earlier recovery in expansions is explained by larger amount of transfer receipts during the initial years after displacement.[65] Furthermore, I find that

[65]Figure A.4 and A.5 in Appendix A.3 provide comparisons respectively for relative changes in family earnings and assets upon the head's displacement in recessions and expansions under the current policy

the difference in consumption drop upon displacement between recessions and expansion under the optimal policy is 9 pp ($0.16 - 0.07 = 0.09$), which is the same as this cyclical gap under the current policy ($0.19 - 0.10 = 0.09$). The reason why the optimal policy does not narrow this gap is the offsetting effects of the increase in spousal earnings and the decline in transfer receipts under the optimal policy in recessions. The main conclusion of this section is that the optimal policy reduces the average drop in consumption both in recessions and in expansions, but does not improve the cyclical gap of initial consumption drops.

Effects of optimal policy on the macroeconomic outcomes I now discuss the effects of the optimal policy on the macroeconomic outcomes. Table 1.9 compares the steady state values of macroeconomic outcomes under the current policy and the optimal policy. Compared to the economy under the current policy, the economy under the optimal policy has a similar unemployment rate but much higher female labor force participation rate (LFPR) at 76 percent versus 71 percent. Under the optimal policy, larger spousal labor supply is induced by having lower means-tested transfers on average and lower total transfers in recessions. As a result, the median skill of females is larger under the optimal policy as they spend more time employed. The increase in employment reduces the income tax required to finance a similar average level of government transfers from 16.2 percent to 15.6 percent. The wealth distribution of families in the labor force also shifts right under the optimal policy, as we observe a sizeable decline in the fraction of families with non-positive liquid wealth, and an increase in the median value of asset-to-income distribution. These changes in the macroeconomy increases the average consumption level under the optimal policy for the families in the labor force. I find that the mean and the median of consumption across these families are respectively 1 and 2 pp larger under the optimal policy compared to the current policy. While the gini of consumption distribution is the same under these two policies, the volatility of the average consumption is only slightly lower under the optimal policy because of the offsetting effects of the increase in spousal earnings and the decline in transfer receipts under the optimal policy in recessions.[66]

and the optimal policy, both of which affect changes in family consumption.

[66] Volatility of average consumption is measured by the standard deviation of log deviations from an HP-trend with parameter 1600.

Heterogeneous welfare gains from the optimal policy

Finally, I discuss heterogeneous ex-post welfare gains/losses from the optimal policy across different types of families. I group families by their employment status, asset level, and skill levels of male and female based on their states on the stationary distribution of the economy before the government changes the policy to the optimal policy. I then calculate $\bar{x}$ from Equation (2.15) for each group by only integrating over families which belong to that group.

Table 1.10 shows the heterogeneous welfare impacts of the optimal policy on various type-groups, where columns represent male or female skill groups across families in which only head is employed or both are unemployed, and rows represent the asset holdings of families. I find that most of the welfare gains are enjoyed by wealth-poor families with an unskilled male who is married to a skilled female, both among families in which only head is employed and among families in which the head and spouse are unemployed. Welfare gains are highest for such family types when both members are unemployed. It is precisely for this family for whom a spouse's participation in the labor force can bring the largest gains in consumption to the family especially when a displacement of the head occurs. On the contrary, the lowest welfare gains are enjoyed by wealth-rich families with skilled male and unskilled female for whom spouses are less likely to enter into labor force and the need for any insurance is the least.

1.5.3 Optimal policy in the exogenous spousal labor supply model

I now explore the implications of assuming that spousal labor supply is exogenous to changes in government policy. In particular, I consider an alternative environment in which female labor force participation decisions are invariant to changes in government policy. In order to do so, I fix spousal labor supply decisions to be those under the current (old) policy for any new (proposed) policy n, i.e. $s_f^n(\cdot) = s_f^o(\cdot)\ \forall n$. Then, I solve for the optimal policy of this model using the same methodology as before. Table 1.11 compares per recipient transfer amounts as a multiple of minimum wage under the optimal policy of the baseline model with endogenous female labor supply and under the optimal policy in the exogenous spousal labor supply model.

When labor productivity is at its average level, total transfers paid under the optimal policy of the alternative model is more generous than the optimal policy under the baseline model. Recall that, in Table 1.7, I have documented that spousal labor supply elasticity to government policy is large, especially among low income households. When we abstract from the responsiveness of spousal labor supply to changes in government policy, we disregard the policy's crowding-out effect on spousal labor supply. As a result, the optimal policy features more generous transfers on average in this alternative model. Moreover, according to this optimal policy, around 90 percent of total transfers are paid under means-tested transfers in the exogenous spousal labor supply model since means-tested transfers better target insurance toward families who need it the most and their incentive costs are now small.

Furthermore, the optimal policy in this case features countercyclical means-tested and employment-tested transfers. This is because the optimal cyclicality of government transfers is mostly determined by the cyclicality of insurance benefits, which is larger in recessions during when more families experience unemployment and get closer to borrowing limits. Meanwhile, the incentive costs of transfers are now unaccounted for.

Overall, this exercise shows that endogenizing the spousal labor supply response to changes in government policy is a critical determinant of both the optimal level and cyclicality of transfers.

1.6 Extensions and Robustness

In this section, I provide a list of extensions and robustness checks of the optimal policy analysis. In my main welfare analysis in Section 1.5.2, I have searched for the optimal level and cyclicality of means-tested and employment-tested transfers as well as the implied tax rate that balances the government budget. In Section 1.6.1, I now optimize over the level of asset and income thresholds $\underline{a}$ and $\underline{y}$ of eligibility for means-tested transfers as well as the level and cyclicality of employment-tested transfer expiration rate $e(\cdot)$. In Section 1.6.2, I relax a list of assumptions in the baseline model and compute the welfare gains from the optimal policy of the baseline model. [67]

[67] I also check the implications of these exercises on results of Section 1.4. Sizeable welfare gains from the baseline optimal policy in these cases imply that less generous transfers in recessions still induce spouses

1.6.1 Extensions

Due to computational reasons, in Section 1.5.2, I solved for the optimal policy only by searching over the optimal level and cyclicality of means-tested and employment-tested transfers as well as the implied tax rate that balances the government budget. There are three other policy instruments in this model: the level of asset and income thresholds $\underline{a}$ and $\underline{y}$ of eligibility for means-tested transfers, and employment-tested transfer expiration rate $e(\cdot)$. In this section, I search for the optimal $\underline{a}$, $\underline{y}$, and $e(\cdot)$ in steps, taking as given the optimal level and cyclicality of means-tested and employment-tested transfers obtained in Section 1.5.2.[68]

Table 1.12 first shows the welfare gains from the baseline optimal policy calculated in Section 1.5.2, through optimizing over transfer level and cyclicality of both means-tested and employment-tested transfers (first row). Then, on top of this optimal policy (i.e. under the optimal level and cyclicality of means-tested and employment-tested transfers obtained in Section 1.5.2), it shows welfare gains from optimizing over i) both levels of asset and income thresholds $\underline{a}$ and $\underline{y}$ of eligibility for means-tested transfers (second row), ii) only level of asset threshold $\underline{a}$ (third row), iii) only level of income threshold $\underline{y}$ (fourth row), and finally iv) only level and cyclicality of employment-tested transfer expiration rate $e(\cdot)$ (fifth row). In all of these cases, I solve for the income tax that balances government budget. Welfare gains are in percent lifetime equivalent consumption terms and they are computed relative to the baseline countercyclical policy.

I find that, on top of the baseline optimal policy, jointly optimizing over asset and income thresholds yields welfare gains of 0.81 percent additional lifetime consumption relative to the current policy. In this case, optimal asset and income thresholds are 0.028 and 0.275 respectively. Under the current policy, asset and income thresholds are 0.068 and 0.240. This means that the optimal policy allows families with slightly higher total labor income to be eligible for means-tested transfers, while it makes asset eligibility criteria more restrictive, when compared to the current policy.

In order to understand which of these two instruments are more powerful in increasing

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to supplement family earnings by working.

[68] Again due to computational reasons, it is not feasible to solve for full set of optimal policy instruments at the same time. Thus, I solve for optimal $\underline{a}$, $\underline{y}$, and $e(\cdot)$ one at a time.

welfare gains, I next search for only optimal asset threshold and only optimal income threshold separately, again taking as given the baseline optimal policy. In the former case, welfare gains are 0.63, with an optimal asset threshold of 0.049. In the latter case, welfare gains are 0.77, with an optimal income threshold of 0.272. These results show that optimizing over the income threshold provides higher welfare gains.

Finally, I solve for the optimal level and cyclicality of employment-tested transfer expiration rate $e(\cdot)$, again taking as given the baseline optimal policy. According to the optimal $e(\cdot)$, employment-tested transfers should expire on average in 1.7 quarters, and that the duration should be extended to 1.8 quarters in recessions, implying that the optimal duration is only slightly countercyclical. Under the current policy, the duration is 2 quarters on average, and 7.6 quarters in recessions. Even if there is significant difference between the degree of countercyclicality of the current and optimal policies, this change provides only little welfare gains. Welfare gains from the optimal policy of this case are 0.63, which is only slightly higher than the welfare gains of 0.61 under the baseline optimal policy that does not optimize over $e(\cdot)$.

1.6.2 Robustness

In this section, I relax a list of assumptions in the baseline model and compute the welfare gains from the baseline optimal policy. Specifically, I show welfare gains from the optimal policy in Section 1.5.2, when an assumption of the baseline model is changed.[69] Results are summarized in Table 1.13, where welfare gains are in percent lifetime equivalent consumption terms, and they are computed relative to the baseline countercyclical policy.

Incorporating Medicaid to means-tested transfers In the calibration of the model, I did not incorporate Medicaid transfers into the calibration of the means-tested transfer policy instruments given that the baseline model does not incorporate extra eligibility risk such as health status or presence of a young children requirements. Now, I incorporate Medicaid transfers into the calibration of parameters of means-tested transfers and a new

[69] I acknowledge that the optimal policy of the baseline model may not be the optimal policy of a model when some of the assumptions of the baseline model are different. However, this exercise at least shows us if there is a large quantitative effect of an assumption on welfare results.

eligibility indicator for all means-tested transfers. Means-tested transfers are now given as follows:

$$\phi\left(z;\,a,\,y,\,\chi\right)=\begin{cases}\phi\left(z\right) & \text{if} \quad y<\underline{y},\,a<\underline{a},\,\chi=1\\ \iota\phi\left(z\right) & \text{if} \quad y<\underline{y},\,a<\underline{a},\,\chi=0\\ 0 & \text{otherwise}\end{cases}$$

where χ is a non-financial eligibility indicator for all means-tested transfers, which can be interpreted as health status or presence of a young children requirements. In the above specification, if a family is financially eligible but non-financially ineligible (i.e. $y<\underline{y},\,a<\underline{a},\,\chi=0$), then I assume that family receives only SNAP transfers, which typically does not have any non-financial eligibility requirements, and SNAP is ι fraction of total means-tested transfers. χ is a state variable of family, and a random variable is drawn from a uniform distribution each period to determine the value of χ.

I assume that 60 percent of families are non-financially eligible for means-tested transfers. I externally calibrate $\iota=0.107$ because total SNAP transfers is around 10.7 percent of total means-tested transfers on average across years. I then recalibrate this model and calculate the welfare gains from the optimal policy obtained in Section 5.2 under this model.[70] Here, I implement this exercise in two different ways given the large difference between the levels of $\bar{\phi}$ in the baseline model and in this model. First, I compute welfare gains directly from the baseline optimal policy, in which $\bar{\phi}=0.13$. In this case, I find welfare gains of the baseline optimal policy, relative to the new calibration of the current policy under this model (i.e. $\bar{\phi}=0.51$, $\omega_{\phi}=2.8$, and so on), as much as 1.84 percent in consumption equivalent. In the second way, I replaced the average generosity of means-tested transfers in the optimal policy from $\bar{\phi}=0.13$ to $\bar{\phi}=0.51$ to understand the effects of only changing the cyclicality of means-tested transfers (from $\omega_{\phi}=2.8$ in the current policy to $\omega_{\phi}=-3.54$ in the optimal policy, together with the changes in other policy parameters except $\bar{\phi}$). In

[70] Among the changes to the parameter values, important ones to mention here are as follows. Average generosity of means-tested transfers $\bar{\phi}=0.51$ instead of $\bar{\phi}=0.15$ in the baseline calibration given the inclusion of generous Medicaid transfers. Moreover, the cyclicality of means-tested transfers now becomes $\omega_{\phi}=2.8$ instead of $\omega_{\phi}=0.96$ in the baseline model. In fact, the standard deviation of detrended means-tested transfers per recipient is still 0.06, as in the baseline calibration, but the increase in level of means-tested transfers requires adjustments in ω_{ϕ} as well to match the same value. Finally, income tax rate that balances the budget $\tau=20.6$ percent instead of $\tau=16.2$ percent.

this case, welfare gains are 0.51 in consumption equivalent, which is the value I report in Table 1.13. Both of these exercises show that less generous and procyclical means-tested transfer policy is welfare improving, which is consistent with my main results.

Removing job search requirements for employment-tested transfers In the baseline model, I assume that government can observe the search behavior of the unemployed. Here, I remove that assumption and check the implications on welfare gains from the baseline optimal policy.

In this case, employment-tested transfers are now given as follows:

$$b\left(z;\, l_i\right) = \begin{cases} b\left(z\right) & \text{if} \quad l_i = U_b \\ 0 & \text{otherwise} \end{cases}.$$

Then, I recalibrate the model and calculate welfare gains from the baseline optimal policy. I find that the optimal policy yields 0.48 percent additional lifetime consumption relative to the current policy in this model. Thus, I find smaller welfare gains in this model. This is possibly because of the increase in incentive costs of employment-tested transfers due to removal of job search requirement for eligibility.

Progressive taxation In the baseline model, I assume that government levies a flat income tax τ to finance the transfer programs. Now, I change this assumption and study the effects of progressive income taxation on the welfare gains from the optimal policy of the baseline model.

Let x be the total taxable income of family. For families in the labor force, x includes total labor income and income from employment-tested transfers. For retired families, x includes only retirement income.[71] Then, following Heathcote, Storesletten, and Violante (2014), after tax income of family is given by $\tilde{x} = \lambda x^{1-\nu}$ where λ determines the level of taxation and $\nu \geq 0$ determines the rate of progressivity built into the tax system. Then, tax revenues of the government from a family with total taxable income x is given by $T\left(x\right) = x - \lambda x^{1-\nu}$.

[71] For a better comparison of results with the baseline model, I assume that x does not include capital (savings) income, which is also not taxed in the baseline model.

In this case, I recalibrate the parameters of the model, where I set $\nu = 0.151$ as in Heathcote, Storesletten, and Violante (2014), and search for λ that balance the government budget in the long-run and find $\lambda = 0.834$. Then, I calculate welfare gains from the optimal policy of the baseline model, where tax policy is also progressive at the same degree, and level parameter under the optimal policy becomes $\lambda = 0.844$ in equilibrium. I find that the optimal policy yields 0.95 percent additional lifetime consumption relative to the current policy in this model. Thus, I find larger welfare gains when taxation is progressive. This is intuitive given that most of the welfare gains are enjoyed by poor families as shown in Section 1.5.2. When the tax system is progressive, it is this group of families whose spouses are induced to work more under the optimal policy and they receive higher net earnings since they have low marginal tax rates.

Non-separable preferences I consider a utility function in which consumption and leisure are non-separable, following Blundell, Browning, and Meghir (1994) and Attanasio and Weber (1995). I now define preferences as follows:

$$U\left(c,\, l_m,\, l_f,\, s_m,\, s_f\right) \;=\; \frac{\left[c \times \prod_{i\in\{m,\,f\}} \exp\left(\eta_i \times \mathbf{1}\left(l_i \neq E,\ \text{and}\ s_i = 0\right)\right)\right]^{1-\sigma}}{1-\sigma}$$

This is similar to functional form used in Low, Meghir, and Pistaferri (2010). Then, I recalibrate the model under this preference. Next, I calculate welfare gains from the baseline optimal policy and find that it yields 0.68 percent additional lifetime consumption relative to the current policy in this model. This implies that welfare gains from the baseline optimal policy are not much affected when we change the preferences.

Model with endogenous wages Finally, in the baseline model, I assume that the wage for each human capital level is a fraction of period aggregate labor productivity. This assumption implies that wages and firm vacancy posting decisions are exogenous to changes in government policy in the baseline model, which allowed me to isolate the effects of transfers on labor supply.

To analyze the quantitative effects of this assumption on the welfare gains from the optimal policy, I now consider a directed search model in which wage choices of unemployed individuals are endogeneous. In this model, submarkets in the labor market are indexed by the wage offer w of the firms and human capital level h of the job. This means that unemployed individuals now direct their search effort toward a specific wage offered by a job that is compatible with their own skill level. In this case, wage levels of the employed members of the household become extra state variables. Household and firm optimization problems as well as a discussion on the equilibrium of this model are given in Appendix A.4.

I recalibrate the parameters of this model and find that the baseline optimal policy yields 0.66 percent additional lifetime consumption relative to the current policy. Changes in government transfer generosity now affect the wage choice of the unemployed endogeneously. Less generous public insurance in recessions induces unemployed individuals to look for low paying jobs for which job finding rates are higher. Thus, under the baseline optimal policy, reemployment wages are lower but unemployment duration is shorter compared to the baseline model. While the former channel reduces the welfare gains from the baseline optimal policy, the latter channel increases welfare gains. As a result, welfare gains from the baseline optimal policy in this model are similar to the welfare gains in the baseline model.

1.7 Conclusion

Previous literature has documented that a large negative and persistent effect of job displacement on individual labor earnings. Moreover, these effects are more pronounced when the displacement happens in recessions. In this paper, I first analyze the change in spousal earnings upon the head's job displacement both in recessions and in expansions using PSID data. I show that the change in spousal earnings in response to the head's job displacement is small. The response is even smaller upon displacements that occur in recessions. This result is particularly interesting because one might expect a stronger spousal earnings response during times when the head experiences larger earnings losses.

I investigate whether this small response is an outcome of the crowding-out effects of existing government transfers. To achieve this, I use an incomplete asset markets model with family labor supply and aggregate fluctuations. I first show that the model implied female labor supply elasticities with respect to transfers are in line with microeconomic estimates both in aggregate and across subpopulations. Then, in a model counterfactual, I find that existing generous transfers in recessions discourage spousal labor supply significantly after the head's job displacement. The results of this counterfactual experiment imply that the incentive costs of transfers in the form of reduced spousal labor supply are larger in recessions and smaller in expansions. Given that existing transfers are more generous in recessions, this motivates an analysis of redesigning the government transfers over the business cycle.

Next, I solve for optimal means-tested transfers paid to low-income and low-wealth families and employment-tested transfers paid to the unemployed. Unlike the existing policy that maintains generous transfers of both types in recessions, I find that the optimal policy features procyclical means-tested and countercyclical employment-tested transfers. Overall, the optimal policy is procyclical because there are welfare gains of reducing transfers in recessions to induce spouses to work more when the head experiences larger earnings losses. This is a direct implication of the model's result that spousal labor supply is more elastic to transfers in recessions, which is in line with the data.

In an alternative environment in which spousal labor supply were invariant to transfer generosity, I show that the average transfer generosity of the optimal policy increases. Moreover, the optimal policy in this case would instead feature countercyclical transfers of both types since the insurance benefits are larger in recessions and the incentive costs in on spousal labor supply would be unaccounted for. As a result, I argue that endogenizing the spousal labor supply response to changes in government policy is critical in determining both the optimal level and cyclicality of government transfers.

In this paper, I focus on the macroeconomic implications of how public insurance programs interact with private insurance for married households. Hence, policy implications of this study may not apply to singles. Importantly, when we consider an environment with married and single households, government transfers would affect incentives to marry, and thus the amount and the distribution of private insurance in the economy. I will pursue this in future research.

Table 1.1: Summary statistics for families with and without job displacement

	Never Displaced*	Displaced°
Head's age	36.49	32.90
Spouse's age	34.38	30.99
Head's education	15.49	13.19
Spouse's education	15.02	13.07
White (%)	67.96	57.03
Number of children	1.30	1.52
Number of young children	0.51	0.65
Head's annual hours	2,154	1,851
Spouse's annual hours	1,288	1,142
Head's industry - Manufacturing (%)	18.38	19.76
Number of families	6,584	2,799

Note: This table shows unweighted averages of selected characteristics for never displaced families (i.e. families in which the head of the family is never displaced during all times the family is observed in the survey), and displaced families (i.e. families in which the head of the family is displaced at least once). Data is obtained from PSID 1968-2015 surveys for families in which both the husband and the wife are between the ages of 20 and 60 and are not in the Latino sample.

* Averages are obtained using all observations for families with never-displaced head.

° Averages are obtained from the survey year prior to the displacement year of the head.

Table 1.2: Externally calibrated parameters

Parameter	Explanation	Value
ρ	Autocorrelation of productivity process	0.7612
σ_ϵ	Standard deviation of productivity process	0.0086
σ	Risk aversion	2
η_m	Value of leisure for male	0
r	Interest rate	0.005
ζ_R	Retirement probability	0.00625
ζ_D	Death probability	0.01666
α	Worker's share of output	0.477
h_L	Lowest human capital	0.2
h_H	Highest human capital	1.8
Δ^E	Human capital increase when employed	0.084
π^U	Prob. of human capital depreciation when unemployed	0.75
$\underline{a}$	Asset threshold of means-tested transfers	0.068
$\underline{y}$	Income threshold of means-tested transfers	0.240
e	Mean expiration rate of employment-tested transfers	0.5

Note: This table summarizes the parameters that are calibrated outside of the model. Please refer to the main text for the interpretation of the values.

Table 1.3: Internally calibrated parameters

Parameter	Explanation	Value	Target	Data	Model
β	Discount factor	0.983	Frac. of households with non-positive liquid wealth	0.097	0.13
a_L	Borrowing limit	-0.67	Median ratio of credit limit to quarterly labor income	0.64	0.65
η_f	Leisure value (female)	0.51	Relative female LFPR	0.77	0.77
			Labor Market		
κ	Vacancy posting cost	2.9	Unemployment rate	0.056	0.051
γ	Matching function	1.43	Std. dev of job finding rate	0.08	0.08
$\bar{\delta}$	Average job sep. rate	0.053	Employment exit rate	0.034	0.034
ω_z^δ	Separation rate vol.	-5.8	Std. dev. of emp. exit rate	0.06	0.06
ω_h^δ	Separation rate across h	-0.52	Ratio of median earnings displaced to nondisplaced	0.76	0.77
			Human Capital Process		
Δ^U	Human capital decrease (unemp.)	$[0.59, 0.34]$	Cyclicality of head's initial earnings loss upon disp.	$[0.39, 0.22]$	$[0.39, 0.22]$
π^E	Prob. of human capital increase (emp.)	0.04	Labor earnings p90/p10	7.60	6.20
			Government Transfers		
$\bar{\phi}$	Average means-tested transfers	0.15	Ratio of total means-tested trans. per rec. to min. wage	0.74	0.76
$\bar{b}$	Average emp.-tested transfers	0.08	Ratio of total UI trans. per unemployed to min. wage	0.36	0.37
ω_ϕ	Cyclicality of means-tested transfers	0.96	Std. dev of means-tested transfers per recipient	0.06	0.08
ω_b	Cyclicality of emp.-tested transfers	0.64	Std. dev of total UI per unemployed	0.15	0.14
b_R	Retirement transfers	0.36	Ratio of social security transfers to GDP	0.041	0.04

Note: This table summarizes internally calibrated parameters. Please refer to the main text for the interpretation of the values.

Table 1.4: Average MPCs: Model vs data

	Model	Data
Average economy-wide quarterly MPC	0.22	$0.12 - 0.30$
Semiannual MPC increase for borrowing-constrained in recessions	0.10	0.08

Note: This table shows the average quarterly economy-wide MPC, and the average increase in semiannual MPC of borrowing-constrained individuals in a recession implied by the model's simulation. I group families with non-positive wealth as borrowing-constrained families. MPC of each family type are calculated by computing the fraction consumed out of an unexpected $500 worth transfer. These model-generated average values are then compared to available empirical estimates in the literature.

Table 1.5: MPCs across heteregeneous families in the model

Family employment: Only head employed

		Head skill	
		$\leq p50$	$> p50$
Asset	$\leq p50$	0.58	0.07
	$> p50$	0.02	0.02

Family employment: Both unemployed

		Head skill	
		$\leq p50$	$> p50$
Asset	$\leq p50$	0.67	0.17
	$> p50$	0.02	0.02

Note: This table shows the average quarterly MPCs across families grouped by their employment status, assets holdings, and skill level of the head. Cutoffs for the asset and skill groups are obtained from the respective distributions under the stationary distribution of the economy. MPC of each family type are calculated by computing the fraction consumed out of an unexpected $500 worth transfer.

Table 1.6: Distribution of liquid asset holdings relative to quarterly family labor earnings

	Percentiles					Fraction of population
	10th	25th	50th	75th	90th	with non-positive wealth
PSID 2015	0.05	0.48	1.20	2.88	14.38	0.091
SCF 2007	0.02	0.48	1.20	2.71	6.45	0.097
Model	-0.18	0.37	1.10	4.23	4.86	0.13

Note: This table shows the liquid asset to quarterly family labor earnings distribution in both the model and in the data. The empirical distributions are separately calculated from the PSID 2015 and the SCF 2007. The main text provides the details of these calculations.

Table 1.7: Magnitudes of female labor supply elasticities: Data vs model

	All households	Low income households	High income households
	Female participation elasticity with respect to net wages		
Data	0.15 − 0.43	0.27 − 0.43	0.15
Model	0.31	0.38	0.21
	Female labor earnings elasticity with respect to transfers		
Data	0.44		
Model $\bar{\phi}$	0.36	0.47	0.23
Model $\bar{b}$	0.01	0.03	0.002

Note: This table compares female participation elasticity with respect to net wages and female labor earnings elasticity with respect to transfers both in the data and in the model. Comparisons are made for all females, females in low income households, and females in high income households. Empirical estimates of participation elasticities are summarized by Chetty, Guren, Manoli, and Weber (2012), and the empirical estimate of earnings elasticity is obtained by the author from the PSID. Participation elasticity is calculated as the change in log female employment rates divided by the change in log net-of-tax wage rates, while earnings elasticity is calculated as the change in log female labor earnings divided by the change in log transfer amounts.

Table 1.8: Current policy vs optimal policy in the baseline model

Labor Productivity	Means-tested	Employment-tested	Total
	Current Policy		
Average	1.61	0.86	2.48
Recession	1.90	1.04	2.94
	Optimal Policy		
Average	1.40	1.18	2.58
Recession	0.40	1.34	1.74

Note: This table compares per recipient transfer amount as a multiple of minimum wage in the model paid under the means-tested and employment-tested transfers in the current policy and the optimal policy. Separate comparisons are presented for when the aggregate labor productivity z is at its average level $\bar{z}$, and its minimum level, i.e. deep recession. Minimum wage in the model is exogeneous to changes in policy and thus reporting transfer amounts as a multiple of minimum wage presents a useful interpretation.

Table 1.9: Macroeconomic effects of the optimal policy

	Current Policy	Optimal Policy
Labor market and taxation		
Unemployment rate (%)	5.05	5.08
Female LFPR (%)	71	76
Median skill of female	0.98	1.1
Income tax (%)	16.2	15.6
Asset-to-income distribution		
Median asset-to-income ratio	1.1	1.45
Fraction with non. pos. wealth (%)	13	9.1
Consumption		
Mean	0.85	0.86
Median	0.77	0.79
Std. dev. of mean	0.0181	0.0178
Gini	0.41	0.41

Note: This table compares the stochastic steady state values of macroeconomic outcomes under the current policy and the optimal policy. These values are obtained by using model simulated data under these two policies. Moments related to asset-to-income distribution and consumption are calculated for families who are in the labor force. Volatility of average consumption is measured by the standard deviation of log deviations from an HP-trend with parameter 1600.

Table 1.10: Heterogeneous welfare gains from the optimal policy

Family employment: Only head employed

		Female skill	
		$\leq p50$	$> p50$
Asset	$\leq p50$	0.50	1.09
	$> p50$	0.29	0.38

Family employment: Only head employed

		Male skill	
		$\leq p50$	$> p50$
Asset	$\leq p50$	0.73	0.42
	$> p50$	0.35	0.25

Family employment: Both unemployed

		Female skill	
		$\leq p50$	$> p50$
Asset	$\leq p50$	1.21	1.66
	$> p50$	0.28	0.78

Family employment: Both unemployed

		Male skill	
		$\leq p50$	$> p50$
Asset	$\leq p50$	1.31	0.91
	$> p50$	0.76	0.41

Note: This table shows the heterogeneous welfare gains from the optimal policy on various type-groups. Cutoffs for the asset and skill groups are obtained from the respective distributions under the stationary distribution of the economy before the government changes the policy to the optimal policy. Welfare gains are in percent lifetime equivalent consumption terms and they are computed relative to the baseline countercyclical policy.

Table 1.11: Optimal policy in the baseline vs exogeneous spousal labor supply model

Labor Productivity	Means-tested	Employment-tested	Total
Optimal Policy in the Baseline Model			
Average	1.40	1.18	2.58
Recession	0.40	1.34	1.74
Optimal Policy in the Exogeneous Spousal Labor Supply Model			
Average	2.58	0.32	2.90
Recession	2.69	0.40	3.09

Note: This table compares per recipient transfer amounts as a multiple of minimum wage under the optimal policy of the baseline model and under the optimal policy in the exogenous spousal labor supply model. Separate comparisons are presented for when the aggregate labor productivity z is at its average level $\bar{z}$, and its minimum level, i.e. deep recession. Minimum wage in the model is exogeneous to changes in policy and thus reporting transfer amounts as a multiple of minimum wage presents a useful interpretation.

Table 1.12: Welfare gains under optimality of other policy instruments

	Welfare gains
Baseline optimal	0.61
Optimal $\underline{a}$, $\underline{y}$	0.81
Optimal $\underline{a}$	0.63
Optimal $\underline{y}$	0.77
Optimal e	0.63

Note: This table first shows the welfare gains from the baseline optimal policy calculated in Section 5.2, through optimizing over transfer level and cyclicality of both means-tested and employment-tested transfers (first row). Then, on top of this optimal policy, it shows welfare gains from optimizing over i) both levels of asset and income thresholds $\underline{a}$ and $\underline{y}$ of eligibility for means-tested transfers (second row), ii) only level of asset threshold $\underline{a}$ (third row), iii) only level of income threshold $\underline{y}$ (fourth row), and finally iv) only level and cyclicality of employment-tested transfer expiration rate $e(\cdot)$ (fifth row). In all of these cases, I solve for the income tax that balances government budget. Welfare gains are in percent lifetime equivalent consumption terms and they are computed relative to the baseline countercyclical policy.

Table 1.13: Welfare gains from the baseline optimal policy under alternative assumptions

	Welfare gains
Baseline optimal	0.61
Incorporating Medicaid to means-tested transfers	0.51
Removing job search requirements for employment-tested transfers	0.48
Progressive taxation	0.95
Non-separable preferences	0.68
Endogenous wages	0.66

Note: This table provides a list of robustness checks for the optimal policy analysis. It first shows the welfare gains from the optimal policy for the baseline model (first row). Then, it shows welfare gains from the same optimal policy, when an assumption of the baseline model is changed. Welfare gains are in percent lifetime equivalent consumption terms and they are computed relative to the baseline countercyclical policy.

Chapter 2

How Should Unemployment Insurance Vary Over the Business Cycle?

2.1 Introduction

The sharp increase in unemployment during the Great Recession was associated with dramatic expansions to the unemployment insurance (UI) program. While intended to provide adequate insurance to the large pool of jobless individuals, the question of whether UI policy played a quantitatively significant role in slowing the recovery of employment remains at the center of discussion.[1] Alongside this positive debate, an equally important policy question emerges: how then should UI policy vary over the business cycle? Addressing this question will shed light on how UI policy must adjust to economic fluctuations, especially during economic downturns.

Our main contribution to the growing literature on optimal UI over the business cycle is to study the endogeneous interaction between precautionary savings and changes in UI policy

[1]For example, Hagedorn et al. (2016) find that a generous UI policy during the recession is partly responsible for the drastic and sustained rise in unemployment that followed. On the other hand, Chodorow-Reich and Karabarbounis (2017) show that the extensions have had limited influence on macroeconomic outcomes.

over recessions and expansions, a mechanism that we show is crucial to correctly measure the welfare benefits and costs of any proposed policy. This is because the level of wealth determines not only the insurance value of any public transfer but also its incentive costs, since the labor market behavior of individuals holding different levels of assets responds in varying degrees to changes in the level of generosity of these programs. Moreover, as wealth holdings and the strength of precautionary saving motives vary over the business cycle, they inevitably influence the cyclicality of the insurance benefits and incentive costs of UI payments. It is precisely the cyclicality of the net benefits of UI that will determine how benefit generosity should vary over the business cycle.

We address this question using a heterogeneous agent job search model that incorporates labor productivity driven business cycles and incomplete asset markets. To overcome the computational difficulties encountered in models of this nature, we show that the model's market structure admits a block recursive equilibrium, a subset of recursive equilibria where the endogenous distributions generated by the model are not part of the state space (Menzio and Shi 2010, 2011). This allows us to compute the optimal UI policy in a model with aggregate shocks and saving decisions.

We find that the optimal UI policy is countercyclical. In particular, when the aggregate labor productivity is at its mean, it features a 30 percent replacement rate for 4 quarters. When aggregate labor productivity is depressed by 3.5 percent, however, it offers more generous benefits of a 54 percent replacement rate for 10 quarters, financed by higher labor income taxes. Compared to a UI policy that mimics the policy implemented by the U.S. government during the Great Recession, the optimal policy represents an ex-ante welfare gain of 0.58 percent additional lifetime consumption.

The countercyclicality of the optimal policy is explained by how the insurance benefits of extra UI payments expand during recessions relative to expansions while relative incentive costs contract. Two important insurance benefit channels expand during recessions: (1) consumption insurance against unemployment risk and (2) consumption insurance against aggregate labor productivity risk. First, generous benefits insure against unemployment risk by alleviating the consumption drop experienced by job losers. This is especially important in recessions when unemployment rises and spells are prolonged. Second, it also insures against aggregate risk since it reduces the burden of having to engage in (costly) precautionary savings during economic downturns. Recessions trigger a strong need to accumulate a buffer stock of savings, which in turn entails a concomitant reduction in consumption. In the absence of public insurance, this makes consumption fluctuate heavily with the business cycle. However, this effect is mitigated when individuals are promised more generous payments for future unemployment spells.[2] Remarkably, this results in sizeable welfare gains not only for job losers but also for those who are employed.

Insurance benefits come with a trade-off: generous UI payments during recessions decrease the job finding rates of the unemployed through a decline in job search effort and an increase in the wages that they seek. This results in longer unemployment durations. However, we show that these costs are relatively lower in recessions for two reasons: (1) the value of job search is low during recessions, and (2) borrowing constraints impose discipline on the unemployed's job search behavior. First, the value of job search during recessions is low because, to begin with, jobs are difficult to find and available jobs offer relatively lower wages. Hence, even if generous benefits were to discourage job search during a recession, the forgone search effort would not have been very productive anyway. Second, a reduction in wealth holdings during recessions induces the unemployed to find a job more quickly as they get closer to becoming borrowing constrained. In this sense, the presence of borrowing constraints is a device to discipline the job search behavior of the unemployed. For both of these reasons, the incentive costs associated with generous benefits are partially offset in recessions.[3]

These channels remain active even under a high level of the opportunity cost of employment calibration. In this case, we find that while the mean replacement rate and duration of the optimal policy reduce to a 19 percent replacement rate for one quarter, the degree of countercyclicality remains roughly similar. As fluctuations in consumption are less pronounced under this calibration, the government implements a low replacement rate for short durations when aggregate labor productivity is at its mean value. Still, insurance benefits expand and incentive costs contract in recessions. Thus, the government finds it optimal to transfer funds from expansions toward recessions. The resulting optimal policy

[2]This channel is consistent with Engen and Gruber's (2001) empirical finding that UI payments crowd out private savings.

[3]This result is consistent with Kroft and Notowidigdo (2016), who empirically find that the moral hazard cost of UI is procyclical.

in this case provides ex-ante welfare gains of 0.25 percent lifetime consumption, which is less than half of the welfare gains provided by the optimal policy under the baseline calibration of the opportunity cost of employment.

We quantify various sources of ex-ante welfare gains of the optimal policy and find that most of them are attributable to changes in consumption patterns, whereas the welfare gains from economizing on relatively unproductive search during recessions are negligible. These changes in consumption patterns can potentially increase ex-ante welfare for three reasons: (1) an increase in consumption levels, (2) a decrease in consumption volatility, and (3) a reduction in consumption inequality across individuals. We find large welfare gains due to an increase in the average consumption level along the transition path after the implementation of the optimal UI policy. This is because agents decumulate savings and consume more of their labor income when public insurance is generous, and this effect dominates the increase in labor income taxes. Steady state welfare decomposition reveals that long-run welfare gains are attributable mostly to reduced consumption uncertainty, but at the cost of lower consumption levels. The reduction in the consumption level is due to higher taxes and lower wealth holdings once the economy converges to a new steady state, although this change is not large enough to overturn uncertainty gains. Finally, welfare gains due to a reduction in consumption inequality are small because the optimal policy has two offsetting effects on consumption inequality. On the one hand, the redistribution of labor income from workers to the unemployed creates more equal consumption paths across heterogeneous agents. On the other hand, the optimal policy increases wealth inequality in the stationary distribution. This is because while most of the individuals in the economy under the optimal policy reduce their savings, the response of the agents in the top percentiles of the distribution is very small. The rise in wealth inequality, in turn, increases consumption inequality among heterogeneous agents. We find that these two opposing effects quantitatively cancel each other out and thus result in negligible welfare gains attributable to a decline in consumption inequality.

Next, we analyze the heterogeneous welfare effects of the optimal policy. Unsurprisingly, the unemployed who are eligible for UI benefits gain significantly, with the poor within this group enjoying the largest welfare gains, since each additional dollar of benefit payments is more valuable to them. Workers also enjoy a sizeable welfare gain, albeit to a smaller degree due to two opposing effects. Although they are the primary financers of the increased government expenditures because of the generous policy, they also experience large consumption smoothing benefits over the business cycle. Similarly, gains are also much larger among poor workers for whom a reduction in precautionary savings diverted toward consumption is most beneficial. Finally, the unemployed who are ineligible for UI gain the least because they will enjoy benefits only if they find a job and become eligible through the loss of that job. They are also adversely affected by lower job finding rates during recessions without the insurance that UI provides.

When solving for the optimal UI policy, we follow a large strand of literature that uses calibrated models to study the optimal policy for a restricted class of policy instruments.[4] The model simultaneously matches the liquid asset-to-income distribution and salient features of the labor market prior to the Great Recession. The policy instruments in our welfare analysis are restricted to take the form of the UI replacement rate and UI payment duration as functions of current aggregate labor productivity, and a constant labor income tax used to balance the government's budget for any proposed UI program.

Related Literature Our paper contributes to the growing literature on optimal UI over the business cycle. Recent papers in this literature are Landais et al. (2017), Jung and Kuester (2015), Mitman and Rabinovich (2015). However, in these models, risk-averse agents do not have access to asset markets for self-insurance purposes.[5] This assumption has several important implications for the level and cyclicality of the insurance benefits and incentive costs of any proposed UI policy. First, the insurance value of UI payments for job losers is overstated because public insurance is the only way of smoothing consumption upon job loss. Second, since the elasticity of search effort and the wage choice of the unemployed are both decreasing in wealth holdings, a model that abstracts from self-insurance altogether also overestimates the level of the moral hazard costs associated

[4]See Hansen and Imrohoroğlu (1992), Acemoglu and Shimer (2000), Abdulkadiroğlu et al. (2002), Wang and Williamson (2002), Krusell et al. (2010), Koehne and Kuhn (2015), and Eeckhout and Sepahsalari (2015).

[5]In addition to this difference, there are other important modeling differences between our paper and these papers. For example, Jung and Kuester (2015) and Landais et al. (2017) do not consider UI expiration. See Mitman and Rabinovich (2015) for a discussion on the implications of these assumptions.

with introducing a more generous UI policy. Third, disregarding asset markets completely eliminates the interaction between self-insurance and public insurance. Importantly, the decline in precautionary saving motives as a response to a generous UI policy contributes to the expansion of insurance benefits of UI in recessions because it also provides consumption insurance against aggregate risk. The novelty of our analysis is to study this endogenous response of the asset distribution to changes in UI policy over the business cycle, which is crucial for the true measurement of the cyclicality of insurance benefits of UI. Among these papers, our model is closest to Mitman and Rabinovich (2015) with two differences: our model 1) allows for self-insurance through incomplete asset markets, and 2) features directed search, making the model still tractable due to block recursivity even under the presence of incomplete asset markets, whereas job search is random in their model. In terms of welfare exercise, Mitman and Rabinovich (2015) are able to solve a Ramsey problem to obtain the optimal UI policy as a function of the entire history of past aggregate shocks, whereas we use our calibrated model to study the optimal policy for a restricted class of policy instruments that only depend on the current period realization of the aggregate shock in order to maintain tractability.

Another strand of literature studies the optimal design of UI policy under the presence of asset markets. However, these papers use models that do not incorporate either unemployment risk (Kroft and Notowidigdo 2016) or aggregate risk (Hansen and Imrohoroğlu 1992, Acemoglu and Shimer 2000, Abdulkadiroğlu et al. 2002, Wang and Williamson 2002, Lentz 2009, Krusell et al. 2010, Koehne and Kuhn 2015, and Eeckhout and Sepahsalari 2015) or both features (Shimer and Werning 2008, Chetty 2008).[6] Absent unemployment risk, assets have no role for precautionary savings purposes, and they are simply used for consumption smoothing until the single spell ends and a permanent job is found.[7] Importantly, we show in our model that saving decisions interact with the changes in UI policy because wealth is a substitute for UI payments for self-insurance purposes. The

[6]Although the baseline model in Krusell et al. (2010) incorporates aggregate fluctuations, they study the welfare effects of changes in UI policy in a steady-state experiment. The baseline model in Chetty (2008) has no unemployment risk, but he presents an extension to incorporate it, and he shows that his main results hold under extra assumptions.

[7]Typically, in these models, all agents are initially unemployed, and they decide when to accept a permanent employment offer. These models are often called single-spell models.

changes in saving decisions in turn significantly affect the search effort and wage choices of the unemployed as well as the consumption patterns of everyone in the economy. On the other hand, a model in which aggregate risk is absent makes the insurance value of UI time-invariant. In our framework with aggregate risk, the strength of precautionary saving motives significantly varies with the level of unemployment risk over the business cycle. Incorporating this feature is especially important to understand the optimality of time-varying UI policy.[8]

Finally, other papers investigate the impact of the Great Recession extensions of UI duration on macroeconomic outcomes.[9] Pei and Xie (2016) relax the perfect commitment assumption and analyze the effects of time-consistent policy over the business cycle in a model with search frictions but risk averse agents are not allowed to save or borrow. They find that while benefit extensions resulted in higher unemployment, it provided welfare gains ex post compared to a no-extensions policy. We show that even when government can commit perfectly to its UI policy, the optimal policy is countercyclical when we account for changes in precautionary saving motives over the cycle. Two recent papers study this question in a framework with search frictions and incomplete markets. First, Nakajima (2012) carefully models UI extensions during the Great Recession and its subsequent recovery using a model with business cycle dynamics and then measures the effect of these extensions on the unemployment rate. He does not, however, study the welfare effects of these changes in UI policy. We extend his model to a general equilibrium model in which the government finances the UI benefits and use the model to study how UI policy must vary over the business cycle. Second, Kekre (2017) studies the macroeconomic and welfare effects of UI extensions during the Great Recession in a model with nominal rigidities and

[8]Our paper has other important features compared to these papers in the literature. In terms of modeling, previous papers (except for Krusell et al. 2010 and Eeckhout and Sepahsalari 2015) use partial equlibrium models of the labor market. In these models, the changes in aggregate conditions of the economy or in UI policy do not affect firm hiring decisions and offered wages. In terms of welfare analysis, Shimer and Werning (2008) use an optimal contracting approach to study the optimal variation of UI over the unemployment duration. Chetty (2008) and Kroft and Notowidigdo (2016) find a locally optimal UI policy in a welfare exercise that can be used only to calculate the marginal welfare effects of small changes in the UI benefit level, relative to the observed UI benefit level in the data.

[9]See Hagedorn et al. (2016), Mitman and Rabinovich (2014), and Chodorow-Reich and Karabarbounis (2017), among many others.

constraints on monetary policy but without business cycle dynamics in the real business cycle tradition. In his model, when the unemployed have a higher marginal propensity to consume than the employed, generous UI policy increases the aggregate demand for consumption both in the current period and in the previous period because individuals endogenously reduce precautionary savings when they expect generous public transfers in the future. As a result, he finds that UI extensions reduced the unemployment rate and provided welfare gains during the Great Recession. Rather than only focusing on discretionary UI policy changes during the Great Recession, we solve for the optimal UI policy over the business cycle and find that it should be countercyclical even when business cycles are completely exogenous and that UI policy has no role on smoothing these fluctuations through its impact on aggregate demand. Complementary to his findings, we also show that the endogenous response of precautionary savings to changes in UI generosity is key to understanding the true welfare benefits and costs of UI benefits.

On the theoretical side, our model is a heterogeneous agent general equilibrium directed search model of the labor market with aggregate labor productivity driven business cycles as in Menzio and Shi (2010, 2011). The market structure enables us to overcome the computational difficulties of solving a model of this type by utilizing the block recursive equilibrium. We extend their framework by incorporating asset markets as in Herkenhoff (2017) to study the optimal UI over the business cycle with endogenous wealth distribution. To the best of our knowledge, our model is the first to study this question in a model with endogenous wage determination, search frictions, incomplete markets, and aggregate fluctuations.

This paper is organized as follows. We present our model in Section 2.2. Then, Section 2.3 describes the calibration strategy and model fit. Section 2.4 explains the calculation of the welfare effects of various UI policies. Section 2.5 contains the main results. In Section 2.6, we provide a detailed discussion on our results and conduct robustness checks. Section 2.7 provides preliminary evidence from the micro-data that support the model's main mechanism. Finally, Section 2.8 concludes.

2.2 Model

This section first introduces the environment of the model in Section 2.2.1. We then lay out the problem of the household and firm in Section 2.2.2 and Section 2.2.3, respectively. Next, we explain the government's UI policy in Section 2.2.4. Finally, Section 2.2.5 defines the equilibrium of the model and characterizes the job search behavior of the unemployed.

2.2.1 Environment

Time is discrete and denoted by $t = 0, 1, 2, ...$ Individuals are infinitely lived and ex-ante identical, with preferences given by

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_t \Big[u\left(c_t\right) - \mathbf{1}_U \Big[\nu\left(s_t\right) \Big] \Big]$$

where $u\left(\cdot\right)$ is a strictly increasing and strictly concave utility function over consumption level c that satisfies Inada conditions, $\mathbf{1}_U$ is an indicator function that takes the value of one if the agent is unemployed, and $\nu\left(\cdot\right)$ represents the disutility associated with search effort of the unemployed and is a strictly increasing and strictly convex function of search intensity s. Moreover, β_t is a stochastic variable that is idiosyncratic - i.i.d. across agents - and describes the cumulative discounting between period 0 and period t. In particular, $\beta_{t+1} = \tilde{\beta}\beta_t$, where $\tilde{\beta}$ is a five-state, first-order Markov process as in Krusell et al. (2009). The heterogeneity in discount rates allows us to match important features of the empirical asset distribution, as we will discuss in Section 2.3.1.

In the model, individuals are heterogeneous in terms of their labor market status, asset holdings, labor market earnings, and stochastic discount rate. An agent can be classified into one of the following labor market statuses: a worker W, an unemployed individual who is eligible for unemployment insurance benefits UE, or an unemployed individual who is ineligible for unemployment insurance benefits UI.[10]

[10] Farber et al. (2015) find that UI extensions reduced the labor force exits by 20 to 30 percent during 2008-2011 and 2012-2014 respectively. Notice that even if our model does not incorporate a labor force participation margin, we find that the optimal policy is countercyclical. As a result, given that UI genorosity increases labor force participation, the welfare gains from the optimal policy actually constitute a lower bound in our model.

The labor market features directed search. Unemployed individuals direct their search effort $s \in [0,1]$ toward wage submarkets indexed by w. Once matched with a firm within submarket w, the household is paid a fixed wage w every period until the match exogenously dissolves, as in Menzio and Shi (2010).[11] Unemployed individuals who are eligible for UI benefits receive a fraction of the wage they received during their last employment, whereas the unemployed ineligible do not receive any benefits. In order to finance the unemployment insurance program, the worker and unemployed eligible pay a fraction τ of their wages/benefits to the government every period. In addition to labor earnings, all households have access to incomplete asset markets where they can save/borrow at an exogenous interest rate r.[12] On the other side of the labor market, firms decide the wage submarket in which to post a vacancy. Once matched with a worker, the firm-worker pair operates a constant returns to scale technology that converts one indivisible unit of labor into final consumption goods. All firm-worker pairs are assumed to be identical in terms of their production efficiency; that is, the amount of production only depends on aggregate labor productivity.

The timing of the model is as follows. At the beginning of each time period t, aggregate labor productivity p and the idiosyncratic discount rate β for each agent realize. The period labor productivity level p completely determines 1) the UI replacement rate $\phi(p) \in [0,1]$ and the stochastic UI expiration rate $e(p) \in [0,1]$, and 2) the exogenous job separation rate $\delta(p) \in [0,1]$. This implies that $\delta(p)$ fraction of those who were workers in $t-1$ lose their jobs and must spend at least one period being unemployed. Among those who lose their job, $e(p)$ fraction become ineligible for unemployment benefits. After the realization of the exogenous shocks, there are two stages in each time period t where agents make endogenous decisions.

First, in the labor market stage, firms decide the wage submarket in which to post a

[11] In Section 2.6.1, we extend our baseline model to endogenize the quit decisions of workers and explore the quantitative implications of this assumption on our main results.

[12] We could endogenize the interest rate by modeling an asset market in which financial intermediaries post asset returns in different locations and individuals look for saving/borrowing opportunities in these different locations depending on their state variables. This is similar to Herkenhoff (2017). In our baseline model, we abstract from this and assume a constant and exogenous interest rate. In Section 2.6.1, we explore the quantitative implications of this assumption.

vacancy, while the unemployed choose a wage submarket w within which to look for a job. Second, the production and consumption stage of time t open where each firm-worker pair produces p units of consumption goods, wages are paid to workers, UI benefits are paid to eligible unemployed as a fraction $\phi(p)$ of their previous wages, and any unemployed receive the monetized value of non market activities h.[13] The households then make their saving/borrowing decision. Finally, prior to time $t+1$, unemployed households decide the search effort level s they will exert in the labor market stage of time $t+1$ where the utility cost of that search effort is incurred at time t.

It is important to discuss the reasons why this environment is useful in answering our question. Beyond the obvious features of the presence of incomplete markets, a UI program, and equilibrium unemployment, we would like to consider an equilibrium model of the labor market in which firm and household decisions are affected by both aggregate fluctuations and changes in UI policy. This way, we are able to incorporate the moral hazard costs of generous UI policies on the job search intensity and wage choice behavior of the unemployed, as well as changes in the vacancy creation incentives of firms over the business cycle. Moreover, directed search is useful not only because of tractability reasons but also because of its implications for equilibrium efficiency. In particular, under some conditions, the equilibrium is efficient in the directed search model but not in a random search model with Nash bargaining.[14] Hence, in our framework, the government insurance program aims to fix the inefficiencies caused by incomplete asset markets.

2.2.2 Household problem

A household's state vector consists of current employment status $l \in \{W, UE, UI\}$, net asset level $a \in \mathcal{A} \equiv [\underline{a}, \bar{a}] \subseteq \mathbb{R}$, the current wage level $w \in \mathcal{W} \equiv [\underline{w}, \bar{w}] \subseteq \mathbb{R}_+$ if the

[13]The variable h encompasses both the value of leisure/home production and other income such as spousal and family income and other transfers. Our results would be similar if h is a utility value instead of a monetary value.

[14]See Acemoglu and Shimer (1999), Burdett, Shi, and Wright (2001), Shi (2001), and Menzio and Shi (2011) for the efficiency of directed search equilibrium. As discussed by Menzio and Shi (2011), however, the equilibrium of our baseline model does not maximize the joint value of a match (and thus it is not bilaterally efficient) because of the limitations in the contract space. In Section 2.6.1, we extend our baseline model to a model with endogenous quit decisions and show that the effects of inefficiencies present in the labor market of the baseline model on our main results are negligible.

employment status is W or the wage level from the previous job if the employment status is UE, and the current discount rate $\beta \in \mathcal{B} \equiv \left[\underline{\beta}, \bar{\beta}\right] \subset (0,1)$.

The aggregate state is denoted by $\mu = (p, \Gamma)$, where $p \in \mathcal{P} \subseteq \mathbb{R}_+$ denotes the current aggregate labor productivity and $\Gamma: \{W, UE, UI\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{B} \to [0,1]$ denotes the distribution of agents across employment status, asset level, current/previous wage level, and discount rate. The law of motion for the aggregate states is given by $\Gamma' = H(\mu, p')$ and $p' \sim F(p' \mid p)$.

The recursive problem of the worker is given by

$$\begin{aligned}
V^{W}(a, w, \beta; \mu) \quad = \quad \max_{c, a'} \quad & u(c) + \beta \mathbb{E}\Bigg[\delta\left(p'\right)\left(1 - e\left(p'\right)\right) V^{UE}\left(a', w, \beta'; \mu'\right) \\
& + \delta\left(p'\right) e\left(p'\right) V^{UI}\left(a', \beta'; \mu'\right) \\
& + \left(1 - \delta\left(p'\right)\right) V^{W}\left(a', w, \beta'; \mu'\right) \Bigg| \beta, \mu\Bigg] \qquad (2.1) \\
\text{subject to} \quad & \\
& c + a' \leq (1 + r)\, a + w\,(1 - \tau) \\
& a' \geq -\underline{a} \\
& \Gamma' = H\left(\mu, p'\right) \quad \text{and} \quad p' \sim F\left(p' \mid p\right).
\end{aligned}$$

Notice in the above problem that the worker may not qualify for UI benefits with probability e after losing her job due to exogenous job separation, which captures both voluntary and involuntary reasons for job loss in our model. This feature intends to capture the fact that according to the current UI policy in the United States, not all workers transitioning into unemployment qualify for UI benefits. In particular, individuals do not qualify for benefits if they voluntarily quit their job or if they do not meet certain work/earnings requirements.[15]

The unemployed directs her job search effort toward a wage submarket indexed by w with an associated market tightness given by $\theta(w; \mu)$, which is an equilibrium object defined later. Let $f(\theta(w; \mu))$ be the job finding probability for the unemployed who visits submarket w when the aggregate state is μ. Then, we lay out the recursive problem of eligible

[15] The unemployed must meet requirements for wages earned or time worked during an established period of time referred to as the base period. In most states of the United States, this is usually the first four out of the last five completed calendar quarters prior to the time that a UI application is filed.

unemployed as follows:

$$
\begin{aligned}
V^{UE}(a,w,\beta;\mu) \;\; = \;\; & \max_{c,a',s} \;\; u\left(c\right)-\nu\left(s\right)+\beta\mathbb{E}\Bigg[\max_{\tilde{w}}\Big\{sf\left(\theta\left(\tilde{w};\mu'\right)\right)V^{W}\left(a',\tilde{w},\beta';\mu'\right) \\
& +\left(1-sf\left(\theta\left(\tilde{w};\mu'\right)\right)\right)\left(1-e\left(p'\right)\right)V^{UE}\left(a',w,\beta';\mu'\right) \\
& +\left(1-sf\left(\theta\left(\tilde{w};\mu'\right)\right)\right)e\left(p'\right)V^{UI}\left(a',\beta';\mu'\right)\Big]\Big\}\Big|\beta,\mu\Bigg]
\end{aligned}
\tag{2.2}
$$

subject to

$$
\begin{aligned}
& c+a' \leq \left(1+r\right)a+h+\phi\left(p\right)w\left(1-\tau\right) \\
& a' \geq -\underline{a} \\
& \Gamma' = H\left(\mu,p'\right) \quad \text{and} \quad p' \sim F\left(p'\,|\,p\right).
\end{aligned}
$$

where the eligible unemployed receives a fraction ϕ of her previous wage as UI benefits and pays τ fraction as labor income tax. As described earlier, she may lose her eligibility with probability e if she is unable to find a job during the labor market stage of the current period. When choosing the wage submarket to search for jobs, the unemployed individual faces the trade-off between the level of surplus from a possible match (i.e., the wage level) and the probability of finding a job because of the lower number of vacancies posted for high-paying jobs.

Finally, the recursive problem of the ineligible unemployed is given by

$$
\begin{aligned}
V^{UI}(a,\beta;\mu) \;\; = \;\; & \max_{c,a',s} \;\; u\left(c\right)-\nu\left(s\right)+\beta\mathbb{E}\Bigg[\max_{\tilde{w}}\Big\{sf\left(\theta\left(\tilde{w};\mu'\right)\right)V^{W}\left(a',\tilde{w},\beta';\mu'\right) \\
& +\left(1-sf\left(\theta\left(\tilde{w};\mu'\right)\right)\right)V^{UI}\left(a',\beta';\mu'\right)\Big\}\Big|\beta,\mu\Bigg]
\end{aligned}
\tag{2.3}
$$

subject to

$$
\begin{aligned}
& c+a' \leq \left(1+r\right)a+h \\
& a' \geq -\underline{a} \\
& \Gamma' = H\left(\mu,p'\right) \quad \text{and} \quad p' \sim F\left(p'\,|\,p\right).
\end{aligned}
$$

Notice that in the above problem, the unemployed ineligible is unable to regain eligibility for UI benefits if job search fails. This captures the fact that according to current UI policy in the United States, the unemployed receive UI benefits only for a certain number of weeks - which varies over the business cycle - and once that threshold is reached, the unemployed cannot continue to collect UI benefits.

2.2.3 Firm problem

Firms post vacancies offering fixed wage contracts in certain wage submarkets. The labor market tightness of submarket w is defined as the ratio of vacancies v posted in the submarket to the aggregate search effort S exerted by all the unemployed searching for a job within that submarket. It is denoted as $\theta(w;\mu) = \frac{v(w;\mu)}{S(w;\mu)}$. Let $M(v,u)$ be a constant returns to scale matching function that determines the number of matches in a submarket with S level of aggregate search effort and v vacancies. We can then define $q(w;\mu) = \frac{M(v(w;\mu),S(w;\mu))}{v(w;\mu)}$ to be the vacancy filling rate and $f(w;\mu) = \frac{M(v(w;\mu),S(w;\mu))}{S(w;\mu)}$ to be the job finding rate in submarket w when aggregate state is μ. The constant returns to scale assumption on the matching function guarantees that the equilibrium object θ suffices to determine job finding and vacancy filling rates since $q(\theta) = \frac{M(v,S)}{v} = M\left(1, \frac{1}{\theta}\right)$ while $f(\theta) = \frac{M(v,S)}{S} = M(\theta, 1)$.
First, consider a firm that is matched with a worker in submarket w when the aggregate state is μ. The pair operates under a linear production technology and produces p units of output, and there is no capital in the economy. The worker is paid a fixed wage of w and with some probability $\delta(p)$, the match dissolves. Hence, the value of a matched firm is given by

$$J(w;\mu) = p - w + \frac{1}{1+r}\mathbb{E}\left[\left(1-\delta\left(p'\right)\right) J\left(w;\mu'\right) \middle| \mu\right] \tag{2.4}$$

subject to

$$\Gamma' = H\left(\mu, p'\right) \quad \text{and} \quad p' \sim F\left(p' \mid p\right).$$

Meanwhile, the value of a firm that posts a vacancy in submarket w under aggregate state μ is given by

$$V(w;\mu) = -\kappa + q(\theta(w;\mu)) J(w;\mu), \tag{2.5}$$

where κ is a fixed cost of posting a vacancy that is financed by risk-neutral foreign entrepreneurs who own the firms.
When firms decide the submarket in which to post vacancies to maximize profits, they face the trade-off between the probability of filling a vacancy and the level of surplus from a

possible match. This is because if a firm posts a vacancy in a low (high) wage submarket, then the level of the surplus from the match in that submarket will be higher (lower) for the firm, but the probability of filling the vacancy will be lower (higher) as less (more) unemployed individuals visit that submarket to search for a job.

The free entry condition implies that profits are just enough to cover the cost of filling a vacancy in expectation. As a result, the owner of the firm makes zero profits in expectation. Thus, we have $V(w;\mu) = 0$ for any submarket w such that $\theta(w;\mu) > 0$. Then, we impose the free entry condition to Equation (2.5) and obtain the equilibrium market tightness:

$$\theta(w;\mu) = \begin{cases} q^{-1}\left(\frac{\kappa}{J(w;\mu)}\right) & \text{if} \quad w \in \mathcal{W}(\mu) \\ 0 & \text{otherwise.} \end{cases} \tag{2.6}$$

The equilibrium market tightness contains all the relevant information needed by households to evaluate the job finding probabilities at each submarket.

2.2.4 Government policy

The UI policy is characterized by $\{\phi(p), e(p), \tau\}$, where $\phi(p)$ is the replacement rate and $e(p)$ is the expiration rate, both of which may vary with current aggregate labor productivity p.[16] A labor income tax τ is levied on the labor earnings of the worker and on the UI benefits of the eligible unemployed in order to finance the UI program.[17] The benefit expiration rate $e(\cdot)$ is stochastic, as in Fredriksson and Holmlund (2001), Albrecht and Vroman (2005), Faig and Zhang (2012), and Mitman and Rabinovich (2015). This assumption simplifies the solution of the model because we do not need to carry the unemployment duration as another state variable for the eligible unemployed.

[16] We restrict the UI policy to depend on the aggregate state of the economy μ only through the current aggregate labor productivity p and not through the distribution of individuals across states Γ. This restriction allows our model to retain the block recursitivity, which we will explain in Section 2.2.5.

[17] We focus on the optimality of government policies that can be conditioned on the employment status of the individuals so that the government policies provide insurance against unemployment risk. Also, if the government finds it optimal to make transfers (by reducing taxes) during recessions, it can obviously do this by increasing the UI replacement rate and duration. For these reasons, we consider time-invariant income tax schedules in our analysis.

The government balances the following budget constaint in expectation:[18]

$$\sum_{t=0}^{\infty}\sum_{i}\left(\frac{1}{1+r}\right)^{t}\times\left[\mathbf{1}_{\{l_{it}=W\}}\times w_{it}+\mathbf{1}_{\{l_{it}=UE\}}\times w_{it}\phi\left(p_{t}\right)\right]\times\tau$$
$$=\sum_{t=0}^{\infty}\sum_{i}\left(\frac{1}{1+r}\right)^{t}\times w_{it}\phi\left(p_{t}\right)\times\mathbf{1}_{\{l_{it}=UE\}} \tag{2.7}$$

where the left-hand side is the present discounted value of tax revenues collected from the labor income of workers and the unemployed eligible, and the right-hand side is the present discounted value of UI payments to the unemployed eligible.

2.2.5 Equilibrium

Definition of the Recursive Equilibrium: Given a UI policy $\left\{\tau,\phi\left(p\right),e\left(p\right)\right\}_{p\in\mathcal{P}}$, a recursive equilibrium for this economy is a list of household policy functions for assets $\left\{g_{a}^{l}\left(a,w,\beta;\mu\right)\right\}_{l=\{W,UE\}}$ and $g_{a}^{UI}\left(a,\beta;\mu\right)$, wage choices $g_{w}^{UE}\left(a,w,\beta;\mu\right)$ and $g_{w}^{UI}\left(a,\beta;\mu\right)$, search effort $g_{s}^{UE}\left(a,w,\beta;\mu\right)$ and $g_{s}^{UI}\left(a,\beta;\mu\right)$, a labor market tightness function $\theta\left(w;\mu\right)$, and an aggregate law of motion $\mu'=\left(p',\Gamma'\right)$ such that

1. Given government policy, shock processes, and the aggregate law of motion, the household's policy functions solve their respective dynamic programming problems (2.1), (2.2), and (2.3).

2. The labor market tightness is consistent with the free entry condition (2.6).

3. The government budget constraint (2.7) is satisfied.

4. The law of motion of the aggregate state is consistent with household policy functions.

Notice that in order to solve the recursive equilibrium defined above, one must keep track of an infinite dimensional object Γ in the state space, making the solution of the model infeasible. To address this issue, we utilize the structure of the model and use the notion of block recursive equilibrium developed by Menzio and Shi (2010, 2011).

[18]This assumption is motivated by the fact that according to the current UI system in the United States, states are allowed to borrow from a federal UI trust fund when they meet certain federal requirements, and thus they are allowed to run budget deficits during some periods.

Definition of the Block Recursive Equilibrium (BRE): A BRE for this economy is an equilibrium in which the value functions, policy functions, and labor market tightness depend on the aggregate state of the economy μ, only through the aggregate productivity p, and not through the aggregate distribution of agents across states Γ.

Now, we prove that our model admits block recursitivity.

Proposition 1: *If i) utility function $u(\cdot)$ is strictly increasing, strictly concave, and satisfies Inada conditions; $\nu(\cdot)$ is strictly increasing and strictly convex, ii) choice sets $\mathcal{W}$ and $\mathcal{A}$, and sets of exogenous processes $\mathcal{P}$ and $\mathcal{B}$ are bounded, iii) matching function M exhibits constant returns to scale, and iv) UI policy is restricted to be only a function of current aggregate labor productivity, then there exists a Block Recursive Equilibrium for this economy. If, in addition, $M = min\{v, S\}$, then the Block Recursive Equilibrium is the only recursive equilibrium.*

Proof: See Appendix B.2

Proposition 1 is very useful because it allows us to solve the model numerically without keeping track of the aggregate distribution of agents across states Γ. One should be careful when interpreting this result. Even though we can solve for the policy functions, value functions, and labor market tightness independent of Γ, it does not mean that the distribution of agents is irrelevant for our analysis. Notice that the evolution of macroeconomic aggregates such as the unemployment rate, average spell duration, and wealth distribution of the economy is determined by household decision rules in the labor market and financial market. These decisions, in turn, are functions of individual states whose distribution is determined by Γ. Hence, the evolution of aggregate variables after a change in UI policy will depend on the distribution of agents in the economy at the time of the policy change. Notice that if the UI policy instruments were to depend on the unemployment rate of the economy, then it would break the block recursivity of the model. This is because agents would need to calculate next period's unemployment rate to know the replacement rate and UI duration next period. However, this requires calculating the flows in and out of unemployment, the latter of which depends on the distribution of agents across states Γ. Although the changes in UI policy are triggered by the changes in the unemployment rate according to the current UI program in the United States, the assumption that UI policy depends on aggregate productivity is not too restrictive because of the strong correlation between the unemployment rate and aggregate labor productivity in the model.

Job search decision rules We now characterize the job search behavior of the unemployed. This will supplement our discussions of the main results of the paper in Section 2.5.

Figure 2.1 plots the labor market behavior of the eligible unemployed holding various levels of wealth under a less generous UI policy and a generous UI policy. It shows that the search intensity is decreasing in wealth, whereas the wage choice is increasing in wealth for any UI policy.[19]

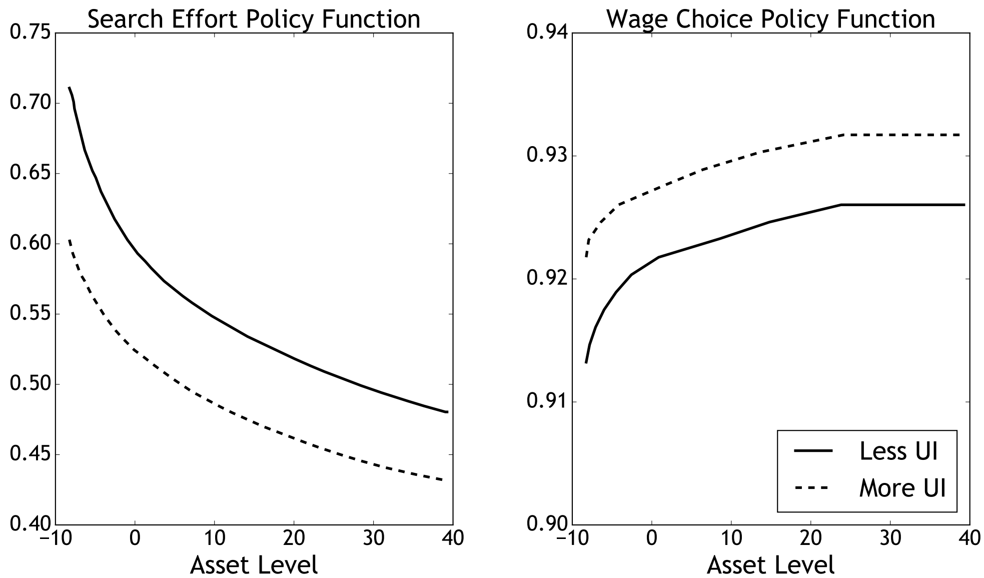
Moreover, similar to Krusell et al. (2010), the marginal effect of an increase in assets on wage choice and search effort is relatively higher for the borrowing-constrained unemployed.[20] While this result is unsurprising and intuitive, it highlights the importance of accounting for wealth heterogeneity across agents, since the aggregate search effort and wage levels in the economy now crucially depend on the underlying wealth distribution. An economy where agents are relatively wealthy is likely to exhibit lower levels of aggregate search and higher wages, whereas the opposite is true when wealth levels are low. Since business cycles induce changes in precautionary savings and thus variation in aggregate search effort and wage choices, the optimal design of UI policy over the business cycle must account for this channel. For instance, in a recession where many individuals deplete their existing wealth, this channel exerts an upward pressure on search effort and downward pressure on wage choices as agents seek to find jobs more quickly. This effect dampens the moral hazard costs induced by introducing a more generous UI policy during recessions, since poorer agents tend to ramp up job-finding efforts themselves.

Next, a comparison of the two policy functions across UI policies highlights two important points. First, generous UI payments entail incentive costs because they lead the eligible

[19]Notice that there is little dispersion across wage choices of the unemployed holding different levels of wealth. Hornstein et al. (2011) show that frictional wage dispersion - measured by the mean-min wage ratio - is very small in a directed search model. When calibrated to match the empirical asset distribution and salient features of the labor market prior to the Great Recession in the United States, our model generates a mean-min wage ratio of 1.034, in line with their conclusion (less than 1.05).

[20]These patterns are also present for the ineligible unemployed.

Figure 2.1: Search effort and wage choice policy functions of the eligible unemployed



Note: These figures plot the search effort and wage choice policy functions of the eligible unemployed holding different levels of wealth for average levels of labor productivity, discount rate, and previous wage under a less generous and a more generous UI policy.

unemployed to decrease their search effort and increase their wage choices.[21] The combined effect of lower search effort and a shift toward higher-paying jobs, which are more difficult to find, results in a lower aggregate job finding rate and prolonged unemployment spells. Second, the unemployed holding different levels of wealth respond in varying degrees to changes in UI policy. Similar to Chetty (2008), wealthier agents are less responsive to changes in UI policy because the insurance value of a marginal increase in benefits is less important to them. This implies that a model that abstracts from self-insurance altogether overestimates the level of the moral hazard costs of introducing a more generous UI policy. The assumption that agents have no access to asset markets effectively raises the aggregate elasticity of search effort and wage choice to changes in UI policy, since the most responsive agents are precisely those with the least available self-insurance. As a result, it is crucial for the model to match the observed asset distribution in the data in order to generate the

[21]This result is also established in the previous literature. See Shavell and Weiss (1979), Hopenhayn and Nicolini (1997), and Acemoglu and Shimer (1999), among many others.

true magnitude of moral hazard costs in the model.

2.3 Calibration

We calibrate the stochastic steady state of our model to match salient features of the labor market and asset distribution of the U.S. economy prior to the Great Recession. In doing so, we feed into the model a constant replacement rate and expiration rate, which we call the *acyclical/flat* policy.

The model period is taken to be a week. We use the following separable functional form for the period utility function:

$$u(c_t) - \mathbf{1}_U [\nu(s_t)] = \frac{c_t^{1-\sigma}}{1-\sigma} - \mathbf{1}_U \left[\alpha \frac{s_t^{1+\chi}}{1+\chi} \right],$$

which is also used by Chetty (2008) and Nakajima (2012). We restrict the values of discount rates to be symmetric around an average value $\bar{\beta}$ with a difference of η between two adjacent values. Moreover, we allow β to take five different values. In our simulations of the model, we set 40 percent of the population to the middle discount rate value and 10 percent to each extreme point in any time period. The expected duration of being in the extreme discount rate value is set to be 50 years, where transitions can only occur between adjacent values.

The labor market matching function is $M(v, S) = \frac{vS}{[v^\gamma + S^\gamma]^{1/\gamma}}$ as in den Haan et al. (2000). This CES functional form of the matching function implies that both the job finding rate $f(\theta) = \theta (1 + \theta^\gamma)^{-1/\gamma}$ and the vacancy filling rate $q(\theta) = (1 + \theta^\gamma)^{-1/\gamma}$ are between 0 and 1.

Following Shimer (2005), we use a process for the job destruction rate that depends only on labor productivity, $\delta_t = \bar{\delta} \times \exp(\omega(p_t - 1))$, where $\bar{\delta}$ is the average weekly exogenous job destruction rate in the data. These separation shocks can be interpreted as idiosyncratic match quality shocks that drive down the productivity of a match to a low enough level so that the match endogenously finds it optimal to dissolve, as in Lise and Robin (2017). Moreover, the probability of this idiosyncratic event is correlated with the aggregate state of the economy. As a result, this specification allows the model to capture the cyclicality of employment-to-unemployment (E-U) transitions.[22] We then calibrate ω so that the volatility of quarterly E-U transitions in the model matches its data counterpart, which we calculate using E-U transition rates measured by Fujita and Ramey (2009) for the time period 1976:I-2005:IV.[23]

The logarithm of the aggregate labor productivity p_t follows an AR(1) process:

$$\ln p_{t+1} = \rho \ln p_t + \sigma_\epsilon \epsilon_{t+1}.$$

We take p_t as the mean real output per person in the non-farm business sector. Using the quarterly data constructed by the Bureau of Labor Statistics (BLS) for the time period 1951:I-2007:IV, we estimate the above process at a weekly frequency and find that $\rho = 0.9720$ and $\sigma_\epsilon = 0.0025$.

Next, we calibrate the replacement rate and expiration rate of the acyclical/flat policy by matching the long-run empirical averages of U.S. government policy. First, we discuss the calibration of the replacement rate. Chodorow-Reich and Karabarbounis (2016) measure the mean of pretax benefits per recipient as 21.5 percent of pretax marginal product.[24] Under a mean take-up rate of UI benefits among the eligible unemployed of 65 percent, this implies setting the mean of pretax benefits per recipient to 14 percent, since we do not model UI take-up decisions given the completixity of our framework.[25] Second, we take the UI benefit duration as 26 weeks (2 quarters), which is the standard benefit duration

[22]Empirically, Elsby et al. (2009), Fujita and Ramey (2006, 2009), Yashiv (2007), and Fujita (2011a) show that the separation rate into unemployment is countercyclical.

[23]The model-implied Beveridge curve, which plots the relationship between unemployment and vacancies, exhibits a negative slope as in the data. This is because when labor productivity declines, firms cut back on vacancies, which translates to lower job finding rates and higher unemployment. Moreover, the rise in separation shocks further amplifies the increase in unemployment. As a result, unemployment and vacancies move in the opposite direction.

[24]This value is consistent with a replacement rate level that accounts for the difference between wage and total compensation, the difference between compensation and the marginal product, and the gap in productivity and compensation between those receiving UI and the economywide average. In our model, wages are not exactly equal to marginal product because of frictions, but the difference between the two is small.

[25]Estimates in the literature for the fraction of all eligibles who receive UI range from 50 to 77 percent using Current Population Survey (CPS) data for different samples. Fuller, Ravikumar, and Zhang (2013) find that during the Great Recession, only about 50 percent of those eligible collected their benefits. Vroman (1991) uses CPS supplements from 1989 and 1990 and finds 53 percent. Blank and Card (1991) estimate

without extensions. Under the stochastic steady state calibration of our model, these two numbers require us to set $\phi_t = 0.14$ and $e_t = 1/26\ \forall t$ as the acyclical/flat policy.[26] Then, a labor income tax rate of $\tau = 0.36$ percent balances the government budget in equilibrium when the unemployment rate is 4.8 percent.

Having specified functional forms, the law of motion of the productivity process, and UI policy, we now calibrate several parameters outside of our model. We choose a coefficient of relative risk aversion $\sigma = 2$ and set $r = 0.095$ percent, which generates an annual return on assets of around 5 percent. Hagedorn and Manovskii (2008) estimate the combined capital and labor costs of vacancy creation as 58 percent of weekly labor productivity. Following their estimate, we set the cost of vacancy creation as $\kappa = 0.58$.

We measure the average weekly job separation rate $\bar{\delta}$ using data from the Survey of Income and Program Participation (SIPP) for the time period between 2005 and 2007. The SIPP comprises individual level longitudinal data in which each respondent provides information on monthly income and government transfers as well as weekly labor force status. We restrict our sample to individuals between the ages of 24 and 65 who do not own a business or derive income from self-employment. We classify the individual as employed (E) if he/she reports having a job and either working or not on layoff, but absent without pay. We classify the individual as unemployed (U) if he/she reports either having no job and actively looking for work or having a job but currently laid off. We then calculate the average E-U transition rate in the data where we account for seasonality by removing weekly fixed effects and obtain $\bar{\delta} = 0.0022$.

This leaves us eight parameters to be calibrated: i) the average value of discount rates $\bar{\beta}$, ii) the difference between two adjacent discount rates η, iii) the borrowing limit $\underline{a}$, iv) the

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the take-up rate as 71 percent for the period 1977–1987. Auray, Fuller, and Lkhagvasuren (2013) estimate the average take-up rate as 77 percent from 1989 to 2012 using detailed state-level eligibility criteria. Meanwhile, Anderson and Meyer (1997) use administrative data between the late 1970s and early 1980s and find that the take-up rate is 54 percent for a subsample that represents mainly separations from mass layoffs. In our baseline calibration, we set the take-up rate as 65 percent, which is around the mean of the above estimates in the literature.

[26] In Section 6.1, we also calculate the welfare gains from the optimal policy under 40 percent of the replacement rate (i.e., $\phi = 0.4\ \forall t$), which is the unadjusted replacement rate value calculated by the Department of Labor. We show that the optimal UI policy still yields significant welfare gains relative to the benchmark policy under this alternative high calibration of the replacement rate.

level parameter of the search cost function α, v) the curvature parameter of the search cost function χ, vi) the matching function parameter γ, vii) the separation rate parameter ω, and viii) the monetized value of non-market activity h. We jointly calibrate these parameters to match the following eight data moments, respectively: i) the median value of liquid asset holdings relative to weekly after-tax labor income distribution, ii) fraction of the population with non-positive liquid wealth, iii) the median value of the credit limit to labor income ratio, iv) the average unemployment rate, v) the response of the average unemployment duration to changes in the replacement rate, vi) the standard deviation of the unemployment rate, vii) the standard deviation of the job separation rate, and viii) the level of the opportunity cost of employment.

The first two moments related to the asset-to-income distribution is calculated from SIPP 2004 data and details are given in Section 2.3.1. Kaplan and Violante (2014) calculate the median value of the credit limit to quarterly labor income ratio for households aged 22 to 59 as 74 percent using Survey of Consumer Finances (SCF) data. We choose the borrowing limit parameter $\underline{a}$ so that the median value of the ratio of $\underline{a}$ to after-tax quarterly labor income in the model is 0.74.

The average unemployment rate and its standard deviation are calculated from U.S. data. In our baseline calibration, we choose the curvature parameter of the search cost function χ so that a 10 percentage point increase in the replacement rate generates an increase of 0.5 week in average unemployment duration among the UI eligible, which is within the range of available empirical estimates.[27] Hence, this parameter is important because it controls the magnitude of the incentive costs associated with the increase in UI payments.

Finally, Chodorow-Reich and Karabarbounis (2016) use a complete markets model and estimate the level of the opportunity cost of employment as 47 percent of the marginal product of employment under separable preferences. We choose the monetized value of non-market activity h so that the opportunity cost of employment generated by our model is 0.47. Given the incomplete markets model we have, to make the calibration comparable, we only simulate agents from the top 1 percent of the stationary asset-to-income distribution

[27]See Nakajima (2012) for the summary of empirical estimates. We evaluate the welfare gains from the optimal policy under different values of χ that match other levels of the available estimates in the literature. We find that the welfare gains from the optimal policy remain similar for different values of χ. These results are available upon request.

Table 2.1: Internally calibrated parameters

Parameter	Explanation	Value	Target	Model	Data
$\bar{\beta}$	Average discount rate	0.9986	Median asset-to-income ratio	6.17	6.22
η	Deviation from $\bar{\beta}$	0.0005	Frac. of pop. with non-positive wealth	0.27	0.27
$\underline{a}$	Borrowing limit	-8.25	Median credit-limit-to-income ratio	0.74	0.74
α	Level of search cost	5.02	Average unemployment rate	0.048	0.048
χ	Curvature of search cost	1.49	Response of average unemp. duration to changes in replacement rate	0.5	0.5
γ	Matching function parameter	0.217	Std. dev. of unemployment rate	0.10	0.12
ω	Separation rate parameter	-14.3	Std. dev. of separation rate	0.18	0.16
h	Value of nonmarket activity	0.342	Level of opportunity cost of emp.	0.47	0.47

Note: The average unemployment rate is calculated using monthly data between January 2005 and December 2007 provided by FRED - Federal Reserve Economic Data from the Federal Reserve Bank of St. Louis. The average standard deviation of the unemployment rate is reported in logs as quarterly deviations from an HP-filtered trend with a smoothing parameter of 1600, using quarterly data between 1951:I–2007:IV provided by FRED. The same procedure is applied to obtain the volatility of separation rates using data from Fujita and Ramey (2009) from 1976:I–2005:IV. The rest of the data moments are discussed in the main text.

when calculating the opportunity cost of employment using our model. This is because the behavior of the very rich agents in the incomplete markets model converges to the behavior of agents in the complete markets model. Section 2.3.2 explains how we calculate the opportunity cost of employment in our model. Later in Section 2.6.2, we target 0.955 as an alternative level of the opportunity cost of employment, which is the value calibrated by Hagedorn and Manovskii (2008), and discuss its implications for our main results.
Table 2.1 summarizes these calibrated parameters and compares the model's match to these data moments.

2.3.1 Asset distribution

In addition to monthly data on income and government transfers as well as weekly data on employment status, the SIPP also contains data on respondents' asset holdings. In each SIPP panel, respondents provide information on various types of asset holdings during two or three waves within the panel, usually one year or, equivalently, three waves apart. We use Wave 6 of the 2004 panel of SIPP, which covers interview months October 2005 - January 2006 and is the wave closest to the Great Recession that provides wealth holding information. We restrict our sample to individuals ages 24-65 and to those who neither own a business nor derive income from self-employment.

We use individual net liquid asset holdings as our primary measure of wealth because of its immediate availability as a means to smooth consumption in the event of job loss. The net liquid asset holdings of an individual are calculated by adding transaction accounts (checking, saving, money market, call accounts) and tradable assets (mutual funds, stocks, bonds), and then deducting unsecured debt. We follow Koehne and Khun (2015) and include net vehicle equity when calculating net liquid asset holdings. The reason is that income can decrease substantially upon unemployment, and some unemployed could resort to liquidating other forms of assets (i.e., the sale of vehicles) to smooth consumption upon job loss.

To normalize wealth and better capture the level of self-insurance, we compute respondents' asset-to-income ratio by dividing net liquid assets by weekly after-tax labor income.[28] We determine after-tax income using the statutory income tax codes. Table 2.2 shows the computed quantiles of the asset distribution in the data and model. The calibrated model comes close to matching the empirical asset distribution. In particular, our model reasonably captures the left tail of the distribution and at the same time exactly matches the fraction of the population holding non-positive liquid wealth. Matching the left tail of the distribution matters for our analysis because agents in this region of the distribution are the most affected by changes in UI policy. Job losers with low wealth have little to no

[28] We use weekly employment status information to obtain weekly labor earnings from monthly labor earnings data. We simply divide the monthly labor earnings by the number of weeks with a job for that month to obtain weekly labor earnings. Appendix B.1 provides more details on the calculation of the asset holdings and after-tax labor income.

Table 2.2: Percentiles of the distribution of liquid asset holdings relative to weekly after-tax labor income

	Quantiles					Fraction of population
	10th	25th	50th	75th	90th	with non-positive wealth
Data	-8.59	0.00	6.22	20.23	56.57	0.27
Model	-3.84	-0.85	6.17	33.32	42.46	0.27

Note: This table shows the liquid asset to after-tax labor income distribution in both the data and the model. The empirical distribution is calculated by the authors using the SIPP 2004 Panel. The main text provides the details of the calculation.

capacity to self-insure or smooth consumption using their own liquid assets and are thus very sensitive to changes in unemployment insurance generosity.

2.3.2 Opportunity cost of employment

To calculate the opportunity cost of employment across individual and aggregate states, we first derive surpluses obtained from moving from eligible unemployment to employment, and from ineligible unemployment to employment separately. Let $S^{UE}\left(a, w^{UE}, \beta; p\right)$ be the surplus derived by an unemployed eligible with state $\left(a, w^{UE}, \beta; p\right)$ who transitions into employment in a job that pays her optimal wage choice $\tilde{w}\left(a, w^{UE}, \beta; p\right)$. Similary, let $S^{UI}\left(a, \beta; p\right)$ be the surplus associated with moving from ineligible unemployment with state $(a, \beta; p)$ to a job that pays the optimal wage choice $\tilde{w}\left(a, \beta; p\right)$. We can then write

$$S^{UE}\left(a, w^{UE}, \beta; p\right) = V^{W}\left(a, \tilde{w}\left(a, w^{UE}, \beta; p\right), \beta; p\right) - V^{UE}\left(a, w^{UE}, \beta; p\right) \tag{2.8}$$

and

$$S^{UI}\left(a, \beta; p\right) = V^{W}\left(a, \tilde{w}\left(a, \beta; p\right), \beta; p\right) - V^{UI}\left(a, \beta; p\right). \tag{2.9}$$

Now consider the same individual who loses the aforementioned job that pays $\tilde{w}\left(a, w^{UE}, \beta; p\right)$. We can define the next period surplus of an eligible unemployed as

$$S\left(a'^{W}, \tilde{w}\left(a, w^{UE}, \beta; p\right), \beta'; p'\right) = V^{W}\left(a'^{W}, \tilde{w}\left(a'^{W}, \tilde{w}\left(a, w^{UE}, \beta; p\right), \beta'; p'\right), \beta'; p'\right) \\ - V^{UE}\left(a'^{W}, \tilde{w}\left(a, w^{UE}, \beta; p\right), \beta'; p'\right), \tag{2.10}$$

where the right-hand side is the difference in the value of again finding a job that pays optimal wage choice $\tilde{w}\left(a'^{W}, \tilde{w}\left(a, w^{UE}, \beta; p\right), \beta'; p'\right)$ and remaining as unemployed eligible. Similarly, the next period surplus for the ineligible unemployed is given by

$$S^{UI}\left(a'^{W}, \beta'; p'\right) = V^{W}\left(a'^{W}, \tilde{w}\left(a'^{W}, \beta'; p'\right), \beta'; p'\right) - V^{UI}\left(a'^{W}, \beta'; p'\right) \tag{2.11}$$

Evaluating V^{W}, V^{UE}, and V^{UI} at a'^{W} in Equations (2.10) and (2.11) restricts the continuation surpluses to only that part associated with entering next period in the employed state. Next, substituting (2.1), (2.2), and (2.3) into (2.8) and (2.9), we obtain

$$\frac{S^{UE}\left(a, w^{UE}, \beta; p\right)}{\lambda^{W}} = \tilde{w}\left(a, w^{UE}, \beta; p\right) \times (1-\tau) - \underbrace{\left(z^{UE}_{flow} + z^{UE}_{a} + z^{UE}_{w} + z^{UE}_{elg}\right)}_{z^{UE}} \\ + \beta \mathbb{E}\left[\frac{\lambda'^{W}}{\lambda^{W}} \times \frac{\left(1 - \delta\left(p'\right) - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right) S^{UE}\left(a'^{W}, \tilde{w}\left(\cdot\right), \beta'; p'\right)}{\lambda'^{W}}\right] \tag{2.12}$$

and

$$\frac{S^{UI}\left(a, \beta; p\right)}{\lambda^{W}} = \tilde{w}\left(a, \beta; p\right) \times (1-\tau) - \underbrace{\left(z^{UI}_{flow} + z^{UI}_{a} + z^{UI}_{w} + z^{UI}_{elg}\right)}_{z^{UI}} \\ + \beta \mathbb{E}\left[\frac{\lambda'^{W}}{\lambda^{W}} \times \frac{\left(1 - \delta\left(p'\right) - sf\left(\theta\left(\tilde{w}\left(a'^{UI}, \beta'; p'\right); p'\right)\right)\right) S^{UI}\left(a'^{W}, \beta'; p'\right)}{\lambda'^{W}}\right], \tag{2.13}$$

where λ^{W} is the the marginal utility of consumption for the worker. The opportunity cost of employment z^{l} for each unemployed type $l = \{UE, UI\}$ consists of four components: z^{l}_{flow} is simply the flow utility difference between a worker and an unemployed type l, z^{l}_{a} is the change in value due to differential asset accumulation between the employed and the unemployed type l, z^{l}_{w} measures the change in value due to wage differences that result from the possibility of losing a job the next period and finding another job with a different wage as opposed to keeping the same job, and finally, z^{l}_{elg} represents the difference in value due to changes in the likelihood of ineligibility. Appendix B.2 provides derivations of these terms in detail.[29] This calculation yields the opportunity cost of employment $z^{UE}\left(a, w^{UE}, \beta; p\right)$ and $z^{UI}(a, \beta; p)$ for each state. As discussed above, we then simulate agents from the top 1 percent of the stationary asset-to-income distribution and calculate a weighted average of the opportunity cost of employment among this group. We then choose the monetized value of non-market activity h so that the average opportunity cost of employment for the richest agents in our model is 0.47.

The derivations above show that the opportunity cost of employment in our model is beyond the flow utility difference between the employed and unemployed. Importantly, our calculation takes into account the dynamic effects of one period of additional employment on the opportunity cost of employment. Intuitively, one period of additional employment causes a relative decline in the budget, since the employed typically accumulate more assets. However, entering next period with higher levels of wealth creates an offsetting gain in the continuation value. Moreover, higher wealth holdings encourage the unemployed to search for higher wages and thus increase the possibility of higher labor income. Finally, one extra period of employment decreases the probability of ineligibility because the worker must separate from his job first before being subject to eligibility risk, as opposed to an unemployed eligible who constantly faces the risk of losing benefits. As a result, these dynamic benefits of employment measured respectively by z_a^l, z_w^l, and z_{elg}^l jointly dampen the flow opportunity cost of employment z_{flow}^l.[30]

[29] Our calculation extends the opportunity cost of employment derivation in Chodorow-Reich and Karabarbounis (2016). In addition to the asset differential z_a in the incomplete markets version of their model, we account for the wage differential z_w^l and ineligibility probability differential z_{elg}^l in our opportunity cost of employment formula for each unemployment type l. In addition, z_a varies for each unemployment type l in our setup.

[30] In our model, $z_a^l + z_w^l + z_{elg}^l$ is small for the richest agents, and thus z^l approaches z_{flow}^l in the calibration. This is because the dynamic benefits of one period of extra employment have little value for this group of agents. While disregarding these benefits does not affect the calibration of value of non-market activity h, $z_a^l + z_w^l + z_{elg}^l$ is relatively large for poorer agents. Thus, it is crucial to account for these dynamic benefits when calculating the opportunity cost of employment across different agents in the economy so that the insurance benefits and the incentive costs of any proposed UI policy are correctly measured.

2.3.3 Testable implications

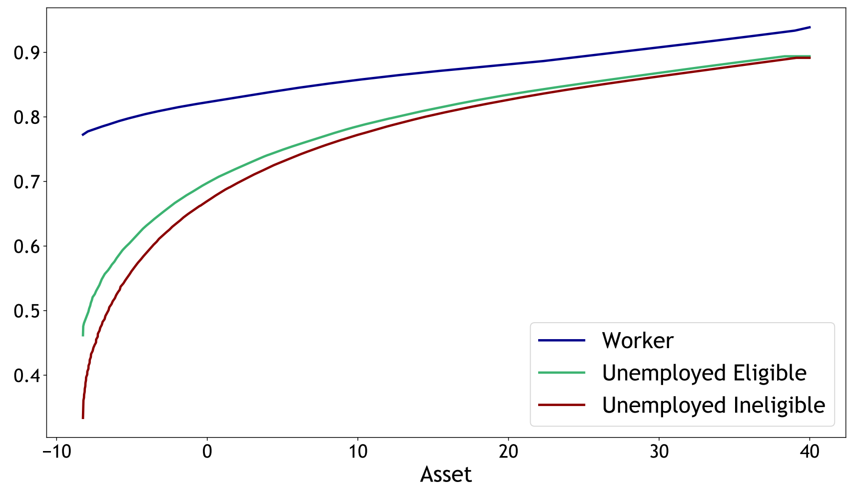
In this section, we discuss our model's implications for several important untargeted moments of the data. First, we measure the economy wide size and cyclicality of marginal propensity to consume (MPC) as well as the average consumption drop upon job loss predicted by the model. These are then compared to available empirical estimates in the literature. It is important for the model to generate a reasonable level and cyclicality of MPCs and average consumption drop in order to properly measure the insurance benefits of any proposed UI policy. For example, if the consumption drop were very low, then the insurance benefit of UI would be understated. Second, we present how the model compares to the data on labor market transitions, survival probabilities into unemployment, and the aggregate impact of UI extensions on the unemployment rate. Generating transition rates and unemployment survival functions, that are in line with the data is crucial to understanding the individual labor market response (incentive costs) of the unemployed to changes in UI policy, and generating a reasonable response of the unemployment rate ensures that the aggregate effects of UI are well accounted for. The following sections present the results of these exercises.

Marginal propensity to consume

Figure 2.2 qualitatively demonstrates the consumption choices of agents across different asset holdings and employment states. The unemployed not only consume less than workers but also exhibit higher marginal propensities to consume. The differences in MPCs between workers and the unemployed is most evident for agents holding little wealth, but this differential eventually diminishes as wealth increases.

In order to quantitatively understand how MPCs differ across heterogeneous agents in the economy, Table 2.3 presents the average quarterly MPC of different asset-to-income and employment groups based on the stationary distribution of the economy. We compute the MPC of an agent by calculating the fraction of an unexpected transfer, scaled such that it is equivalent to \$500, that an agent spends on consumption. As in Kaplan and Violante (2014), we implement a \$500 rebate in order to ensure consistency with available empirical estimates that study the impact of tax rebates on consumption. Noticeably, the poor unemployed ineligible exhibit the highest MPC given the absence of both public and

Figure 2.2: Consumption policy function



Note: This figure plots the consumption choices of agents with different employment statuses and asset holdings. The wages of workers and the unemployed eligible are set to be the economy's mean wage. Productivity and discount rates are also set to their means.

private insurance. Across employment states, the unemployed have significantly higher MPCs than workers, especially for agents in the lower end of the wealth distribution. Meanwhile, for any given employment status, the MPC is decreasing in wealth holdings.

The empirical literature documents two aggregate MPC data moments that we can use to validate our model. To do so, we calculate two untargeted average quarterly MPC moments in our model using the stationary distribution of agents across states and compare it to these available empirical estimates. Results are summarized in Table 2.4.

First, we find that the average quarterly economy wide MPC is 8 percent in our model. On the empirical side, Parker et al. (2013) measure that households, under different specifications, spend between 12 and 30 percent of unexpected tax rebates in the quarter that they are received. Thus, the fraction of borrowing-constrained individuals who have large MPCs as shown in Table 2.3 is too small to generate a sizeable response in the aggregate in our model.[31] Second, Gross et al. (2016) measure the cyclicality of the

[31] Notice that since our model generates a lower average MPC than its empirical counterpart, the households spend a relatively lower fraction of UI receipt on consumption. However, even if this is the case, we still find that the optimal policy is countercyclical. Thus, welfare gains provided by the optimal policy can

Table 2.3: Heterogeneous MPCs

	Asset-to-Income Groups				
Employment	a_1	a_2	a_3	a_4	a_5
Worker	0.13	0.11	0.07	0.05	0.04
Unemployed Eligible	0.34	0.18	0.12	0.07	0.04
Unemployed Ineligible	0.64	0.20	0.12	0.06	0.04

Note: This table shows the average quarterly MPCs of various type-groups, where columns represent agents with varying asset-to-income ratios and rows represent agents of differing employment statuses. Individual MPCs are calculated by computing the fraction consumed out of an unexpected \$500 transfer. Asset-to-income groups are $a_1 < p(10)$, $a_2 \in [p(10), p(25))$, $a_3 \in [p(25), p(50))$, $a_4 \in [p(50), p(75))$, and $a_5 \geq p(75)$, where percentiles are from the stationary asset-to-income distribution.

Table 2.4: Model fit of average MPCs

	Model	Data
Economy wide MPC	0.08	0.12 – 0.30
MPC difference of borrowing-constrained between 2008 and 2011	0.08	0.08

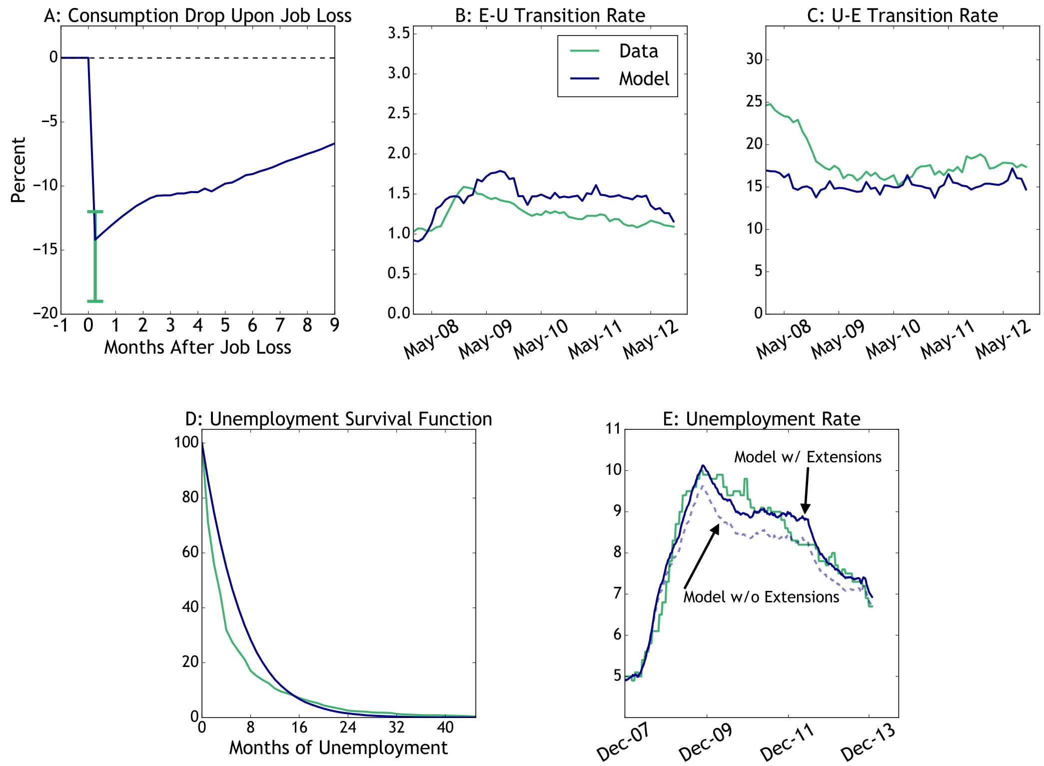
Note: This table shows the average quarterly economy wide MPC, and the average semiannual MPC of borrowing-constrained individuals between 2008 and 2011 implied by the model's simulations. Individual MPCs are calculated by computing the fraction consumed out of an unexpected \$500 transfer. These model-generated average values are then compared to available empirical estimates in the literature.

MPC by exploiting the unexpected changes in credit card borrowing limits of previously bankrupt individuals and find that the MPC is countercyclical over the Great Recession. In particular, they show that the average semiannual MPC difference of borrowing-constrained individuals between 2008 and 2011 is 8 percent. Using the Great Recession simulation of our model, we calculate the same moment and find that it is also 8 percent.[32] Hence, while the economy wide average MPC in our model is lower than its empirical counterpart, our model replicates the observed variation in the average MPC over the business cycle. This implies that our model successfully generates cyclical variation in the insurance value of

be considered as a lower bound.

[32]Section 2.5.1 explains the details on how we simulate the Great Recession using the model.

Figure 2.3: Model fit



Note: This figure shows our model's implications for several important untargeted moments of the data. The main text discusses the details of this comparison.

UI, which is crucial when studying the optimal design of UI policy over the business cycle.

Average consumption drop upon job loss

First, we compare the model-implied value of the average drop in consumption upon experiencing a job loss to the available empirical estimates in the literature. To do so, we estimate the following distributed-lag regression using the simulation data:

$$\log\left(c_{it}\right) = \alpha_i + \gamma_t + \beta a_{it} + \sum_{k=-4}^{36} \delta_k D_{it}^{k,} + \epsilon_{it}, \tag{2.14}$$

where the outcome variable $\log(c_{it})$ is the logarithm of consumption of individual i in week t, α_i are coefficients on individual fixed effects, γ_t are coefficients on week fixed effects, a_{it} is the net asset level of individual i in week t, and the error ϵ_{it} represents random factors. The indicator variables D_{it}^k identify all individuals k weeks prior to or after a job loss, where $k = 0$ is the week of job loss. For instance, $D_{it}^4 = 1$ for individual i who experiences job loss at time $t - 4$, and zero otherwise.

Our treatment group consists of individuals who experience at least one job loss during the simulation period. Thus, the control group consists of individuals who never lost their jobs. Thus, $D_{it}^k = 0$ for all weeks t for individuals who belong to the control group.[33] Thus, the coefficients $\{\delta_k\}_{k\in\{-4,\ldots,36\}}$ measure the effect of job loss on consumption k weeks prior-to or after the incident relative to individuals who do not experience any job loss. Panel A of Figure 2.3 plots the estimated values for $\{\delta_k\}_{k\in\{-4,\ldots,36\}}$. It shows that in the week of job loss, consumption drops 14 percent on average and then slowly recovers over time.

Several papers in the literature estimated the average consumption drop upon job loss from various data sources. Gruber (1997) finds a decline in food expenditure of 6.8 percent using the Panel Study of Income Dynamics (PSID) for the period up to 1987. Saporta-Eksten (2014) uses cross-sectional variation in the PSID and estimates an 8 percent decline in consumption expenditure in the year during which a job loss occurs.[34] Stephens (2004) estimates the average decline in food expenditure upon job loss in the Health and Retirement Survey (HRS) and the PSID and finds that the decline is between 12 percent (PSID) and 15 percent (HRS) when an individual experiences a job loss between interviews. Browning and Crossley (2001) report a 14 percent decline using Canadian Out of Employment Panel (COEP) survey data. Chodorow-Reich and Karabarbounis (2016) conduct an analysis of the effects of job loss on consumption in both the PSID and the Consumer Expenditure Survey (CE) and find that the decline in total food expenditure is between 14 percent (PSID) and 21 percent (CE). Finally, Aguiar and Hurst (2005) report a 19 percent decline in food expenditure among the unemployed using scanner data.

[33] Notice that since the job loss event is exogenous in our model, simulated groups should not exhibit any selection bias.

[34] However, this estimate does not condition on the fraction of the year spent as unemployed. When we assume an average unemployment duration of 17 weeks, this would imply a decline in consumption of around 24 percent.

In summary, our model generates an estimate for the average decline in consumption upon job loss that is in line with available empirical estimates in the literature.[35]

Labor market transitions

We focus on the employment-to-unemployment (E-U) and unemployment-to-employment (U-E) transition rates implied by the model during the Great Recession and how they compare with the data. This way, we are able to evaluate the model's implications for the cyclical patterns of labor market transition rates. Since the timing of SIPP panels misses the rise in the E-U rate and the decline in the U-E rate during the first months of the Great Recession, the transition rates in Panel B and C of Figure 2.3 are taken from Current Population Survey (CPS) data as calculated by Kroft et al. (2016).[36] First, Panel B shows that the model is able to generate the initial rise in the E-U rate due to the rise in exogenous job separations in the model. It is also able to match the observed slow decline throughout the recovery, although the model-implied E-U rate decreases relatively earlier due to the recovery of aggregate labor productivity and the resulting decline in job separation shocks. Second, Panel C reveals that the model generates a smaller decline in job finding rates at the start of the Great Recession relative to the drastic decline in the data, but the levels of the model and the data become similar afterward. This is because in the model, when labor productivity decreases and firms do not post vacancies in submarkets offering high wages, the unemployed optimally direct their search effort toward submarkets offering lower wages where job-finding rates are relatively higher. As a result, the magnitude of the drop in the average job finding rate of the model during economic downturns is relatively smaller than its data counterpart. This, however, does

[35] Notice that the magnitude of the average consumption drop upon job loss in our model is largely controlled by the value of non-market activity h, which is calibrated to match the level of the opportunity cost of employment. Hence, the result that our model generates a similar magnitude of the average consumption drop upon job loss to the data lends support to our baseline calibration of the level of the value of non-market activity h.

[36] Kroft et al. (2016) report that CPS transition rates are not consistent with the stock levels of unemployment, employment, and non-participation. Then, they describe a procedure to adjust these rates so that the transition rates become consistent with observed changes in stocks between months. The data also account for seasonality by residualizing out month fixed effects and are smoothed by taking three-month moving averages.

not mean that the model underestimates the costs of recessions. While not as drastic as the Great Recession, the drop in the job finding rate is still sizeable and is accompanied by a significant decline in offered wages. Furthermore, even if the model generates a smaller drop in job finding rates in response to changes in aggregate productivity, it generates the observed elasticity of average unemployment duration with respect to changes in UI generosity, as this is one of the data moments in our calibration. This is also evident in Figure 2.8, where we show the impact of a countercyclical UI policy on the job finding rate.

Unemployment survival function

In the model, the likelihood of exiting from an unemployment spell depends on the aggregate labor productivity as well as the unemployed agent's choice of search intensity and wage submarket. A useful summary of how long individuals spend unemployed is given by the unemployment survival function, which shows the probability that an agent will remain unemployed beyond a given unemployment duration.

First, we use the SIPP 2008 panel to measure the survival function in the data. We restrict our sample to working-aged individuals age 24 to 65 who do not own a business or derive income from self-employment. As in Rothstein and Valletta (2017), we require at least one quarter of employment prior to the spell in order to focus on individuals who have sufficient attachment to the labor market. Spells that are left-truncated and spells with missing information for which we cannot ascertain the employment status of the respondents are dropped. Finally, we define spells to be uninterrupted months of unemployment and thus do not consider time spent out of the labor force, since we do not model the non-participation margin. Panel D of Figure 2.3 shows that the unemployment survival function generated by the model under the baseline calibration is close to its data counterpart. While survival data exhibit sharp drops during early months, the model survival function decays in a smooth fashion given the probabilistic nature of eligibility and job-finding rates in the model.

Impact of UI extensions on aggregate unemployment

In order to understand the model's predictions about the aggregate effect of benefit extensions on the labor market during the Great Recession, we simulate the model for the Great

Recession period with and without UI benefit extensions and measure the time path of the unemployment rate. Panel E of Figure 2.3 shows that during the depth of the recession, the model-implied unemployment rate would have been 0.6 percentage points lower in the absence of benefit extensions.

The body of work that studies the impact of UI on macroeconomic aggregates has found mixed results. Rothstein (2011) exploits variation in UI benefits across states with similar economic conditions, the behavior of UI ineligible as a control group, and several other strategies to address endogeneity problems in measuring the impact of UI on labor market conditions. Using CPS data, he finds that UI extensions raised the unemployment rate in early 2011 by only about 0.1 to 0.5 percentage points. Consistent with this finding, Chodorow-Reich and Karabarbounis (2017) implement a novel empirical strategy by using exogenous variation coming from measurement error in real-time state unemployment rates and find that benefit extensions increased the unemployment rate by at most 0.3 percentage points. Coglianese (2015) uses a similar strategy and also finds small effects. Meanwhile, Farber and Valletta (2015) use variation in individuals' time-to-exhaustion and find that extended benefits account for an increase of around 0.4 percentage points in the 9 percent unemployment rate in 2010. Valletta and Kuang (2010) find that in the absence of extended benefits, the unemployment rate would have been about 0.4 percentage points lower at the end of 2009, while Marinescu (2017) also finds small effects due to the reduced congestion resulting in a higher job-finding rate of any given job application.

On the other hand, Hagedorn et al. (2016) highlight that benefit extensions lead to higher equilibrium wages and thus lower vacancies. They also emphasize the role of firm expectations on future UI policies when making vacancy or hiring decisions. Accounting for this additional channel, they find that UI generosity increased the unemployment rate by 2.0 to 2.7 percentage points. This result is consistent with the findings of Johnston and Mas (2016), who find large effects of reductions in UI duration on unemployment. Fujita (2011b) also finds that extensions led to a substantial 1.2 percentage points increase in male workers' unemployment rate.

2.4 Welfare Calculation

We measure the welfare effects of any proposed UI policy by answering the following question: how much additional lifetime consumption must be endowed to all agents in an economy where some benchmark policy is being implemented so that average welfare will be equal to an economy where the proposed policy is implemented? In effect, we are evaluating whether an alternate UI policy will be welfare improving when compared to a benchmark policy, a natural choice being the actual UI policy implemented during the recession. Henceforth, we will refer to the UI policy implemented by the U.S. government during the Great Recession as the *benchmark policy*.[37]

Let b denote the benchmark policy and n denote the new/proposed policy. We can compute the additional percent lifetime consumption $\bar{\pi}$ that makes the average welfare equal across these two economies using the following equation:

$$\int_i \left[E_0 \sum_{t=0}^{\infty} \beta_{it} U \left(c_{it}^b \left(1+\bar{\pi}\right), s_{it}^b \right) \right] d\Gamma_{ss}\left(i\right) = \int_i \left[E_0 \sum_{t=0}^{\infty} \beta_{it} U \left(c_{it}^n, s_{it}^n \right) \right] d\Gamma_{ss}\left(i\right) \tag{2.15}$$

where c_{it}^j and s_{it}^j denote the consumption and search effort levels of agent i at time t under UI policy $j \in \{b, n\}$, and Γ_{ss} is the stationary distribution of the economy.

One can interpret the welfare exercise in Equation (2.15) as follows. Consider two countries populated by people with the same type-distribution. The only difference between both countries is that the government of the first country changes UI policy to policy b, while the second changes UI policy to policy n. The question is how much additional lifetime consumption $\bar{\pi}$ should the first government compensate an individual who is behind the veil of ignorance (i.e., does not know her initial type in the stationary distribution) in order to make her indifferent between being part of one of these two countries? Thus, the best UI policy n that the second government can implement is the one that makes the first

[37] During the Great Recession, the U.S. government increased the duration of UI payments to as much as 99 weeks in some states but kept replacement rates almost constant. We set a duration of UI payments that increases from 26 weeks (2 quarters) to up to 90 weeks (7 quarters) over the decline in aggregate productivity p, while the replacement rate of UI payments is kept fixed at its long-run average of 14 percent for all levels of p. This policy closely mimics the UI policy in the United States during the Great Recession and its recovery, assuming the United States as a single state.

government pay the highest compensation $\bar{\pi}_{max}$ to weakly attract this prospective citizen. This policy will be the optimal UI policy.

We restrict the class of candidate UI policies to be linear in current productivity level p such that $\phi(p) = q_\phi + m_\phi p$ and $e(p) = q_e + m_e p$. Under this restriction of UI policy instruments, we search over five UI policy parameters $(q_\phi,\, m_\phi,\, q_e,\, m_e,\, \tau)$ to solve for the optimal UI policy.

In order to obtain ex-ante welfare gains/losses $\bar{\pi}$ for each policy n, we begin from the stationary distribution of our calibrated economy Γ_{ss} where (1) aggregate labor productivity is constant at its mean level and (2) the unemployment benefit policy is fixed at a 14 percent replacement rate and 26 weeks expiration, which we call the *acyclical/flat* UI policy f. In each economy, an unanticipated but permanent policy change toward benchmark policy b and proposed policy n, respectively, is implemented. Given any guess of $\bar{\pi}$, we can now compute for both sides of Equation (2.15) by integrating over the stationary distribution. We then solve for the $\bar{\pi}$ that equates both sides of Equation (2.15) and select the UI policy that yields the highest welfare gain $\bar{\pi}_{max}$ as the optimal UI policy.[38]

2.5 Main Results

We find that $m_\phi = -6.44$, $q_\phi = 6.75$, $m_e = 0.34$, $q_e = -0.32$, and $\tau = 1.06$ percent, implying that the optimal UI policy should be countercyclical in both replacement rate and duration. These values imply that the optimal policy offers a 30 percent replacement rate for 4 quarters when aggregate labor productivity is at its mean value, and a 54 percent replacement rate for 10 quarters when aggregate labor productivity is depressed by 3.5 percent. This means that the optimal policy offers a more generous replacement rate for a longer duration compared to the U.S. government's UI policy during the Great Recession, which provided 14 percent of the replacement rate for around 7 quarters of payments for the same drop in labor productivity. Compared to this benchmark policy, the optimal policy increases welfare by 0.58 percent additional lifetime consumption for all agents. Meanwhile, compared to an acyclical policy that offers 14 percent of the replacement rate for 2 quarters for all levels of aggregate labor productivity, the optimal policy yields a

[38] Given the functional form of the utility function, there is no closed-form solution for $\bar{\pi}$.

welfare gain equivalent to 0.74 percent additional lifetime consumption.[39]

These welfare gains from the optimal UI policy are much larger when compared to welfare gains of eliminating the business cycle obtained by Lucas (1987), who finds that the welfare of an infinitely lived representative agent increases by only 0.008 percent in consumption equivalents for logarithmic preferences if cycles are removed. A more relevant comparison to our model is Krusell et al. (2009), who extend this analysis in an incomplete asset markets model with heterogeneous households and study the welfare effects of eliminating both aggregate risk and its impact on idiosyncratic risk when there is a correlation between these two shocks. They find that the welfare gains of eliminating the cycle and its effect on idiosyncratic risk are as much as 1 percent in consumption equivalents for the same period utility function. Importantly, they show that the effect of business cycles on idiosyncratic risk has great quantitative consequences. Specifically, if one does not correctly integrate out the effect of cycles on idiosyncratic risk, then the welfare gains of eliminating cycles are only slightly larger than those calculated by Lucas (1987). Similar to Krusell et al. (2009), our model features aggregate shocks and incomplete asset markets in which aggregate risk significantly affects the magnitude of idiosyncratic risk, as job finding and job separation rates are functions of aggregate labor productivity. Both models are also similar in that households are heterogeneous in terms of their employment status, discount rates, and wealth holdings. These similarities suggest that welfare results in their study are a useful benchmark against our model. In our model, optimal UI smooths aggregate shocks by introducing cyclicality into the generosity of benefits and also attenuates idiosyncratic unemployment risk by providing higher benefit levels on average. Nonetheless, as the optimal UI policy in our framework can only partially smooth the effect of cycles on consumption, welfare gains are much lower than the upper bound provided by Krusell et al. (2009).

The following discussions elucidate on the sources and distribution of welfare gains brought about by the countercyclical policy. First, we simulate the Great Recession using our model and compare how consumption patterns and labor market aggregates differ between the optimal policy and an acyclical policy. This will provide useful insight about the insurance

[39]To obtain this number, we repeat the welfare calculation procedure in Section 2.4 where we set the benchmark policy b as the acyclical/flat policy f. In this case, the first country continues to implement UI policy f, while the second country changes it to the optimal UI policy.

benefits and incentive costs of the countercyclical optimal policy, especially when a recession triggers more generous benefits. We then proceed to quantitatively decompose ex-ante welfare gains of the optimal policy attributable either to changes in consumption patterns resulting from altered saving and wage choices, or to changes in the search intensity exerted by the unemployed. Finally, we look at ex-post welfare outcomes among heterogeneous agents in order to understand how welfare gains are distributed across agents with different employment statuses and wealth holdings.

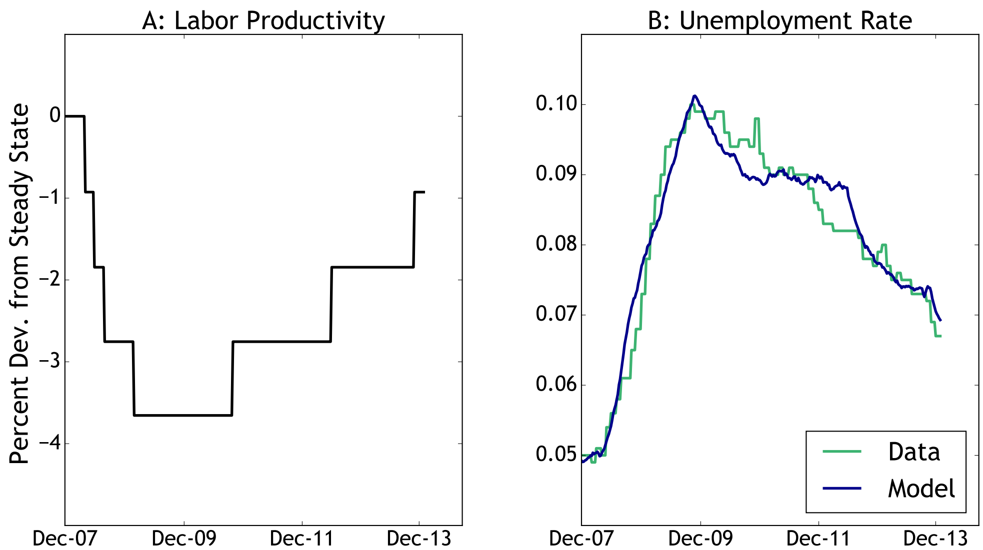
2.5.1 Great Recession exercise

We now use the Great Recession as an interesting test case that allows us to understand the insurance benefits and incentive costs associated with the countercyclical optimal policy. In order to discipline this exercise, we take as given the U.S. government's UI extension policy during the Great Recession and then pick the realizations of aggregate labor productivity to match the unemployment rate from December 2007 to December 2013 – the period that spans the beginning of the recession until the time when the Emergency Unemployment Compensation Act of 2008 (EUC08) was no longer renewed. Matching the realized unemployment rate by imposing that government policy mimics benefit extensions during the Great Recession is important, since using the model's aggregate labor productivity alone to match the unemployment rate disregards the fact that more generous UI policies implemented during the recession and recovery may have contributed to the heightened level of unemployment. Thus, in this exercise, the drop in labor productivity triggers lower job finding rates, higher separation rates, and longer benefit durations, all of which contribute to the rise in unemployment. Figure 2.4A shows the realizations of the labor productivity process that we obtain from this procedure, while Figure 2.4B compares the unemployment rate generated by the model to its counterpart in the data.[40]

In this exericse, we consider two economies that both experience the Great Recession between December 2007 and December 2013 but differ in the UI policy that is implemented.

[40]We acknowledge that labor productivity in the data during the Great Recession did not decline in a similar way. However, given that labor productivity in our model is the only source of aggregate fluctuations, we place more emphasis on matching the observed unemployment rate and less on the manner by which we do it. While we call the decline in p "labor productivity shock", it can stand in for other forms of shocks such as TFP, aggregate demand, or financial shocks.

Figure 2.4: Labor productivity and unemployment rate



Note: Panel A shows the labor productivity series that we use in our model to generate the observed time series of the unemployment rate in the data during the Great Recession. Panel B compares the paths of the unemployment rate in the data and the model.

In both economies, the simulation begins under the stationary distribution.[41] At $t = 0$, we introduce a recession to both economies by feeding the labor productivity series into Figure 2.4A. It must be noted, however, that agents use the AR(1) process to take expectations on labor productivity. One economy introduces the optimal policy o, and the other maintains the less generous acyclical policy f. In both cases, the policy change is unanticipated by agents. This is a reasonable assumption, as UI extensions during deep recessions (such as the EUC08) are typically beyond the scope of pre-existing triggers that households are aware of. This policy change is permanent and will thus apply the same UI policy to future fluctuations of the same magnitude.

In the following sections, we separately analyze the consumption-smoothing benefits and

[41]We select the number of agents to simulate N to be large enough such that $\bar{\pi}$ does not change with further increases in N. We find that $N = 120,000$ is sufficient for this goal.

incentive costs of the optimal policy if it had been implemented during the Great Recession and compare them to that of the acyclical policy.[42] We place emphasis on how the cyclicality of these benefits and costs rationalizes a countercyclical optimal policy.

Insurance Benefits

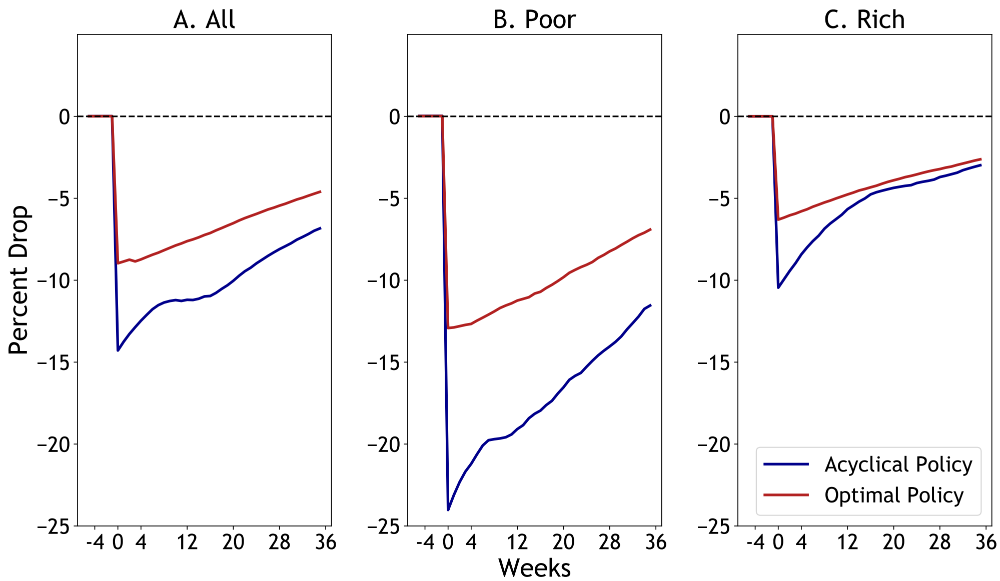
Consumption Smoothing Upon Job Loss We first show the effect of the optimal UI policy on the consumption drop experienced upon job loss. We ask what would happen to the consumption profile of agents who experience a job loss in the economy that introduces the optimal policy and the economy that remains under the acyclical policy. The comparison of consumption profiles across these two economies will reveal the welfare benefits of the generous optimal policy coming from smoothing consumption between E-U transitions. Using model-generated data, we run the same distributed-lag regression in Equation (2.14) for each economy.

Figure 2.5 compares the consumption drop upon job loss between an acyclical policy and the generous optimal policy. On average, the consumption drop upon job loss is 15 percent under the acyclical policy, and 9 percent under the optimal policy, implying that the decline is 6 percentage points less under the optimal policy. This simply demonstrates the role of UI in dampening large fluctuations in consumption when job loss occurs, an insurance benefit on which the literature has traditionally focused. Moreover, this lower drop in consumption upon job loss is enjoyed by a larger number of agents in a recession due to the higher incidence of unemployment and longer spells during which wealth is depleted. As a result, the insurance value of UI payments in smoothing consumption upon job loss is larger in recessions.

Note that the reduction in the consumption drop is the net effect of two opposing forces: a more generous UI policy (1) directly increases consumption upon job loss due to higher benefits but also (2) indirectly crowds out precautionary savings. The first channel raises public insurance and thus decreases the consumption drop, while the second channel decreases self-insurance and thus increases the consumption drop as individuals enter unemployment

[42] Comparing the optimal and acyclical policies makes the illustration of the idea clear, as the acyclical policy offers the same replacement rate and duration across different realizations of the aggregate state. The intuition provided by the exercise also holds qualitatively when comparing the optimal policy with the benchmark policy.

Figure 2.5: Average consumption drop upon job loss



Note: Panel A plots the path of the average consumption drop upon job loss between 4 weeks prior to job loss and 36 weeks after the job loss. Two different consumption profiles are obtained from a distribution-lag regression in Equation (2.14) using model-generated data under the acyclical policy and the optimal policy. Panels B and C repeat this exercise for poor and rich agents experiencing job loss. "Poor" refers to agents who enter unemployment with an asset-to-income ratio below the 75th percentile of the stationary asset-to-income distribution, while "Rich" refers to those above the threshold.

with less wealth. In addition, notice that the recovery of consumption is slightly faster under the acyclical policy given how agents are forced to find jobs more quickly compared to an economy where the optimal policy is implemented.

It is also insightful to understand the effect of the optimal policy on the consumption drop upon job loss among rich and poor households. In Figure 2.5, we group individuals based on their asset-to-income ratio at the moment of job loss when the acyclical policy is implemented and then plot their consumption profiles. The first group consists of those who enter unemployment with an asset-to-income ratio below the 75th percentile of the stationary asset-to-income distribution, while the second group consists of those above that threshold. Using the same grouping (and the same job destruction shocks), we calculate the consumption drop that individuals would have experienced had the optimal policy been implemented instead. Panels B and C of Figure 2.5 demonstrate substantial heterogeneity in the consumption-smoothing benefits agents derive from the optimal policy. Among the poor, the consumption drop is reduced by around 12 percent, while for the rich, it is only around 4 percent. This result highlights the need to carefully calibrate the model's wealth distribution to match the data in order to correctly evaluate the true magnitude of any proposed policy's insurance benefits.

In summary, the optimal policy provides substantial insurance against E-U transitions, the magnitude of which varies significantly across the wealth distribution. More importantly, these benefits are larger during recessions simply because more agents experience job loss and remain unemployed for longer durations during which wealth declines.

Consumption Smoothing over the Business Cycle Although the insurance benefits of UI are traditionally seen to accrue mostly to job losers, we show in this section that in the presence of aggregate shocks and incomplete asset markets, UI also provides consumption-smoothing benefits even to those who do not lose their jobs. Under this framework, UI policy plays an important role in smoothing consumption over the business cycle. In order to demonstrate this channel, consider for the moment a worker in an economy that does not have a UI program. When a recession occurs, the worker anticipates that there is a higher risk of losing her job and that the unemployment spell is likely to be prolonged given the persistence of negative shocks. In the absence of government insurance, the worker self-insures by cutting back on consumption in order to build a buffer stock of savings that she could use to attenuate the impact of potential job loss. This means that consumption fluctuates heavily with aggregate fluctuations even if job loss does not actually occur. This reaction is simply a manifestation of the inefficiencies resulting from over-saving in an incomplete markets model, relative to its first best. The government then uses its UI program to reduce the excessive precautionary saving behavior of workers by promising higher public insurance during times when the unemployment risk is large in order to bring the economy closer to the efficient allocation. When UI is generous during recessions, individuals are relieved of the burden to reduce consumption in order to build savings, since UI makes the prospect of losing one's job less painful. This further contributes to the expansion of insurance benefits during recessions because it is precisely during this time when excessive precautionary saving behavior is triggered. While this channel is also present in previous models with incomplete markets, the literature on the optimal design of UI over the business cycle has not quantified the effect, possibly because of computational difficulties, which we are able to overcome.

Panel A of Figure 2.6 demonstrates this channel by comparing the average consumption of the economy during the Great Recession under the optimal and acyclical UI policies. It reveals that average consumption is much smoother under the optimal policy. The large drop in consumption at the onset of the recession when UI is acyclical is caused precisely by agents diverting consumption toward savings. This is corroborated by Panel A of Figure 2.7 which plots the average wealth of job losers during the first week of entering unemployment. At the start of the recession when labor productivity starts declining, it is clear that workers in the economy under the acyclical policy engage in precautionary savings due to the higher risk of losing a job and staying unemployed for longer durations. Thus, we see that average asset holdings upon entering unemployment rise during this period and only begin to decline during the recovery. In the case of the optimal policy, however, the need for precautionary saving is offset by the generous UI payments, implying that agents enter their unemployment spell with less self-insurance compared to their counterparts under the acyclical policy. The same idea is also apparent in Panel B of Figure 2.7, which plots the evolution of various percentiles of the asset distribution when a recession hits both economies. It shows that the level of precautionary savings under the generous optimal policy is markedly muted. Furthermore, similar to the consumption-smoothing benefits upon job loss, consumption smoothing through this channel is also cyclical. It is stronger during recessions precisely because it is during this time when precautionary saving motives are strong and thus significant cuts in consumption occur.

Next, we analyze the consumption-smoothing benefits of the optimal policy over the business cycle for agents with varying wealth levels. To do this, we again group agents based on their asset-to-income level at the start of the Great Recession. The first group consists of agents whose asset-to-income level at the start of this period is below the 75th percentile of the stationary asset-to-income distribution, while the second group comprises of those above this threshold. Panels B and C of Figure 2.6 then plot the average consumption paths of these two groups over the Great Recession. Comparing average consumption paths under the acyclical and optimal policies shows intuitively that the consumption-smoothing benefits of the optimal policy over the business cycle are largely different for poor and rich agents. While the optimal policy improves consumption smoothing for the poor, it does not for the rich, as they are already well insured.

Incentive Costs

While the optimal policy provides consumption-smoothing benefits to a large fraction of agents in the economy, it also induces certain moral hazard costs. This section discusses the magnitude of these costs associated with introducing the optimal UI policy vis-a-vis the acyclical UI policy. First, we look at how these costs manifest through lower job-finding probabilities and thus longer durations in unemployment. Second, we discuss how the magnitude of these moral hazard costs varies over the business cycle.

When a more generous UI policy is implemented, the unemployed eligible reduce their search effort and ask for higher wages because of an increase in the opportunity cost of employment. To provide a useful summary of the combined effects of both margins, in Figure 2.8, we look at how job finding rates and survival in unemployment change between the two economies. Panel A demonstrates that job finding rates during the recession shift downward when the optimal policy is introduced. Meanwhile, Panel B plots the Kaplan-Meier estimates of the unemployment survival function under both policies, as described in Section 2.3.3. The lower job finding rates result in the outward shift of the unemployment survival function under the optimal policy when compared to that of the less generous acyclical policy. This simply means that the likelihood that a duration will last beyond t months is always higher in the economy under the optimal policy. For instance, the probability that an unemployment spell will last beyond one month is around 40 percent under the acyclical policy, whereas it goes up to 60 percent under the optimal policy.

It is now evident that the optimal UI policy induces nontrivial costs through lower job-finding rates and thus longer unemployment durations. However, what is key to determining the optimal policy over the business cycle is the cyclicality of the size of these moral hazard costs, that is, how they expand and contract over the business cycle.

First, the value of job search is cyclical. A forgone unit of search during a recession is less costly than a forgone unit of search during a boom because jobs are difficult to find during a recession and conditional on finding a job, wages are likely to be lower as well. This means that while an extra dollar of benefits received during a recession induces the unemployed to search less, this reduction in search effort is not as costly compared to when the same dollar is received in an expansion during which firms are posting a lot more vacancies at higher wages. The cyclicality of the value of search effort is evident in Panel A of Figure 2.9 which shows that the consumption value of a unit of search effort is markedly lower during a recession compared to a boom. The same message is conveyed in Panel B, which shows that the average value of job search drops during the Great Recession and rises during the recovery for both eligible and ineligible unemployed, although the change is larger for the eligible unemployed, as they are the direct recipient of UI payments.

Second, wealth effects that discipline job search are more likely to manifest during recessions. For any given UI policy, recessions generally lead to prolonged unemployment spells during which agents draw down their assets to supplement consumption. Getting closer to their borrowing constraints, the unemployed have a higher incentive to ramp up their job finding efforts through a combination of higher search intensity and lower wage choices, as they seek to find work more quickly. This is evident in the household decision rules in Figure 2.1, which shows that for every unit of the decline in asset holdings at the time of unemployment, there is a disproportionate increase in search effort and decline in wage choices as the unemployed get closer to becoming borrowing constrained. Simply put, the presence of borrowing constraints acts like a self-disciplining device for job search efforts of the unemployed during recessions. As a result, the moral hazard costs are dampened by the fact that agents are more ill-prepared in terms of their own private savings during recessions.

In summary, while a generous UI policy decreases the job finding rate and increases the average unemployment spell duration, these moral hazard costs are partially offset in recessions because the consumption value of job search is low during recessions, and the decline in asset holdings in recessions incentivizes the unemployed to ramp up their job search. This result is consistent with Kroft and Notowidigdo (2016), who empirically find that the moral hazard cost of UI is procyclical.

2.5.2 Welfare decomposition

The Great Recession exercise in the previous section demonstrates the qualitative effects of the optimal policy on individual decision rules as well as the aggregate outcomes. We now proceed to quantitatively decompose the welfare contribution of the aforementioned changes. The ex-ante welfare gains of the optimal policy can be decomposed into either its effects on consumption coming from changes in savings and wage choices or its effects on the search intensity exerted by the unemployed. In order to isolate the welfare gains attributable to changes in consumption from those attributable to search effort, we shut down endogenous search decisions in the model.[43] This version of the model is then re-calibrated and used to evaluate the welfare gains coming from the countercyclical optimal policy. When policy has no effects on search intensity, welfare increases by 0.56 percent of additional lifetime consumption for all agents relative to the benchmark policy. Thus, the welfare gains of the optimal policy attributable to changes in search effort are negligible.[44] As a result, we conclude that the welfare gains come largely from changes in consumption patterns.

Having isolated the welfare gains attributable to search, we then want to understand how the optimal policy changes consumption patterns in the model without endogenous search effort. Our first step is to disentangle welfare gains along the transition from the long-run (steady state) gains. To do this, we make a slight but important modification in Equation (2.15). In particular, we change Γ_{ss} to Γ_b (where b denotes the benchmark policy) on the left-hand side, and Γ_{ss} to Γ_n on the right-hand side, where n is set to be the optimal UI policy. This implies that the first economy has implemented the benchmark policy, while the second economy has implemented the optimal policy for a very long time so that these two economies are in their respective steady states. We then ask an unborn agent who does not know her type within the respective stationary distributions which economy she prefers to live in. The ex-ante steady state welfare gains/losses from the optimal policy π_{ss} are then given by the percentage of additional lifetime consumption that the first government

[43] We do this by assuming that the unemployed searches for a job full-time, (i.e., $s = 1$), without incurring a disutility from search effort, (i.e., $\alpha = 0$).

[44] The result that changes in UI policy have small effects on the job search intensity of the unemployed is consistent with previous empirical evidence in the literature. For example, Ashenfelter et al. (2005) find that low job search effort is not a significant source of UI overpayments using evidence from randomized trials in four U.S. sites. Recently, Hagedorn et al. (2016) carefully analyze the effect of changes in UI policies on both the search intensity of unemployed workers (the micro effect), and the aggregate job finding rate per unit of search effort through vacancy posting decisions of the firms (the macro effect). They also find a small micro effect.

should compensate this agent in order to make her indifferent between being part of one of these two economies. We find that $\pi_{ss} = 0.18$, which is smaller than the welfare gain with a transition of 0.56. This result suggests sizeable welfare gains along the transition from the economy under the acyclical policy to the economy under the optimal policy. We know from our earlier analysis that the optimal policy reduces the precautionary saving motives, as agents substitute away from self-insurance to public insurance for consumption-smoothing purposes. As a result, agents decumulate savings and consume more of their labor income along the transition path. This increase in consumption is enough to overcome any rise in taxes brought about by the policy change, thus providing large welfare gains along the transition.

Next, we decompose the steady state welfare gains of the optimal policy. In particular, under a utilitarian equally weighted social welfare function as in Equation (2.15), the optimal policy can increase steady state welfare for three reasons: (1) an increase in the average consumption of the economy (the level effect), (2) a decline in the volatility of individual consumption paths (the volatility effect), and (3) a decline in inequality across individual consumption paths (the egalitarian effect). Following Floden (2001), the welfare gain from the optimal policy under the steady state comparison can be decomposed approximately into (1), (2), and (3):

$$\pi_{ss} = (1 + \pi_{lev})(1 + \pi_{vol})(1 + \pi_{egal}) - 1. \tag{2.16}$$

Comparing the average consumption level of economies under the optimal and benchmark UI policies, we find that average consumption is 0.18 percent *lower* in the steady state of the optimal policy, (i.e., $\pi_{lev} = -0.18$). This is because once the economy converges to a new steady state with lower wealth holdings and higher taxes, consumption levels decrease. On the other hand, we find that the optimal policy significantly reduces the volatility of average consumption and that there are sizeable welfare gains because of this channel. On average, we find that $\pi_{vol} = 0.35$, which implies that uncertainty gains overcome any reduction in long-run consumption levels. This is again due to the endogenous response of saving decisions to changes in UI policy over the business cycle. Recall from our Great Recession exercise in the previous section that the government uses its UI program to reduce the excessive precautionary saving behavior of workers by implementing a generous UI during times when unemployment risk is large in order to bring the economy closer to the efficient allocation. Therefore, the impact of fluctuations in aggregate labor productivity on the consumption path of individuals is lower under the optimal policy relative to that under the benchmark policy. This smoother consumption profile over the business cycle provides significant welfare gains. Finally, we find that $\pi_{egal} = 0.01$, implying that there are negligible welfare gains from the optimal policy due to equalizing the consumption paths across heterogeneous agents. However, this result masks the two opposing effects of the optimal policy on the inequality across individual consumption paths. On the one hand, generous UI payments to the unemployed and higher income tax rates create more equal consumption paths across heterogeneous agents and thus increase π_{egal}. On the other hand, the steady state asset distribution under the optimal policy is more unequal than its counterpart under the benchmark policy. This is because while most of the individuals in the economy under the optimal policy save less, the response of the agents in the top percentiles of the distribution is very small. As a result, the Gini coefficient of the asset distribution increases from 0.68 under the benchmark policy to 0.91 under the optimal policy. This rise in the inequality of the steady-state wealth distribution in fact reduces π_{egal}, as it makes individual consumption paths across heterogeneous agents more unequal. We find that these two opposing effects quantitatively cancel each other out, and thus on average π_{egal} is small.[45]

2.5.3 Heterogeneous welfare effects

While the previous section decomposes the average ex-ante welfare gains into various mechanisms at work in our model, it is also insightful in understanding which type of agents stand to gain or lose from the optimal policy compared to the benchmark policy. In order to measure the ex-post heterogeneous welfare gains/losses from the optimal UI policy, we group agents by their employment status and asset level based on the stationary distribution. We then calculate $\bar{\pi}$ from Equation (2.15) for each group by only integrating over agents that belong to each group.

[45]The welfare decomposition exercise presented here can be modified to incorporate the effects of transition on π_{lev}, π_{unc}, and π_{egal}. The reason why we decompose the welfare gains across two different steady states is to isolate the long-run effects of the optimal policy as the policy change is permanent. However, we also did this exercise with transition and find that the level gains in consumption from the optimal policy are large because of the decline in savings along the transition.

Table 2.5: Heterogeneous welfare impacts of optimal policy

	Asset Groups				
Employment	a_1	a_2	a_3	a_4	a_5
Worker	0.73	0.67	0.58	0.53	0.52
Unemployed Eligible	1.89	1.55	1.28	0.96	0.84
Unemployed Ineligible	0.61	0.58	0.55	0.50	0.51

Note: This table shows the heterogeneous welfare gains from the optimal policy on various type-groups, where columns represent agents holding various levels of assets and rows represent agents of differing employment statuses. Welfare numbers are in percent lifetime equivalent consumption terms. Asset groups are $a_1 < p(10)$, $a_2 \in [p(10), p(25))$, $a_3 \in [p(25), p(50))$, $a_4 \in [p(50), p(75))$, and $a_5 \geq p(75)$, where percentiles are from the stationary asset distribution. Gains are calculated relative to the benchmark policy.

Table 2.5 shows the heterogeneous welfare impacts of the optimal policy on various type-groups, where columns represent agents holding various levels of assets (set to be the different ranges in the asset distribution) and rows represent agents of differing employment statuses.

It is clear that the unemployed eligible stand to gain the most from the optimal policy. This result is unsurprising, since the unemployed eligible are the direct beneficiaries of more generous payments and durations, and thus enjoy the largest consumption-smoothing gains. Intuitively, among the unemployed eligible, poorer individuals also enjoy larger welfare gains compared to their richer counterparts, given how each additional dollar of benefit payment is more valuable to them.

Consistent with our earlier discussion, the unemployment eligible are not the sole beneficiaries of the optimal UI policy. Workers also enjoy a sizeable welfare gain, albeit to a smaller degree, because of two opposing effects. On the one hand, workers maintain smoother consumption over the business cycle given the weaker need to engage in precautionary savings afforded to them by optimal UI benefits; on the other hand, they are the primary financers of the optimal UI policy and would thus face higher taxes and lower consumption levels. Nonetheless, the ability to maintain smoother consumption during economic fluctuations dominates the financing effect. Note that if we had not accounted for this benefit, then we would expect workers to experience welfare losses, as they would be paying taxes without enjoying the benefit of being able to smooth consumption over fluctuations in aggregate labor productivity. Unsurprisingly, welfare gains are also much larger among poor workers for whom savings (and the corresponding forgone consumption) is most costly.

Meanwhile, the unemployed ineligible only receive the generous UI payments in the event that they find a job, lose it, and become eligible, which is a small probability. While they do not contribute to financing the optimal UI policy, they incur costs because of lower job-finding rates resulting from the generous UI payments. Having to spend longer weeks without benefits and being forced to exert more effort in finding a job results in this group experiencing the lowest gains from the optimal policy.

2.6 Robustness

2.6.1 Welfare under different specifications

In this section, we compute the welfare gains or losses from the optimal policy relative to the benchmark policy under different specifications of the baseline model. In these exercises, whenever a change in parametrization is necessary, the model is recalibrated to match the moments found in Section 2.3 and tax rates are adjusted under each UI policy so that the government budget constraint holds in equilibrium. The nature of the first three exercises in this section requires us to simulate a recession in order to compute the welfare gains. To preserve consistency within this section, we report the welfare gains of the remaining specifications under a scenario in which a recession occurs initially as well. The results are summarized in Table 2.6.

First, in order to quantify how welfare gains change depending on the timing of the policy change, we evaluate the welfare gains from the optimal policy when the policy change is introduced at the onset of a recession. This exercise follows the Great Recession simulation discussed in Section 2.5.1 where an unanticipated UI policy change is implemented. The only difference here is that for the first economy, the benchmark policy b is introduced at $t = 0$, whereas in the alternate economy, the optimal UI policy is implemented.

We modify the welfare criterion in Section 2.4 slightly, as we now require a simulation-based welfare calculation. Additional details regarding the computational procedure are provided in Appendix B.3. We compute for $\bar{\pi}$ in Equation (2.15) modified to account for the recession that occurs right at the same time the policy change is made and find that the optimal policy increases ex-ante welfare by 1.25 percent additional lifetime consumption relative to the benchmark policy. The welfare gains of the optimal policy are unsurprisingly much higher when the policy is implemented right before a sharp drop in aggregate labor productivity, since there is a frontloading of gains coming from large net insurance benefits provided during the recession. At the onset of a recession, stronger precautionary motives cause larger drops in consumption, and a larger pool of unemployed individuals experiences the consumption drop upon job loss. This is in contrast to welfare gains of 0.58 when we do not take a stance on the realizations of aggregate productivity.[46]

The second exercise we perform considers how welfare gains change if the policy were temporary. While we study permanent changes in the UI benefit schedule, our framework is also useful to assess the welfare effects of discretionary fiscal policies such as the one implemented during the Great Recession. We now assume that the optimal policy is only implemented during the period of the Great Recession, and it unexpectedly reverts back to the acyclical policy f at the end of this period. This is to closely pattern the simulation of the model to the events that occurred during the Great Recession where the EUC08 was completely terminated in December 2013 and UI policy returned to what it had been prerecession. We find that the welfare gains from the optimal policy become 0.83 percent additional lifetime consumption relative to the benchmark policy. The difference between this value and welfare gains when the policy change is permanent (1.25 percent) reveals that around 35 percent of the total welfare gains are attributable to the expectation of generous UI payments during future economic downturns.

Third, we test the quantitative effects of assuming a time-invariant interest rate r on the welfare gains from the optimal policy. In this exericse, we consider an interest rate that varies with the state of the economy such that it is procyclical and closely mimics its data counterpart during the Great Recession.[47] Under this exercise, we find that the optimal

[46]Furthermore, when the government implements the optimal policy right before a boom, we find that it increases ex-ante welfare by 0.23 percent additional lifetime consumption relative to the benchmark policy. Given that the optimal policy raises welfare more when implemented right before a recessiom compared to that of a boom provides strong evidence about the countercyclicality of insurance benefits net of incentive costs.

[47]The weekly real interest rate reduces from its baseline value of 0.00095 to -0.0003 at the depth of the Great Recession. This way, we are able to measure the quantitative effects of significant changes in the real

Table 2.6: Welfare gains under different specifications

Exercise	Welfare gains (%) from the optimal policy
Great Recession simulation	1.25
Temporary policy change	0.83
Procyclical interest rates	0.64
Endogenous quit decisions	1.10
Replacement rate $\phi = 0.4$	0.77
UI eligibility requirements	0.94
Permanent discount factor	1.24

Note: This table shows welfare gains from the optimal policy under different specifications of the baseline model. Welfare numbers are in percent lifetime equivalent consumption terms. Gains are calculated relative to the benchmark policy under a labor productivity series that generates the observed unemployment rate time path during the Great Recession.

policy yields a welfare gain equivalent to 0.64 percent additional lifetime consumption relative to the benchmark policy. The reason for the reduction in welfare gains from 1.25 percent to 0.64 percent is that the decline in the real interest rate reduces precautionary saving motives during recessions, making agents' consumption profiles relatively smoother over the business cycle even under a less generous benchmark policy. This reduces the welfare gains from the optimal policy. While the welfare gains under a recession are reduced to half their original value, the countercyclical optimal policy still provides substantial gains. Moreover, given that interest rate fluctuates drastically with the state of the economy in this exercise, this result places an upper bound on the likely effects of endogenizing interest rates.

Fourth, we address the feature of the baseline model where a matched worker receives the same wage throughout her tenure within a firm. These fixed-wage contracts introduce "job lock" since an unemployed individual who is desperate for work may land a low-paying job during a recession but be unable to switch to a higher-paying job unless the match exogenously dissolves. This feature of the model may be a source inefficiency that the optimal policy is trying to correct, since generous benefits during recessions can nudge agents toward looking for higher-paying jobs. Hence, generous benefits during recessions not only may be providing consumption insurance but also may serve as a means of convincing the unemployed to look for jobs that will be paying higher even after the recession ends. In order to understand whether the optimal UI policy is also correcting inefficiencies introduced by the fixed-wage contract assumption of the baseline model, we solve for the welfare gains of the optimal policy in an extended model that allows for endogenous quits.[48] In this extended model, workers can choose to quit their jobs in order to begin searching for a new job. Under this setup, the artificial job lock problem is eliminated, as workers who place a higher value on the option of becoming unemployed and looking for a higher-paying job can actually leave their employer. The model details and a modified computational algorithm can be found in Appendices B.4 and B.5, respectively. The welfare gains under the model with endogenous quits is given by 1.10 percent when the optimal policy is implemented at the onset of the Great Recession. Introducing endogenous quit decisions into the model has

interest rate.

[48]Without the fixed-wage contract assumption, solving for the optimal policy will be computationally burdensome, as firms would now need to keep track of household decisions.

a small effect because the option of quitting is not widely used by workers, given that the value of becoming unemployed ineligible is very low. As a result, inefficiencies created by fixed wage contracts in the baseline model have a small quantitative impact on the welfare gains from the optimal policy.

The fifth robustness exercise considers the calibration of the replacement rate of the benchmark UI policy. Recall that our benchmark replacement rate of 14 percent takes into account the effect of partial take-up among those eligible for benefits and adjusts for differences between wages and total compensation. To understand the effects of this adjustment, we calculate the welfare gains from the optimal policy when the benchmark policy replacement rate is set to 40 percent, (i.e., $\phi(p) = 0.4 \quad \forall p$), the (unadjusted) value calculated by the Department of Labor. The goal of this exercise is to understand whether the countercyclical optimal policy would still be welfare improving when compared to a new benchmark policy that has a significantly higher but time-invariant level replacement rate. We find that the optimal policy increases welfare by 0.77 percent relative to the new benchmark. This result implies that there are still sizeable welfare gains when the government transfers funds from booms to recessions, as the insurance value of UI payments expands and incentive costs contract during recessions. This also emphasizes that welfare gains are not mostly driven by more generous benefits levels but by the introduction of cyclical generosity.

The sixth exercise considers eligibility rules for workers at the moment of job loss. According to the UI program in the United States, workers have to satisfy some monetary and nonmonetary requirements to be eligible for UI benefits.[49] Under these requirements, on average, around 75 percent of the workers are in fact eligible for UI benefits upon job loss.[50] When studying the optimal design of UI program, it will be interesting to consider the welfare implications of treating these eligibility requirements as another policy instrument. In our baseline setup, eligibility requirements upon job loss are controlled by the UI expiration rate e. Thus, an extension of UI duration also implies a relaxation of UI eligibility requirements for workers in our baseline model. In order to understand the effects

[49] For example, in terms of monetary requirements, workers must receive enough wages during the base period to establish a claim. In terms of nonmonetary requirements, the reason for the workers' job loss must be through no fault of their own, and they must be actively looking for work while unemployed.

[50] See Chodorow-Reich and Karabarbounis (2016).

of this relationship, we change the problem of the worker in Equation (2.1) such that the probability of being eligible upon job loss is fixed at 75 percent rather than controlled by changes in e. We then evaluate the welfare gains from the optimal policy, and find that it yields 0.94 percent additional lifetime consumption relative to the benchmark policy. Since a lower fraction of workers are now eligible for UI benefits upon job loss relative to the baseline model, the welfare gains from the optimal policy are slightly reduced under this exercise.

Finally, we explore the implications of time-varying discount factors β_t. The stochasticity of discount factors introduces another idiosyncratic shock to households, and so one might be concerned about the presence of an unintended role of UI payments as providing insurance against the discount factor risk. In order to quantify this effect, we set discount factors to be permanent and use an equally weighted social welfare function in computing the welfare gains. We find that the optimal policy yields 1.24 percent additional lifetime consumption relative to the benchmark policy, implying that the effect of time-varying discount factors on welfare gains of the optimal policy is negligible. This result is expected given that discount factors are calibrated to be highly persistent in our baseline calibration.

2.6.2 High level of opportunity cost of employment

We now explore the features of the optimal policy under a high level of opportunity cost of employment calibration. In particular, we recalibrate our baseline economy so that the model matches the same labor market and asset-to-income distribution moments as in our baseline calibration, but the level of opportunity cost of employment is set to be 0.955, as calibrated by Hagedorn and Manovskii (2008). Next, we evaluate the welfare gains/losses of the same set of linear policies and obtain the optimal policy for this case under the welfare criterion in Section 2.4.

We find that the optimal policy is still countercyclical even under a high level of opportunity cost of employment. Specifically, it features a 19 percent replacement rate for one quarter when aggregate labor productivity is at its mean value, and a 59 percent replacement rate for 4 quarters when aggregate labor productivity is depressed by 3.5 percent. Compared to the U.S. government's UI policy during the Great Recession (the benchmark policy), this optimal policy increases welfare by 0.25 percent additional lifetime consumption for all agents. Relative to the optimal policy under the baseline calibration of opportunity cost of employment, the optimal policy in this case offers a lower replacement rate for a much shorter duration when labor productivity is at its mean, while the cyclicality of the optimal policy remains roughly the same. This result is intuitive because when the value of unemployment is close to the value of employment because of a high opportunity cost of employment, the consumption drop upon job loss becomes less pronounced. Thus, the government implements a low replacement rate for short durations under the mean level of aggregate labor productivity. Moreover, consumption still fluctuates because of changes in the saving behavior of agents as a response to fluctuations in aggregate labor productivity. Hence, the government still finds it optimal to transfer funds from expansions to recessions. However, the magnitude of these fluctuations in consumption is relatively smaller, as the precautionary saving motives are not as strong under a high level of opportunity cost of employment. For this reason, the welfare gains from the optimal policy in this case are less than half of the welfare gains provided by the optimal policy under the baseline calibration of opportunity cost of employment.

This exercise is also useful to compare our result to the findings of the previous literature. As we discussed in Section 2.1, Mitman and Rabinovich (2015) also study the optimal cyclicality of UI replacement rate and duration in an equilibrium search model in which agents are not allowed to save/borrow. In their baseline calibration, the summation of UI benefits b and the value of nonmarket activity h is equal to 0.984, implying that the flow opportunity cost of employment is high. In this setup, they find that the optimal UI policy is procyclical. Then, in Section 5.4 of their paper, they discuss the implications of relaxing the no saving/borrowing assumption on their results. In this discussion, they also acknowledge that when agents are allowed to save/borrow, fluctuations in agents' wealth holdings over the business cycle may create a force that has a potential to reverse the cyclicality of their optimal UI policy. In our model, we allow agents to save/borrow through incomplete asset markets and indeed show that this channel is strong enough to rationalize the countercyclicality of the optimal policy even under a high level of opportunity cost of employment.

2.7 Evidence on the Mechanism: A First Pass

In this section, we empirically test the interaction between UI generosity and savings decisions in order to check whether our main mechanism is also observed in the micro data. This exercise builds on Engen and Gruber (2001), who find that UI benefits tend to crowd out individual savings.[51] We focus on the Great Recession period to understand the impact of drastic changes in UI policy on the saving decisions of individuals. Using the SIPP panel 2008 core data, we obtain household employment, labor income, and state of residence information. Wealth data are once again obtained from the topical data of the same panel, which is typically released on a yearly basis as opposed to the monthly frequency of the core data. State-level UI duration data during the Great Recession consist of maximum potential duration by adding up standard weeks, Extended Benefits (EB), and EUC tiers 1-4 (when applicable).[52] Meanwhile, the state-level replacement rate is defined as either (1) the weighted average of the ratio of the weekly benefit amount and average claimants' wage or (2) the ratio of the weighted average of the weekly benefit amount and the weighted average of claimants' wage.[53] To obtain the expected benefit receipt of a worker, we compute the average weekly wage of the respondent for one quarter prior to the wealth observation and multiply it by the replacement rate offered by her state of residence during that time.

Our sample includes workers ages 24 to 65 who report not owning any business in part or in full and has worked for at least one quarter prior to the first observation and are always working in between observations. This more or less guarantees eligibility for UI if the observed worker is displaced in the future. Moreover, focusing only on employed individuals between observations eliminates other reasons for changes in asset holdings, such as experiencing unemployment. We organize the data into person-time information (where $t = \{2009, 2010\}$) and run the following regression:

$$a_{it} = \gamma_{ben} benefit_{it} + \gamma_{dur} dur_{st} + \beta X_{it} + \alpha_i + \alpha_s + \alpha_t + \epsilon_{ist}$$

[51] While Engen and Gruber (2001) study the effect of the UI replacement rate on saving decisions, we also include time- and state-varying UI duration in order to account for the effect of expected length of UI receipts on wealth for the period of the Great Recession.

[52] We thank A. Yusuf Mercan for kindly sharing this dataset with us.

[53] See https://oui.doleta.gov/unemploy/ui_replacement_rates.asp for more details.

where a_{it} is the asset-to-income ratio of individual i at time t, $benefit_{it}$ is the expected weekly benefit receipt of individual i at time t, dur_{st} is the maximum potential duration of UI in state s during time time t, X_{it} is a set of controls which include education, martial status, and age, and $\alpha_{j\in\{i,s,t\}}$ are individual, time, and state fixed effects.[54] The coefficients of interest are the impact of the unemployment benefit level and duration on the asset-to-income ratio given by γ_{ben} and γ_{dur}. Note that a selection problem arises if there is a systematic movement of a certain type of worker to states with high levels of UI generosity. In order to control for this, we also expand the original regression to control for individuals moving from one state to another.

Given that isolating the causal effect of benefit generosity on self-insurance is beyond the scope of this exercise because of endogeneity, our intention is simply to provide correlational evidence on this relationship. Table 2.7 shows that expected benefit receipt has a negative and statistically significant impact on self-insurance. While the length of UI duration has a negative coefficient, it is not statistically significant. For example, $\gamma_{ben} = -.0135$ implies that a \$100 increase in the expected benefit amount received each week should unemployment occur results in a decrease in the asset-to-income ratio that is equivalent to 1.35 weeks' worth of insurance. Alternatively, this would also imply a reduction in savings by around \$1124 for a worker earning the median weekly wage of \$833. This relationship is consistent with the crowding-out effect of UI on precautionary savings documented by Engen and Gruber (2001). This result lends evidentiary support to the idea that the insurance benefits of a generous UI policy during recessions are partially attributable to the relief UI benefits provide workers who no longer need to experience sudden drops in consumption in order to build a buffer stock of savings. Results in the second and fourth columns also indicate that the issue of selection caused by state-to-state moves is not consequential. Finally, comparing the first two columns with the last two reveals that the relationship is robust to the manner by which replacement rates are calculated.

Motivated by the above empirical evidence, we revisit our welfare analysis in the model to understand if the replacement rate is a more important instrument in providing welfare gains relative to the UI duration. We find that a UI policy that consists of an optimal

[54] Notice that $benefit_{it}$ is affected by the replacement rate offered by the state s that individual i resides in during time t.

Table 2.7: Regression results

	Benefit Calculation 1		Benefit Calculation 2	
	(1)	(2)	(1)	(2)
benefit	$-.0135^{***}$	$-.0135^{***}$	$-.0153^{***}$	$-.0153^{***}$
	(.0010)	(.0010)	(.0012)	(.0012)
dur	$-.0122$	$-.0123$	$-.0119$	$-.0119$
	(.0164)	(.0164)	(.0164)	(.0164)
moving		$-.0924$		$-.0933$
		(.2255)		(.2254)
individual fixed effects	Yes	Yes	Yes	Yes
state fixed effects	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes
observations	33,012	33,012	33,012	33,012

Note: The dependent variable is the asset-to-income ratio of individuals. "Benefit Calculation 1" uses a replacement ratio calculated as the weighted average of the following ratio: weekly benefit amount (WBA) / weekly wage. "Benefit Calculation 2" uses a replacement rate ratio calculated as the ratio of the weighted average of WBA and the weighted average of the weekly wage. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

replacement rate but a UI duration of the benchmark policy, together with the tax rate that balances the government's budget constraint for this hybrid policy, yields an average welfare gain that is equivalent to 0.46 percent additional lifetime consumption relative to the benchmark policy. This implies that around 80 percent of the welfare gains from the optimal policy are attributable to the optimality of the UI replacement rate, and the remaining 20 percent of the gains come from the optimality of UI duration. This is consistent with the above empirical result that the changes in replacement rates significantly affect the self-insurance decisions of individuals.

2.8 Conclusion

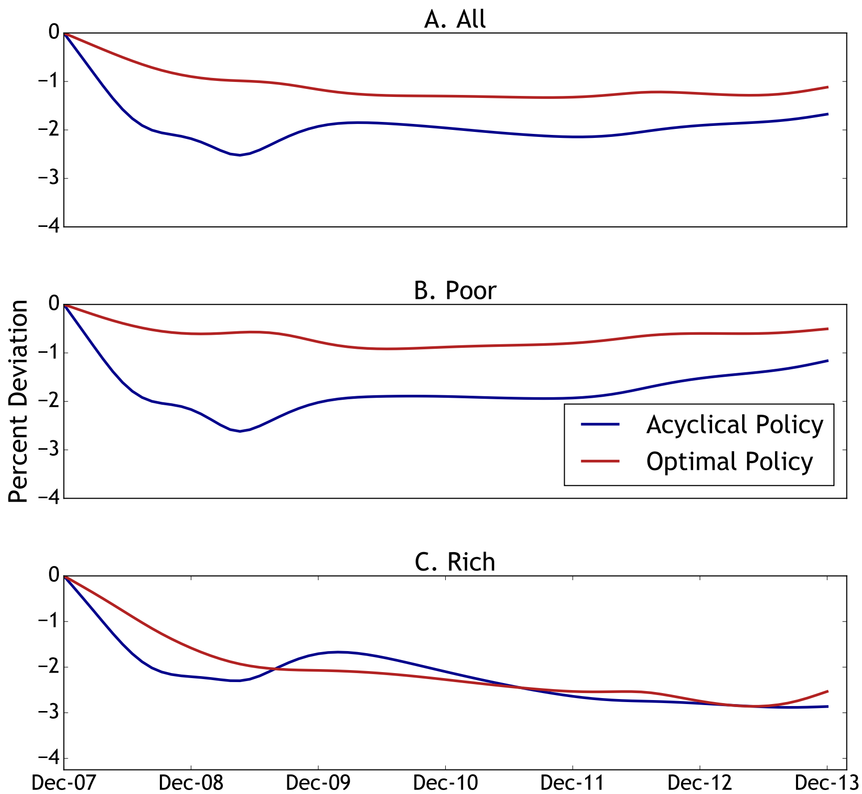
We study optimal UI over the business cycle using a tractable heterogeneous agent job search model that features labor productivity driven business cycles and incomplete asset markets. We find that the optimal UI policy is countercyclical. In particular, when aggregate labor productivity is at its mean, it features a 30 percent replacement rate for 4 quarters, but when aggregate labor productivity is depressed by 3.5 percent, it offers more generous benefits of a 54 percent replacement rate for a duration of 10 quarters financed by higher labor income taxes. Compared to a UI policy that mimics the policy implemented during the Great Recession by the United States government, the optimal policy represents an average welfare increase of 0.58 percent additional lifetime consumption. We show that incorporating the response of individual saving behavior to changes in UI policy is quantitatively important in measuring the welfare benefits and costs of UI policy.

Insurance benefits are larger in recessions relative to expansions, while incentive costs exhibit the opposite pattern. Insurance benefits expand during recessions because (1) consumption insurance upon job loss is provided for a larger pool of unemployed and long jobless spells, and (2) it attenuates the need to engage in precautionary savings by cutting back on consumption at the onset of a recession. Meanwhile, incentive costs are also relatively smaller in recessions because (1) jobs are difficult to find and forgone search is not as worthwhile, and (2) borrowing constraints impose discipline on individual job search behavior because of a wealth effect. As a result, the optimal policy is countercyclical.

A quantitative decomposition of ex-ante welfare gains reveals that in the long run, the optimal policy provides a substantial reduction in consumption uncertainty at the cost of lower consumption levels. Along the transition, however, large consumption level gains are enjoyed by agents as they decumulate savings in response to more generous public insurance during recessions. Meanwhile, gains from reduced inequality and lower search effort are present but limited. In addition, ex-post welfare gains are shown to be heterogeneous across different types of agents. The unemployed eligible gain the most, but the employed remarkably enjoy large gains as well because of the reduced precautionary motives during recessions. Unsurprisingly, gains are largest for the poor across all employment types.

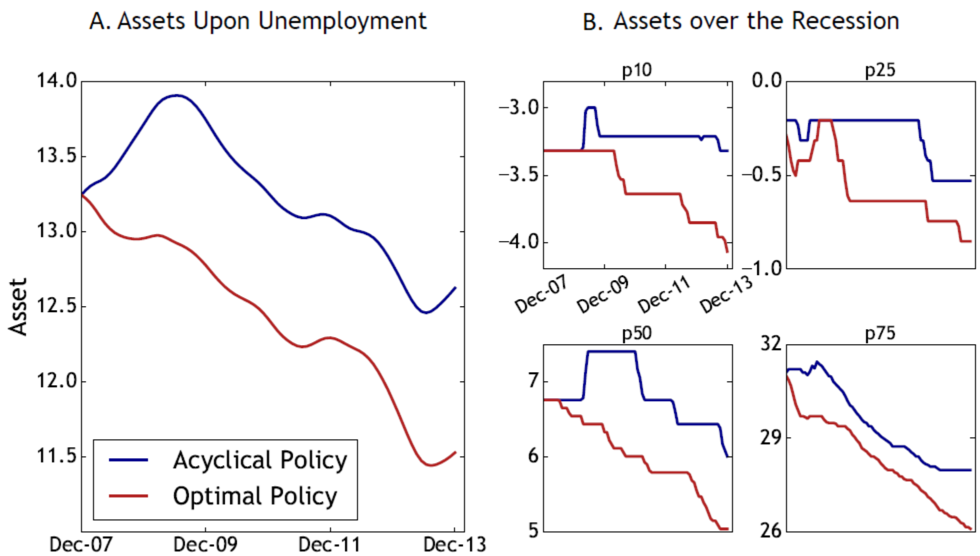
Our contribution to the existing literature lies in carefully accounting for the welfare effects of endogenous interaction between savings and UI policy over the business cycle. The natural extension of our analysis is to analyze how other sources of private insurance (such as family labor supply) react to changes in UI policy and how this interaction would affect the optimal policy. Another avenue for future research is to incorporate capital accumulation in order to account for the effect of government programs on aggregate capital stock. However, given the complexity of our current model, we leave these extensions to future work.

Figure 2.6: Average consumption over the business cycle



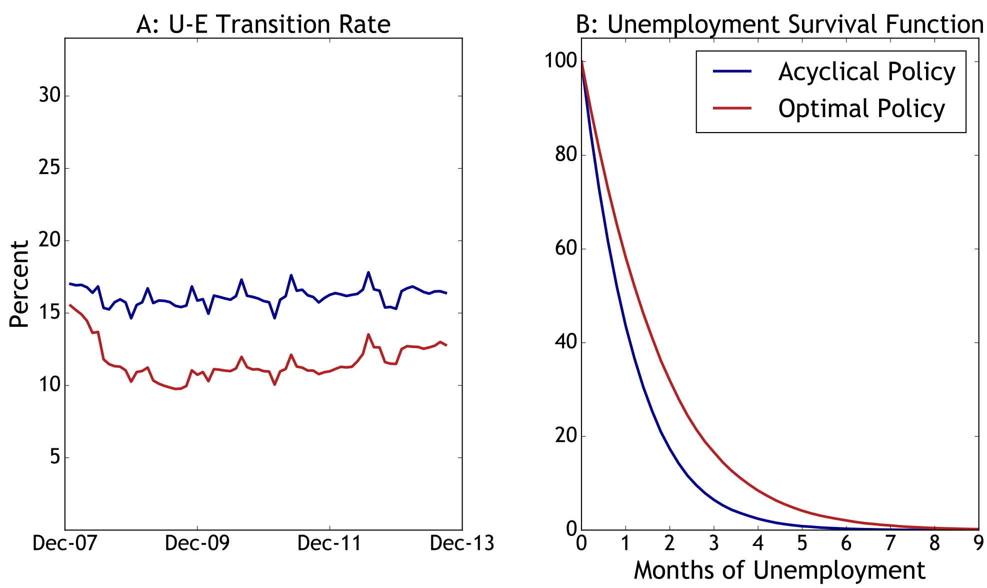
Note: Panel A plots the percent deviation of average consumption's trend during the Great Recession from its steady-state level at the start of this period under the acyclical and optimal UI policies. Panels B and C repeat this exercise for poor and rich agents. "Poor" refers to agents who enter unemployment with an asset-to-income ratio below the 75th percentile of the stationary asset-to-income distribution, while "Rich" refers to those above the threshold.

Figure 2.7: Average assets upon job loss over the business cycle



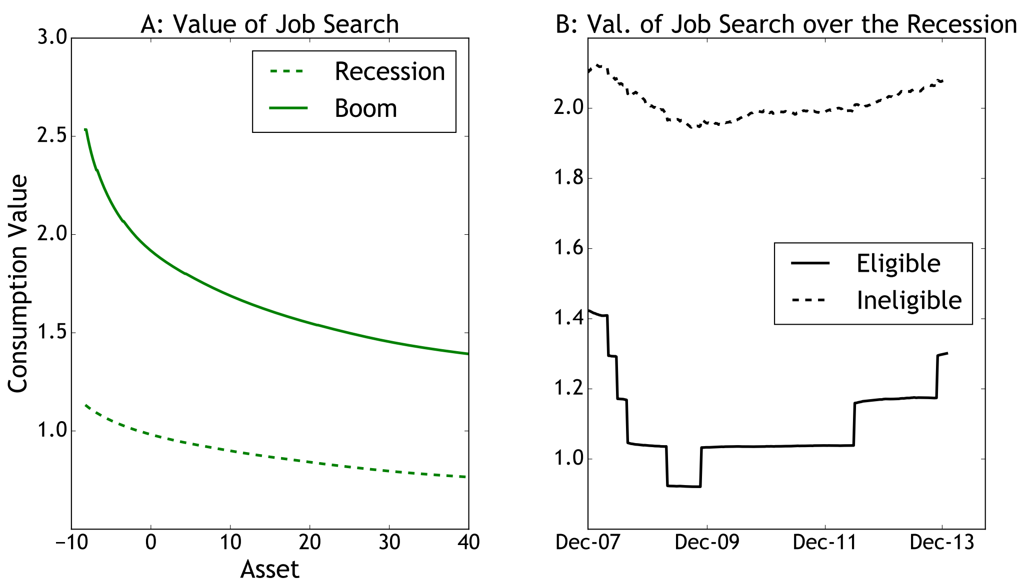
Note: Panel A plots the trend of average asset holdings of the unemployed during the first week of entering unemployment over the Great Recession under the acyclical and optimal UI policies. Panel B shows the evolution of various percentiles of the asset distribution over the Great Recession under these two policies.

Figure 2.8: Incentive costs of the optimal policy



Note: Panel A shows the average job finding rates during the Great Recession under the acyclical and optimal UI policies. Panel B plots the unemployment survival function under these two policies, which shows the probability that an unemployment spell will last beyond t months.

Figure 2.9: Value of job search



Note: Panel A shows the consumption value of job search across different levels of asset holdings in recessions and booms. Panel B plots the average consumption value of job search during the Great Recession for unemployed eligible and ineligible.

Chapter 3

What Do Survey Data Tell Us about U.S. Businesses?

3.1 Introduction

Representative surveys of households and firms have become an important source of data on business owners and their activities, and are now used extensively in studies of wealth inequality and entrepreneurial choice. This paper examines the reliability of these data for research on U.S. businesses, including pass-through entities and subchapter C corporations.[1] Pass-through businesses account for roughly half of business net income in the United States and have been a focus of recent tax reforms and debates about income inequality.[2] Subchapter C corporations account for the remaining half and include all publicly traded firms. We document issues arising from nonrepresentative samples and measurement errors in survey data and discuss the implications of the errors for economic research.

[1]For tax purposes, pass-through entities classify themselves as sole proprietorships, S corporations, or partnerships. They are called "pass-through" because the income earned by such businesses is taxed under the owners' individual income tax. In contrast, C corporations pay corporate taxes on income earned, and individual shareholders pay dividend or capital gains taxes when profits are distributed.

[2]Smith et al. (2017) use tax audit data to conclude that rising business income accounts for all of the growth in the top 1 percent income share since 2000. Furthermore, the majority of rising top business income resulted from rising income of pass-through businesses.

We start by examining the reliability of measures of business incomes, receipts, and valuations in the Federal Reserve's Survey of Consumer Finances (SCF), which is a publicly available and widely used triennial cross-sectional survey of U.S. households. Households with actively managed businesses are asked to report business receipts and net income from specific lines on their tax forms.[3] This aspect of the survey design makes it easy for us to compare the household responses with administrative data from the IRS *Statistics of Income* (SOI).[4] Averaging across survey years, we find that the SCF overstates pass-through business income per tax return by 400 percent and business receipts per return by 169 percent. For C corporations, net income and receipts are on average understated in the SCF by 26 and 21 percent, respectively, but the SCF does not include publicly traded corporations, whereas the IRS does. Since publicly traded corporations have much higher receipts and net incomes per tax return than private corporations, including them would result in a significant overstatement for all business entities.

The overstatement of incomes and receipts in the SCF varies in the cross section and year by year, making it difficult, if not impossible, to systematically correct for the errors. To demonstrate this, we provide evidence of both sampling and measurement errors. Sampling errors arise from an understatement or overstatement of the reported number of tax returns in the SCF relative to the IRS. We find that the SCF significantly understates the number of sole proprietorships, S corporations, and C corporations and significantly overstates the number of partnerships, with the degree of under- or overstatement varying across the income distribution. Looking at data in the cross section, our findings suggest a significant underrepresentation of low-income businesses driving the overstatement of business incomes. This may be attributable to measurement error resulting from how the questions are framed. For example, there are many IRS businesses with net losses but few in the SCF, possibly because the respondents answered that they had no net income rather

[3]Sole proprietors are asked to report business gross receipts and net income from Form 1040 Schedule C (lines 1 and 31), shareholders of partnerships from Form 1065 (lines 1c and 22), shareholders of S corporations from Form 1120S (lines 1c and 21), and shareholders of C corporations from Form 1120 (lines 1c and 30).

[4]The IRS compiles the SOI based on stratified probability samples of income tax returns and other forms. We use information from the SOI Corporation Income Tax Returns, Individual Income Tax Returns, and Partnership Returns that are available in the historical data tables from www.irs.gov/statistics.

than a negative net income. Another measurement issue we document is that the frequency of referencing supporting documents is strikingly low. For example, if we condition on all business owners in the SCF, we find that 75 percent never referenced any tax document.

The SCF survey has also been used extensively to study the level and dispersion of business wealth. Households with actively managed businesses are asked to assess the value of their business, net of all loans, if they were to sell it. Since there are no measures of total valuations for ongoing businesses other than publicly traded C corporations, we construct net income-to-value ratios in the SCF and compare them to available income yields from brokered private business sales recorded by Pratt's Stats and publicly traded companies, both small and large, recorded by the Center for Research in Security Prices (CRSP) (merged with Compustat). For virtually all subsamples and all years, the SCF income yields are significantly higher than comparable measures from the other datasets. The overstatement in yields is even greater than for incomes, which is suggestive of an understatement in business valuations. For example, the SCF average value-weighted income yield is 19 percent, much higher than the Pratt's Stats estimates of 2 percent or the CRSP estimates of 7 percent for all businesses, and −9 percent for those in the bottom quintile when firms are ranked by total assets. We also find that the SCF distributions are more right-skewed than those based on Pratt's Stats or CRSP-Compustat data.

For unincorporated businesses, we can compare the SCF estimates of business incomes per owner and, if available, income yields to those of three other widely used surveys: the Current Population Survey (CPS), the Panel Study of Income Dynamics (PSID), and the Survey of Income and Program Participation (SIPP).[5] We show that all four surveys overstate incomes per owner relative to the IRS data, but by differing amounts. Averaging across survey years, business income per owner for unincorporated businesses is overestimated by 586 percent in the SCF, 179 percent in the CPS, 185 percent in the PSID, and 34 percent in the SIPP. Average value-weighted income yields calculated for the PSID and SIPP are high relative to Pratt's Stats and CRSP data in all cases but are not very different from those in the SCF. The main differences in yields across surveys are found

[5] We also compare the SCF results to the results of Gurley-Calvez et al. (2016), who match responses of new businesses in the Kauffman Firm Survey (KFS) with IRS tax data and find that these firms understate business incomes. For some other surveys of businesses, such as the Panel Study of Entrepreneurial Dynamics (PSED), we find the response rates of business-related questions to be too low to be reliable.

when we compare the distributional statistics.

An overstatement of business incomes in the survey data relative to the IRS could be the result of misreporting in the IRS or miscategorization of incomes by survey respondents. To check misreporting, we use auxiliary tax audit data to adjust the IRS data but still find a significant mismatch with the survey data. For example, for pass-through businesses, the SCF overstates the average income per return by 178 percent relative to the tax audit data. To check miscategorizations, we use a broader definition of business income. For example, business owners might confuse business incomes on Schedule C, E, and F, overstating one category and understating another. When we combine these categories into a broader concept of business income, we still find incomes to be significantly overstated. Respondents are not miscategorizing the incomes but rather are often overstating all categories of business income. Other adjustments, such as correcting for within-survey inconsistencies regarding business ownership and income and correcting for the fact that the survey only includes individual owners, do not alleviate the measurement issues.

The inconsistencies across surveys and the conceptual measurement issues that we highlight suggest that the "facts" about business income and wealth based on current survey data should be treated with caution. Measurement problems related to business incomes are surmountable given that respondents are asked about specific lines on the tax forms. Measurement problems related to business valuations and returns may be insurmountable without data on actual business sales transactions. First, it is difficult for owners to estimate business valuations when one considers that businesses are heavily invested in intangible assets.[6] Second, survey business owners answer questions separately about income and valuations. For example, if the net incomes derive from both capital and labor inputs, while the business valuations are based on fixed assets owned by the business, then the estimated income yields from surveys may not be comparable across owners who interpret the question differently. Interpreting survey-based measures of business returns or valuations requires a consistent framework for true returns, stocks, and valuations. Given current measurement issues, such interpretations may not be possible.

[6]McGrattan and Prescott (2010a,b) and Bhandari and McGrattan (2018) both find estimates of the value for intangible assets to be close to estimates of tangible assets used by businesses. Intangible assets come in the form of research and development, software, advertising, brands, and investments in customer lists, goodwill, and other forms of investments in building organizations.

This paper is organized as follows. Section 3.2 discusses the related literature and the implications of our findings for theoretical and applied research on businesses. In Section 3.3, we document that business incomes and receipts measured from the SCF survey data are largely inconsistent, and we discuss problems regarding nonrepresentativeness and measurement errors. Section 3.4 studies business valuations and rates of return. Section 3.5 presents robustness checks. Section 3.6 compares the SCF results with other widely used surveys. Finally, Section 3.7 concludes.

3.2 Related Literature

Our findings have implications for three active areas of economic research. The first area is the empirical literature that documents levels and trends in the dispersion of income and wealth and emphasizes the role of entrepreneurs in wealth accumulation. The second area, which is motivated by and builds upon the first, is the theoretical literature developing models of entrepreneurial choice, which are specifically designed to fit the "stylized facts" of the empirical literature. The third area includes quantitative policy analyses that use the empirical findings and theoretical developments of the first two literatures as their laboratory for the study of counterfactual policies. Our findings cast doubt on the facts that have been uncovered in the empirical literature—specifically documenting that survey data are unreliable for business-related statistics—and thus raise issues concerning the theoretical developments and policy analyses that have been designed around them.

A large and burgeoning empirical literature documents trends in income and wealth and has been particularly focused on increased dispersion over time. Greater dispersion is attributed to top earners, and therefore researchers work primarily with survey data from the SCF or administrative tax data from the IRS. For example, Kuhn and Rios-Rull (2016) provide a nearly exhaustive summary of distributional facts about U.S. earnings, income, and wealth based on the SCF. A starting point for several papers in this literature is the observation that, for broad income categories, aggregated SCF responses match up well to the aggregated IRS data. In Figure 3.1, we replicate the time series plot for adjusted gross income (AGI) from the SCF and plot it against the corresponding data from the IRS. We see that the SCF tracks the level and cyclical trends for AGI in the IRS.

Our focus is on measures that relate to business activity. Of particular relevance are the findings in Kuhn and Rios-Rull (2016) that business income is one of the main contributors to income inequality and that business equity is one of the main contributors to wealth inequality, which they document for the history of the SCF surveys between 1989 and 2013. Bricker et al. (2016) also use the SCF to document the rise of the top share of wealth holdings over time and find that the share of wealth attributable to the top 1 percent rose from 30 percent in 1992 to 36 percent in 2013. Our paper exploits the fact that SCF answers can be compared to administrative data from the IRS and finds that respondents are not reliably or consistently answering questions about their business income or business equity, and therefore we cannot trust the SCF distributions.

Given issues with measuring business incomes, researchers might be tempted to combine all nonwage income into a residual "capital income" category, since SCF aggregates match up well with aggregated IRS data. Here, we argue that this capital income measure would not be appropriate for either research on U.S. businesses or research on U.S. capital. For research on businesses, the residual income measure would be inappropriate because significant nonbusiness income is included with interest payments, capital gains, pensions and annuities, alimony, trusts, and government transfers. Furthermore, as we noted earlier, there is evidence that owners are not miscategorizing income categories, and therefore using broader categories of income would do little to ameliorate the measurement issues. For research on capital, the nonwage income in AGI would be inappropriate because a significant fraction of capital income is untaxed and the corresponding assets are held by fiduciaries. Furthermore, as we show later, the majority of respondents do not reference financial documents, making it nearly impossible to have reliable estimates of their total capital income or wealth.

Saez and Zucman (2016) document trends in wealth dispersion by capitalizing incomes from administrative tax data. They compare their results to the SCF and find similar levels and trends for wealth in the top 10 percent of the distribution but differences for the top 1 percent.[7] The Saez and Zucman (2016) capitalization method is inappropriate for estimating wealth in business for several reasons. First, there is no way to validate the procedure except by comparing to survey data, which we find are unreliable. Second,

[7] They also compare results to estate taxes and foundation records, but these data are not informative about most businesses in the United States.

the U.S. flow of funds aggregates used to compute capitalization factors include ad hoc imputations made by the Federal Reserve for private businesses.[8] Third, the assumption that returns are the same for everyone and constant over time is hard to reconcile with the fact that there is significant entry into and exit out of business (see Bhandari and McGrattan (2018)).

Because of the problems with data from the SCF and the capitalized IRS incomes, the main message of our findings for the theoretical literature is a cautionary one, namely, that these data tell us little about business valuations or returns, and therefore theorists should not insist on models that replicate "stylized facts," which are not actually facts. The most popular stylized facts are that entrepreneurs, as a group, own a substantial share of household wealth and income, with shares increasing throughout the distribution, and that entrepreneurs have high savings rates relative to the population, implying much more dispersion in wealth than in income (see De Nardi, Doctor, and Karen (2007) and Gentry and Hubbard (2004)). These findings have led researchers to model entrepreneurs as overcoming significant market frictions to run highly risky businesses with the expectation of earning high returns and amassing significant wealth (see, for example, Quadrini (2000), Cagetti and De Nardi (2006), and Buera (2009)). Furthermore, the theoretical frameworks parameterized to match the survey data have been used as a laboratory for policy work, especially when considering tax policy reform (see, for example, Meh (2005), Kitao (2008), Bohacek and Zubricky (2012), and Scheuer (2013)). Our results cast doubt on the survey data underlying the models of financial frictions and, hence, the subsequent policy recommendations.

Our paper is also related to a second strand of the empirical literature, which reaches

[8]For example, when constructing capitalization factors, Saez and Zucman (2016) use aggregate flow of funds wealth measures for closely held corporations (both subchapter C and S) and unincorporated businesses. These businesses are not publicly traded and thus have no market valuations. The Federal Reserve imputes market values for closely held corporations by taking a ratio of market value to revenues for publicly traded companies and then applying that ratio to private businesses with similar industry, employment, and revenue profiles—after arbitrarily adjusting the estimate downward by 25 percent to reflect the lack of liquidity of closely held shares. Valuations for unincorporated businesses are based on balance sheet data reported to the IRS, which are historical-cost accounting measures, not market valuations.

different conclusions about the payoffs to entrepreneurial activity.[9] Hamilton (2000) uses survey data from the 1984 SIPP and finds that self-employed individuals—who could be running an incorporated or unincorporated business—have lower median earnings than similar individuals in paid employment. Moskowitz and Vissing-Jorgensen (2002) extend his analysis and work with SCF data, allowing for a more comprehensive treatment of equity returns and including adjustments for firm entry and exit. They find that returns to private businesses are no higher than returns to publicly traded firms and thus puzzlingly low given the risks entrepreneurs face.[10] Using PSED data, Hurst and Pugsley (2011) report that more than 50 percent of new business owners cite flexible hours and being one's own boss as the primary reason for starting their own business. These findings have led researchers to conclude that the nonpecuniary benefits of self-employment play an important role in occupational choice.

We document that survey data *overstate* business incomes, and the overstatement leads to income yields for private businesses that are significantly higher than those for publicly traded companies. In other words, we find that the private returns computed with survey data are puzzlingly high, not puzzlingly low. When comparing our results to Moskowitz and Vissing-Jorgensen (2002), we find that the main difference is the concept of return: they add an imputation for capital gains that drive their results. Regrettably, neither the income yield nor the capital gain imputation are reliable estimates, leaving us with little to say about whether private returns are low or high relative to public returns. This finding is relevant for policy discussions related to business taxation and subsidization. For example, Hurst and Pugsley (2017) followed up on the work of Hamilton (2000) and Moskowitz and Vissing-Jorgensen (2002) by incorporating nonpecuniary benefits in a model of entrepreneurship and then analyzed the impact of small business subsidies. Our results cast doubt on SIPP and SCF survey data and hence on policy recommendations that arise

[9] Later, we document inconsistencies across surveys and across time that could lead to different empirical insights.

[10] Moskowitz and Vissing-Jorgensen (2002) used samples over the period 1989–1998. Kartashova (2014) extended their analysis to 2010 and documented that for the longer sample, the private equity premium is about 6 percent as compared to about 0 percent in the shorter sample. Since the difference in means is swamped by the variability of the CRSP index returns, which has a standard deviation of 20 percent over the period 1988–2015, we would argue that their estimated private returns are not significantly different.

from frameworks that incorporate nonpecuniary benefits of business entrepreneurs.

3.3 Business Incomes

In this section, we compare SCF pretax business incomes that correspond to specific lines on U.S. tax forms with incomes reported to the IRS. We first document that the SCF responses—both in the aggregate and across the distribution—are statistically different and argue that the magnitudes of the differences are economically important. We then explore reasons for the mismatch.[11]

3.3.1 Aggregates

We start with aggregated business incomes and show that, while the SCF does well in matching the IRS total AGI (as shown in Figure 3.1), there are large discrepancies between the survey and tax data for businesses. For pass-through businesses, business income per return is significantly and consistently overstated in the SCF relative to the IRS. For C corporations, the average per-return business income in the SCF is not very different from the IRS but should be much smaller given that the survey excludes publicly traded companies.

To demonstrate that there is a significant discrepancy between SCF and IRS data, we start by defining *business income* as gross receipts from sales minus expenses (including depreciation) incurred in running the business. Information on business incomes is obtained from the respective business tax forms: Form 1040, Schedule C (line 31) for sole proprietors, Form 1065 (line 22) for partnerships, Form 1120S (line 21) for S corporations, and Form 1120 (line 30) for C corporations. In each survey year, we use the SCF sampling weights and ownership information to compute the aggregate business income and the aggregate number of business tax returns by legal form of the business.

Figure 3.2 plots aggregated business income divided by the number of business tax returns using the SCF and the data actually reported to the IRS for tax years between 1988

[11]In Appendix C, cited henceforth as Bhandari, et al. (2019), we provide a comprehensive collection of statistics for all survey years and subsamples.

and 2015.[12] All data are reported in thousands of current dollars. The shaded region in Figure 3.2 shows the 90 percent confidence interval of the average per-return business incomes.[13] Panel A of Figure 3.2 shows the results for sole proprietorships. For this group, average incomes reported in the IRS are about \$8,000 per return in 1988 and rise gradually to \$12,000 per return by 2015. Average incomes per return reported in the SCF are significantly higher, rising from \$32,000 in 1988 to \$40,000 by 2015, and display large year-to-year variation. If we construct a percentage error (that is, 100(SCF−IRS)/IRS) in each year, we find the average error is 289 percent and ranges from 158 percent to 384 percent across all years. We see a similar result in Panel B, which shows the data for S corporations. The SCF S-corporation incomes per return are significantly higher than the IRS analogues for the entire sample period. The errors in this case average 273 percent and range from 142 percent to 387 percent.

In the case of partnerships, a sampling issue implies that the discrepancy between the SCF and IRS income could be even larger than that shown in Panel C of Figure 3.2. The SCF only surveys owners of partnerships who are individuals, whereas the IRS includes information on partnerships owned by individuals and other legal entities such as corporations.[14] The exclusion of corporate partners in the SCF should lead to an understatement of aggregate business income but, in principle, should not affect the business income per

[12] In the SCF, we assume that a business owner who owns multiple sole proprietorships files one return. This assumption is made to be consistent with IRS statistics that state: "For purposes of the statistics, if a proprietor owned more than one business, the statistics for each business were combined with those of the proprietor's dominant business and included in the industrial group for that business activity" (see Dungan (2017, p. 2)). For partnerships, S corporations, and C corporations, we calculate the number of returns taking into account the ownership share of the family from each reported business.

[13] Standard errors are computed using a bootstrap method. For each survey year, the SCF provides a set of 1,000 replicate weights. We use these weights to compute 1,000 values for the relevant statistic, for example, business income per return, and then we compute the confidence intervals using the 5th and 95th percentiles of these 1,000 draws.

[14] For the year 2011, Cooper et al. (2016) estimate that 32 percent of total business income from partnerships is generated by individual partners, who account for 73 percent of all partners.

return.[15] However, we find that both aggregate income and per-return income are overstated for partnerships. Aggregate business income from partnerships in the SCF is *higher* than the IRS by 305 percent on average, with the range of errors between 52 percent and 889 percent across survey years. Per-return income is also overstated by 300 percent on average, with errors between 31 percent and 837 percent, as shown in Panel C of Figure 3.2.

If we include all pass-through businesses in one category (using data in Panels A through C of Figure 3.2), we find that the SCF error is 400 percent on average and ranges from 230 percent to 568 percent for business income per return. Contrast this with business incomes per return for C corporations, shown in Panel D of Figure 3.2. For these businesses, we find that in most years, the average SCF business income per return is actually understated by about 26 percent as compared to the IRS data. However, the IRS data include publicly traded corporations, whereas the SCF data do not. Publicly traded C corporations are typically much larger than their private counterparts. If we could include the incomes from these publicly traded corporations with the SCF estimates, we would find that the SCF total incomes would be significantly higher than the IRS estimates, as is the case for the pass-through businesses. Despite these measurement issues, we compare business incomes of C corporations in the SCF with the IRS and interpret the results with the understanding that the SCF will underrepresent large businesses.

While incomes per return are overstated in the SCF relative to the IRS, the number of returns filed by businesses are significantly understated for sole proprietors and corporations in all years. Figure 3.3 plots the number of business returns filed as reported by the IRS and the SCF, over time and by legal entity, with shading marking the 90 percent confidence interval. In the case of sole proprietors and S corporations shown in Panels A and B, the understatement has worsened over time as the number of IRS filings has grown and the number reported in the SCF has not. In Panel C, we see that the number of partnership returns in the SCF is undercounted in only a few years and not by as much as in the case of the other business types. However, as mentioned before, the SCF data only include partners who are individuals, implying that the SCF significantly *overstates* the number

[15] Here, we are operating under the assumption that the SCF is representative and partnerships with all corporate partners (which are entirely missed by the SCF) either are small in terms of their share of aggregate business income or else are not systematically different from the rest of the partnerships.

of returns for partnerships owned by individuals. The number of C-corporate returns is shown in Panel D of Figure 3.3. In this case, part of the difference between the IRS and SCF results is the exclusion of publicly traded companies in the SCF, but these businesses only account for about 5,000 out of the roughly 1.6 million C corporations and therefore cannot account for the large understatement of returns shown in the figure.

One possible reason for understated returns is that the SCF data may not include owners that earn very little business income (for example, part-time Uber drivers or AER referees), while the IRS includes all business tax filers. If this were indeed the case, then the aggregate business incomes—found by multiplying values in Figure 3.3 by values in Figure 3.2—would be similar for the IRS and SCF. We find that this is not the case: aggregate business incomes are significantly overstated in the SCF. For example, in the case of pass-through businesses, we find average overstatements of 34, 137, and 305 percent for sole proprietors, S corporations, and partnerships, respectively, with a large range in the errors over time. (See Bhandari et al. (2019) for details.) The large overstatement of aggregate incomes, especially in S corporations and partnerships, is clearly inconsistent with the hypothesis that nonactive business owners explain the differences between the SCF and IRS results.

Finally, we extend the analysis to business receipts and again find large and variable errors in the SCF responses when compared to the IRS counterparts. (Full details are provided in Bhandari et al. (2019).) For example, in the case of pass-through businesses, we find that the average error in business receipts per return over the period 1988–2015 is 169 percent, with errors over the period in the range of 89 percent to 367 percent. Thus, our main finding is an overstatement of aggregated business incomes and receipts in the SCF across all legal forms, with large variation in the discrepancies across survey years.

3.3.2 Distributions

Next, we show that the overstatement of business income per return documented in the previous section varies in the cross section and year by year, making it impossible to systematically correct the SCF responses. The discrepancies between the SCF and IRS statistics are so large and variable as to make the cross-sectional moments based on the survey data unusable for applied work.

To demonstrate this, we compute percentage errors by grouping businesses in two different ways. First, we group those with positive business income (profits) separately from those with negative business income (losses). For pass-through businesses, the SCF overstates business income per return for those that have profits by 277 percent on average, with the year by year errors in the range of 151 percent to 446 percent. The SCF understates the business income per return for those that have losses by about 82 percent, with the errors in the range of 66 percent to 94 percent. Both the overstatement of profits and the understatement of losses affect the errors in cross-sectional statistics in quantitatively important ways. We demonstrate this in Table 3.1 for pass-through businesses by decomposing the percentage errors in the aggregate business income into the fraction that arises due to overstatement of profits and the fraction that arises due to understatement of losses. For example, in tax year 1988, the overstatement of profits and understatement of losses each account for about 50 percent of the aggregate error. In subsequent years, these fractions vary but are nontrivial in both the overstatement of profits and understatement of losses. (See Bhandari et al. (2019) for results across all legal forms and survey years.)

A second method of grouping businesses is by ranking them according to total income of the owners. Here, we do this in the case of sole proprietorships since we have comparable IRS data in all SCF survey years. (See Bhandari et al. (2019) for a more limited analysis of S corporations.) Specifically, we rank sole proprietors in the SCF by their AGI and then assign them to income brackets using the same bins as the IRS. In Figure 3.4, we plot the fractions of business income for owners with below-median AGI and for those with AGIs in the top 1st percentile. For most years, the SCF income shares for these two groups are understated and display large year by year variation. For example, the share for those with below-median AGI is nearly doubled or halved from one survey to the next. Since the fractions sum to 100 percent across all AGI groups, the SCF must necessarily overstate incomes for some bins. We find the largest overstatement of shares for those with AGIs between the 50th and 75th percentile.

In Figure 3.5, we see that the overstatement of business income per return in the SCF data also varies a lot across years and across AGI bins, with no systematic pattern. The panels of this figure can be compared to the aggregate data for sole proprietorships in Panel A of Figure 3.2. In contrast, the incomes per return in the IRS data show little variation over time and vary similarly across AGI bins.

3.3.3 Nonrepresentativeness and measurement error

We now investigate the reasons behind the discrepancies in business incomes between the SCF and IRS and provide evidence for two types of errors in the SCF: nonrepresentativeness of business owners and misreporting of business income by business owners. The evidence of both types of errors again demonstrates that there is no easy correction for the survey data.

To fix ideas, we decompose the difference between a survey aggregate, X^S, and an IRS aggregate, X^I, for some measure into three terms as follows:

$$X^S - X^I = \left(\frac{\sum_i (\omega_i^S - \omega_i^I)}{\sum_i \omega_i^I} \right) X^I + \sum_i w_i^I X_i^I \left(\frac{\omega_i^S}{\omega_i^I} - \frac{\sum_i \omega_i^S}{\sum_i \omega_i^I} \right) + \sum_i \omega_i^S \left(X_i^S - X_i^I \right), \quad (3.1)$$

where sums are taken over household types indexed by i. The average X for type i is denoted by X_i^s, and the population weight for type i is denoted by ω_i^s, with $s \in \{S, I\}$. The first two terms capture differences in weights, $\omega_i^S \neq \omega_i^I$, which we refer to as "sampling errors," and the last term captures differences in averages, $X_i^S \neq X_i^I$, which we refer to as "measurement errors."

With linked survey-IRS data, one can fully decompose the difference on the left-hand side of (3.1) into the sampling and measurement error components. For the SCF, we do not have access to such linked data but can provide evidence that is strongly indicative that both sampling and measurement errors are nontrivial. We start with evidence on the sampling errors. Earlier, we provided evidence based on the total number of business returns that the first term in (3.1) is significantly different from zero. Recall that we found a significant underrepresentation of sole proprietors and corporations and an overrepresentation of partnerships, indicating severe sampling issues.

To shed light on the second term in (3.1), we analyze how the returns are distributed in the cross section. We define the groups of businesses as we did previously in Section 3.3.2, first on the basis of whether they earned profits or losses and second by ranking them according to their owners' AGI. We then compare ratios of population weights, ω_i^S/ω_i^I, across types and across time. For example, if we compare these ratios for pass-through businesses that have profits with those that have losses, we find significant differences in most years, with the highest difference being 35 percentage points. Similarly, if we compare ratios for sole proprietors in different AGI bins, we find significant differences across AGI bins. Figure

3.6 shows this in the case of sole proprietors with AGIs per return below and above the median. For businesses that have owners with below-median AGIs, the number of IRS returns (ω_i^I) has risen from about 5 million in 1988 to over 12 million in 2015, but the SCF estimate (ω_i^S) has remained at roughly 2 million for the entire period. For businesses with above-median AGIs, the number of IRS returns has risen from a little over 8 million to above 12 million, but the SCF estimate has hovered around 5 million. Comparing these data to the full sample in Figure 3.6, we find that the share of sole proprietorship returns below the median AGI is around 25 percent in the SCF and 43 percent in the IRS. These findings suggest a significant underrepresentation of low-income businesses, which leads to an overstatement of business incomes if business income is positively correlated with AGI.

Finally, we provide evidence on the last term in (3.1), which summarizes the measurement error. As mentioned earlier, without linked records, it is impossible to directly validate measurement errors, but we document several aspects of the SCF survey results that suggest they are nontrivial. The first is related to the aforementioned observation that a significant part of the overstatement of income is due to an understatement of losses. This could arise from the framing of the question "What is your net income?" which could be misinterpreted as being a question about positive net income. For instance, consider the distribution of losses by AGI bins for tax year 2015 as shown in Table 3.2. We see that 10 out of 19 bins, which account for 23 percent of the total number of returns and 26 percent of the total losses in the IRS, have an aggregate zero (that is, all respondents in those income brackets reported a zero net income) in the SCF data.

A second reason to be suspicious about misreported incomes in the SCF is that a very small fraction of respondents refer to their tax documents when responding to questions about the specific line items on tax forms. At the end of the survey, SCF interviewers note how frequently respondents accessed particular documents while answering questions and the type of documents they referenced, if any. Using this information, we calculate the frequency with which business owners referenced either tax or other financial documents in tax year 2015.[16] These tabulations are shown in Table 3.3. The first row shows that 75 percent of business owners in the SCF never referenced tax documents, 2 percent rarely

[16] Other financial documents include account statements, investment and business records, loan documents, and pension documents. If any of these documents are referenced, we assume all are.

did, 9 percent sometimes did, and 14 percent frequently did. The second row shows that 64 percent never referenced any other financial documents, 6 percent rarely did, 15 percent sometimes did, and 15 percent frequently did.

To provide further evidence on measurement errors, we show that the SCF fails a simple consistency check by comparing answers to two closely related questions. In the case of sole proprietors, respondents are asked to report incomes listed on lines 12 and 18 of their Form 1040, which correspond to Schedule C and F incomes, respectively. Separately, they are asked about business income from a sole proprietorship and told it is listed on line 31 of Schedule C.[17] By design, the difference in responses to these two questions must be farm income from Schedule F. In Figure 3.7, we see that the differences across the two answers vary between $17,000 and $40,000 per return, considerably more than could be attributable to farm incomes. In a typical year, only 4 percent of business profits listed on Form 1040 are farm income, and farm losses exceed profits in many of the years of our sample.

A related exercise is to check whether there are SCF respondents who report that they do not own or actively manage a sole proprietorship but still report nonzero income from a sole proprietorship or farm. For example, in 2015, of the 16 million who reported a nonzero income (coded as X5704), only 6 million reported that they actively manage a sole proprietorship (coded as X3119, X3219, or X3319), while 10 million reported that they did not. More importantly, the fraction of misreported income is significant. According to SCF data, 65 percent of the business income from Schedule C and F was earned by those reporting that they did not actively manage a sole proprietorship.

We turn next to measures of business valuations and rates of return, which are key for measuring wealth inequality as well as disciplining theories of entrepreneurial activity.

3.4 Business Valuations and Rates of Return

A challenge in estimating valuations and returns for privately held businesses is that they are not frequently traded, and for this reason, most researchers use the SCF to study the

[17]The first answer is coded as X5704 and the second as X3132, X3232, and X3332, combined with the response to legal status of the actively managed business with codes X3119, X3219, and X3319.

distributional aspects of business wealth and returns.[18] SCF business valuations are self-reported evaluations of the current net worth of the business if sold. We can use these estimates along with net incomes to construct SCF income yields that are comparable to available yields from brokered private business sales and publicly traded firms, both small and large. We find that for virtually all subsamples and all years, the SCF yields are significantly higher and more right-skewed than comparable measures from the brokered sales and public firms. We relate this finding to a previous empirical literature that has documented a puzzlingly small private equity premium and show that the earlier estimates are driven by an inconsistent imputation of capital gains on private businesses.

We start by describing the measurement of SCF income yields, which will be compared to yields based on broker data from Pratt's Stats and public firm data from the CRSP-Compustat merged database. The SCF income yield, which is computed for each business, is the ratio of total pretax net income from businesses divided by the self-reported total net worth of businesses. Let $\{\omega_{i,t}\}$ be the SCF population weights for survey year t. We compute an equally weighted and value-weighted mean yield for t, denoted as R_t^{ew} and R_t^{vw}, respectively:

$$R_t^{ew} = \sum_i \omega_{i,t} \left(\frac{NI_{i,t}}{V_{i,t}} \right), \quad R_t^{vw} = \sum_i \left(\frac{\omega_{i,t} V_{i,t}}{\sum_i \omega_{i,t} V_{i,t}} \right) \left(\frac{NI_{i,t}}{V_{i,t}} \right), \tag{3.2}$$

where NI is total pretax net income and V is the self-reported total business value. In Figure 3.8, we plot time series of yields for all businesses by legal form across years. Across SCF survey years 1989–2016, the average equally weighted yield, R_t^{ew}, is 102 percent for all businesses, 104 percent for pass-through businesses, and 57 percent for C corporations. The average value-weighted yield, R_t^{vw}, is 19 percent for all businesses, 20 percent for pass-through businesses, and 17 percent for C corporations. Yields vary significantly across surveys. For example, in the case of C corporations, R_t^{ew} is in the range of 14 to 102 percent, and R_t^{vw} is in the range of 11 to 28 percent.

Next, we compare the SCF income yields to comparable statistics from Pratt's Stats and show that the SCF yields are much higher and more right-skewed. The Pratt's Stats

[18] Some studies use aggregate business valuations from the Federal Reserve's flow of funds, which imputes values for privately held businesses using estimates of private business revenues, publicly traded business revenue-to-value ratios, and an estimate of the liquidity premium on public versus private business.

database has transaction-level data on sales of private and public businesses over the period 1988–2017. The dataset includes financial information about the target business and other attributes of the sale including payment terms, purchase price allocations, and employment agreements. We compute the income yield in Pratt's Stats by dividing the pretax income earned by the business in the year before the sale by the sale price. The advantage of Pratt's Stats is that it records the price at which the business was actually sold, thus, it is conceptually close to the ideal answer to the SCF question on business valuation. The results of this comparison are shown in Table 3.4. In the first two rows and columns, we report equally weighted and value-weighted mean yields for all businesses in the SCF dataset and the Pratt's Stats dataset. The differences are dramatic: the Pratt's Stats equally weighted yield is 27 percent as compared to 102 percent for the SCF, and the Pratt's Stats value-weighted yield is 2 percent as compared to 19 percent for the SCF. The fact that there is a larger discrepancy in the equally weighted yield than in the value-weighted yield suggests that there are also discrepancies in the distribution of yields. In the last three rows of Table 3.4, we report percentiles of the income yield distribution across data sources. Here, we see that the 75th percentile yield in the SCF is substantially higher than the counterpart in Pratt's Stats. This result suggests that the SCF overestimates the right-skewness of the cross-sectional distribution of business returns.

An obvious concern about the broker data is its representativeness. There may be a bias in business returns arising from the comparison of ongoing concerns (in the SCF) and a possibly selected subset of businesses that were sold. For instance, if businesses with higher rates of return also have a higher probability of finding potential buyers, then Pratt's Stats returns will be biased upward. On the other hand, there could be factors that lead to a downward bias in the Pratt's Stats returns. Sales triggered by distress, say because of health-related issues facing the owner, would imply a lower yield. Similarly, sales of technology- or research-intensive businesses would imply lower yields because of the significant expensing done by these firms. We can partially correct for the downward bias by ignoring transactions in which the target company is in technology- and research-intensive sectors (that is, with NAICS codes 51, 5415, or 5417) and those for which the stated reason for the sale was health related. In the third column of Table 3.4, we report the data for this subset of firms and find the results are nearly the same as for all businesses.

Next, we compare SCF income yields to those of publicly traded firms in the CRSP-Compustat database. This comparison has the advantage that we have a sample of businesses that are active, but it has the disadvantage that the typical firm in CRSP is much larger than the typical firm in the SCF. To address this issue, we restrict our attention to larger firms in the SCF (S and C corporations) and compare them to both the full sample of CRSP-Compustat firms and a subset of small firms. Our baseline definition of "small" is a firm that belongs to the bottom quintile of firms ranked by the book value of assets.[19] The income yield for a firm in CRSP-Compustat is computed by dividing business income (before taxes and retained earnings) by the firms' market capitalization. The equally weighted and value-weighted means are computed as in (3.2) where we use the end-of-year market capitalization as a measure of business value. In Table 3.5, we see that the equally weighted income yield is negative for both the full sample (-9 percent) and the subsample of small firms (-27 percent) in the CRSP-Compustat database, whereas the yield is large and positive for both C corporations (57 percent) and S corporations (76 percent) in the SCF. Similarly, SCF value-weighted yields are significantly higher than CRSP yields, although less dramatically different. Considering the distribution, we again find that the SCF yields are more right-skewed than those in CRSP-Compustat. For example, at the 75th percentile, the SCF C-corporate yield is 36 percent, while the CRSP yield for all businesses is 10 percent.

Our results thus far would appear to be inconsistent with Moskowitz and Vissing-Jorgensen (2002), who constructed private business returns using SCF data and concluded that they were surprisingly low when compared to those of publicly traded firms. We use a longer sample than they do, but we know from Kartashova (2014) that this would account for only about a 6 percentage point difference in the SCF estimates. The more important difference for the quantitative results is the concept of return. The earlier results are based on a measure of return equal to the sum of a value-weighted income yield and an imputed capital gain. In theory, one would need a panel of firm valuations to compute a value-weighted capital gain, namely,

$$R^{cg}_{t+1} = \sum_i \left(\frac{\omega_{i,t} V_{i,t}}{\sum_i \omega_{i,t} V_{i,t}} \right) \left(\frac{V_{i,t+1}}{V_{i,t}} \right), \tag{3.3}$$

[19] In Bhandari et al. (2019), we also report results separately for each survey year and for different definitions of "small," for example, based on gross sales or market capitalization.

using survey weights $\{\omega_{i,t}\}$ and valuations $\{V_{i,t}\}$ for each firm i in year t. Given that the SCF survey is triennial with virtually no panel aspect (other than two surveys), there is no way to compute $V_{i,t+1}/V_{i,t}$ firm by firm. Moskowitz and Vissing-Jorgensen (2002) instead compute their capital gains measure using the following annualized index:

$$\tilde{R}^{cg}_{t+3} = \left(\frac{\sum_i \omega_{i,t+3} V_{i,t+3}}{\sum_i \omega_{i,t} V_{i,t}} \right)^{\frac{1}{3}} - 1. \tag{3.4}$$

Their concept of rate of return is given by $R^{vw}_t + \tilde{R}^{cg}_t$, where R^{vw}_t is defined in (3.2). They adjust the SCF net income by subtracting imputed measures of taxes and retained earnings and compare their measure of return to the value weighted mean holding period return on the CRSP index portfolio.[20] This procedure generates private returns that are similar in magnitude to the CRSP returns. Considering the higher risk for private businesses, Moskowitz and Vissing-Jorgensen (2002) conclude that there is a puzzle as to why individuals become entrepreneurs. Their preferred explanation is that there are non-pecuniary benefits of running a business.[21]

Replicating the exercise of Moskowitz and Vissing-Jorgensen (2002) for our full sample with income yields and capital gains compared separately, we find that the capital gain imputation drives the differences between our findings and theirs. The results are summarized in Table 3.6. The first two columns show estimates of SCF and CRSP-Compustat income yields, R^{vw}_t, in all SCF survey years. The last three columns show estimates of $\tilde{R}^{cg}_t$ for SCF and both R^{cg}_t and $\tilde{R}^{cg}_t$ for the CRSP-Compustat sample. The table reveals several noteworthy patterns. First, consistent with our findings for the average income yields, the yearly SCF yields are substantially higher than the CRSP-Compustat counterparts for all survey years. Second, the annualized SCF capital gains vary substantially less than those for firms in the CRSP-Compustat gains R^{cg}_t over the sample, which is not surprising given the conceptual differences in the measures and the long interval between survey years.[22] If

[20] Since the assumptions underlying the imputations of taxes and retained earnings are ad hoc, we measure R^{vw}_t using pretax income in both the SCF and CRSP samples.

[21] See also Hamilton (2000) and Hurst and Pugsley (2011), who reach a similar conclusion using data from the SIPP and the PSED, respectively.

[22] Incidentally, the time variation in the capital gains components explains why Moskowitz and Vissing-Jorgensen (2002) and Kartashova (2014) estimate different average returns for the different sample periods they study.

we were to add R_t^{vw} plus $\tilde{R}_t^{cg}$ for SCF and R_t^{vw} plus R_t^{cg} for CRSP-Compustat firms, we would confound two discrepancies and conclude that the private and public returns are not very different on average: 26 percent for SCF versus 21 percent for CRSP-Compustat. If we were to restrict attention to comparable measures, either R_t^{vw} or $R_t^{vw} + \tilde{R}_t^{cg}$, we would instead conclude that the private business yields and the imputed total returns are relatively high for private businesses when compared to public returns, not low as previously thought.

As we discussed in Section 3.3.3, we find that SCF returns are relatively high because there are significant measurement and sampling errors. In the case of self-reported business valuations, respondents would understate values of intangible assets or nontransferable human capital (for example, reputation of the owner). Given that the SCF incomes are verifiably overstated, an understatement of business value would bias the SCF returns upward even more. Furthermore, a rate of return is the ratio of two terms, both of which have measurement errors. This injects a much larger error in the ratio and can cause large discrepancies in the distribution of measured returns with no obvious correction. A constructive way to deal with the measurement issues in the SCF and estimate aggregate and distributional statistics for business valuations is to rely more heavily on a theory that is disciplined by the flows measured from the IRS and business sales data such as Pratt's Stats. A theory featuring business sales would take a stand on the selection bias and also provide a way to impute the valuations for ongoing concerns.[23]

3.5 Robustness

In this section, we show that the overstatement of business incomes in the SCF is robust to potential misreporting in the IRS and to potential miscategorization by SCF respondents across closely related categories of business income.

3.5.1 Adjusting for misreporting in the IRS

One explanation for the overstated business incomes in the SCF is that individuals might report true incomes in the surveys but underreport their incomes to the tax authorities. In

[23] An attempt in this direction is some ongoing work in Bhandari and McGrattan (2018).

principle, this should not be a concern for our analysis because the SCF specifically asks them to report what they *wrote* on their tax forms. Nevertheless, we analyze data from several sources on the extent of misreporting on tax forms to evaluate this hypothesis and conclude that tax misreporting is far from sufficient to close the gap between the SCF and IRS business incomes.

The Bureau of Economic Analysis (BEA) estimates tax misreporting for noncorporate income (that is, incomes from sole proprietorships and partnerships) to reconcile the national accounts with the data from tax audits. For the years 1988–2015, the BEA estimates that reported noncorporate tax incomes are lower by roughly 50 percent because of misreporting. These BEA estimates are in line with studies such as Johns and Slemrod (2010), who used tax audit data for the year 2001 and document that Schedule C income is underreported by 54 percent. For S- and C-corporate business incomes, measures of tax misreporting are hard to obtain. Johns and Slemrod (2010) document underreporting of 18 percent for Schedule E income, which includes all supplemental income from S corporations, partnerships, rental real estate, royalties, estates, trusts, and farm rentals. Based on reviews of documents stemming from the National Research Program at the IRS, the Government Accountability Office (GAO) estimates net misreporting margins for S-corporate incomes on the order of 15 to 20 percent. We construct a measure of adjusted IRS pass-through income by adding back the BEA estimates of misreporting for noncorporate incomes, along with an adjustment of 18 percent for income from S corporations based on the study of Johns and Slemrod (2010) and the reports of the GAO. In Figure 3.9, we compare the SCF business incomes per return to the adjusted IRS incomes per return and find that they are still significantly higher. Computing the SCF errors as before, we find that the average error with the tax audit adjustment is 178 percent, with a range of errors of 98 percent to 274 percent over the sample.

3.5.2 Adjusting for categorization of business income

Another source of measurement error in the SCF is the respondent's possible confusion about closely related categories of business income. For example, when asked about income from a sole proprietorship appearing on line 31 of Schedule C, business owners might also include income appearing on Schedule E, which includes income from real estate, royalties, partnerships, S corporations, estates, and trusts. From our previous analysis, we know that business incomes from Schedule C are overstated in the SCF. If the overstatement was due to classification errors, we should see an understatement in categories of income corresponding to Schedule E. In Table 3.7, we report the percentage errors for Schedule E income and document that they are overstated for most survey years.

Johnson and Moore (2008) conducted a similar exercise but constructed an even broader category of business income by including capital gains and losses (lines 13 and 14 of Form 1040) to the incomes individuals report on Schedules C, E, and F. Neither the IRS nor SCF data allow us to isolate the capital gains for business owners or for business-related assets. Hence, we did not include these data in our baseline analysis of business income. In Bhandari et al. (2019), we replicate the findings of Johnson and Moore (2008) and extend them to all survey years. We find that, although the capital gains in the SCF are lower when compared to the IRS gains, the Johnson and Moore (2008) measure of broader business income in the SCF is still larger in all years than its counterpart in the IRS. The average error is 47 percent, with a range of 18 percent to 115 percent across survey years.

3.6 Other Surveys

In this section, we review evidence from other surveys, namely, the CPS, PSID, SIPP, KFS, and PSED. These surveys contain information about businesses and have been widely used by researchers. When comparing business incomes and valuations across these surveys and with the SCF, we find that there are significant inconsistencies but similar concerns related to sampling and measurement.

We start with the CPS, PSID, and SIPP. All three surveys contain questions about business incomes and organizational forms (that is, whether they are incorporated or unincorporated). The PSID and SIPP additionally contain self-reported estimates of business valuations.[24] Unlike the SCF, the surveys have less detailed information on the legal form of the businesses. For example, these surveys do not distinguish among types of pass-through businesses, and the questionnaires do not specifically connect responses to line items on tax forms. In order to compare across surveys, we focus on business income per owner and

[24] See Bhandari et al. (2019) for more details.

income yields for unincorporated businesses.

In Figure 3.10, we plot incomes per owner for four surveys (SCF, CPS, PSID, and SIPP) and the IRS in Panel A and the number of owners for all surveys in Panel B.[25] As with the SCF, the CPS, PSID, and SIPP have higher business income per owner than is reported by the IRS, but the magnitudes are statistically different across surveys. The SCF is highest with estimates in the range of \$29,000–\$100,000, the PSID is next with a range of \$15,000–\$55,000, the CPS after that with a range of \$15,000–\$35,000, and the SIPP is lowest with a range of \$13,000–\$18,000. All are higher than the IRS, which has a range of \$5,000–\$15,000.[26] The inconsistencies between surveys are driven primarily by differences in aggregate business incomes. The number of owners across these surveys are not significantly different from each other—on the order of 10 to 13 million and stable across years—but are far lower than the IRS, which reports roughly 35 million owners in 1988 and over 50 million by 2015.[27]

Next, we use the responses on self-reported business valuations to compute income yields, as we did for the SCF in Section 3.4. In Table 3.8, we see that value weighted income yields in the PSID and SIPP are comparable to the SCF even though business income per owner is lower than that in the SCF by a factor of two or three. This implies that average business values are even lower in these other surveys. However, if we compare yields across the distribution, we see large differences, especially in the right tail. These observations point to the lack of representativeness in the PSID and SIPP for the universe of unincorporated businesses as well as their lack of comparability to the SCF.

[25] Our sample in the PSID starts in 1992 and provides annual data until 1996 and biennially after that until 2014. The SIPP reports business incomes every four months for the years 2004–2006 and 2009–2012, and valuations are reported once a year for 2004, 2005, and 2009–2011 depending on when the "topical" modules are available.

[26] Hurst, Li, and Pugsley (2014) combine spending data from the Consumer Expenditure (CE) survey with the PSID and estimate that self-employed individuals underreport income by about 25 percent relative to an imputed measure of true income. The imputation relies on estimating the relationship between expenditures and incomes for wage and salary workers and using it along with food expenditures for the self-employed to infer "true" income of the self-employed. We instead compare survey responses directly to IRS data.

[27] As in the SCF, these surveys only account for partners who are individuals. However, as we mentioned before, using estimates from Cooper et al. (2016), this fact alone does not help to account for the massive understatement in the number of owners.

For KFS, Gurley-Calvez et al. (2016) compare responses about receipts, expenses, and profits with matched tax forms for an eight-year panel of new businesses beginning in 2004. They match responses from Form 1040, Schedule C for sole proprietorships, Form 1065 for partnerships, and Form 1120S or 1120 for corporations. Eighty percent of firms are matched to tax files, and the matched data file includes 3,940 firms. They find that the businesses in the survey overstate receipts and overstate expenses by even more, implying that the businesses understate profits across the distribution. These findings are for the most part in contrast to the SCF and IRS comparison, as the SCF overstates business income, while the KFS firms understate business income. We report estimates from their study in Table 3.9 for ease of comparison.

The PSED provides information about business start-ups using a nationally representative sample. However, from the perspective of our study, the PSED suffers from a critical measurement issue: the response rates for business-related questions is very low in all years of the survey. For example, among the 1,214 entrepreneurs in the 2005 panel, only 115 (that is, 9 percent) responded to the question that asks about calculated profits and losses during a follow-up interview for tax year 2006. Thus, we would caution against any use of statistics for quantitative research on entrepreneurial activity from this survey given the small sample size.

In summary, we find severe measurement issues with other surveys currently being used to study U.S. businesses. Key statistics drawn from these surveys are inconsistent with administrative data from the IRS and are inconsistent with each other.

3.7 Conclusion

This paper has examined the reliability of widely used survey data for studies of U.S. businesses. We compared key statistics for net incomes and receipts to counterparts in administrative data from the IRS and found large sampling and measurement errors. In all surveys examined, we found that incomes are significantly overstated relative to IRS data, even when respondents are asked to provide incomes from specific lines on their tax forms. The errors we document are large on average and vary wildly across years and across surveys. We provide evidence that the overstatements of income may be due to the nonrepresentativeness of business owners with lower incomes and to the fact that the majority of respondents do not reference any tax or financial documents. We also consider the implications for key statistics used in economic research, such as the level and dispersion of wealth and the return on businesses.

We hope and expect that our analysis will lead to improved measurement in future surveys. Studies of wealth inequality, entrepreneurial choice, and business taxation are using current surveys as predictive tests for economic theory. Our findings suggest that the current data should be treated with great caution, but we hope improvements in sampling will lead to improvements in quantitative predictions in the future. Attempts should be made to link responses to administrative data where possible. Questions should be limited to queries that are verifiable. In the case of businesses, care should be taken to ensure representative samples of all types of legal organizations.

Table 3.1: Decomposition of SCF-IRS pass-through business income gap

		Percentage of Gap	
Tax Year	SCF−IRS $ Bill.	Overstatement of Profit	Understatement of Loss
1988	159	50	50
1991	307	64	36
1994	624	83	17
1997	386	63	37
2000	635	68	32
2003	785	71	29
2006	1,096	77	23
2009	750	41	59
2012	218	−56	156
Mean	551	51	49

Note: This table shows the difference (gap) between aggregated business income of all pass-through businesses in the SCF and the IRS. The gap is then decomposed into the fraction attributable to an overstatement of profits or that attributable to an understatement of losses.

Table 3.2: Sole proprietorships with net losses in the IRS and SCF by AGI bins, 2015

	IRS		SCF	
AGI	Returns	Losses	Returns	Losses
Bins	’000	$ Bil.	’000	$ Bil.
No adjusted gross income	426.0	12.2	91.4	0.2
$1 under $5,000	138.3	0.9	39.7	0.2
$5,000 under $10,000	185.7	1.5	33.3	0.0
$10,000 under $15,000	270.8	2.4	10.6	0.0
$15,000 under $20,000	344.3	3.5	47.9	0.0
$20,000 under $25,000	351.4	3.1	60.0	0.2
$25,000 under $30,000	316.8	3.0	77.5	0.2
$30,000 under $40,000	533.0	3.9	102.2	0.6
$40,000 under $50,000	469.3	3.4	62.8	0.0
$50,000 under $75,000	833.7	5.8	159.3	0.1
$75,000 under $100,000	626.4	4.3	199.5	0.8
$100,000 under $200,000	1047.9	7.7	216.2	0.8
$200,000 under $500,000	312.4	3.7	71.6	0.4
$500,000 under $1,000,000	50.4	1.3	0.0	0.0
$1,000,000 under $1,500,000	11.6	0.6	0.6	0.0
$1,500,000 under $2,000,000	5.3	0.4	0.0	0.0
$2,000,000 under $5,000,000	8.4	1.0	0.1	0.0
$5,000,000 under $10,000,000	2.3	0.5	0.7	0.0
$10,000,000 or more	1.8	1.3	36.6	0.0

Note: This table shows the number of business returns that report a net loss and the corresponding amount of these net losses across various AGI bins for tax year 2015.

Table 3.3: Percentage of respondents checking documents in SCF 2016

	Never	Rarely	Sometimes	Frequently
Income tax document	75	2	9	14
Other financial documents	64	6	15	15

Note: This table shows the fraction of business owners that refer to their income tax documents or other relevant financial documents in varying frequency. A respondent who referred to account statements, investment/business records, or loan documents is considered to have checked other financial documents.

Table 3.4: Net income yields in the SCF and Pratt's Stats

	SCF	Pratt's Stats	
	All	All	Non-tech &
Moments	businesses	businesses	nondistressed
Equally weighted mean	102.5	27.4	29.3
Value weighted mean	19.1	1.9	3.5
p25	0.9	3.8	5.0
p50	17.6	21.7	23.1
p75	63.0	46.8	48.3

Note: This table shows moments of the net income yield distribution from the SCF and Pratt's Stats. For Pratt's Stats, we also consider income yields for a subset of businesses that excludes those in technology- and research-intensive sectors (NAICS codes 51, 5415, or 5417) and those for which the stated reason for the sale was health related.

Table 3.5: Net income yields in the SCF and CRSP-Compustat

	SCF		CRSP-Compustat	
	C Corps	S Corps	All businesses	Small businesses
Equally weighted mean	56.8	76.4	−9.2	−26.6
Value weighted mean	16.9	15.2	7.3	−8.5
p25	1.3	2.2	−5.5	−29.0
p50	10.6	14.2	5.4	−7.7
p75	36.2	50.5	10.4	4.0

Note: This table shows moments of the net income yield distribution from the SCF and the CRSP-Compustat database. For the CRSP-Compustat sample, small businesses refer to publicly traded firms in the CRSP database that belong to the bottom 20 percent when ranked by total assets.

Table 3.6: Net income yields and capital gains

Tax Year	Net Income Yields		Capital Gains		
	SCF	CRSP	SCF	CRSP-Compustat	
				$(t-1) \to t$	$(t-3) \to t$
1988	16.6	12.4	—	—	—
1991	20.7	6.2	0.2	26.9	13.2
1994	31.5	9.8	5.3	-3.2	8.5
1997	20.6	6.2	11.4	30.2	29.7
2000	22.6	4.6	11.7	3.7	13.8
2003	17.7	6.2	6.6	28.6	-4.8
2006	18.1	8.0	15.9	10.3	8.9
2009	14.8	5.7	−7.9	21.6	-8.6
2012	14.1	8.0	2.9	12.0	9.6
2015	14.6	5.4	12.8	-3.0	10.7
Mean	19.1	7.3	6.6	14.6	9.0

Note: This table shows estimates of income yields and capital gains for businesses in the SCF and CRSP-Compustat firms. For the SCF, capital gains are computed using Equation 3.4 found in the main text, as in Moskowitz and Vissing-Jorgensen (2002). For the CRSP-Compustat firms, we report two measures of capital gains. The column $(t-1) \to t$ measures the realized capital gains using Equation 3.3 for year t where t corresponds to the fiscal year for which income is reported in the SCF. The column $(t-3) \to t$ measures a geometric mean of the capital gains for the index over the past three periods using equation 3.4.

Table 3.7: Schedule E income comparison

Tax Year	IRS $ Bill.	SCF $ Bill.	Error %
1988	57.3	116.1	102.6
1991	69.9	129.6	85.6
1994	133.0	121.8	−8.4
1997	195.3	147.0	−24.7
2000	249.0	180.3	−27.6
2003	292.7	427.1	45.9
2006	463.1	805.6	74.0
2009	380.8	720.7	89.3
2012	613.3	949.3	54.8
2015	713.2	1142.1	60.1

Note: This table shows aggregated Schedule E income from the IRS and respondents' reported Schedule E income in the SCF. Dollar amounts are in billions.

Table 3.8: Income yield distribution of noncorporate businesses in the SCF, SIPP, and PSID

	SCF	SIPP	PSID
Value-weighted mean	22.6	17.7	14.9
p25	0.8	2.2	3.2
p50	19.6	33.2	27.0
p75	70.6	230.1	114.9

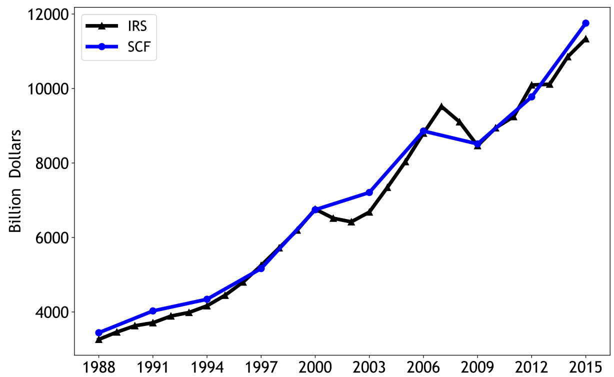
Note: This table shows moments of the income yield distribution for noncorporate businesses for the SCF, SIPP, and PSID. The columns average the income yields for all years that the data are available. The SCF is available triennially between 1989 and 2016, the SIPP for the years 2004–2005 and 2009–2011, and the PSID biennially between 1988 and 2014.

Table 3.9: Comparison of KFS and IRS business tax data, 2004–2011

	Receipts			Expenses			Profit		
	KFS	IRS	Error	KFS	IRS	Error	KFS	IRS	Error
Statistic	'000	'000	%	'000	'000	%	'000	'000	%
Mean	552	417	32	369	188	96	30	169	−82
Median	92	66	29	57	36	57	5	24	−79
p25	21	11	74	1	12	-1,400	-3	1	−700
p75	350	281	25	236	152	55	31	142	−78
p99	11,500	7,434	55	7,450	2,680	178	810	2,478	−67

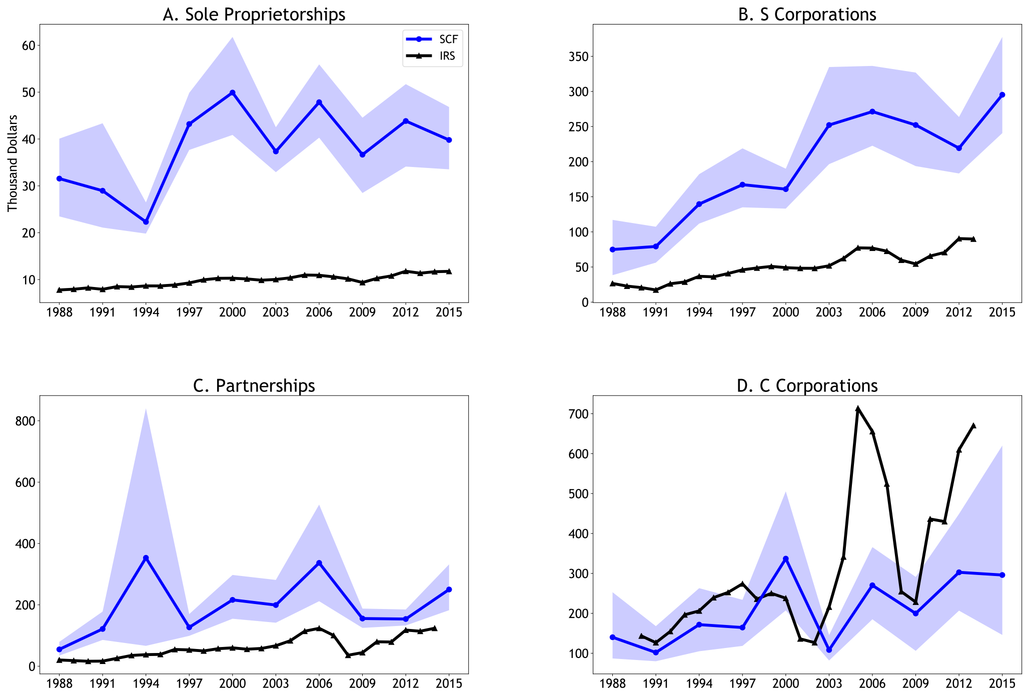
Note: The source of statistics is Gurley-Calvez et al. (2016).

Figure 3.1: Adjusted gross incomes: SCF vs. IRS



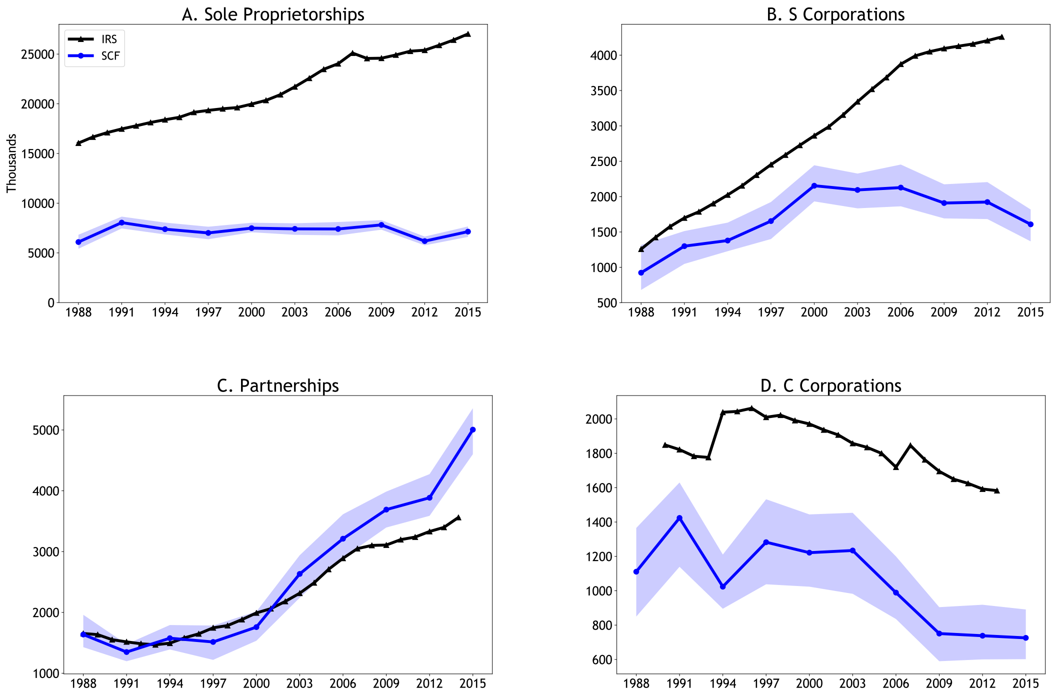
Note: For the IRS, adjusted gross income is obtained from Form 1040. For the SCF, if AGI is not available, we construct it by adding the appropriate income categories.

Figure 3.2: Business income per return by legal entity: SCF vs. IRS



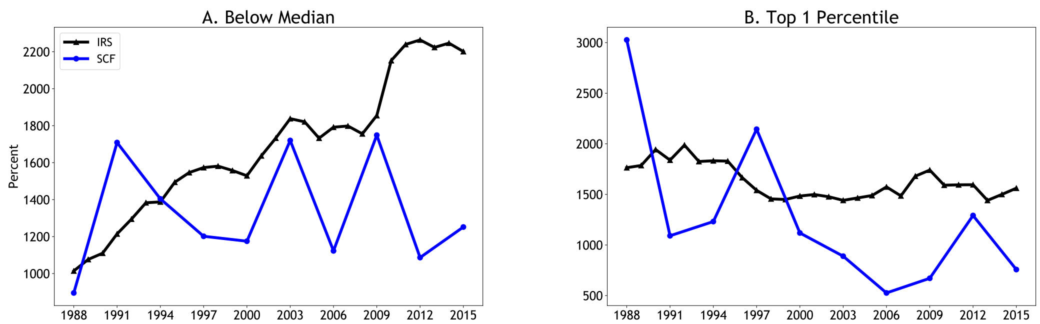
Note: This figure plots business income per business tax return in the IRS and the SCF as reported on Form 1040 Schedule C for sole proprietorships, Form 1120S for S corporations, Form 1065 for partnerships, and Form 1120 for C corporations. IRS data for partnerships, S corporations, and C corporations are available only until 2013. IRS data for C corporations exclude data for those filing 1120A, 1120F, 1120L, 1120PC, 1120REIT, 1120RIC. Prior to 1990, only consolidated information is available and thus is not comparable to the series plotted here. The shaded region for the SCF shows the 90 percent confidence interval.

Figure 3.3: Number of returns by legal entity: SCF vs. IRS



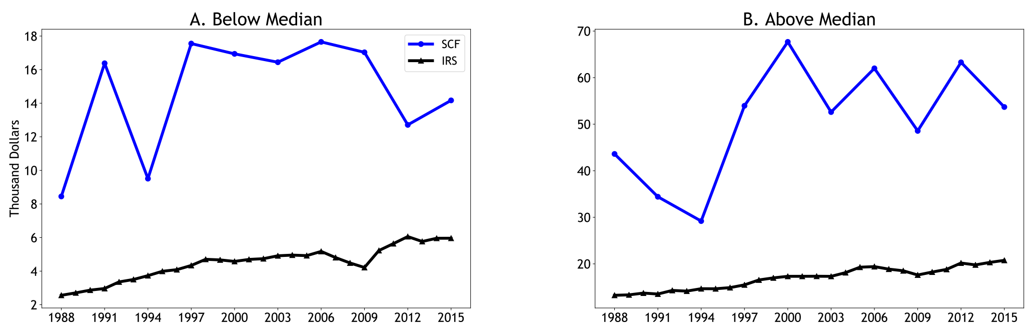
Note: This figure plots the number of business returns of sole proprietorships, S corporations, partnerships, and C corporations over time in the IRS and the SCF. IRS data for partnerships, S corporations, and C corporations are available only until 2013, and C-corporation data are unavailable prior to 1990 when only consolidated information is available and thus is not comparable to the series plotted here. The shaded region for the SCF shows the 90 percent confidence interval.

Figure 3.4: Proprietor income shares: SCF vs. IRS



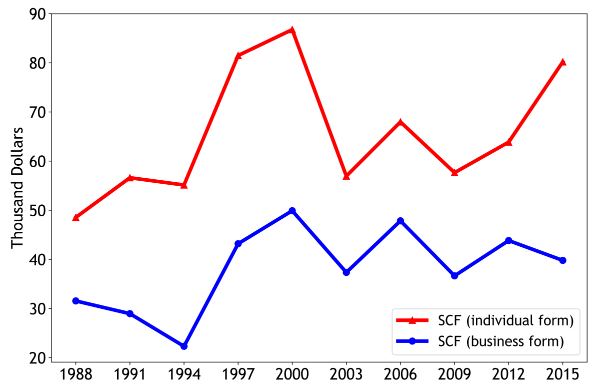
Note: This figure plots the fraction of business income from sole proprietorships attributable to returns with AGI below the median and above the 99th percentile.

Figure 3.5: Income per return, proprietors with below- and above-median AGI: SCF vs. IRS



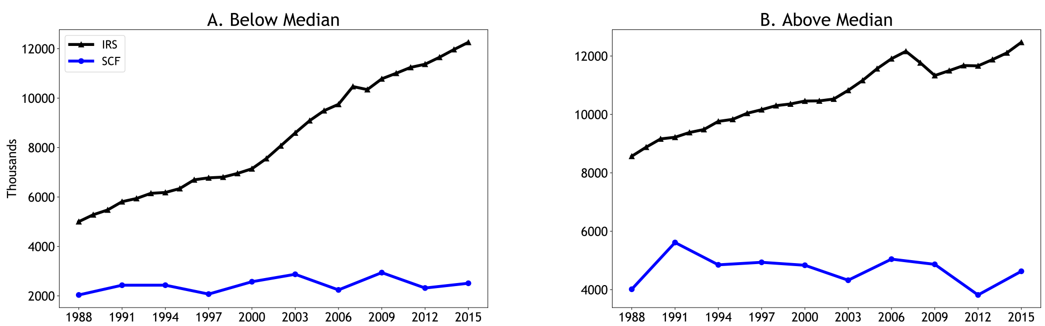
Note: This figure plots sole proprietorship business income per return for those with below- and above-median AGI.

Figure 3.7: Comparing proprietors' individual and business incomes, SCF



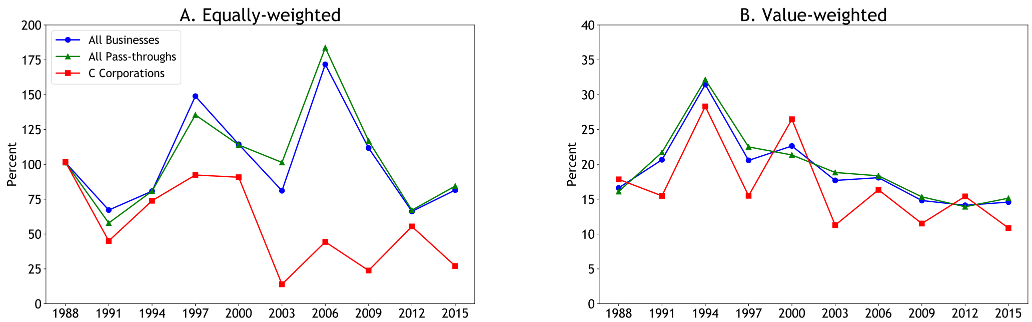
Note: This figure plots business income per return in the SCF for questions that ask respondents to report individual incomes listed on Form 1040, lines 12 plus 18, and business income on Schedule C of 1040, line 31.

Figure 3.6: Number of returns, proprietors with below- and above-median AGI: SCF vs. IRS



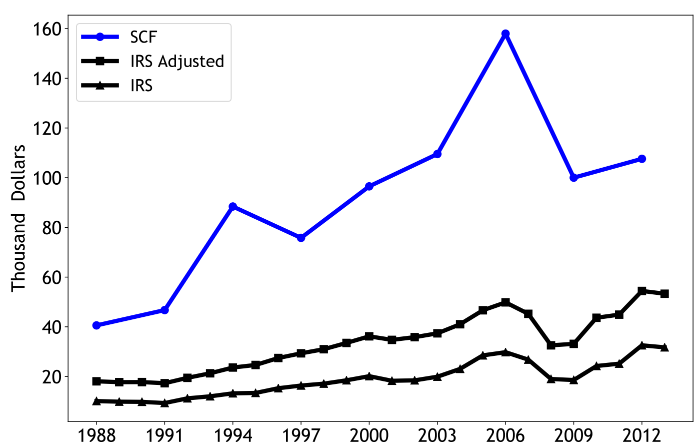
Note: This figure plots the number of sole proprietorship returns (Form 1040 Schedule C) filed by business owners with below- and above median AGI.

Figure 3.8: Equally and value-weighted average net income yields, SCF



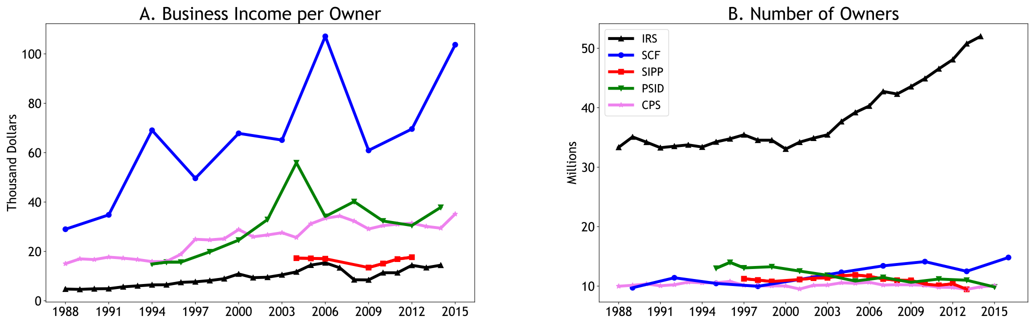
Note: This figure plots equally weighted and value-weighted average net income yields. The SCF sample includes businesses with positive net worth and excludes the bottom 1st percentile of these businesses. The business income of each business that the family members own in the SCF is obtained from SCF variables that correspond to information on business tax forms.

Figure 3.9: Pass-through business income per return with tax misreporting adjustments, SCF vs. IRS



Note: In this figure, we use BEA estimates for misreporting of pass-through business incomes and reports from the Government Accountability Office (GAO) on misreporting of S-corporation business incomes to adjust IRS pass-through business income per return. We add these yearly adjustments to the sum of pass-through income in the IRS, calculate total business income per tax return, and compare it with estimates from the SCF.

Figure 3.10: Unincorporated business income per owner and number of owners



Note: This figure plots the total business income per owner of unincorporated businesses (Panel A) and total number of unincorporated business owners (Panel B) in the SCF, CPS, PSID, SIPP, and the IRS. Before 2004, the SIPP does not provide information about an individual's own share of business income from an unincorporated business. Instead, it contains information about the total income of the business, which is not enough information to calculate the total business income of unincorporated businesses.

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Appendix A

Appendix to Chapter 1

A.1 Model

In this section, I lay out and discuss the expectation over the transition of employment statuses of unemployed - unemployed and employed - employed households respectively. These supplement the discussion in Section 1.2.2 of the main text.

Unemployed - unemployed household

$$
\begin{aligned}
\mathbb{E}_{\mathbf{l}',\mathbf{h}',\mu'}\left[V^{l'}\left(a',\mathbf{h}';\mu'\right)\right] = \mathbb{E}_{\mathbf{h}',\mu'}\Bigg[& s_m s_f p'_m p'_f V^{EE}\left(a',\mathbf{h}';\mu'\right) \\
& + s_m s_f p'_m\left(1-p'_f\right)\sum_{k\in\{b,n\}}\lambda'_k V^{EU_k}\left(a',\mathbf{h}';\mu'\right) \\
& + s_m s_f\left(1-p'_m\right)p'_f\sum_k \lambda'_k V^{U_kE}\left(a',\mathbf{h}';\mu'\right) \\
& + s_m s_f\left(1-p'_m\right)\left(1-p'_f\right)\sum_{k,d\in\{b,n\}}\lambda'_k\lambda'_d V^{U_kU_d}\left(a',\mathbf{h}';\mu'\right) \\
& + s_m\left(1-s_f\right)p'_m\sum_k \lambda'_k V^{EU_k}\left(a',\mathbf{h}';\mu'\right) \\
& + s_m\left(1-s_f\right)\left(1-p'_m\right)\sum_{k,d\in\{b,n\}}\lambda'_k\lambda'_d V^{U_kU_d}\left(a',\mathbf{h}';\mu'\right) \\
& + \left(1-s_m\right)s_f p'_f\sum_k \lambda'_k V^{U_kE}\left(a',\mathbf{h}';\mu'\right) \\
& + \left(1-s_m\right)s_f\left(1-p'_f\right)\sum_{k,d\in\{b,n\}}\lambda'_k\lambda'_d V^{U_kU_d}\left(a',\mathbf{h}';\mu'\right) \\
& + \left(1-s_m\right)\left(1-s_f\right)\sum_{k,d\in\{b,n\}}\lambda'_k\lambda'_d V^{U_kU_d}\left(a',\mathbf{h}';\mu'\right)\Bigg|\,\mathbf{h},\mu\Bigg]
\end{aligned}
$$

where I drop the conditions of the expectation in the left hand side to save space. The first two lines in the right hand side show the case when both male and female search for a job in the current period, and he finds a job. In this case, if she finds a job, the household will be an employed - employed household, otherwise the household will be an employed - unemployed household but she may retain or lose eligibility for employment-tested transfers. The third and fourth lines is the case when both of them search for a job and he does not find it. Then, if she finds a job, the household will be an unemployed - employed household where he may or may not be eligible for employment-tested transfers. If she cannot find a job, then both members of the household will continue to be unemployed, and they will both face eligibility risk for the employment-tested transfers. The fifth to eighth lines are cases when one of them searches for a job and the other does not. In these cases, if the searcher finds a job, then the household will have one employed member and the other faces eligibility risk, otherwise both members will continue to be unemployed and both face eligibility risk. Finally, the last line shows the case when both members do not search for a job, continue to be unemployed, and face eligibility risk.

Similarly, for the household in which any unemployed member is ineligible unemployed, the above expectation is the same except that this member stays ineligible for employment-tested transfers if he/she does not find a job.

Employed - employed household

$$\begin{aligned}
\mathbb{E}_{\mathbf{l}',\mathbf{h}',\mu'}\left[V^{l'}\left(a',\, h';\, \mu'\right)\right] = \mathbb{E}_{\mathbf{h}',\mu'}\Bigg[&\left(1-\delta_m'\right)\left(1-\delta_f'\right)V^{EE}\left(a',\mathbf{h}';\mu'\right)\\
&+\left(1-\delta_m'\right)\delta_f'\sum_{k\in\{b,n\}}\lambda_k' V^{EU_k}\left(a',\mathbf{h}';\mu'\right)\Big)\\
&+\delta_m'\left(1-\delta_f'\right)\sum_{k}\lambda_k' V^{U_kE}\left(a',\mathbf{h}';\mu'\right)\\
&+\delta_m'\delta_f'\sum_{k,d\in\{b,n\}}\lambda_k'\lambda_d' V^{U_kU_d}\left(a',\mathbf{h}';\mu'\right)\Bigg|\mathbf{h},\mu\Bigg]
\end{aligned}$$

where I drop the conditions of the expectation in the left hand side to save space. The first two lines in the right hand side show cases when male keeps his job, female may or may not lose her job, and face eligibility risk if she loses it. The last two lines give cases in which he loses his job and face eligibility risk, and again female may or may not lose her job, and face eligibility risk if she loses it.

A.2 Data

In this section, I first discuss sample selection and construction of some of the important variables for the PSID data that is used in Section 1.3.1 of the main text. Second, I show that the main empirical conclusions of Section 1.3.1 remain almost unaltered if under alternative data samples. Third, I document the relative change in annual working hours of the head and the spouse upon head's job displacement in recessions and in expansions. These supplement the discussions in Section 1.3.1. Finally, I explain the details of calculating asset-to-income distribution from the PSID and the SCF data, both of which are used in Section 1.3.3 of the main text.

PSID data

In Section 1.3.1, I use data from PSID in order to analyze the impact of head's job displacement over the business cycle on his own labor earnings, spousal labor earnings, and family labor earnings as well as working hours of the head and the spouse. The PSID is a nationally representative survey that was conducted in the United States annually from 1968 to 1997 and biannualy from 1997 to 2015. I use all of these waves of the data. The PSID provides information on labor market outcomes such as annual labor earnings and working hours, as well as characteristics of the family such as age, education, and number of children of the couples. Labor earnings of the head or spouse include wages and salaries, bonuses, overtime, tips, commissions, professional practice or trade, market gardening, miscellaneous labor income, and extra job income.[1]

While I take many of the variables that I use in the main analysis directly from the PSID, there are several variables I must create using the other available information in the data. First, to address inconsistencies for the variable defining the age of the individuals, I create a new age variable separately for the head and the spouse by an increase based on the age reported in the first observation of the family. Next, I use completed years of education to create potential years of labor market experience for both head and spouse in any of their available observation as $Age - Education - 6$ if the individual's years of completed education is larger than or equal to 12, and as $Age - 18$ if otherwise. This way, individuals with fewer years of completed education are not assigned large values for their labor market experience. I also create the total number of children and young children (defined as the number of children with age less than 6) of the family in any of their available observation using the relation of each individual in the family unit to the head of the family.

I create variables for involuntary job displacement using a question that asks the reason for loss of the previous job to the individuals who are either without a job or have been

[1] PSID defines the head of a family unit as the individual with the most financial responsibility who is at least 18 years old. In the case that this person is a female and she has a spouse or partner or a boyfriend with whom she has been living for at least one year, then he is assigned to be the head of the family unit.

employed in their current job for less than a year. Following the literature, I define an involuntary job loss as a separation due to firm closure, layoff or firing. As Stevens (1997) and Stephens (2002) point out, the timing of the displacement is not precisely identified in all years of the survey. This is because while the earnings and hours questions are designed to obtain information for the previous year, the question that I use to determine job displacement is not year specific. To better understand this, consider a head of the family who reports to be displaced according to the definition above in 1992 survey of the PSID. This implies that the head may be displaced in any time between January of 1991 and the survey date in 1992. Thus, the econometrician may assign such displacement either in 1991 (previous calendar year) or in 1992 (survey year). In my analysis, following Stephens (2002), I assume that displacements occur in the previous calendar year to align the displacement year with the earnings and hours information.

Given that I also use the data from biannual survey years of the PSID (1997-2015), displacements that occur in between these years have information only for every other year. However, I still prefer to keep this time period in my main sample especially to incorporate the Great Recession period to my analysis to better analyze the differential effects of displacements over the business cycle on the labor market outcomes of couples. Furthermore, given that 1968 survey only identifies workers who have been displaced within the past ten years, it is not possible to determine the exact year of such displacement within these ten years. Therefore, I do not incorporate displacements that occur in 1968 into my analysis.

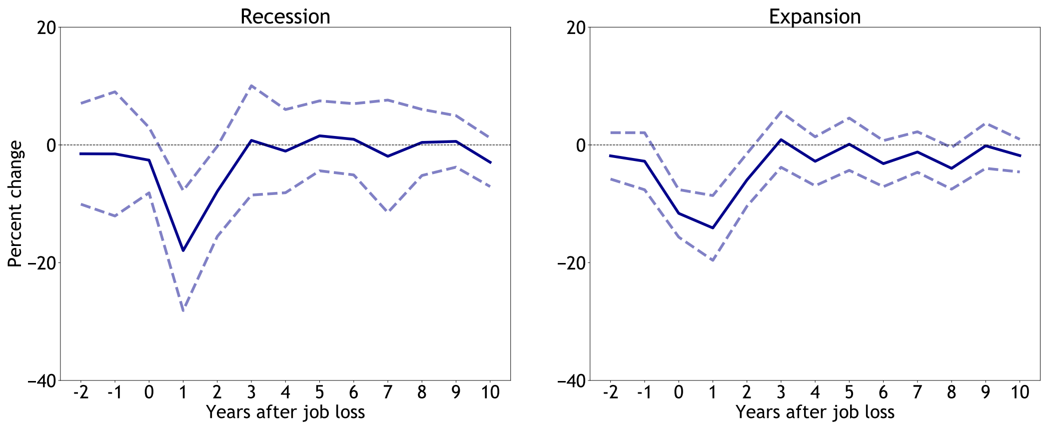
The PSID has four samples: Survey Research Center (SRC), Survey of Economic Opportunities (SEO), Immigrant, and Latino samples. I obtain the main results in Section 1.3.1 using SRC, SEO, and Immigrant samples. However, the main conclusions of the empirical section remain almost unaltered if I use other combinations of these samples. I find similar results to those obtained in the main text, given that spousal earnings and hours response is small on average in recessions, and slightly positive in expansions.

In Section 1.3.1, I restrict the baseline sample to families in which both the husband and the wife are between the ages of 20 and 60 with at least two years of observation. I also drop families whose family labor income is above the 99th percentile of family labor income distribution. I check my empirical results under alternative restrictions in the baseline sample. First, I change the age limits in the baseline sample so that I only use information until age 55 as in Davis and von Wachter (2011). Second, I include family head's who are single into the baseline sample. Third, I keep families whose family labor income is above the 99th percentile of family labor income distribution. Fourth, I drop families with family labor income below the bottom 1 percentile and families with family labor income above the top 1 percentile. Fifth, I drop families when any member of the family is not living in the family unit. Finally, in Section 1.3.1, I estimate Equation (1.9) separately for i) a treatment group where the head is displaced only in recessions and a control group where the head is never displaced, and ii) a treatment group where head is displaced only in expansions and a control group where head is never displaced. This allows me to better isolate the differential effect of head's displacement in recessions and expansions on families since I do not incorporate families whose head is displaced both in recessions and expansions in these separate regressions. Finally, I analyze results when I incorporate such families to each of the two separate regressions. Overall, I find that the main result remains robust across all of these alternative restrictions, given that spousal earnings and hours response is small on average in recessions, and slightly positive in expansions.

Head and spouse hours upon head's job displacement Figure A.1 shows that magnitude of the drop in head's relative hours when the head is displaced in recessions (18 percent) is similar to the one in expansions (14 percent) in the year following displacement. Moreover, it shows that the relative hours recover just after 2 years upon displacement both in recessions and expansions. These suggest that both the cyclical gap in earnings loss upon displacements over the business cycle and the persistence of the earnings loss are largely explained by drop in wages rather than drop in hours. Previously, Ruhm (1991), Stevens (1997), and Huckfeldt (2016) have already documented this quick recovery of relative hours of the displaced workers using PSID. My findings complement their results as I provide additional evidence that hours recover relatively quickly upon displacements both in recessions and expansions, and that it wage losses explain most of the cyclical gap in earnings losses.

Figure A.2 shows the change in relative spousal hours upon head's job displacement in recessions and in expansions. I find that the average change in spousal hours upon head's displacements in recessions is small, while spousal hours upon head's displacements in expansions increases by up to 15 percent and coefficients remain significant after 3 years

Figure A.1: Relative working hours of family head upon job displacement



Note: This figure plots the changes in relative working hours of the family head upon his job displacement in recessions (left panel) and expansions (right panel). I estimate the changes in relative labor earnings from a distributed lag-recession model using PSID. The solid blue line shows the point estimates and the dashed light blue line shows the 90 percent confidence interval.

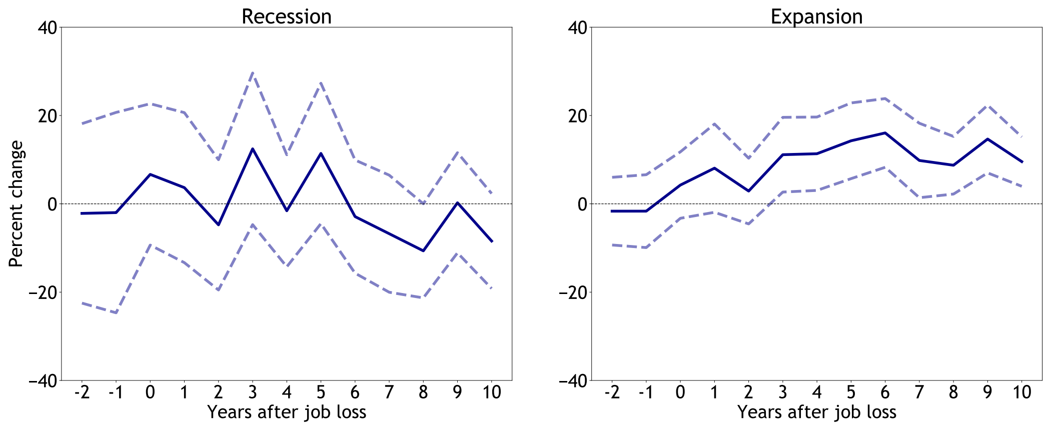
following the displacement. According to my results, the average postdisplacement change is -0.1 percent in recessions and 10.1 percent in expansions.[2]

Asset-to-income distribution Starting from 1999 survey, PSID provides information on asset holdings of households in every two years. However, the amount of credit card debt is only available after 2011. For this reason, I choose to present the asset-to-income distribution for the latest survey of PSID in 2015.

I calculate the net liquid wealth of each households in my main sample for the PSID by adding the amount of checking and saving account, the amount of bonds and other assets, the amount of stocks, and the amount of vehicle equity, and then deducting the amount of credit card debt. Then, fraction of families of non-positive liquid wealth is simply given by ratio of the total number of families with non-positive values of this net liquid wealth measure to the total number of families. Next, I calculate the net liquid wealth to quarterly labor income ratio by dividing this measure of net liquid wealth to total quarterly family

[2]Previously, Stephens (2002) uses PSID to study the impact of head's job displacement on relative working hours of spouses and finds that the average increase in relative spousal hours is 11 percent across all years after head's displacement.

Figure A.2: Relative working hours of spouse upon job displacement



This figure plots the changes in relative working hours of the spouse upon family head's job displacement in recessions (left panel) and expansions (right panel). I estimate the changes in relative spousal hours from a distributed lag-recession model using PSID. The solid blue line shows the point estimates and the dashed light blue line shows the 90 percent confidence interval.

labor income (i.e. sum of head and spouse labor income) for each family with positive total family labor income.[3] Finally, I calculate the weighted distribution of this net liquid wealth to quarterly labor income ratio across these families. The percentiles of the PSID 2015 distribution given in Table 2.2 in the main text are obtained from this calculation.

SCF data

I also calculate the net liquid asset-to-income distribution from the SCF 2007. In order to do so, I first construct a sample of family head's with the following restrictions: i) marital status is married or cohabiting, and ii) ages of the head and spouse are between 20 and 60. This way, the SCF sample will be similar to the PSID sample.

The SCF provides information on the i) amount in up to seven different checking accounts, ii) amount in up to seven different savings/money market accounts, iii) value of all certificates of deposits, iv) total value of all types of mutual funds, v) total value of all savings bonds, vi) total value of all bonds other than saving bonds, vii) total value of publicly traded stocks, viii) total value of all the cash or call money (brokerage) accounts,

[3] I obtain the total quarterly family labor income by dividing the annual amount of total family labor income by 4.

ix) amount in annuity and trust accounts, x) other assets such as money owed to family or gold, silver, and other jewelry, and xi) value in vehicle equity. Summation of these values gives the total liquid wealth of the family. I then subtract the total credit card debt to obtain the net liquid wealth of each family. Then, fraction of families of non-positive liquid wealth is simply given by ratio of the total number of families with non-positive values of this net liquid wealth measure to the total number of families. Next, I calculate the net liquid wealth to quarterly labor income ratio by dividing this measure of net liquid wealth to total quarterly family labor income for each family with positive total family labor income.[4] Finally, I calculate the weighted distribution of this net liquid wealth to quarterly labor income ratio across these families. The percentiles of the SCF 2007 distribution given in Table 2.2 in the main text are obtained from this calculation. Moreover, the median ratio of credit limit to quarterly labor income in Table 1.3 is also obtained from this dataset, using the information on the total credit limit and total quarterly family labor income of each family.

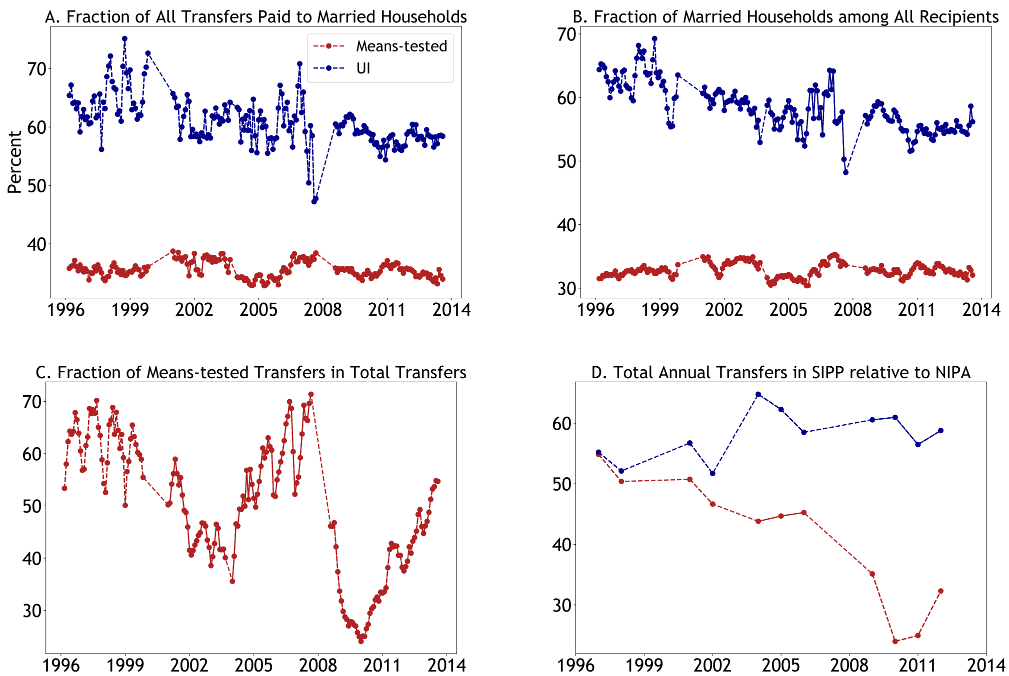
SIPP data

In this section, I document the amount and incidence of transfer receipts by married households. To do so, I use monthly data from the SIPP 1996 to 2008 Panels (covering December 1995 to August 2013) that provide information on monthly amounts of means-tested transfers and unemployment insurance transfers received by the family. Figure A.3 shows the results.

In Panel A, I show the total means-tested and employment-tested (UI) transfers paid to married households as a fraction of aggregate means-tested and employment-tested transfers separately. On average, around 35 percent of all means-tested transfers and 60 percent of total UI transfers are paid to married households. According to Panel B, married households constitute around 33 percent of all means-tested transfer recipients and 58 percent of all UI recipients. Finally, Panel C shows that around 60 percent of all transfers received by the married households are means-tested transfers. However, this value drops to as low as 30 percent after 2008. This is because, starting from this year, the

[4] I obtain the total quarterly family labor income by dividing the annual amount of total wages and salaries income of family (IRS Form 1040 Line 7) by 4.

Figure A.3: Transfer receipts by married households



Note: Panel A plots the total means-tested and employment-tested (UI) transfers paid to married households as a fraction of aggregate means-tested and employment-tested transfers separately. Panel B shows the total number of married household heads receiving means-tested and employment-tested transfers as a fraction of all recepients of these transfers separately. Panel C shows the ratio of total means-tested transfers to total transfers (sum of means-tested and UI) received by married households. Finally, Panel D plots the total annual transfer amounts in SIPP data as a fraction of aggregate transfer amounts in NIPA tables, separately for means-tested and employment-tested transfers. Values in Panel A-C are obtained from SIPP 1996-2008 panels. NIPA amounts in Panel D are obtained from Table 3.12, where I classify EITC, SNAP, and TANF payments as means-tested transfers, and UI as employment-tested transfer. Dashed lines indicate time periods when the data is not available.

survey data drastically underestimates total annual means-tested transfers when compared to total government means-tested government transfers in NIPA tables, as shown in Panel D.

Overall, Figure A.3 documents that means-tested transfers consitute a large fraction of total transfer receipts of married households.

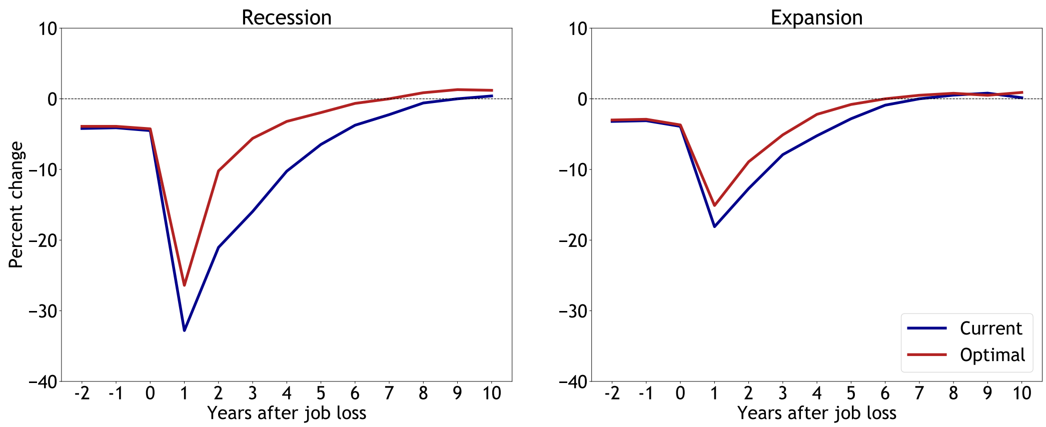
A.3 Effects of Optimal Policy on Family upon Displacement

In Section 1.5.2, I discuss the change in family outcomes upon head's job displacement in recessions and expansions in the model under the countercyclical baseline (current) policy and the optimal policy. In the main text, I show comparisons for spouse earnings, transfer receipts, and family consumption. The goal of this section is now to understand the effects of the optimal policy on the other components of the household budget: total family earnings and assets. This allows us to decompose the changes in family consumption.

Figure A.4 compares the change in family earnings upon head's job displacement in recessions and in expansions in the model under the countercyclical baseline (current) policy and the optimal policy. There are three results that I want to highlight. First, the magnitudes of initial drops of family earnings upon head's job displacement both in recessions and in expansions are lower under the optimal policy than their counterparts under the current policy. This is because of higher labor force participation rates of spouses and their higher labor earnings due to the increase in their human capital. Second, the gap between the magnitudes of initial drops under the current and optimal policies are larger in recessions $(0.33 - 0.26 = 0.07)$ than in expansions $(0.18 - 0.15 = 0.03)$. This is because, under the optimal policy, the change in spousal earnings in response to head's displacement in recessions is larger than its counterpart in expansions, as shown in Figure 1.8 in the main text. As a result, the contribution of spouses to their family income under the optimal policy is larger in recessions. Finally, while the recovery of family earnings under the optimal policy is faster than the recovery under the current policy in recessions, the recovery under the optimal policy is similar to the recovery under the current policy in expansions. This is due to the persistent increase in spousal earnings upon head's displacement in recessions under the optimal policy, as shown in Figure 1.8 in the main text.

Figure A.5 compares the change in family assets upon head's job displacement in recessions

Figure A.4: Relative labor earnings of the family upon job displacement: Current policy vs optimal policy



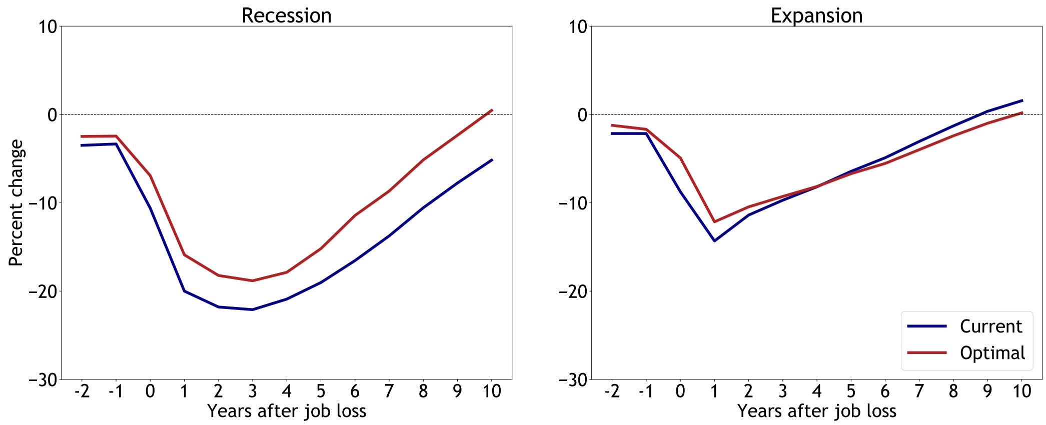
Note: This figure plots the changes in relative labor earnings of the family upon head's job displacement in recessions (left panel) and expansions (right panel) in the model under the countercyclical baseline policy and the optimal policy. I estimate the changes in relative family earnings from a distributed lag-recession model using model simulated data, which is aggregated up to yearly period.

and in expansions in the model under the current policy and the optimal policy. I find that families dissave less upon head's displacement both in recessions and expansions under the optimal policy since larger fraction of spouses are already working at the time of head's displacement under the optimal policy, and this allows families to self-insure more through spousal earnings and less through savings. Similarly, this effect is more pronounced in recessions due to larger spousal labor earnings response. As a result, family assets recover earlier in recessions under the optimal policy. However, the recovery of assets in expansions is a bit slower under the optimal policy due to slightly smaller increase in spousal earnings upon head's displacement in expansions under the optimal policy than under the current policy, as shown in Figure 1.8 in the main text.

A.4 Model with Endogenous Wages

In this section, I present an extension of the baseline model with endogenous wages. This is a directed search model in which wage choices of unemployed individuals are endogeneous. In this model, submarkets in the labor market are indexed by the wage offer w of the firms

Figure A.5: Relative assets of the family upon job displacement: Current policy vs optimal policy



Note: This figure plots the changes in relative asset holdings of the family upon head's job displacement in recessions (left panel) and expansions (right panel) in the model under the countercyclical baseline policy and the optimal policy. I estimate the changes in relative family earnings from a distributed lag-recession model using model simulated data, which is aggregated up to yearly period.

and human capital level h of the job. This means that unemployed individuals now direct their search effort toward a specific wage offered by a job that is compatible with their own skill level. In this case, wage levels of the employed members of the household become extra state variables.

Below, I first lay out household problem, and then show firm problem. Next, I prove the existence of BRE of this model.

Household problem I write down the problems of several types of households, and the rest follows from similar explanations as in the baseline model.

Employed - unemployed household First, consider a household in which the male is employed and the female is eligible unemployed. The recursive problem of this household is given as follows:

$$
\begin{aligned}
V^{EU_b}\left(a, w_m, \mathbf{h}; \mu\right) &= \max_{a' \geq a_L,\, s_f \in \{0,1\}} \quad u\left(c\right) + \eta_f\left(1 - s_f\right) \\
&+ \max_{\tilde{w}_f} \left\{ \beta\left(1 - \zeta_R\right) \mathbb{E}_{\mathbf{l}', \mathbf{h}', \mu'} \left[V^{l'}\left(a', w_m, \mathbf{h}'; \mu'\right) \middle| s_f, \tilde{w}_f, \mathbf{l}, \mathbf{h}; \mu \right] \right\}
\end{aligned}
$$

subject to

$$
\begin{aligned}
& c + a' \leq \left(1 + r\right) a + y + \phi\left(z;\, a,\, y\right) + b\left(z;\, U_b,\, s_f\right)\left(1 - \tau\right) \\
& y = w_m\left(1 - \tau\right) \\
& \Gamma' = \Lambda\left(\mu,\, z'\right) \quad \text{and} \quad z' \sim \Phi\left(z' \,|\, z\right).
\end{aligned}
$$

where we now have to keep track of wage level of the employed member of the household. Notice also that wage of the employed is not a direct function of the human capital level. Instead, unemployed members of the household may direct their search effort toward any wage submarket $\tilde{w}_f$, but the job finding rate for that wage submarket varies across human capital level of the unemployed. In that sense, we can think of different human capital submarkets that are present inside each wage submarket. Moreover, the expectation is also indexed by wage choice of the unemployed member of the household, given that her job finding rate will be affected by her wage choice. The rest of the explanation of this problem is similar to its counterpart in the baseline model.

It is also insightful to show the expectation over the transition of employment statuses of this household, which I lay out below:

$$
\begin{aligned}
\mathbb{E}_{\mathbf{l}', \mathbf{h}', \mu'} \left[V^{l'}\left(a', w_m, \mathbf{h}'; \mu'\right) \middle| \cdot \right] = \mathbb{E}_{\mathbf{h}', \mu'} \Bigg[& s_f\left(1 - \delta_m'\right) \Bigg(p_f'\left(\tilde{w}_f, h_f\right) V^{EE}\left(a', w_m, \tilde{w}_f, \mathbf{h}'; \mu'\right) \\
& + \left(1 - p_f'\left(\tilde{w}_f, h_f\right)\right) \sum_{k \in \{b,n\}} \lambda_k' V^{EU_k}\left(a', w_m, \mathbf{h}'; \mu'\right) \Bigg) \\
& + s_f \delta_m' \Bigg(p_f'\left(\tilde{w}_f, h_f\right) \sum_k \lambda_k' V^{U_k E}\left(a', \tilde{w}_f, \mathbf{h}'; \mu'\right) \\
& + \left(1 - p_f'\left(\tilde{w}_f, h_f\right)\right) \sum_{k,d \in \{b,n\}} \lambda_k' \lambda_d' V^{U_k U_d}\left(a', \mathbf{h}'; \mu'\right) \Bigg) \\
& + \left(1 - s_f\right)\left(1 - \delta_m'\right) \sum_k \lambda_k' V^{EU_k}\left(a', w_m, \mathbf{h}'; \mu'\right) \\
& + \left(1 - s_f\right) \delta_m' \sum_{k,d \in \{b,n\}} \lambda_k' \lambda_d' V^{U_k U_d}\left(a', \mathbf{h}'; \mu'\right) \Bigg) \Bigg| \mathbf{h}, \mu \Bigg]
\end{aligned}
$$

where $p'_i(\tilde{w}_i, h_i) \equiv p(\theta(\tilde{w}_i,\, h'_i;\, \mu'))\ \forall i \in \{m,\, f\}$. The explanation of the terms in the right hand side is similar to its counterpart in the baseline model.

Unemployed - unemployed household Second, consider a household in which both male and female are eligible unemployed. The recursive problem of this household is given as follows:

$$\begin{aligned} V^{U_b U_b}(a, \mathbf{h}; \mu) &= \max_{a' \geq a_L,\, s_m, s_f \in \{0,1\}} \quad u(c) + \sum_{i \in \{m,\, f\}} \eta_i (1 - s_i) \\ &+ \max_{\tilde{w}_m, \tilde{w}_f} \left\{ \beta (1 - \zeta_R) \mathbb{E}_{\mathbf{l}', \mathbf{h}', \mu'} \left[V^{l'} \left(a', \mathbf{h}'; \mu' \right) \middle| s_m, s_f, \tilde{w}_m, \tilde{w}_f, \mathbf{l}, \mathbf{h}, \mu \right] \right\} \end{aligned}$$

subject to

$$\begin{aligned} & c + a' \leq (1 + r) a + \phi(z; a, 0) + [b(z; U_b, s_m) + b(z; U_b, s_f)](1 - \tau) \\ & \Gamma' = \Lambda\left(\mu,\, z'\right) \quad \text{and} \quad z' \sim \Phi\left(z' \mid z\right). \end{aligned}$$

Again, I show the expectation over the transition of employment statuses of this household, which is given below:

$$
\begin{aligned}
\mathbb{E}_{\mathbf{l}',\mathbf{h}',\mu'}\left[V^{l'}\left(a',\mathbf{h}';\mu'\right)\middle|\cdot\right] = \mathbb{E}_{\mathbf{h}',\mu'}\Bigg[& s_m s_f p_m'\left(\tilde{w}_m,h_m\right)\Bigg(p_f'\left(\tilde{w}_f,h_f\right)V^{EE}\left(a',\tilde{w}_m,\tilde{w}_f,\mathbf{h}';\mu'\right) \\
& +\left(1-p_f'\left(\tilde{w}_f,h_f\right)\right)\sum_{k\in\{b,n\}}\lambda_k' V^{EU_k}\left(a',\tilde{w}_m,\mathbf{h}';\mu'\right)\Bigg) \\
& +s_m s_f\left(1-p_m'\left(\tilde{w}_m,h_m\right)\right)\Bigg(p_f'\left(\tilde{w}_f,h_f\right)\sum_k \lambda_k' V^{U_k E}\left(a',\tilde{w}_f,\mathbf{h}';\mu'\right) \\
& +\left(1-p_f'\left(\tilde{w}_f,h_f\right)\right)\sum_{k,d\in\{b,n\}}\lambda_k'\lambda_d' V^{U_k U_d}\left(a',\mathbf{h}';\mu'\right) \\
& +s_m\left(1-s_f\right)\Bigg(p_m'\left(\tilde{w}_m,h_m\right)\sum_k \lambda_k' V^{EU_k}\left(a',\tilde{w}_m,\mathbf{h}';\mu'\right) \\
& +\left(1-p_m'\left(\tilde{w}_m,h_m\right)\right)\sum_{k,d\in\{b,n\}}\lambda_k'\lambda_d' V^{U_k U_d}\left(a',\mathbf{h}';\mu'\right)\Bigg) \\
& +\left(1-s_m\right)s_f\Bigg(p_f'\left(\tilde{w}_f,h_f\right)\sum_k \lambda_k' V^{U_k E}\left(a',\tilde{w}_f,\mathbf{h}';\mu'\right) \\
& +\left(1-p_m'\left(\tilde{w}_m,h_m\right)\right)\sum_{k,d\in\{b,n\}}\lambda_k'\lambda_d' V^{U_k U_d}\left(a',\mathbf{h}';\mu'\right)\Bigg) \\
& \quad +\left(1-s_m\right)\left(1-s_f\right)\sum_{k,d\in\{b,n\}}\lambda_k'\lambda_d' V^{U_k U_d}\left(a',\mathbf{h}';\mu'\right)\Bigg)\Bigg|\,\mathbf{h},\mu\Bigg].
\end{aligned}
$$

The explanation of the terms in the right hand side is similar to its counterpart in the baseline model.

Employed - employed household Next, consider a household in which both male and female are employed. The recursive problem of this household is given as follows:

$$
\begin{aligned}
V^{EE}\left(a,w_m,w_f,\mathbf{h};\mu\right) &= \max_{a'\geq a_L} u\left(c\right)+\beta\left(1-\zeta_R\right)\mathbb{E}_{\mathbf{l}',\mathbf{h}',\mu'}\left[V^{l'}\left(a',w_m,w_f,\mathbf{h}';\mu'\right)\middle|\mathbf{l},\mathbf{h},\mu\right] \\
\text{subject to} & \\
& c+a'\leq\left(1+r\right)a+y+\phi\left(z;\,a,\,y\right) \\
& y=\left[w_m+w_f\right]\left(1-\tau\right) \\
& \Gamma'=\Lambda\left(\mu,\,z'\right)\quad\text{and}\quad z'\sim\Phi\left(z'\,|\,z\right).
\end{aligned}
$$

Similarly, I lay out the expectation over the transition of employment statuses of this household, which is given below:

$$\begin{aligned}\mathbb{E}_{\mathbf{l}',\mathbf{h}',\mu'}\left[V^{l'}\left(a',w_m,w_f,\mathbf{h}';\mu'\right)\Big|\cdot\right] = \mathbb{E}_{h',\mu'}\Bigg[&\left(1-\delta_m'\right)\Bigg(\left(1-\delta_f'\right)V^{EE}\left(a',w_m,w_f,\mathbf{h}';\mu'\right)\\
&+\delta_f'\sum_{k\in\{b,n\}}\lambda_k' V^{EU_k}\left(a',w_m,\mathbf{h}';\mu'\right)\Bigg)\\
&+\delta_m'\Bigg(\left(1-\delta_f'\right)\sum_k \lambda_k' V^{U_kE}\left(a',w_f,\mathbf{h}';\mu'\right)\\
&+\delta_f'\sum_{k,d\in\{b,n\}}\lambda_k'\lambda_d' V^{U_kU_d}\left(a',\mathbf{h}';\mu'\right)\Bigg)\Bigg|\mathbf{h},\mu\Bigg]\end{aligned}$$

The explanation of the terms in the right hand side is similar to its counterpart in the baseline model.

Finally, the problem of retired households is identical to their problem in the baseline model.

Firm problem First, consider a firm that is matched with a worker in submarket $(w,\,h)$ when the aggregate state is μ. The pair operates under a constant returns to scale technology and produces $g\,(h,\,z)$ units of output, and the worker is paid a wage of w. With some probability $\delta\,(h,\,z)$ the match dissolves, and the worker retires with probability ζ_R. Let $J\,(w,\,h;\,\mu)$ be the value of a matched firm in submarket $(w,\,h)$ when the aggregate state is μ. The recursive problem of this firm is given as follows:

$$\begin{aligned}J\,(w,\,h;\,\mu) \;&=\; g\,(h,\,z)-w+\frac{1}{1+r}\left(1-\zeta_R\right)\mathbb{E}_{h',\mu'}\left[\left(1-\delta\left(h',\,z'\right)\right)J\left(w,\,h';\,\mu'\right)\Big|h,\,\mu\right]\\
&\text{subject to}\\
&\Gamma'=\Lambda\left(\mu,\,z'\right)\quad\text{and}\quad z'\sim\Phi\left(z'\,|\,z\right).\end{aligned}\tag{A.1}$$

Meanwhile, the value of a firm that posts a vacancy in submarket $(w,\,h)$ under aggregate state μ is given by

$$V\,(w,\,h;\,\mu)=-\kappa+q\,(\theta\,(w,\,h;\,\mu))\,J\,(w,\,h;\,\mu)$$

where κ is a fixed cost of posting a vacancy that is financed by risk-neutral foreign entrepreneurs who own the firms.

The free entry condition implies that profits are just enough to cover the cost of filling a vacancy in expectation. As a result, the owner of the firm makes zero profits in expectation. Thus, $V(w,\, h;\, \mu) = 0$ for any submarket $(w,\, h)$ such that $\theta(w,\, h;\, \mu) > 0$. Then, imposing the free entry condition yields the equilibrium market tightness:

$$\theta(w,\, h;\, \mu) = \begin{cases} q^{-1}\left(\frac{\kappa}{J(w,\, h;\, \mu)}\right) & \text{if} \quad w \in \mathcal{W}(\mu) \text{ and } h \in \mathcal{H}(\mu) \\ 0 & \text{otherwise.} \end{cases} \tag{A.2}$$

The equilibrium market tightness contains all the relevant information needed by households to evaluate the job finding probabilities at each submarket.

Equilibrium Definition of Recursive Equilibrium is very similar to that under Section 1.2.4 of the main text, with indexing relevant policy functions with extra state of wage level w. The directed search feature of this model, together with the other assumptions discussed in Section 1.2.4, allows this model to admit a BRE as well. This time unemployed endogenously choose wage submarkets compatible with their own skill to direct their search effort, rather than being automatically assigned to skill submarkets based on their own skill. This extra feature of the extended model deserve a proof on the existence of BRE.

Proposition: *If i) utility function $u(\cdot)$ is strictly increasing, strictly concave, and satisfies Inada conditions; ii) choice sets $\mathcal{W}$ and $\mathcal{A}$, human capital set $\mathcal{H}$, and set of exogenous process $\mathcal{Z}$ are bounded, iii) matching function M exhibits constant returns to scale, and iv) government policy instruments are restricted to be only a function of current aggregate labor productivity, then there exists a Block Recursive Equilibrium for this economy.*

Proof: This proof is an extension of the proof given in Birinci and See (2017) in two ways: i) this model incorporates endogenous labor supply decision, and ii) submarkets are also indexed by skill levels.

I prove the existence of the BRE in two steps. In the first step, I show that the firm value functions and the corresponding labor market tightness depend on the aggregate state of the economy only through the current aggregate labor productivity. Then, in the second step, given that government policy instruments are restricted to be a function of the current aggregate labor productivity z, I show that the household value functions do not depend on the aggregate distribution of households across states Γ. As a result, I show that given the government policy, the solution of the household's problem together with the solution of the firm's problem and labor market tightness, constitute a block recursive equilibrium. Let $\mathcal{J}(\mathcal{W}, \mathcal{H}, \mathcal{Z})$ be the set of bounded and continuous functions J such that $J : \mathcal{W} \times \mathcal{H} \times \mathcal{Z} \rightarrow \mathbb{R}$ and let T_J be an operator associated with (A.1) such that $T_J : \mathcal{J} \rightarrow \mathcal{J}$. Then, using Blackwell's sufficiency conditions for a contraction and the assumptions of the boundedness of sets of exogenous process $\mathcal{Z}$, choice set $\mathcal{W}$, and human capital set $\mathcal{H}$, we know that T_J is a contraction and has a unique fixed point $J^* \in \mathcal{J}$. Thus, the firm value function satisfying (A.1) depends on the aggregate state of the economy μ only through the aggregate labor productivity z. This means that the set of wages posted by the firms in equilibrium $\mathcal{W}$ for each element in the set of possible skill level $\mathcal{H}$ is determined by the aggregate labor productivity z as well. Then, plugging J^* into (A.2) yields

$$\theta^*(w, h; z) = \begin{cases} q^{-1}\left(\frac{\kappa}{J^*(w, h; z)}\right) & \text{if} \quad w \in \mathcal{W}(z) \text{ and } h \in \mathcal{H}(z) \\ 0 & \text{otherwise.} \end{cases}$$

Notice that, as explained in the main text for the baseline model, the constant-returns-to-scale property of the matching function M is crucial here so that we can write the job finding rate and vacancy filling rate as a function of θ only.[5] Hence, I show that equilibrium market tightness θ^* does not depend on the distribution of households across states Γ as well.

Next, using this result and the assumption that the government policy only depends on z, I show that the household value functions do not depend on the aggregate distribution of households across states Γ. To do so, I first collapse the problem of households into one functional equation and show that it is a contraction. Then, I show that the functional equation maps the set of functions that depend on the aggregate state μ only through z. Let $\mathit{\Omega}$ denote the possible realizations of the aggregate state μ and define a value function

[5] The free entry condition (2.6) is also important to pin down market tightness.

$K : \{0,1,2\} \times \{0,1,2\} \times \{0,1\} \times \{0,1\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{W} \times \mathcal{H} \times \mathcal{H} \times \Omega \to \mathbb{R}$ such that

$$\begin{aligned}
K(l_m = 1, l_f = 1, d_m = 0, d_f = 0, a, w_m, w_f, h_m, h_f; \mu) &= V^{EE}(a, w_m, w_f, h_m, h_f; \mu) \\
K(l_m = 1, l_f = 0, d_m = 0, d_f = 1, a, w_m, w_f, h_m, h_f; \mu) &= V^{EU_b}(a, w_m, h_m, h_f; \mu) \\
K(l_m = 1, l_f = 0, d_m = 0, d_f = 0, a, w_m, w_f, h_m, h_f; \mu) &= V^{EU_n}(a, w_m, h_m, h_f; \mu) \\
K(l_m = 0, l_f = 0, d_m = 1, d_f = 0, a, w_m, w_f, h_m, h_f; \mu) &= V^{U_bU_n}(a, h_m, h_f; \mu) \\
K(l_m = 2, l_f = 2, d_m = 0, d_f = 0, a, w_m, w_f, h_m, h_f; \mu) &= V^{R}(a)
\end{aligned}$$

and so on for other types of households with different employment statuses.
Then, we define the set of functions $\mathcal{K} : \{0,1\} \times \{0,1\} \times \{0,1\} \times \{0,1\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{W} \times \mathcal{H} \times \mathcal{H} \times \mathcal{Z} \to \mathbb{R}$ and let T_K be an operator such that

$$\begin{aligned}
T_K K(\cdot) = {} & l_m l_f \left[\max_{a' \geq a_L} \quad u(c) + \beta \Big[(1-\zeta_R)\, \mathbb{E}_{\mathbf{l}', \mathbf{h}', \mu'} K(\cdot) + \zeta_R K\left(\mathbf{l}' = \mathbf{2}, \cdot\right) \Big] \right] \\
& + l_m (1 - l_f) \left[\max_{a' \geq a_L, s_f \in \{0,1\}} u(c) + \eta_f (1 - s_f) + \max_{\tilde{w}_f} \beta \Big[(1-\zeta_R)\, \mathbb{E} K(\cdot) + \zeta_R K\left(\mathbf{l}' = \mathbf{2}, \cdot\right) \Big] \right] \\
& + (1 - l_m) l_f \left[\max_{a' \geq a_L, s_m \in \{0,1\}} u(c) + \eta_m (1 - s_m) + \max_{\tilde{w}_m} \beta \Big[(1-\zeta_R)\, \mathbb{E} K(\cdot) + \zeta_R K\left(\mathbf{l}' = \mathbf{2}, \cdot\right) \Big] \right] \\
& + (1 - l_m)(1 - l_f) \Bigg[\max_{a' \geq a_L,\ s_m, s_f \in \{0,1\}} \quad u(c) + \sum_{i \in \{m,f\}} \eta_i (1 - s_i) \\
& + \max_{\tilde{w}_m, \tilde{w}_f} \left\{ \beta \Big[(1-\zeta_R)\, \mathbb{E} K(\cdot) + \zeta_R K\left(\mathbf{l}' = \mathbf{2}, \cdot\right) \Big] \right\} \Bigg]
\end{aligned}$$

subject to

$$\begin{aligned}
& c + a' \leq (1+r) a + y + \phi(z; a, y) + \Big[(1 - l_m) d_m b(z; U_b, s_m) + (1 - l_f) d_f b(z; U_b, s_f) \Big] (1 - \tau) \\
& y = \Big[l_m w_m + l_f w_f \Big] (1 - \tau) \\
& z' \sim \Phi\left(z' \mid z\right)
\end{aligned}$$

where none of the terms inside expectations (δ'_m, δ'_f , λ'_b, λ'_n, p'_m, or p'_f) and value functions K inside these expectations depend on Γ.[6]

[6]Here, I refrain the write out expectation explicitly to save space. However, these expectations are shown above for reference.

Assuming the utility function is bounded and continuous, $\mathcal{K}$ is the set of continuous and bounded functions. Then, we can show that the operator T_K maps a function from $\mathcal{K}$ into $\mathcal{K}$ (i.e., $T_K : \mathcal{K} \to \mathcal{K}$). Then, using Blackwell's sufficiency conditions for a contraction and the assumptions of boundedness of sets of exogenous process $\mathcal{Z}$, choice set $\mathcal{W}$ and $\mathcal{A}$, and human capital set $\mathcal{H}$, we can show that T_K is a contraction and has a unique fixed point $K^* \in \mathcal{K}$. Thus, the solution to the household problem does depend on Γ. This constitutes a BRE along with the solution to the firm's problem and the implied labor market tightness that does not depend on Γ, given that the government policy is a function of z only.

A.5 Computational Algorithm

Given that the model is block recursive, none of the equilibrium value functions, policy functions, or market tightness depend on aggregate distribution of agents across states Γ. This means that block recursive equilibrium (BRE) depends on μ only through z. BRE is solved using the following steps:

1. Solve for the value function of the firm $J(h, z)$.

2. Using the free-entry condition $0 = -\kappa + q(\theta(h, z)) J(h, z)$ and the functional form of $q(\theta)$, we can solve for market tightness for any given human capital submarket h and aggregate productivity z:

$$\theta(h, z) = q^{-1}\left(\frac{\kappa}{J(h, z)}\right),$$

   where we set $\theta(h, z) = 0$ when the market is inactive.

3. Given the function θ, I can then solve for the household value functions and policy functions using standard value function iteration. In order to decrease computation time, I implement Howard's improvement algorithm (policy-function iteration).

4. Once household policy functions are obtained, I simulate aggregate dynamics of the model.

Computational algorithm of the model with endogenous wages is the same as the baseline model with an addition that equilibrium objects are also functions of wage.

Appendix B

Appendix to Chapter 2

B.1 Data

SIPP data

We use the U.S. Census Bureau's Survey of Income and Program Participation (SIPP) to document the liquid asset holdings of individuals. The SIPP is a longitudinal survey that follows individuals for a duration of up to five years, with interviews being held in four-month intervals called waves. Each respondent is then assigned to one of four rotation groups. The rotation group determines which month within a wave a respondent is interviewed. Each interview covers information about the four months (reference months) preceding the interview month. For example, when a new SIPP panel starts and Wave 1 (the first four months of the new panel) commences, the first rotation group is interviewed in the first month of Wave 1, the second rotation group is interviewed in the second month of Wave 1, and so on. Once all four rotation groups are interviewed at the end of the fourth month of Wave 1, Wave 2 begins with the second interview of the first rotation group. This way, all four rotation groups, and thus all respondents, will have been interviewed at the end of each wave.

In each interview, respondents are asked questions about their income, labor force status and government transfer receipts over the previous four months not including the interview month. In the end, the SIPP provides monthly data on income and government transfers and weekly data on labor force status. Most importantly, the SIPP also contains data on the asset holdings of the respondent. In each SIPP panel, respondents provide information on various types of asset holdings at two or three waves of the panel, usually one year or, equivalently, three waves apart. We use the 2004 panel of the SIPP, which contains 12 waves covering information between January 2004 and December 2007. This particular panel allows us to observe data on asset holdings at Waves 3 and 6. Since it is the closest date to the Great Recession, we calculate the asset distribution using Wave 6.

Asset distribution

We focus on the liquid asset holdings of individuals. The SIPP contains individual level data on financial liquid assets such as interest-earning financial assets in banking and other instutitions, amount in non-interest-earning checking accounts, equity in stocks and mutual funds, and face value of U.S. savings bonds. Moreover, for married individuals, the survey asks about the amount of these assets in joint accounts. Only one spouse is asked about joint accounts; the response is then divided by two, and the divided amount is copied to both spouses' records. The SIPP also contains information about revolving debt on credit card balances at the individual level for both single and joint accounts in the same fashion. The summation of the amounts in liquid asset accounts net of revolving debt gives us the net financial asset holdings of the individual. Finally, the SIPP provides data on equity in cars at the household level. We split that amount between the members of the household who are age 16 or older, and record that value as the amount of equity in cars for each individual within the household. Adding this value to net financial asset holdings of the individual gives us the measure of liquid asset holdings for each individual.[1]

[1] Net financial asset holdings are calculated as follows by using the following variables in SIPP data: Net financial assets = TALICHA+TALJCHA+TALSBV+TIMIA+TIMJA+TIAITA+TIAJTA+ESMIV+ESMJV-(EALIDAB+EALJDAB) where TALICHA (TALJCHA) is the amount of non-interest-earning checking accounts in own name (joint account), TALSBV is the face value of U.S. savings bonds, TIMIA (TIMJA) is amount of bonds/securities in own name (joint account), TIAITA (TIAJTA) is the amount in interest earning account in own name (joint account), ESMIV (ESMJV) value of stocks/funds in own name (joint account), and EALIDAB (EALJDAB) amount owed for store bills/credit cards in own name (joint account). Then, net equity in vehicles of the household is given by THHVEHCL. We divide this value among the members of the household above age 16. Thus, we get the net liquid asset holdings of the individual as follows: Net liquid assets = Net financial assets +THHVEHCL /number of persons within

The SIPP also provides information about the monthly gross job earnings for each individual. We use this information to determine the monthly gross labor income of the individual. If the individual is unemployed during the interview month, we use her gross labor income associated with the last employment from earlier waves. Next, using the weekly employment status of the individual for that month, we calculate the weekly gross labor income of the individual by dividing monthly gross labor income by the number of weeks with a job during the interview month.

We then calculate annual income and payroll tax rates using the statutory U.S. income tax codes in the following steps. First, we calculate the annual income of each individual. Annual income includes labor income, capital income, and all kinds of government transfers including UI received in the fiscal year. Next, we apply the year-specific federal income tax schedule to the annual income net of year-specific personal exemptions and deductions to obtain the total annual income tax for each respondent. After that, we calculate the total annual payroll tax (Social Security and Medicare tax) for each individual. We obtain the total annual payroll tax for each individual by applying the year-specific Social Security and Medicare tax schedule to the total annual labor income of the individual for the time period. [2] Then, our measure for the tax rate is

$$\tau = \frac{\text{Share of labor income} \times \text{Annual income tax} + \text{Annual payroll tax}}{\text{Annual labor income}},$$

where the share of labor income is the ratio of annual labor income to annual income. We then apply the tax rate τ for each individual in our sample and obtain weekly after-tax labor income. Last, dividing the liquid asset holdings measure to weekly after-tax labor income gives us the asset-to-income ratio for each individual.

B.2 Proofs

Opportunity cost of employment

In this section, we show the derivations of Equations (2.12) and (2.13) in the main text.

the household age 16 and above.

[2] We also consider the fact that there is a maximum taxable annual labor income for Social Security tax, while Medicare tax does not have such a limit. As a result, we get total annual tax as the sum of total annual income and payroll taxes.

First, substituting (2.1) and (2.2) into (2.8), we have

$$
\begin{aligned}
S^{UE}\left(a, w^{UE}, \beta; p\right) =& V^{W}\left(a, \tilde{w}\left(\cdot\right), \beta; p\right) - V^{UE}\left(a, w^{UE}, \beta; p\right) \\
=& u\left(c^{W}\right) - u\left(c^{UE}\right) + \nu\left(s\right) \\
&+ \beta\mathbb{E}\left[\delta\left(p'\right)\left(1 - e\left(p'\right)\right) V^{UE}\left(a'^{W}, \tilde{w}\left(\cdot\right), \beta'; p'\right)\right. \\
&\left. + \delta\left(p'\right) e\left(p'\right) V^{UI}\left(a'^{W}, \beta'; p'\right)\right] \\
&+ \beta\mathbb{E}\left[\left(1 - \delta\left(p'\right)\right) V^{W}\left(a'^{W}, \tilde{w}\left(\cdot\right), \beta'; p'\right)\right] \\
&- \beta\mathbb{E}\left[sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right) V^{W}\left(a'^{UE}, \tilde{w}\left(\cdot\right), \beta'; p'\right)\right] \\
&- \beta\mathbb{E}\left[\left(1 - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right)\left(1 - e\left(p'\right)\right) V^{UE}\left(a'^{UE}, w^{UE}, \beta'; p'\right)\right] \\
&- \beta\mathbb{E}\left[\left(1 - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right) e\left(p'\right) V^{UI}\left(a'^{UE}, \beta'; p'\right)\right]
\end{aligned}
$$

In order to obtain (2.12), we add and subtract terms, rearrange them, then use (2.10), and divide both sides by λ^{W}. This yields

$$
\begin{aligned}
\frac{S^{UE}\left(a, w^{UE}, \beta; p\right)}{\lambda^{W}} =& \frac{u\left(c^{W}\right) - u\left(c^{UE}\right) + \nu\left(s\right)}{\lambda^{W}} \\
&+ \frac{\beta}{\lambda^{W}}\mathbb{E}\Big[sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right) \\
&\times \left(V^{W}\left(a'^{W}, \tilde{w}\left(\cdot\right), \beta'; p'\right) - V^{W}\left(a'^{UE}, \tilde{w}\left(\cdot\right), \beta'; p'\right)\right)\Big] \\
&+ \frac{\beta}{\lambda^{W}}\mathbb{E}\Big[\left(1 - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right) - \delta\left(p'\right) e\left(p'\right)\right) \\
&\times \left(V^{UE}\left(a'^{W}, \tilde{w}\left(\cdot\right), \beta'; p'\right) - V^{UE}\left(a'^{UE}, w^{UE}, \beta'; p'\right)\right)\Big] \\
&+ \frac{\beta}{\lambda^{W}}\mathbb{E}\Big[\left(1 - \delta\left(p'\right) - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right) \\
&\times \left(V^{W}\left(a'^{W}, \tilde{w}\left(\cdot\right), \beta'; p'\right) - V^{W}\left(a'^{W}, \tilde{w}\left(a'^{W}, \tilde{w}\left(\cdot\right), \beta'; p'\right), \beta'; p'\right)\right)\Big] \\
&+ \frac{\beta}{\lambda^{W}}\mathbb{E}\Big[\left(1 - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right) - \delta\left(p'\right)\right) e\left(p'\right) \\
&\times \left(V^{UE}\left(a'^{UE}, w^{UE}, \beta'; p'\right) - V^{UI}\left(a'^{UE}, \beta'; p'\right)\right)\Big] \\
&+ \beta\mathbb{E}\left[\frac{\lambda'^{W}}{\lambda^{W}} \frac{\left(1 - \delta\left(p'\right) - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right) S\left(a'^{W}, \tilde{w}\left(\cdot\right), \beta'; p'\right)}{\lambda'^{W}}\right]
\end{aligned}
$$

where the summation of the second and third terms on the right-hand side is $-z_{a}^{UE}$, the fourth term is $-z_{w}^{UE}$, and the fifth term is $-z_{elg}^{UE}$. Given the form of the utility function, we cannot isolate z^{UE}_{flow} from the first term on the right-hand side. However, since we know that the flow value of employment is $\tilde{w}\left(a, w^{UE}, \beta; p\right) \times (1-\tau)$, we can numerically calculate z^{UE}_{flow} using the above equation as follows:

$$\begin{aligned} z^{UE}_{flow} = & \frac{S^{UE}\left(a, w^{UE}, \beta; p\right)}{\lambda^W} - \tilde{w}\left(a, w^{UE}, \beta; p\right) \times (1-\tau) + z^{UE}_a + z^{UE}_w + z^{UE}_{elg} \\ & - \beta \mathbb{E}\left[\frac{\lambda'^W}{\lambda^W} \frac{\left(1-\delta\left(p'\right) - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right) S\left(a'^W, \tilde{w}\left(\cdot\right), \beta'; p'\right)}{\lambda'^W}\right]. \end{aligned}$$

This gives us the opportunity cost of employment for the eligible unemployed $z^{UE} = z^{UE}_{flow} + z^{UE}_a + z^{UE}_w + z^{UE}_{elg}$ for each state $\left(a, w^{UE}, \beta; p\right)$.
Second, substituting (2.1) and (2.3) into (2.9), we have

$$\begin{aligned} S^{UI}\left(a, \beta; p\right) = & V^W\left(a, \tilde{w}\left(\cdot\right), \beta; p\right) - V^{UI}\left(a, \beta; p\right) \\ = & u\left(c^W\right) - u\left(c^{UI}\right) + \nu\left(s\right) \\ & + \beta \mathbb{E}\left[\delta\left(p'\right)\left[\left(1-e\left(p'\right)\right) V^{UE}\left(a'^W, \tilde{w}\left(\cdot\right), \beta'; p'\right) + e\left(p'\right) V^{UI}\left(a'^W, \beta'; p'\right)\right]\right] \\ & + \beta \mathbb{E}\left[\left(1-\delta\left(p'\right)\right) V^W\left(a'^W, \tilde{w}\left(\cdot\right), \beta'; p'\right)\right] \\ & - \beta \mathbb{E}\left[sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right) V^W\left(a'^{UI}, \tilde{w}\left(\cdot\right), \beta'; p'\right)\right] \\ & - \beta \mathbb{E}\left[\left(1-sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right) V^{UI}\left(a'^{UI}, \beta'; p'\right)\right] \end{aligned}$$

Similarly, in order to obtain (2.13), we again add and subtract terms, rearrange them, then use (2.11), and divide both sides by λ^W. This yields

$$\begin{aligned} \frac{S^{UI}\left(a, \beta; p\right)}{\lambda^W} = & \frac{u\left(c^W\right) - u\left(c^{UI}\right) + \nu\left(s\right)}{\lambda^W} \\ & + \frac{\beta}{\lambda^W} \mathbb{E}\left[sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\left[V^W\left(a'^W, \tilde{w}\left(\cdot\right), \beta'; p'\right) - V^W\left(a'^{UI}, \tilde{w}\left(\cdot\right), \beta'; p'\right)\right]\right] \\ & + \frac{\beta}{\lambda^W} \mathbb{E}\left[\left(1-sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right)\left[V^{UI}\left(a'^W, \beta'; p'\right) - V^{UI}\left(a'^{UI}, \beta'; p'\right)\right]\right] \\ & + \frac{\beta}{\lambda^W} \mathbb{E}\Big[\left(1-\delta\left(p'\right) - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right) \\ & \times \left(V^W\left(a'^W, \tilde{w}\left(\cdot\right), \beta'; p'\right) - V^W\left(a'^W, \tilde{w}\left(\cdot\right), \beta'; p'\right)\right)\Big] \\ & + \frac{\beta}{\lambda^W} \mathbb{E}\left[\delta\left(p'\right)\left(1-e\left(p'\right)\right)\left[V^{UE}\left(a'^W, \tilde{w}\left(\cdot\right), \beta'; p'\right) - V^{UI}\left(a'^W, \beta'; p'\right)\right]\right] \\ & + \beta \mathbb{E}\left[\frac{\lambda'^W}{\lambda^W} \frac{\left(1-\delta\left(p'\right) - sf\left(\theta\left(\tilde{w}\left(\cdot\right); p'\right)\right)\right) S^{UI}\left(a'^W, \beta'; p'\right)}{\lambda'^W}\right], \end{aligned}$$

where the summation of the second and third terms on the right-hand side is $-z_a^{UI}$, the fourth term is $-z_w^{UI}$, and the fifth term is $-z_{elg}^{UI}$. Similarly, we numerically calculate z_{flow}^{UI} as follows:

$$z_{flow}^{UI} = \frac{S^{UI}(a,\beta;p)}{\lambda^W} - \tilde{w}(a,\beta;p) \times (1-\tau) + z_a^{UI} + z_w^{UI} + z_{elg}^{UI}$$
$$- \beta \mathbb{E}\left[\frac{\lambda'^W}{\lambda^W} \frac{\left(1-\delta(p') - sf\left(\theta\left(\tilde{w}\left(a'^{UI},\beta';p'\right);p'\right)\right)\right) S^{UI}\left(a'^W,\beta';p'\right)}{\lambda'^W}\right].$$

This gives us the opportunity cost of employment for the eligible unemployed $z^{UI} = z_{flow}^{UI} + z_a^{UI} + z_w^{UI} + z_{elg}^{UI}$ for each state $(a,\beta;p)$.[3]

Block recursive equilibrium

Proposition 1: *If i) utility function $u(\cdot)$ is strictly increasing, strictly concave, and satisfies Inada conditions; $\nu(\cdot)$ is strictly increasing and strictly convex, ii) choice sets $\mathcal{W}$ and $\mathcal{A}$, and sets of exogenous processes $\mathcal{P}$ and $\mathcal{B}$ are bounded, iii) matching function M exhibits constant returns to scale, and iv) UI policy is restricted to be only a function of current aggregate labor productivity, then there exists a Block Recursive Equilibrium for this economy. If, in addition, $M = min\{v,S\}$, then the Block Recursive Equilibrium is the only recursive equilibrium.*

Proof: The proof presented here follows from Karahan and Rhee (2013) and Herkenhoff (2017), which are extensions of Menzio and Shi (2010, 2011). We extend the former's proof to a model in which government finances the time-varying UI benefits and show that the model still admits block recursivity. We then use the model to study how UI policy must vary over the business cycle. In doing so, the additional assumption we make here is to restrict the class of UI policies to be a function of current aggregate labor productivity.

Existence: We prove the existence of the BRE in two steps. In the first step, we show that the firm value functions and the corresponding labor market tightness depend on the aggregate state of the economy only through the current aggregate labor productivity. Then, in the second step, given that UI policy instruments are restricted to be a function

[3] In this numerical calculation, we calculate the opportunity cost under fixed wages and disregard z_w^{UE} and z_w^{UI}.

of the current aggregate labor productivity, we show that the household value functions do not depend on the aggregate distribution of agents across states. As a result, we show that given the UI policy, the solution of the household's problem together with the solution of the firm's problem and labor market tightness, constitute a block recursive equilibrium.

Let $\mathcal{J}(\mathcal{W},\mathcal{P})$ be the set of bounded and continuous functions J such that $J:\mathcal{W}\times\mathcal{P}\to\mathbb{R}$ and let T_J be an operator associated with (2.4) such that $T_J:\mathcal{J}\to\mathcal{J}$. Then, using Blackwell's sufficiency conditions for a contraction and the assumptions of the boundedness of sets of exogenous processes $\mathcal{P}$ and $\mathcal{B}$, and choice sets $\mathcal{W}$ and $\mathcal{A}$, we can show that T_J is a contraction and has a unique fixed point $J^*\in\mathcal{J}$. Thus, the firm value function satisfying (2.4) depends on the aggregate state of the economy μ only through the aggregate labor productivity p. This means that the set of wages posted by the firms in equilibrium $\mathcal{W}$ is determined by the aggregate labor productivity p as well. Then, plugging J^* into (2.6) yields

$$\theta^*(w;p)=\begin{cases} q^{-1}\left(\frac{\kappa}{J^*(w;p)}\right) & \text{if} \quad w\in\mathcal{W}(p) \\ 0 & \text{otherwise}\end{cases}$$

Notice that, as explained in the main text, the constant-returns-to-scale property of the matching function M is crucial here so that we can write the job finding rate and vacancy filling rate as a function of θ only.[4] Hence, we show that equilibrium market tightness does not depend on the distribution of agents across states as well.

Next, using this result and the assumption that the UI policy only depends on p, we show that the household value functions do not depend on the aggregate distribution of agents across states. To do so, we first collapse the problem of households into one functional equation and show that it is a contraction. Then, we show that the functional equation maps the set of functions that depend on the aggregate state μ only through p.

Let Ω denote the possible realizations of the aggregate state μ and define a value function $R:\{0,1\}\times\{0,1\}\times\mathcal{A}\times\mathcal{W}\times\mathcal{B}\times\Omega\to\mathbb{R}$ such that

$$\begin{aligned} R(l=1,d=0,a,w,\beta;\mu) &= V^{W}(a,w,\beta;\mu) \\ R(l=0,d=1,a,w,\beta;\mu) &= V^{UE}(a,w,\beta;\mu) \\ R(l=0,d=0,a,w,\beta;\mu) &= V^{UI}(a,\beta;\mu) \end{aligned}$$

[4]The free entry condition (2.6) is also important to pin down market tightness.

Then, we define the set of functions $\mathcal{R} : \{0,1\} \times \{0,1\} \times \mathcal{A} \times \mathcal{W} \times \mathcal{B} \times \mathcal{P} \rightarrow \mathbb{R}$ and let T_R be an operator such that

$$
\begin{aligned}
(T_R R)(l,d,a,w,\beta;p) = & l\Bigg[\max_{c,a'} u(c) + \beta\mathbb{E}\Big[\delta(p')\left(1-e(p')\right) R(l=0,d=1,\cdot) \\
& +\delta(p')\, e(p')\, R(l=0,d=0,\cdot) + \left(1-\delta(p')\right) R(l=1,d=0,\cdot)\Big]\Bigg] \\
& +(1-l)\, d\Bigg[\max_{c,a',s} u(c) - \nu(s) + \beta\mathbb{E}\Big[\max_{\tilde{w}}\Big\{sf(\theta(\cdot))\, R(l=1,d=0,\cdot) \\
& +(1-sf(\theta(\cdot)))\left(1-e(p')\right) R(l=0,d=1,\cdot) \\
& +(1-sf(\theta(\cdot)))\, e(p')\, R(l=0,d=0,\cdot)\Big\}\Big]\Bigg] \\
& +(1-l)(1-d)\Bigg[\max_{c,a',s} u(c) - \nu(s) \\
& \quad + \beta\mathbb{E}\Big[\max_{\tilde{w}}\Big\{sf(\theta(\cdot))\, R(l=1,d=0,\cdot) \\
& +(1-sf(\theta(\cdot)))\, R(l=0,d=0,\cdot)\Big\}\Big]\Bigg]
\end{aligned}
$$

subject to

$$
\begin{aligned}
& c + a' \leq (1+r)\, a + lw(1-\tau) + (1-l)\, d\left[\phi(p)\, w(1-\tau) + h\right] \\
& \qquad + (1-l)(1-d)\, h \\
& a' \geq -\underline{a} \\
& p' \sim F\left(p' \,|\, p\right)
\end{aligned}
$$

where we use the result from above that market tightness does depend on Γ.
Assuming the utility function is bounded and continuous, $\mathcal{R}$ is the set of continuous and bounded functions. Then, we can show that the operator T_R maps a function from $\mathcal{R}$ into $\mathcal{R}$ (i.e., $T_R : \mathcal{R} \rightarrow \mathcal{R}$). Then, using Blackwell's sufficiency conditions for a contraction and the assumptions of boundedness of sets of exogenous processes $\mathcal{P}$ and $\mathcal{B}$, and choice sets $\mathcal{W}$ and $\mathcal{A}$, we can show that T_R is a contraction and has a unique fixed point $R^* \in \mathcal{R}$. Thus, the solution to the household problem does depend on Γ. This constitutes a BRE

along with the solution to the firm's problem and the implied labor market tightness that does not depend on Γ, given that the UI policy is a function of p only.

Uniqueness: We know that policy functions of the household do not depend on Γ. Now, we prove the uniqueness of the policy functions for assets $\left\{g_a^l(a, w, \beta; p)\right\}_{l=\{W,UE\}}$, and $g_a^{UI}(a, \beta; p)$, wage choice $g_w^{UE}(a, w, \beta; p)$ and $g_w^{UI}(a, \beta; p)$, and search effort $g_s^{UE}(a, w, \beta; p)$ and $g_s^{UI}(a, \beta; p)$.

Wage policy function: Under the assumptions on $u(\cdot)$ and $\nu(\cdot)$ together with the assumptions of boundedness of sets of exogenous processes $\mathcal{P}$ and $\mathcal{B}$, and choice sets $\mathcal{W}$ and $\mathcal{A}$, value functions V^l are strictly concave in w for $l = \{W, UE\}$ and V^{UI} is constant in w. For simplicity, assume that p is non-stochastic and $\delta(p) = \delta$. We then obtain the equilibrium value of a matched firm using Equation (2.4) as follows:[5]

$$J^*(w; p) = \frac{p - w}{r + \delta}(1 + r)$$

Then, we can write the equilibrium labor market tightness as

$$f(\theta^*(w; p)) = \theta^*(w; p) = \frac{J^*(w; p)}{\kappa}$$

where the first equality uses the assumption that $M = \min\{v, S\}$, and the second equality uses the free entry condition. Using the expression for $J^*(w; p)$ gives

$$f(\theta^*(w; p)) = \frac{1 + r}{\kappa(r + \delta)}[p - w] > 0.$$

This implies that the job finding rate $f(\cdot)$ is linear and decreasing in w. Then, rewriting the objective function for the wage choice of eligible unemployed, we have

$$\begin{aligned} &\max_{\tilde{w}} sf(\theta(\tilde{w}; p)) V^W\left(a', \tilde{w}, \beta'; p\right) + (1 - sf(\theta(\tilde{w}; p))) \\ &\times \left[(1 - e(p)) V^{UE}\left(a', w, \beta'; p\right) + e(p) V^{UI}\left(a', \beta'; p\right)\right] \end{aligned}$$

Using the result that V^l is strictly concave in w for $l = \{W, UE\}$ and V^{UI} is constant in w, and that $f(\cdot)$ is linear and decreasing in w, it is easy to show that the objective function

[5]The following results can be obtained under N state Markov process assumption for p and no restrictions on the job destruction rate.

above is strictly concave in w. This implies that the wage policy function $g_w^{UE}(a, w, \beta; p)$ is unique.

Similarly, rewriting the objective function for the wage choice of ineligible unemployed yields

$$\max_{\tilde{w}} sf(\theta(\tilde{w}; p)) V^W(a', \tilde{w}, \beta'; p) + (1 - sf(\theta(\tilde{w}; p))) V^{UI}(a', \beta'; p),$$

and using the same reasoning implies that the wage policy function $g_w^{UI}(a, \beta; p)$ is also unique.

Asset policy function: Under the assumptions on the utility functions $u(\cdot)$ and $\nu(\cdot)$ and choice sets $\mathcal{A}$, $\mathcal{W}$ and exogenous proceses $\mathcal{B}$, $\mathcal{P}$, value functions V^l are strictly concave in assets. This implies that the objective functions for the asset choice of each employment status are strictly concave in a', and thus asset policy functions $g_a^l(a, w, \beta; p)$ are unique for $l = \{W, UE, UI\}$

Search effort policy function: Using the same reasoning, objective functions for search effort choice of eligible and ineligible unemployed are strictly concave in s. This implies that the search effort policy functions $g_s^{UE}(a, w, \beta; p)$ and $g_s^{UI}(a, \beta; p)$ are unique.

B.3 Welfare Calculation for Great Recession Simulation

First, we focus on individual i. Let $t = 0$ be December 2007 and let T be December 2013. For ease of exposition, we discuss the calculation of welfare in two separate parts: let period (A) include any time $t \in [0, \ldots T]$ during the Great Recession and recovery and (B) represent the terminal time period post-December 2013 $t > T$.

Let $c_i^j(\mathbf{x}_t, p_t)$ and $s_i^j(\mathbf{x}_t, p_t)$ denote the consumption and search effort policy functions of individual i with individual state $\mathbf{x}_t$ at time t when aggregate productivity is p_t and UI policy is $j \in \{b, f, n\}$, where b denotes the benchmark policy, f denotes the flat policy, and n denotes the new/alternative policy.[6] To evaluate the welfare gains from the optimal policy in this exercise, we set policy n to be the optimal policy.

[6]Notice here that we are using the result that policy functions of the agents in our economy depend on the aggregate state of economy only through p as a result of block recursivity.

First consider welfare in period (A). Under the benchmark policy b, the utility of individual i during period (A) when endowed with additional $\bar{\pi}$ percent of consumption for her lifetime is given by

$$\sum_{t=0}^{T} \left(\beta_{i,t}\right)^{t} U\left(c_i^b\left(\mathbf{x}_t, p_t\right)\left(1+\bar{\pi}\right), s_i^b\left(\mathbf{x}_t, p_t\right)\right),$$

where $U\left(c_i^b\left(\mathbf{x}_t, p_t\right)\left(1+\bar{\pi}\right), s_i^b\right) = \frac{\left[c_i^b\left(\mathbf{x}_t, p_t\right)\left(1+\bar{\pi}\right)\right]^{1-\sigma}}{1-\sigma} - \mathbf{1}_U\left[\alpha \frac{s_i^b\left(\mathbf{x}_t, p_t\right)^{1+\chi}}{1+\chi}\right]$. Note that in the above expression, $\{p_t\}_{t=0}^{T}$ represents the labor productivity that is fed into the model during the recession, while $\{\beta_{i,t}\}_{t=0}^{T}$ represents the realized values of discount factor β. Agents, however, take expectations on aggregate labor productivity using the AR(1) process.

Now consider period (B). The continuation value of the individual post-December 2013 is given by

$$\mathbb{E}_{T+1} \sum_{t=T+1}^{\infty} \left(\beta_{i,t}\right)^{t} U\left(c_i^j\left(\mathbf{x}_t, p_t\right)\left(1+\bar{\pi}\right), s_i^j\left(\mathbf{x}_t, p_t\right)\right),$$

which recursively can be written as $\left(\beta_{i,T+1}\right)^{T+1} V_{\bar{\pi}}^{l_i,j}\left(a_{T+1}, w_{T+1}, \beta_{T+1}, p_{T+1}\right)$ where $V_{\bar{\pi}}^{l_i,j}$ denotes the value of individual i with labor force status $l_i \in \{W, UE, UI\}$ under the policy j when consumption is multiplied by $1+\bar{\pi}$ every period from $t = T+1$ onward. Computationally, we can find $V_{\bar{\pi}}^{l_i}$ once we have obtained the policy functions associated with the underlying value function V^{l_i}. We do this recursively by policy function iteration with the difference being that consumption is multiplied by $(1+\bar{\pi})$ at every iteration. Under the original exercise where the policy is permanent, we set $j = b$, while under the exercise when the policy is discretionary/temporary, the government reverts back to the flat policy postrecession and thus $j = f$.

Hence, the welfare of agent i who is endowed with an additional $\bar{\pi}$ percent of lifetime consumption over periods (A) and (B) under the baseline policy b can be written as

$$\sum_{t=0}^{T} \left[\left(\beta_{i,t}\right)^{t} U\left(c_i^b\left(\mathbf{x}_t, p_t\right)\left(1+\bar{\pi}\right), s_i^b\left(\mathbf{x}_t, p_t\right)\right)\right] + \left(\beta_{i,T+1}\right)^{T+1} V_{\bar{\pi}}^{l_i,j}\left(a_{T+1}, w_{T+1}, \beta_{T+1}, p_{T+1}\right).$$

Now, aggregating across individuals at each point in time, we can write the left-hand side of Equation (2.15) as

$$\sum_{t=0}^{T}\left[\int_{i}\left(\beta_{i,t}\right)^{t} U\left(c_{i}^{b}\left(\mathbf{x}_{t}, p_{t}\right)(1+\bar{\pi}), s_{i}^{b}\left(\mathbf{x}_{t}, p_{t}\right)\right) d\Gamma_{t}^{b}(i)\right]$$
$$+\int_{i}\left(\beta_{i,T+1}\right)^{T+1} V_{\bar{\pi}}^{l_{i},j}\left(a_{T+1}, w_{T+1}, \beta_{T+1}, p_{T+1}\right) d\Gamma_{T+1}^{b}(i), \tag{B.1}$$

where Γ_t^b is the distribution of the economy at time t under policy b.
Similarly, the right-hand-side of equation (2.15) is computed by solving

$$\sum_{t=0}^{T}\left[\int_{i}\left(\beta_{i,t}\right)^{t} U\left(c_{i}^{n}\left(\mathbf{x}_{t}, p_{t}\right), s_{i}^{n}\left(\mathbf{x}_{t}, p_{t}\right)\right) d\Gamma_{t}^{n}(i)\right]$$
$$+\int_{i}\left(\beta_{i,T+1}\right)^{T+1} V^{l_{i},j}\left(a_{T+1}, w_{T+1}, \beta_{T+1}, p_{T+1}\right) d\Gamma_{T+1}^{n}(i), \tag{B.2}$$

where Γ_t^n is the corresponding distribution under policy n and the superscript j of the value function in (B) depends on whether the policy is permanent ($j = n$) or temporary ($j = f$).
Under a temporary policy, we emphasize that even if the policy reverts to the flat policy f after December 2013, the terminal value will be different for policy b and n because the distribution of each economy at $t = T + 1$ is going to be different from each other (i.e., $\Gamma_{T+1}^b \neq \Gamma_{T+1}^n$).
Then, we simply use a zero-finder to find $\bar{\pi}$ that makes equations (B.1) and (B.2) the same.[7]

B.4 Model with Endogenous Quits

In this section, we present the extended model that incorporates the endogenous quit decisions of workers.

Worker's problem

Under the model with quits, workers matched with a firm can decide to leave employment. After the separation shock realizes, a firm-worker pair that is not dissolved exogenously

[7] Note that there is no closed-form solution for $\bar{\pi}$ given the functional form of the utility function.

may endogenously be separated if the worker chooses to quit. The worker's problem is now given by

$$\begin{aligned}
V^{W}(a,w,\beta;\mu) &= \max_{c,a'} \quad u(c)+\beta\mathbb{E}\Big[\delta(p')\left(1-e(p')\right)V^{UE}(a',w,\beta';\mu') \\
&\quad +\delta(p')\,e(p')\,V^{UI}(a',\beta';\mu') \\
&\quad +\left(1-\delta(p')\right)\max_{d\in\{0,1\}}\left\{dV^{UI}(a',\beta';\mu')+(1-d)\,V^{W}(a',w,\beta';\mu')\right\}\Big]
\end{aligned}$$

subject to

$$\begin{aligned}
& c+a' \leq (1+r)\,a+w\,(1-\tau) \\
& a' \geq -\underline{a} \\
& \Gamma' = H(\mu,p') \quad \text{and} \quad p' \sim F(p'\,|\,p)\,.
\end{aligned}$$

Firm's problem

The value of a matched firm is modified to account for the possibility of a quit. Even if a match is not dissolved by the exogenous shock δ, it can be dissolved if the worker's decision to quit is $g_d = 1$:

$$\begin{aligned}
J(a,w,\beta;\mu) &= p-w \\
&\times \frac{1}{1+r}\mathbb{E}\Big[\left(1-\delta(p')\right)\left(1-g_d(a',w,\beta',\mu')\right)J(a',w,\beta';\mu')\,\Big|\beta,\mu\Big]
\end{aligned} \tag{B.3}$$

subject to

$$\Gamma' = H(\mu,p') \quad \text{and} \quad p' \sim F(p'\,|\,p)\,,$$

where $a' = g_a(a,w,\beta,\mu)$.

So, the value of posting a vacancy is given by

$$V(a,w,\beta;\mu) = -\kappa + q\left(\theta(a,w,\beta;\mu)\right)J(a,w,\beta;\mu) \tag{B.4}$$

and market tightness can be obtained by solving

$$\theta(a,w,\beta;\mu) = \begin{cases} q^{-1}\left(\frac{\kappa}{J(a,w,\beta;\mu)}\right) & \text{if} \quad w\in\mathcal{W}(\mu) \\ 0 & \text{otherwise.} \end{cases} \tag{B.5}$$

Notice that the value of a firm J depends on individual states $\mathbf{x} = (a, w, \beta, b)$ because heterogeneous workers will have different quit thresholds. This would then imply that market tightness θ is also a function of these states.

Unemployed's problem

The unemployed's problem remains unchanged, except that market tightness is now a function of other individual states $\mathbf{x} = (a, w, \beta, b)$ for reasons stated in the firm's problem.

B.5 Computational Algorithm

Solving the baseline model

The model is solved using the following steps:

1. Solve for the value function of the firm $J(w, p)$.
2. Using the free-entry condition $0 = -\kappa + q(\theta(w, p)) J(w, p)$ and the functional form of $q(\theta)$, we can solve for market tightness for any given wage submarket w and aggregate productivity p:
$$\theta(w, p) = q^{-1}\left(\frac{\kappa}{J(w, p)}\right),$$
where we set $\theta(w, p) = 0$ when the market is inactive.
3. Given the function θ, we can then solve for the household value functions V^W, V^{UE}, and V^{UI} using standard value function iteration. In order to decrease computation time, we implement Howard's improvement algorithm (policy-function iteration).
4. Once household policy functions are obtained, we are able to simulate aggregate dynamics of the model.

Extended model with endogenous quits

Solving the model will require modifying the baseline algorithm above as follows:

1. Guess a market tightness function $\theta_0(a', w, \beta', p')$.

2. Taking θ_0 as given, solve for the household's problem.

3. Using the household's policy function $g_d^W(\theta_0)$ and $g_a^W(\theta_0)$, solve for the firm's problem.

4. After obtaining $J_0(a, w, \beta, p)$, use Equation B.5 to back out the implied market tightness $\theta_1(a', w, \beta', p')$.

5. If convergence criterion $\| \theta_1 - \theta_0 \| \leq \epsilon_\theta$ is not satisfied, use θ_1 as a guess and repeat the steps outlined above.

Appendix C

Appendix to Chapter 3

In this appendix, we provide details on the data sources and construction of variables for our analysis in "What Do Survey Data Tell Us about U.S. Businesses?" We also include the auxiliary tables and figures omitted from the main text.

C.1 Data Sources

The main data sources are:

- Statistics of Income of the Internal Revenue Service (SOI);
- Survey of Consumer Finances of the Board of Governors of the Federal Reserve System (SCF);
- Survey of Income and Program Participation of the U.S. Census Bureau in the Department of Commerce (SIPP);
- Panel Study of Income Dynamics of the Survey Research Center, Institute for Social Research, University of Michigan (PSID);
- Current Population Survey at the Bureau of Labor Statistics (CPS);
- Center for Research in Security Prices and Compustat (CRSP);
- Pratt's Stats (now renamed as DealStats) from Business Valuation Resources.

Besides the main data sources listed above, we also use information from the national income and product accounts and fixed asset tables of the Bureau of Economic Analysis; financial accounts of the Board of Governors of the Federal Reserve System; Panel Study of Entrepreneurial Dynamics of the Survey Research Center, Institute for Social Research, University of Michigan; and the Kauffman Firm Survey of the Kauffman Foundation.

We construct business incomes and numbers of returns and owners by using variables from the IRS, SCF, SIPP, PSID, and CPS. In addition to these variables, we use BEA estimates of income misreporting by noncorporate businesses and General Accountability Office (GAO) estimates of income misreporting by S corporations to adjust IRS pass-through business income. BEA estimates of income misreporting over time are obtained from NIPA Table 7.14 (line 2). The GAO estimates are taken from reports GAO 14-453 and 10-195, which summarize the progress of the tax compliance studies conducted by the IRS through the National Research Program.

To verify the consistency of sole proprietorship income in the SCF, we compared two measures of net income from a sole proprietorship or a farm. Results of the comparison were reported in the main text. The first uses pretax net income variables (coded by X3132, X3232, and X3332) from Form 1040, Schedule C (line 31). The second is X5704, which measures net annual income from a sole proprietorship or a farm before deductions. Specifically, this variable codes responses to the question asking for combined incomes appearing on lines 12 and 18 of IRS Form 1040.

Finally, to verify whether respondents in the SCF check documents, we use variable X6536, which provides information on the frequency of checking any documents when answering interview questions. Variable X7451 informs us about whether the respondent referred to income tax documents, and variables X7452 through X7455 inform us about whether the respondent referred to other financial documents, namely, pension documents, account statements, investment or business records, and loan documents, respectively. If a respondent says that he or she checked the income tax document (X7451=1), we use his or her answers to X6536 to obtain the frequency of checking this document. The respondent did not check the income tax document if either (X7451=5 or X7451=0 or X7451=-7) or (X6536=4). We use the same steps to check referencing of other financial documents by using X7452–X7455 instead of X7451. We classify a respondent who checks at least one of these four documents as someone who refers to any other tax documents. We then obtain the weighted fraction of the group of respondents who check these two types of documents frequently, sometimes, rarely, or never. Roughly 4 percent of all respondents have nonapplicable responses (NaN). We adjust for this nonresponse rate in the results of the main text so that our fractions sum to 100 percent.

C.2 Additional Results

Next, we report on our auxiliary tables and figures that relate to our findings on business incomes, receipts, and returns.

Business income

Aggregate

In Section 3.3.1 of the main text, we discussed business income per return and the number of returns across years and legal forms. In Figure C.1, we report aggregate business incomes and show that they are overstated for all pass-through businesses. In Figure C.2, we compare the aggregate business income from the SCF with other surveys, namely, the SIPP, PSID, and CPS, and extend the analysis from Section 3.6 of the main text.

Distribution

In Section 3.3.2, we discussed the distribution of business income by splitting pass-through businesses into two categories: those that make profits and those that make losses (or no income). In Figures C.3 and C.4, we plot business income per return by legal status for those making profits and losses, respectively. In Figures C.5 and C.6, we plot the number of returns for the same sets of businesses. In Table C.1, we extend the analysis of decomposing the total percentage error into the overstatement of profits and understatement of losses. In Figure C.7, we report the distributional statistics for S corporations. As we noted in the main text, the data for S corporations are only available for limited years, namely 2003–2012, but these data show similar inconsistencies between SCF and IRS data, as was found with sole proprietorships.

Broad business income

In Figure C.8, we extend the analysis of Section 3.5.2 in the main text by replicating the analysis of Johnson and Moore (2008) for all years. As we noted in the main text, the SCF estimates are still larger in all years than the IRS counterpart even with the broader concept of income.

Business receipts

In Section 3.3.1 of the main text, we reported that business receipts per owner are overstated. In Figures C.9 and C.10, we corroborate that finding by showing aggregate business receipts and business receipts per return across legal forms and across years.

Business returns

In this section, we provide additional details for the comparison of the income yields in SCF to CRSP-Compustat, Pratt's Stats, and other surveys to augment the analysis in Section 3.4 of the main text.

In Table C.2, we provide several additional moments for the distribution of income yields in the SCF. In the main text, we showed evidence that the SCF income yields are high when compared to CRSP-Compustat or Pratt's Stats. The additional moments show that this is true regardless of year or legal structure.

In the main text, we compared the income yields for S and C corporations in the SCF to small firms in CRSP where we defined "small" as corporations that are in the bottom quintile of the size distribution as measured by the book value of total assets. In Table C.3, we extend the analysis to two alternative definitions of "small": (i) those in the bottom quintile by market value and (ii) those in the bottom quintile by gross sales. Although there are some differences in the magnitudes, the equally weighted and value-weighted yields are negative in all years, regardless of how we classify the small firms.

In Table C.4, we report income yields from Pratt's Stats for all legal forms. We see that sole proprietors have higher yields than other pass-throughs and C corporations. However, since these businesses have much smaller valuations, the value-weighted yield for all businesses is relatively low when compared to SCF data.

Finally, in Tables C.5 and C.6, we report the income yields in PSID and SIPP for all years that the data are available. As we noted in the main text, the average yields are comparable across the SCF, PSID, and SIPP, while the distributions are not. These tables more clearly demonstrate this finding.

Table C.1: SCF-IRS business income gap by legal structure

Tax	SCF-IRS	Percentage of Gap from	
Year	Gap ($)	Overstatement of Profits (%)	Understatement of Losses (%)
		Sole Proprietorship	
1988	67.09	58	42
1994	5.44	-515	615
2000	168.09	75	25
2006	91.66	29	71
2012	-28.22	359	-259
		Partnership	
1988	56.28	37	63
1994	500.59	92	8
2000	261.03	56	44
2006	724.62	83	17
2012	205.51	0	100
		S Corporation	
1988	35.78	57	43
1994	118.07	74	26
2000	206.06	78	22
2006	279.35	77	23
2012	41.06	-53	153
		C Corporation	
1994	-244.42	148	-48
2000	-57.00	670	-570
2006	-859.87	123	-23
2012	-747.36	138	-38

Note: This table shows the difference (gap) between aggregated business income by legal structure in the SCF and IRS. The gap is then decomposed into the fraction attributable to an overstatement of profits or an understatement of losses. Dollar amounts are in billions. The table shows results for every six years. See my website for the complete results.

Table C.2: Net income yields in the SCF by legal structure

	Sole Proprietorship					Partnership				
Tax Year	Value-Weighted Mean	Equally Weighted Mean	p25	p50	p75	Value-Weighted Mean	Equally Weighted Mean	p25	p50	p75
1988	19.9	105.0	3.2	20.0	80.0	13.6	111.4	0.0	8.0	50.0
1994	19.1	97.8	2.0	24.0	74.0	74.1	49.1	0.3	10.7	42.3
2000	26.6	89.8	0.9	25.5	75.0	24.5	203.1	0.1	11.9	40.0
2006	25.0	254.8	2.3	32.0	100.0	18.8	84.4	0.1	10.0	40.0
2012	24.7	87.4	0.0	23.2	82.4	11.5	36.8	0.0	5.4	33.7
	S Corporation					C Corporation				
1988	12.7	23.5	0.5	6.0	37.5	17.8	101.7	3.2	16.7	30.5
1994	14.3	38.1	0.9	11.7	40.0	28.3	73.9	0.4	8.0	41.1
2000	16.1	120.7	4.4	18.4	40.0	26.5	90.8	2.9	15.8	46.0
2006	15.4	75.1	3.8	16.7	80.0	16.3	44.4	0.0	7.5	36.0
2012	14.4	57.6	2.7	15.2	52.2	15.4	55.4	0.0	9.0	41.3
	All Pass-throughs					All Businesses				
1988	16.1	101.3	1.2	13.3	62.5	16.6	101.3	1.3	14.3	57.0
1994	32.2	80.8	1.1	20.0	64.0	31.5	80.8	1.1	19.0	62.9
2000	21.3	113.9	1.3	21.0	62.9	22.6	114.4	1.6	20.0	62.3
2006	18.4	183.7	2.0	22.0	80.0	18.1	171.7	1.6	20.0	73.3
2012	13.9	67.1	0.0	15.0	60.0	14.1	66.2	0.0	15.0	60.0

Note: This table shows moments of the net income yield distribution of businesses in the SCF by legal structure. The sample includes businesses with positive net worth and excludes the bottom 1st percentile of these businesses. The business income of each business that the family members own in the SCF is obtained from SCF variables that correspond to information on business tax forms. The table shows results for every six years. See my website for the complete results.

Table C.3: Income yield for small firms in CRSP

	by Market Capitalization					by Sales				
Tax Year	EW	VW	p25	p50	p75	EW	VW	p25	p50	p75
1988	−43.6	−27.0	−52.3	−14.3	6.1	−27.2	−8.8	−26.3	−8.6	1.1
1991	−72.9	−49.0	−72.4	−15.9	5.1	−31.7	−6.0	−23.3	−5.6	1.5
1994	−23.3	−14.2	−34.1	−4.1	9.3	−18.1	−9.2	−24.8	−6.6	4.0
1997	−29.9	−19.2	−43.2	−8.5	7.1	−21.1	−8.5	−25.4	−8.0	2.7
2000	−104.1	−71.8	−103.4	−16.4	10.4	−52.8	−12.4	−42.2	−10.7	2.2
2003	−14.2	−9.2	−21.0	−0.9	7.8	−9.5	−7.2	−15.2	−3.3	5.5
2006	−12.1	−8.1	−20.8	−0.2	7.6	−11.9	−8.6	−18.6	−5.1	4.7
2009	−65.0	−47.3	−72.4	−22.5	4.7	−32.6	−11.0	−34.6	−10.8	3.0
2012	−22.7	−12.6	−35.6	−3.8	10.4	−17.1	−5.7	−22.7	−5.4	6.7
2015	−59.6	−35.6	−55.4	−11.5	6.3	−37.6	−11.5	−35.8	−11.9	1.9
Mean	−44.7	−29.4	−51.1	−9.8	7.5	−25.9	−8.9	−26.9	−7.6	3.3

Note: This table shows estimates of income yields for small businesses in CRSP-Compustat firms.The column "EW" reports the equally weighted average, the column "VW" reports the value-weighted average, the column "p25" reports the 25th percentile, the column "p50" reports the 50th percentile, and the column "p75" reports the 75th percentile.

Table C.4: Income yield from Pratt's Stats

Legal Form	EW	VW	p25	p50	p75
Sole Proprietorship	41.3	31.6	13.3	36.7	61.5
Partnership	26.6	4.8	2.7	20.5	48.8
S Corporation	30.3	6.9	6.5	23.3	47.8
C Corporation	6.8	-2.1	-2.3	6.5	29.8

Note: This table shows estimates of income yields from the Pratt's Stats database.The column "EW" reports the equally weighted average, the column "VW" reports the value-weighted average, the column "p25" reports the 25th percentile, the column "p50" reports the 50th percentile, and the column "p75" reports the 75th percentile.

Table C.5: Net income yields of unincorporated businesses in the PSID

Tax Year	Value-Weighted Mean	Equally Weighted Mean	p25	p50	p75
1998	5.2	136.4	0.0	12.5	75.0
2000	21.7	182.4	0.0	7.5	73.3
2002	21.8	187.0	0.0	33.3	139.5
2004	22.2	287.7	3.9	36.9	140.0
2006	20.6	630.1	10.0	42.5	222.2
2008	10.9	175.8	2.7	28.8	125.0
2010	13.9	110.3	3.9	25.0	75.9
2012	10.7	90.8	3.3	23.0	83.3
2014	6.9	182.9	4.8	33.3	100.0
Mean	14.9	220.4	3.2	27.0	114.9

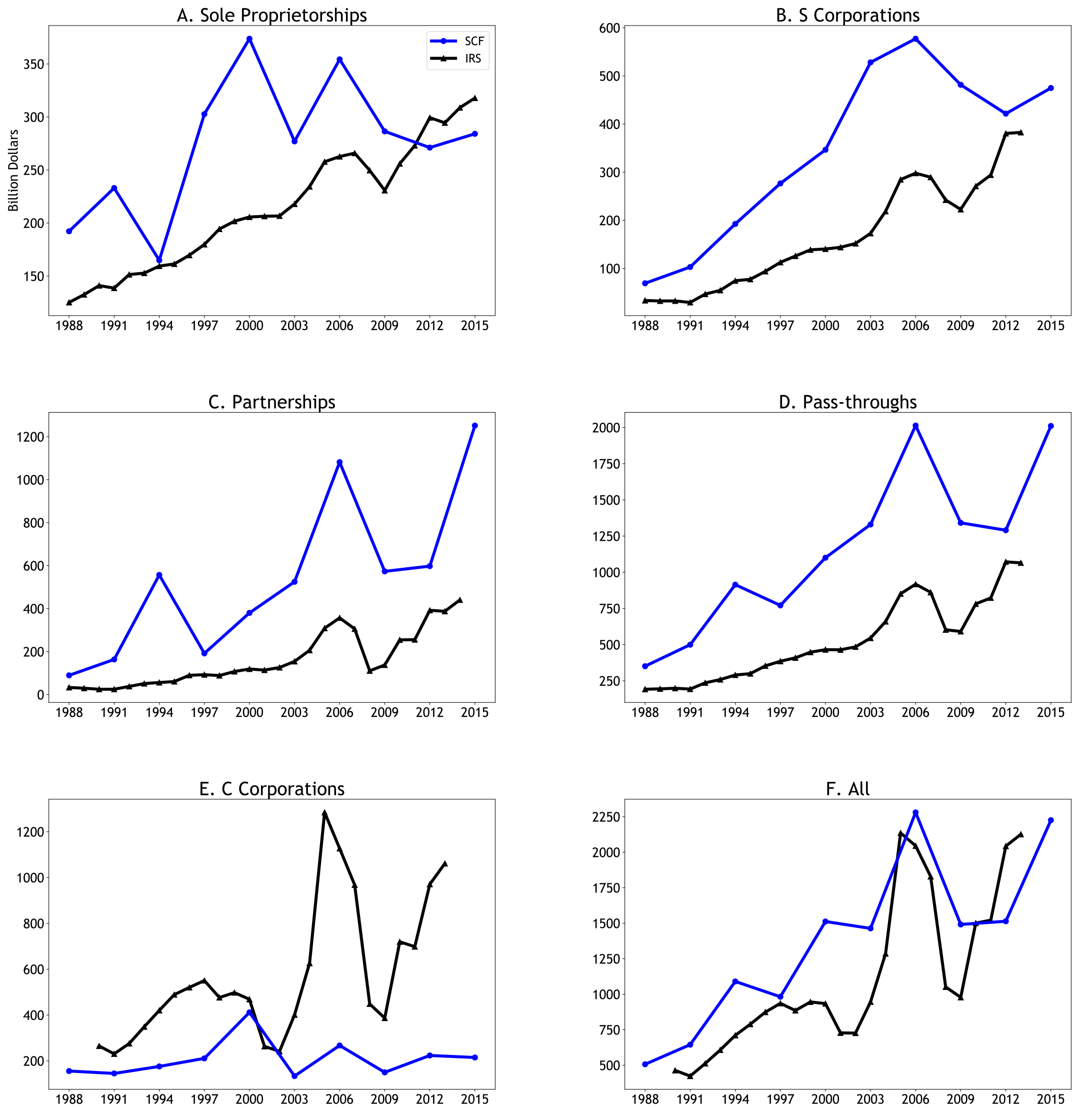
Note: This table shows moments of the net income yield distribution of unincorporated businesses in the PSID. The sample includes businesses with positive net worth and excludes the bottom 1st percentile of these businesses.

Table C.6: Net income yields in the SIPP

Tax Year	Value-Weighted Mean	Equally Weighted Mean	p25	p50	p75
		Sole Proprietorship			
2004	20.2	545.0	6.8	44.8	240.0
2005	19.4	727.7	4.5	41.2	240.0
2009	13.0	3043.1	0.2	24.0	203.3
2010	15.8	5916.6	0.2	31.0	240.0
2011	14.9	8878.2	0.5	29.2	188.0
Mean	16.7	3822.1	2.4	34.0	222.3
		Partnership			
2004	25.1	605.9	0.6	29.2	220.0
2005	19.9	1271.2	0.3	22.6	189.1
2009	17.4	853.4	0.0	7.4	108.0
2010	21.3	2128.0	0.0	22.5	204.0
2011	18.9	1551.7	0.0	11.8	190.7
Mean	20.5	1282.0	0.2	18.7	182.4
		Unincorporated			
2004	22.0	2936.2	6.4	45.7	260.0
2005	19.8	12590.7	4.0	40.4	250.0
2009	14.0	15353.1	0.1	22.5	202.5
2010	17.2	38737.5	0.1	30.8	240.0
2011	15.3	7971.4	0.3	26.7	197.8
Mean	17.6	15517.8	2.2	33.2	230.1

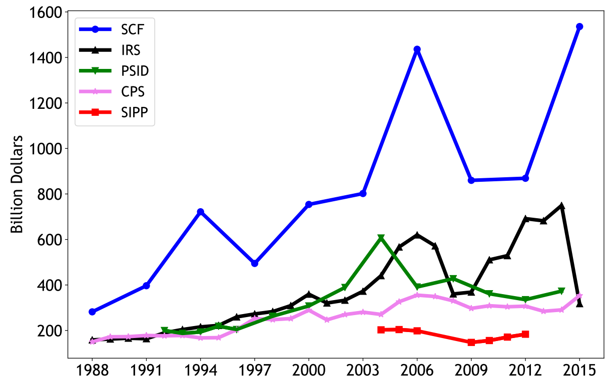
Note: This table shows moments of the net income yield distribution of sole proprietorships, partnerships, and unincorporated businesses in the SIPP 2004 and 2008 panels. Statistics are calculated for years where asset topical modules are available. The sample includes businesses with positive net worth and excludes the bottom 1st percentile of these businesses.

Figure C.1: Business income by legal status, SCF vs. IRS



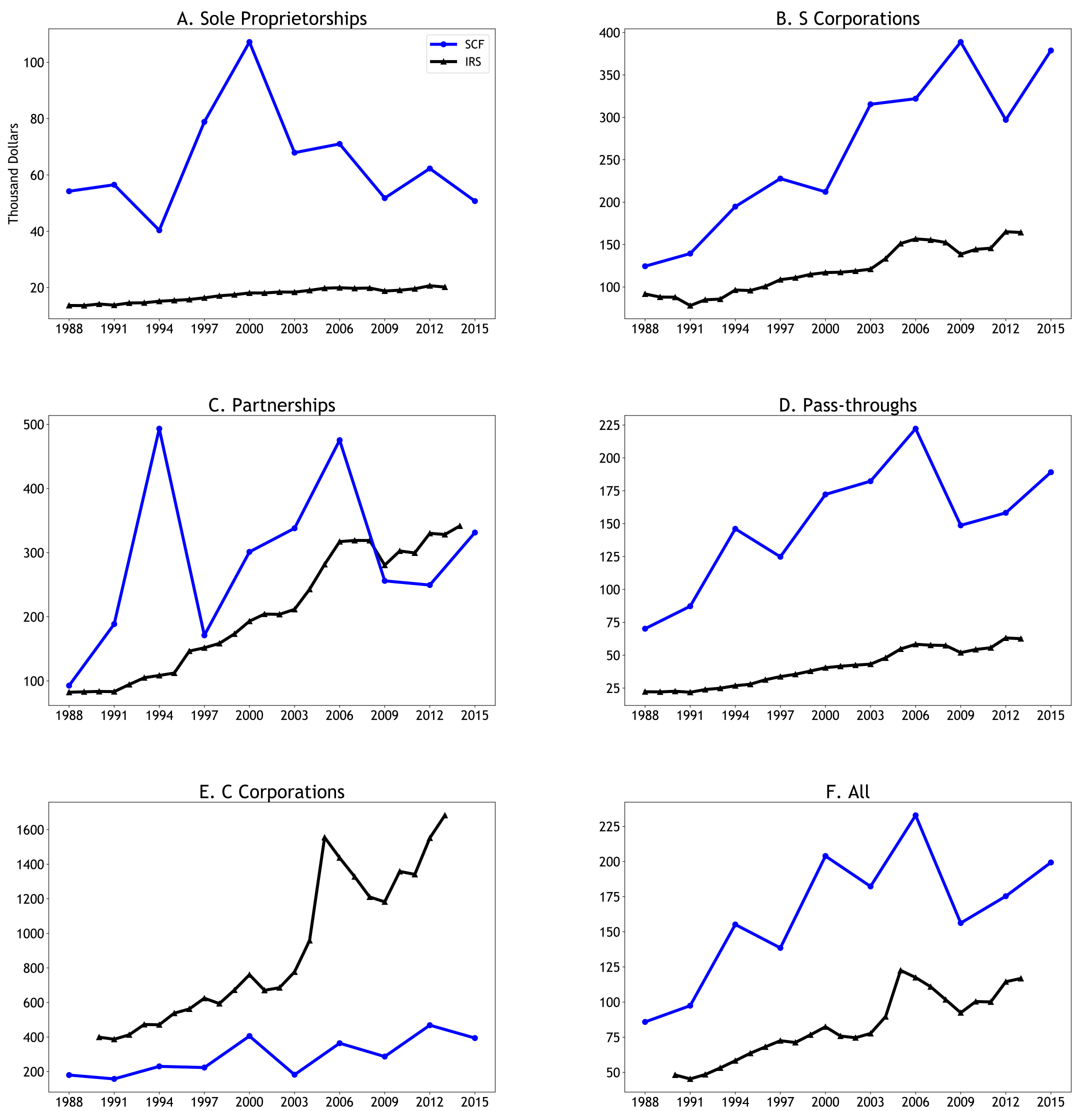
Note: This figure plots the total business income by legal status in the SCF and the IRS. Business income refers to income reported on Form 1040 Schedule C for sole proprietorships, Form 1065 for partnerships, Form 1120S for S corporations, and Form 1120 for C corporations. IRS data for partnerships, S corporations, and C corporations are available only until 2013, and C-corporation data start from 1990 because data for Form 1120 are not available for 1988 and 1989.

Figure C.2: Total unincorporated business income in SCF, SIPP, PSID, and CPS vs. IRS



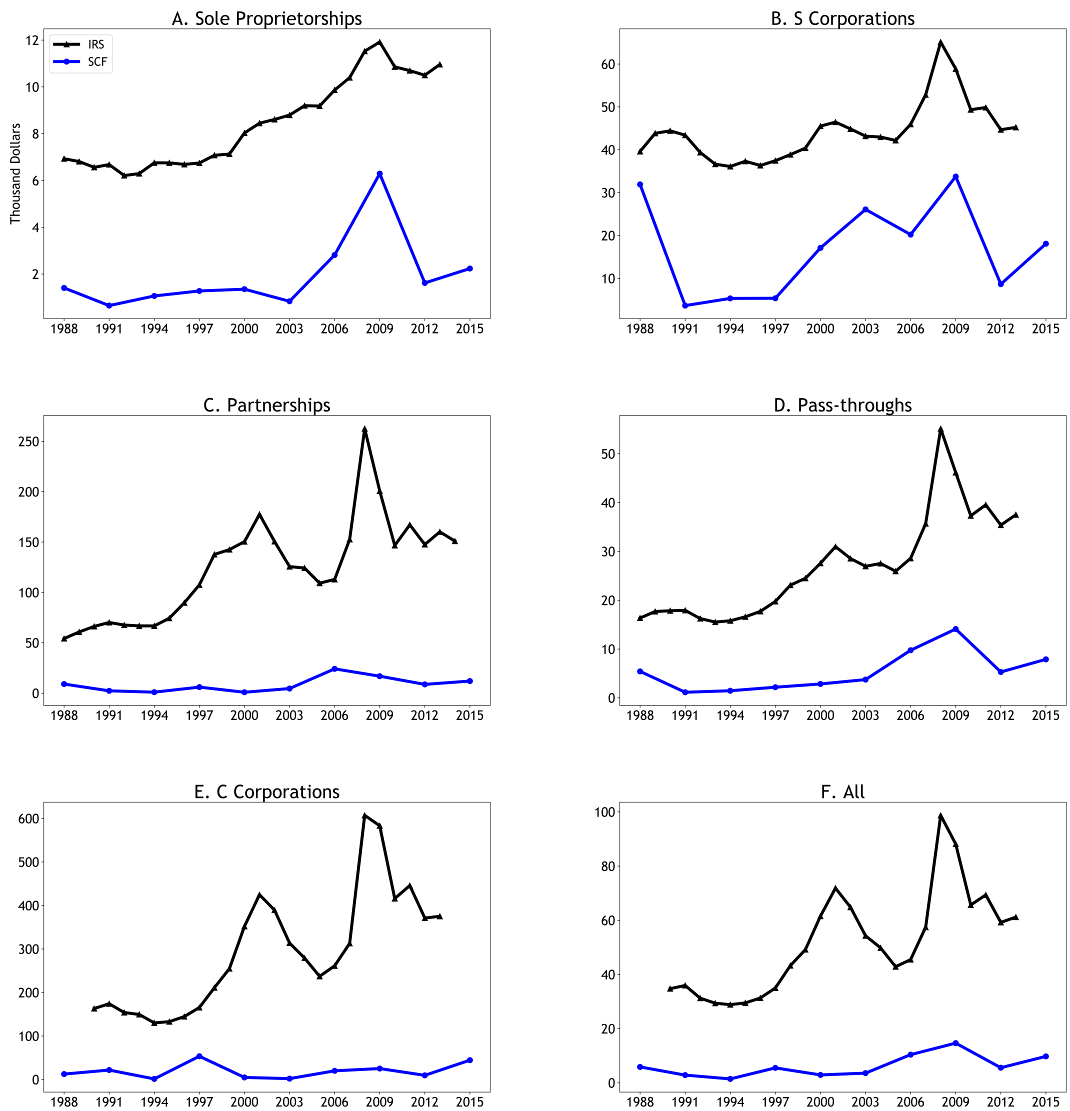
Note: This figure plots the total business income of unincorporated businesses in the SCF, SIPP, PSID, CPS, and IRS. Before 2004, the SIPP does not provide information about an individual's own share of business income from an unincorporated business. Instead, it contains information about the total income of the business, which is not enough information to calculate the total business income of unincorporated businesses.

Figure C.3: Business income per tax return by legal status for businesses with net income, SCF vs. IRS



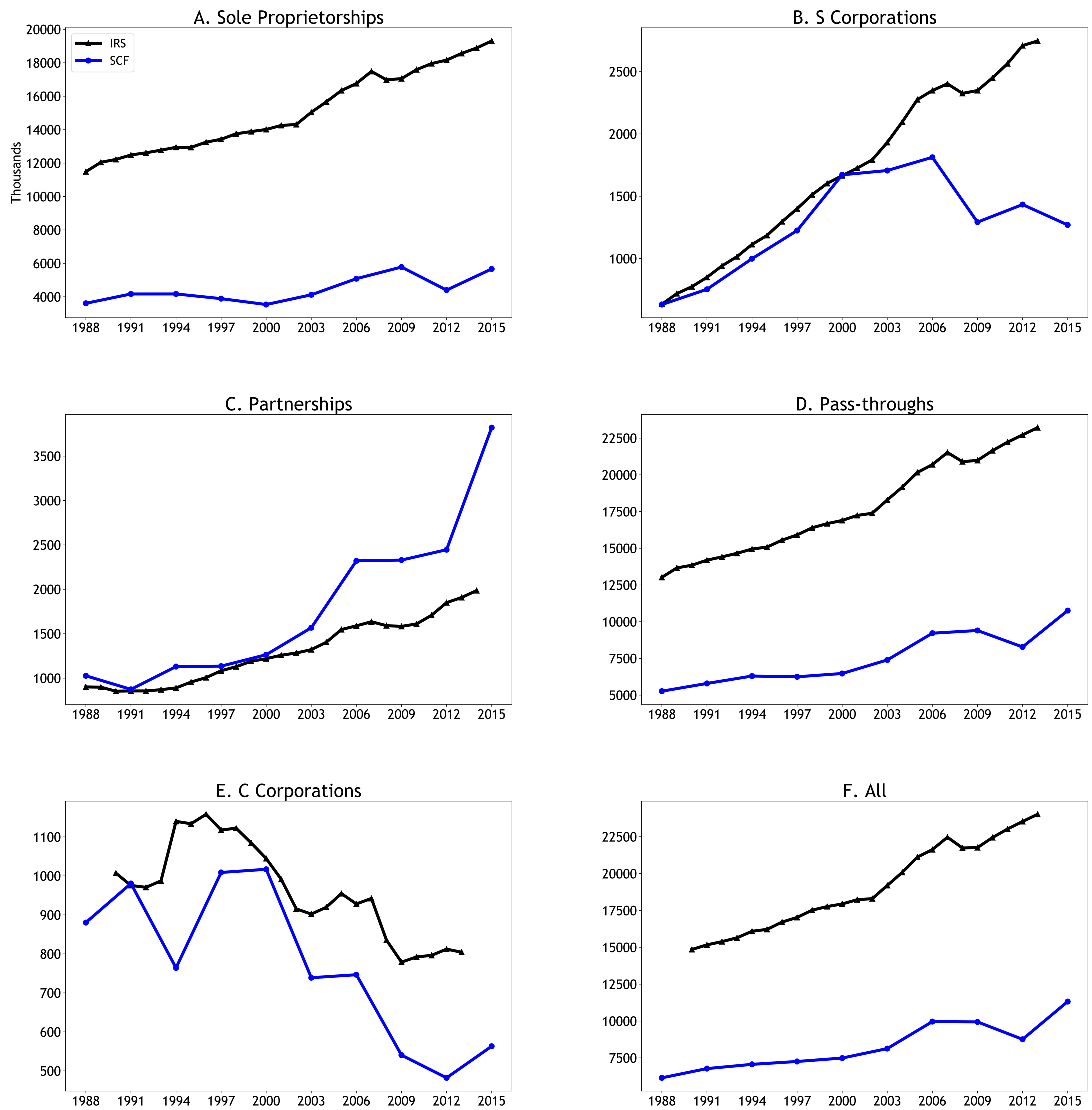
Note: This figure plots the business income per tax return by legal status for businesses with net income in the SCF and IRS. Business income refers to income reported on Form 1040 Schedule C for sole proprietorships, Form 1065 for partnerships, Form 1120S for S corporations, and Form 1120 for C corporations. IRS data for sole proprietorships, partnerships, S corporations, and C corporations are available only until 2013, and C-corporation data start from 1990 because data for Form 1120 are not available for 1988 and 1989.

Figure C.4: Business income per tax return by legal status for businesses with net loss, SCF vs. IRS



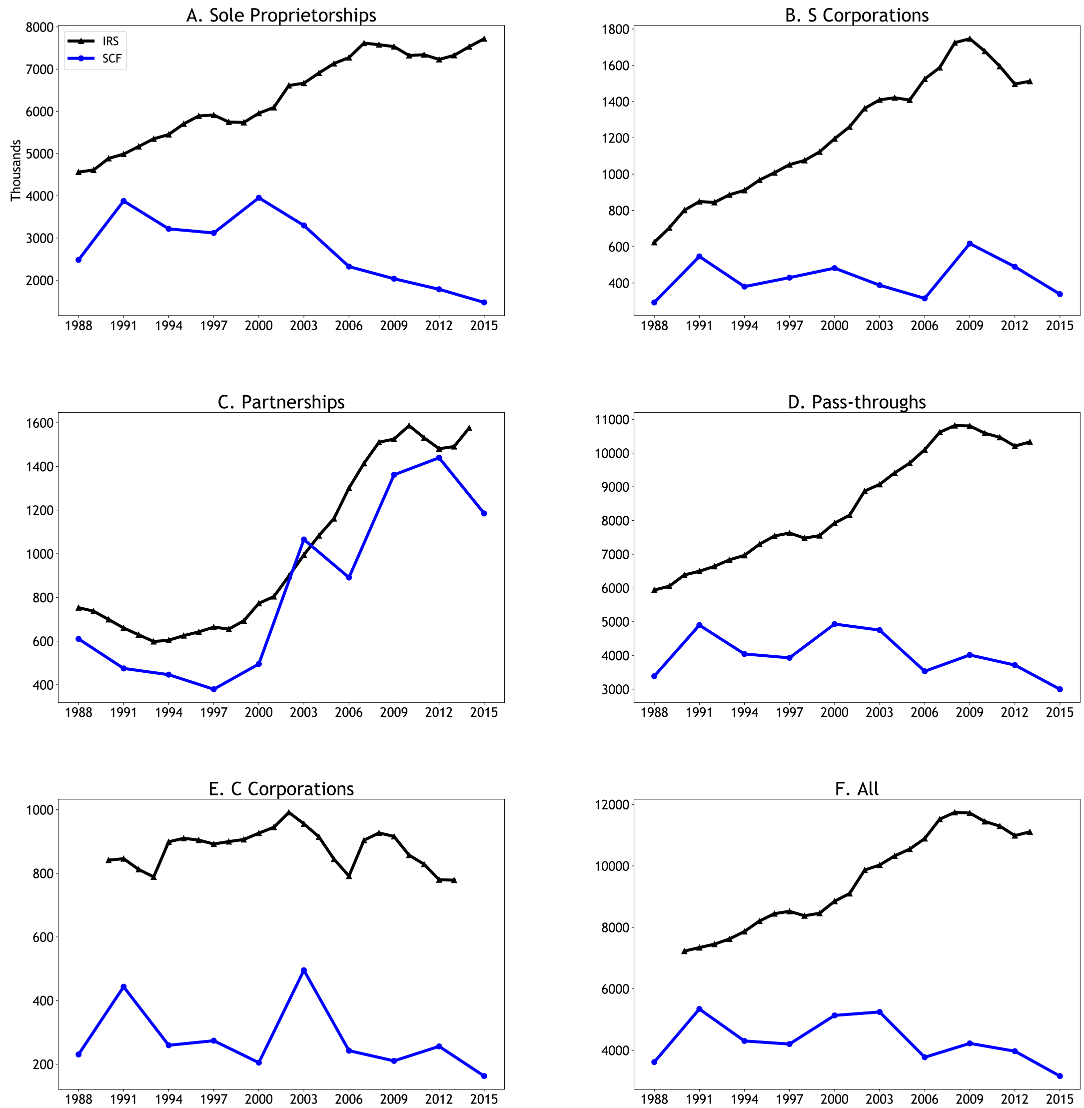
Note: This figure plots the business income per tax return by legal status for businesses with net loss in the SCF and IRS. Business income refers to income reported on Form 1040 Schedule C for sole proprietorships, Form 1065 for partnerships, Form 1120S for S corporations, and Form 1120 for C corporations. IRS data for sole proprietorships, partnerships, S corporations, and C corporations are available only until 2013, and C-corporation data start from 1990 because data for Form 1120 are not available for 1988 and 1989. Businesses with zero net income are included with those that have net losses.

Figure C.5: Number of returns by legal status for businesses with net income, SCF vs. IRS



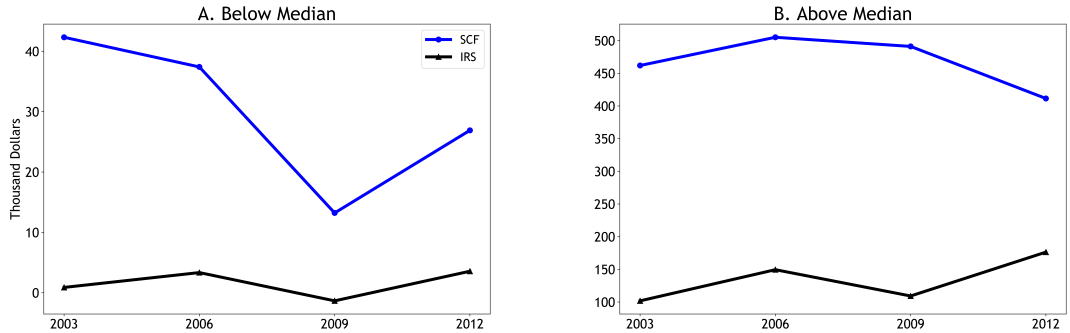
Note: This figure plots the number of business tax returns by legal status for business with net income in the SCF and the IRS. Business income refers to income reported on Form 1040 Schedule C for sole proprietorships, Form 1065 for partnerships, Form 1120S for S corporations, and Form 1120 for C corporations. IRS data for sole proprietorships, partnerships, S corporations, and C corporations are available only until 2013, and C corporations data starts from 1990 because data for Form 1120 is not available for 1988 and 1989.

Figure C.6: Number of returns by legal status for businesses with net loss, SCF vs. IRS



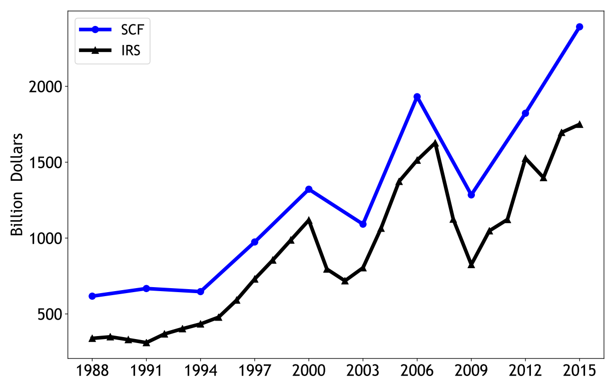
Note: This figure plots the number of business tax returns by legal status for businesses with net loss in the SCF and IRS. Business income refers to income reported on Form 1040 Schedule C for sole proprietorships, Form 1065 for partnerships, Form 1120S for S corporations, and Form 1120 for C corporations. IRS data for sole proprietorships, partnerships, S corporations, and C corporations are available only until 2013, and C- corporation data start from 1990 because data for Form 1120 are not available for 1988 and 1989. Businesses with zero net income are included with those that have net losses.

Figure C.7: Distribution of S-Corporation business income per return, SCF vs. IRS



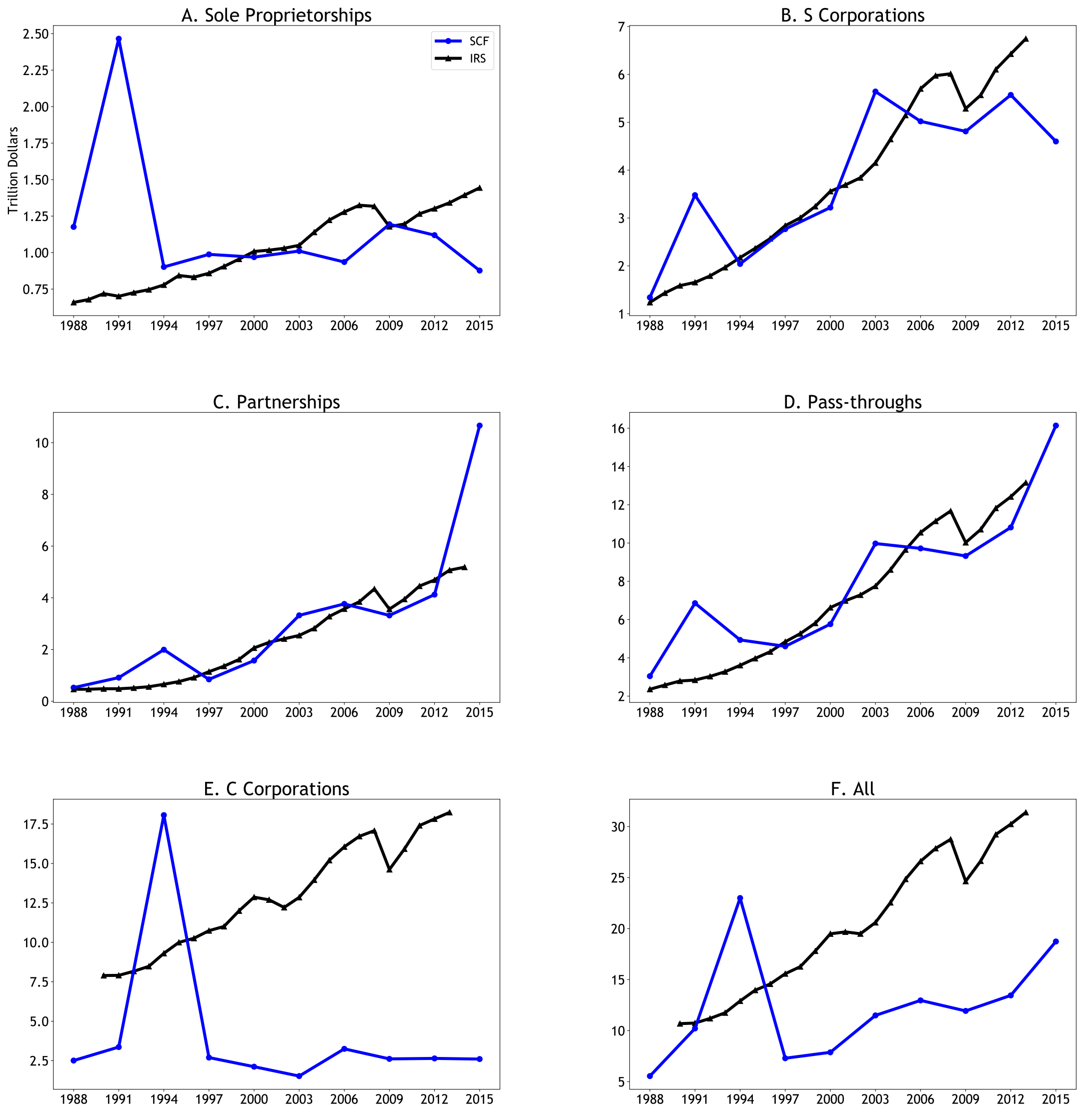
Note: This figure plots S-corporation business income per return for those with below- and above-median business receipts.

Figure C.8: Broad business income, SCF vs. IRS



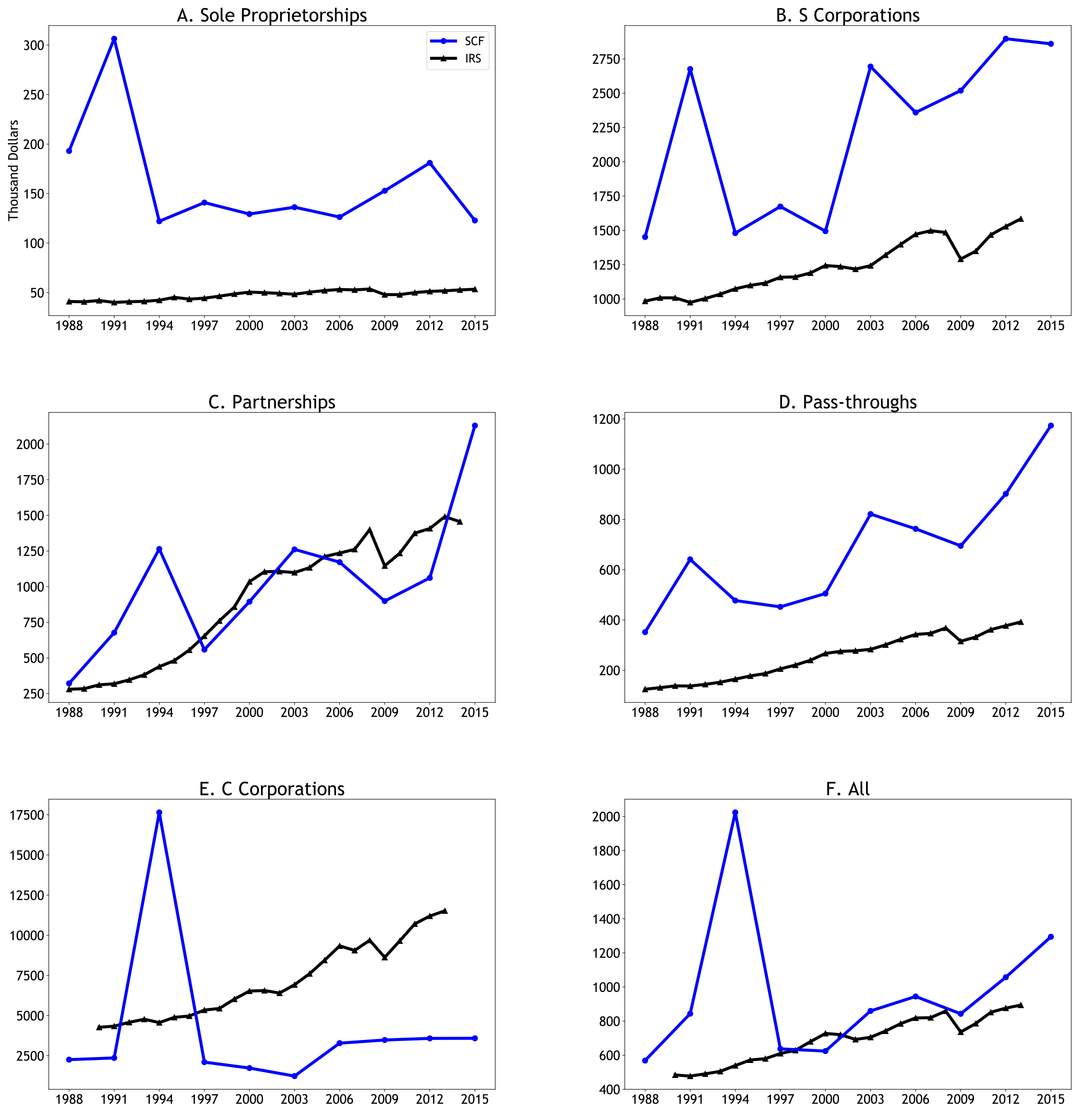
Note: This figure compares a broader measure of business income in the SCF and IRS. Broad business income is defined to be income derived from a business or profession (Form 1040 Schedule C) or farm (Form 1040 Schedule F); income from rental real estate, royalties, partnerships, S corporations, estates, trusts (Form 1040 Schedule E); and income from gains from the sale of capital and other property (Form 1040, lines 13 and 14).

Figure C.9: Business receipts by legal status, SCF vs. IRS



Note: This figure plots the total business receipts by legal status in the SCF and IRS. Business receipts refers to gross sales reported on Form 1040 Schedule C for sole proprietorships, Form 1065 for partnerships, Form 1120S for S corporations, and Form 1120 for C corporations. IRS data for partnerships, S corporations, and C corporations are available only until 2013, and C-corporation data start from 1990 because data for Form 1120 are not available for 1988 and 1989.

Figure C.10: Business receipts per tax return by legal status, SCF vs. IRS



Note: This figure plots the business receipts per tax return by legal status in the SCF and IRS. Business receipts refers to gross sales reported on Form 1040 Schedule C for sole proprietorships, Form 1065 for partnerships, Form 1120S for S corporations, and Form 1120 for C corporations. IRS data for partnerships, S corporations, and C corporations are available only until 2013, and C-corporation data start from 1990 because data for Form 1120 are not available for 1988 and 1989.