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Dedication

To my parents, Hua Wu and Renrong Gu.

Abstract

This dissertation consists of three chapters. In the first, I perform an empirical analysis of China's college expansion policy. First, I estimate the impact of a substantial increase in the college-educated labor supply on the college wage premium. I find that the return to college education is stable within a decade after college expansion. Second, I investigate how college expansion has affected pre-college education expenditure on children and their educational outcomes. The main finding is that the magnitude of the effect depends crucially on parents' socioeconomic backgrounds.

In the second chapter, I quantitatively evaluate how China's public college expansion program impacts human capital investment in children and inequality in the long run. To this end, I introduce a heterogeneous-agent overlapping-generations model in which altruistic parents invest in their children's pre-college education, which can raise their children's future working efficiency and their chance of passing the College Entrance Examination. I find that the increases in college attainment, human capital, and ex ante welfare are substantial but unevenly distributed, with disadvantaged children benefiting the least from the existing policy. The simulation also reveals that the reason for the unequal outcomes is that college expansion primarily incentivizes wealthy parents to spend more on their children's education, which is consistent with the empirical evidence.

Finally, the third chapter (joint with Lichen Zhang) studies the driving forces behind the decline in the formation of new businesses in the U.S. since the 1980s and investigates their macroeconomic implications. We devote our attention to two forces: changes in entry costs and the persistence of shocks to productivity. We develop a quantitative general equilibrium model of entrepreneurship to identify and quantify their relative importance in explaining the observed declines in new business creation. We find that the relative contribution of higher entry cost is 1.5 to 2 times larger than that of the higher persistence of shocks. Moreover, the increases in entry cost have compelled entrepreneurs to pay 15% more in terms of their first year's profit to start a business.

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Chapter 1

An Empirical Analysis of College Expansion Policies in China

1.1 Introduction

Since 1999, China has implemented a large-scale public college expansion program. This policy has led to an additional three million students passing the College Entrance Examination and attending four-year colleges every year. From 1998 to 2015, the enrollment of new undergraduate students grew by 11% annually, from 0.65 million in 1998 to 3.89 million in 2015. Meanwhile, the college admission rate also rose dramatically, which suggests that the exam is less selective than before. In 1998, only about 20% of exam takers could enroll in a four-year college, and the rate has doubled in recent years.

This chapter first demonstrates that college expansion has substantially increased college enrollment, which due not only to a higher admission rate, but also to the higher rate of taking the entrance exam. Specifically, 62% took the exam at age 18 in 2015, which is 45% higher than two decades earlier. Moreover, a direct consequence of a large-scale increase in college capacity is that younger cohorts have a significantly higher college attainment rate than older groups.

Next, I empirically analyze the labor market effect of college expansion. In particular, I focus on estimating changes in the college wage premium, because it is unclear whether a sizable rise in the college-educated labor supply has caused a decline in returns to education in China. I find that although millions of college graduates have entered the labor force since college expansion, the college wage premium was stable until 2009. This suggests that the technological progress that favors college graduates on the demand side has mitigated the change on the supply side. However, survey data collected in 2013 show that the college wage premium has moderately declined. Therefore, newer versions of survey data are required to determine whether we have witnessed a turning point.

Finally, using household-level survey data, I investigate how college expansion has affected pre-college education expenditure on children and their educational outcomes. In particular, I focus on understanding their relationship with parental characteristics, including income and education background. The main findings are summarized as follows. (1) Pre-college education expenditure increased by 38% during 2002-2009, but the share of education expenditure in household income declined during this period. (2) Education investment in children is associated with their parents' socioeconomic background, and the gap in education expenditure between parent groups (rich vs. poor and college-educated vs. non-college-educated) became larger during 2002-2009. (3) The share of education expenditure in household income increases in children's age, and household income has a stronger effect on education expenditure on children during early childhood. (4) Children of high-income and college-educated parents are more likely to attend four-year colleges. (5) After college expansion, there is a substantial but unequal increase in education expenditure and in children's college attainment across parent socioeconomic groups, with disadvantaged children benefiting least from the policy.

Related Literature. This chapter contributes to the empirical literature that examines the impact of college expansion and the college admission system in China. Zhang, Zhao, Park, and Song (2005) document a dramatic increase in return to education and college wage premium prior to the college expansion policy in China. Li, Whalley, and Xing (2014) examine the short-run labor market outcomes of college expansion and find that it increased the unemployment rate for young college graduates. Ge and Yang (2014) document the changes in China's wage structure and estimate the labor market effects of the upsurge in educational attainment. Meng (2012) review the labor market outcomes of various reform implemented in China. Jia and Li (2016) find that access to elite education through the College Entrance Examination does not guarantee one's entry into the elite class, or alter the intergenerational link between parents' status and children's status. Lee and Malin (2013) quantify a novel channel through which expanded access to higher education can reduce labor market friction in China.

The novel aspect of my empirical analysis is that I demonstrate a connection between the college expansion policy and household education expenditure on children, which is absent in the related literature. This finding is crucial, because both the accessibility of higher education and the college return play essential roles in pre-college educational investment. Furthermore, early childhood human capital investment, which shapes children's ability and influences their educational attainment, has an endogenous impact on inequality, intergenerational mobility, and social welfare.

The rest of the chapter is organized as follows. Section 1.2 introduces the institutional background of China's higher education system and its college expansion program. Section 1.3 presents the empirical evidence on China's college-educated labor supply and college wage premium. Section 1.4 documents the effect of college expansion on education expenditure on children and their educational outcomes and examines the connection with parental socioeconomic background. Section 1.5 concludes.

1.2 Institutional Background

This section briefly introduces the institutional background of China's college system, selection mechanism, and education reform. The main purpose is to motivate the empirical investigation on the effect of college expansion on labor market and educational investment on children.

Higher education system and types of college. In 2015, the total number of Chinese national higher institutions was 2,845, most of which were funded by the government. Private universities in China are a complement to public universities to meet the needs of those students who failed in their College Entrance Examination but could not afford the tuition fees to study abroad.

Students are sorted into different public universities through the college entrance exam. The public university has two tiers: regular university (four-year college), and vocational college (three-year college). Test takers are required to receive much higher scores on the exam to attend regular universities. This feature suggests that, other things held constant, parents have to spend more on their children's education to make children more likely to enter a four-year college. As a result, skill accumulation plays a more crucial role in determining the four-year college admission probability.[1] Zhang, Zhao, Park, and Song (2005) estimate that the return to completing vocational college relative to high-school graduates was 17.8% in 2001, whereas regular university graduates earned 37.3% more than high-school graduates. This evidence suggests that an individual's labor market result can be very different if they attend a four-year, rather than a three-year college.

College Entrance Examination. The National College Entrance Examination is a standardized test taken by high-school graduates who want to pursue their undergraduate studies at college. This exam is uniformly designed by the Ministry of Education of China based on the curriculum of (senior) high school and is held annually in summer. Since the test is knowledge-based and highly selective, students normally spend their entire high-school years to prepare for the exam.[2] All of the students take tests on Chinese, English, and mathematics. In addition, students choose between two concentrations, either the social science-oriented area or the natural science-oriented area.

College admission entirely depends on students' performance on the College Entrance Examination. Students are required to apply for their intended university prior to the exam. The authority will announce official cutoff scores for universities

[1] In recent years, the total college admission rate (including both three- and four-year colleges) in China has been as high as 80%, whereas the admission rate of four-year colleges has been only 40%. Therefore, whether or not one can attend college indicates more about her education choice, but whether or not one can attend the four-year college indicates more about her skill level.

[2] Since high-school education mainly serves as a mechanism to select college students, it does not teach students much practical knowledge for working. That is why Li, Liu, and Zhang (2012) estimate that the return to high-school education is low in China.

in different tiers after all the exams have been graded. Each university also announces a cutoff score (must be higher than the official cutoff) based on the number of applicants and vacancies. If a student's test score can make the official cutoff, as well as the cutoff of the university to which they applied, they will be enrolled in that institution. Although students can apply for several universities by filling a list of ordered preferences, many good institutions only admit students who apply to it as their first choice, which means a student with a test score higher than the official cutoff may end up failing in the test[3] if they cannot make their first-choice university's cutoff.

College expansion. The four-year college admission rate in 1998 was 20.4%. In 1999, the Chinese government suddenly announced its first-wave college expansion plan, and the admission rate dramatically increased to 32.5%.[4] The second wave college expansion is conducted in the late 2000s, which ultimately raises the admission rate of four-year college to around 40%.

Throughout the last two decades, college capacity has been continuously expanding in China. From 1998 to 2015, the enrollment of new undergraduate students grew by 11.1% annually, increasing from 0.65 million in 1998 to 3.89 million in 2015. In recent years, the government has begun to control the rapid expansion of college education.

1.3 College Enrollment and the Wage Premium

This section presents the main results of the paper. First, I empirically illustrate how college expansion has affected China's college enrollment and college-educated labor supply. Second, I estimate changes in the college wage premium since college expansion.

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[3]Because this paper defines college as a four-year institution (regular university), attending a three-year college (vocational college) is also considered failing the test.

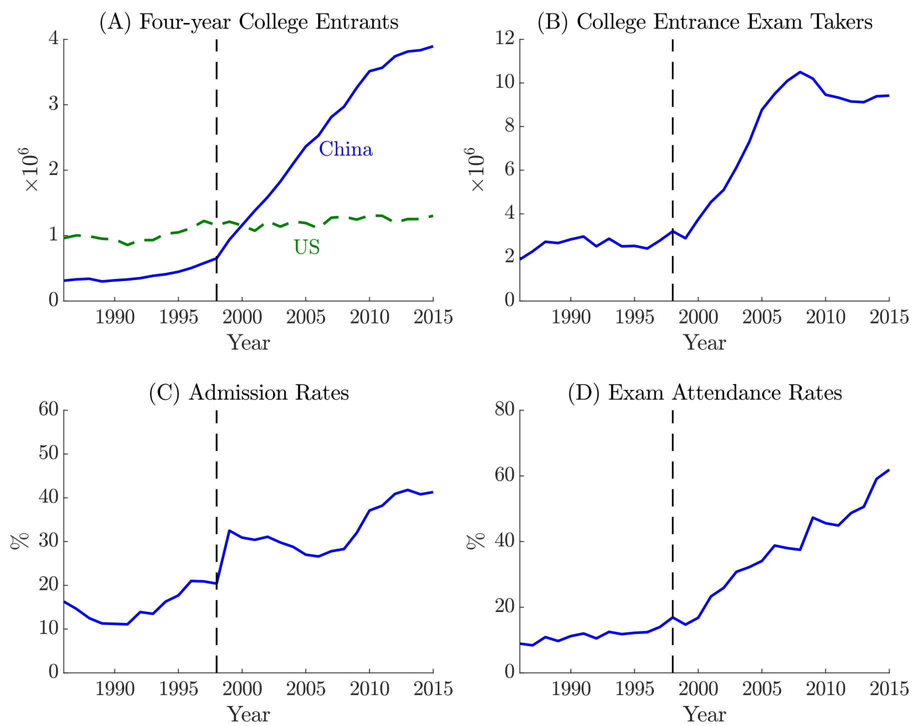
[4]The policy was announced just four months before the exam, but the exam preparation takes years. Hence, the policy did not boost the number of exam takers.

1.3.1 College Enrollment

In this subsection, I provide two sets of empirical evidence to demonstrate how college expansion has affected college enrollment and the college-educated labor supply. First, I show that both the number of entrants to four-year colleges and the number of College Entrance Examination takers have substantially increased since 1999. Second, I show that younger cohorts have a significantly higher college attainment rate than older cohorts, due to the expansion in college capacity over the last two decades.

College admission and exam attendance. To identify the effect of the college expansion policy on education choice and college capacity, I examine aggregate educational statistics that report exam attendance and college admission over three decades.

Figure 1.1: Four-year College Admission and Exam Attendance



Note: Data source: various issues of China Statistical Yearbook and Educational Statistical Yearbook of China.

As shown in Figure 1.1 (A), the college expansion policy has led to an additional 3 million students passing the College Entrance Examination and attending four-year colleges every year, and the annual number of college entrants rose from 30% to 300% of its U.S. counterpart. Figure 1.1 (B) shows that the number of exam takers has dramatically increased since the early 2000s, and Figure 1.1 (D) shows that the exam attendance rate rises from 17% to 62%. This demonstrates that an increasing fraction of high school graduates prefers going to college over immediately entering the labor force.[5]

Figure 1.1 (C) shows that immediately following the announcement of college expansion in 1999, the four-year college admission rate increased by about twelve percentage points. However, due to the rapid increase of exam takers, the admission rate fell gradually to 27% in 2006. As a result of the second wave of the college expansion policy, in recent years, the admission rates are stable around 40%.

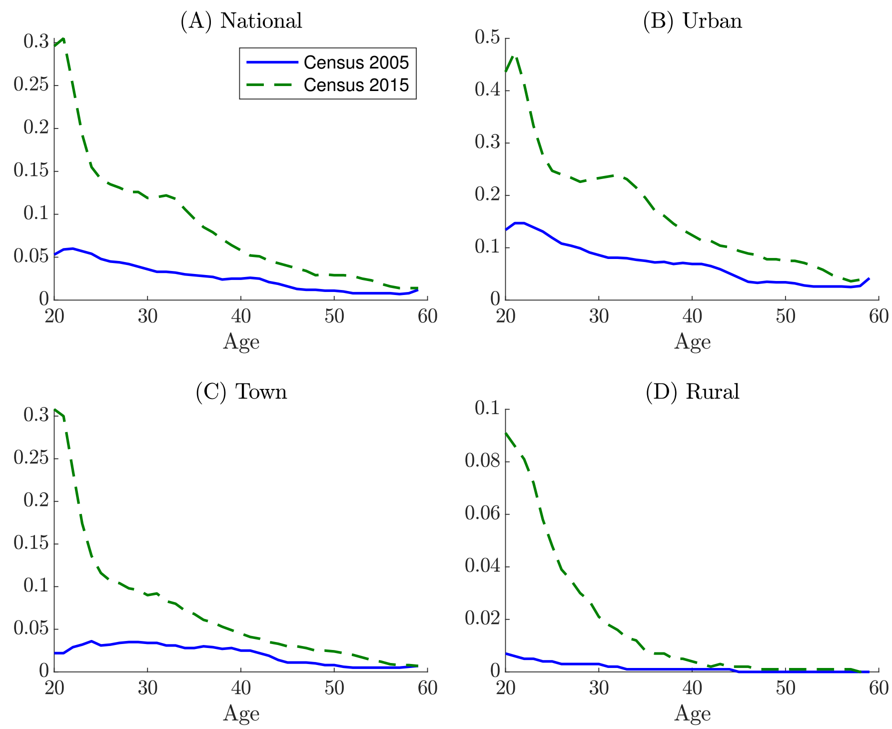
College attainment by age. An immediate consequence of college expansion is that younger cohorts have a substantially higher four-year college attainment rate than older groups. Figure 1.2 plots college attainment rates against age cohort. The data come from two mini censuses (the 1% Population Survey) conducted by the National Bureau of Statistics of China in 2005 and 2015.

As shown in Figure 1.3 (A), at the national level, the four-year college attainment rate of individuals at age 20 increased from 5% to 30% within a decade. This suggests that over half of the college attainment rate's rise is the result of the second wave of college expansion since the late 2000s.

It is also notable that the college attainment rate varies significantly across urban and rural areas, as shown in Figures 1.2 (B), (C), and (D). Here, I provide three potential explanations for the phenomenon, although which plays the most critical role is an open question. First, students from urban areas have greater access to high-quality education resources, which helps them perform a better outcome on the College Entrance Examination. Second, college education is more valuable and affordable for students (also for their parents) from urban areas, which can influence their

[5]As indicated in Section 1.2, since the college entrance examination is a knowledge-based test, attending the exam suggests that the college is both optimal and affordable for an individual.

Figure 1.2: Four-year College Attainment Rates by Age (2005-2015)



Note: Data source: 1% Population Survey (2005, 2015).

college choices. Third, a large number of rural students, after completing their college education, move to urban areas, where more jobs and entrepreneurial opportunities are available.

1.3.2 The College Wage Premium

I use three datasets to estimate China's college wage premium. The Urban Household Survey (UHS) collects household information for eight consecutive years from 2002 to 2009.[6] However, it may not fully reveal the labor market effect of college expansion, because only a few cohorts of college graduates (who took the exam after 1999) had entered the labor force in 2009. The Chinese Household Income Project (CHIP) collects individuals' information from 1999 to 2013. However, the survey is only conducted every 3 or 5 years. Additionally, the UHS and CHIP only include households in several representative provinces or cities in China. The 1% Population Survey (2005) contains information about demographic characteristics and income for over ten million individuals living in all provinces. However, the information on income is omitted in a similar survey conducted in 2015, which makes it impossible to track changes in the college wage premium.

Given each dataset's strengths and weaknesses, I validate my estimation of the college wage premium using the following strategy. The estimation obtained from the UHS will be considered to be the baseline. Then, I check whether the estimates obtained from the 2002, 2007, and 2008 waves of the CHIP are consistent with those from the UHS. If so, the estimate produced by CHIP2013 will be informative. Moreover, results from the two small-sample surveys (the UHS and the CHIP) can be validated if the large-sample survey (the 1% Population Survey) yields a similar result.

Let $w_{e,j}$ be the annual wage of individual with education level e and age j . For each observed year, I run an ordinary least-squares regression of wages on a college education dummy (e), and a cubic polynomial in potential experience (age minus

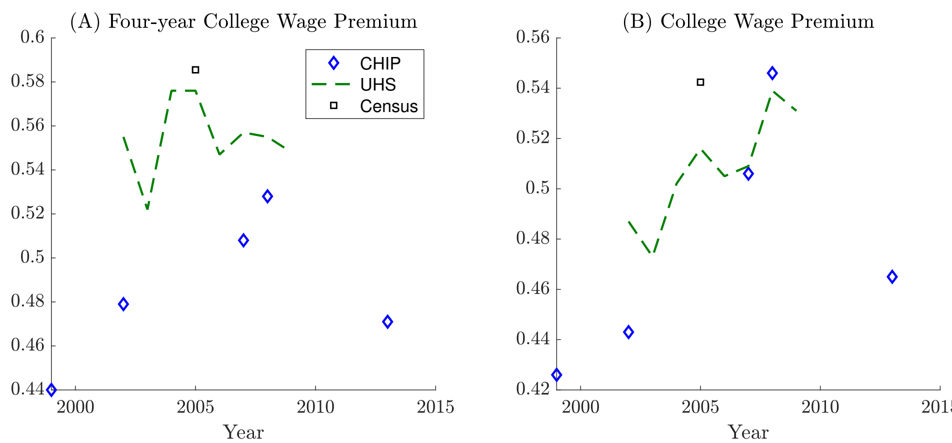
[6] I do not have access to earlier waves since UHS is a restricted dataset. The rotating structure of the UHS enables the construction of a two or three-year panel. One can also treat the UHS as a repeated cross-section survey. Ding and He (2018) discuss more details about UHS's design.

years of education minus 6) $L(j)$:

$$log(w_{e,j}) = \beta_0 + \beta_1 e + L(j) + \epsilon,$$

where ϵ is an error term.[7] In this specification, the regression coefficient β_1 captures the college wage premium. Notice that I separately check the case in which college is defined as: (1) a four-year institution or (2) both three-year and four-year institutions.

Figure 1.3: The College Wage Premium since College Expansion



Note: Data source: UHS (2002-2009), CHIP (1999, 2002, 2007, 2008, 2013), and 1% Population Survey (2005).

The main findings are displayed in Figure 1.3. Panel (A) shows that the four-year college wage premium calculated from the UHS over 2002-2009 is stable around 0.55, and Panel (B) shows that the (three-year and four-year) college wage premium over the same period moderately increases from 0.48 to 0.53. The four-year college wage premium produced by the CHIP is slightly lower than that of the UHS, but the three-year college wage premium is very close. In addition, the 1% Population Survey yields a higher college wage premium in 2005 than the UHS, but the magnitude of the difference is small.

[7] I also add a province dummy and a gender dummy to control individual's idiosyncratic characteristics.

Next, I summarize the main implications of the empirical estimation. First, even though millions of college graduates have entered the labor force since college expansion, the college wage premium does not move much until 2009. This suggests that there is a technological change on the demand side that accompanies an increase in the supply of college-educated labor, which substantially increases the job vacancies for college graduates. Second, the estimate from CHIP2013 shows that the college wage premium moderately declines. However, in order to check whether the second wave of college expansion has led to a significant fall in the college wage premium, I would need access to newer versions of the UHS or CHIP, which are temporarily unavailable.

1.4 Education Expenditure and Outcomes

From 2002 to 2009, the UHS collected detailed information about individual and household income, consumption expenditure (including education expenditure), and demographic characteristics. I have access to the portion that covers nine provinces, representing over 14,000 households and 60,000 individuals per year.

With the UHS, I can examine how pre-college household education expenditure on children depends on the parents' characteristics (e.g., income and education level) and children's developmental stages. These sets of evidence are helpful in identifying the patterns of Chinese households' early-childhood educational investment, as well as constructing moments for estimating the skill formation technology. Unfortunately, the UHS's rotating structure does not allow me to track human capital investment on children and their education outcomes over a long period. However, it does allow me to observe children's terminal education attainments and their respective parents' income and education levels, which can be informative for empirical analysis.

1.4.1 The Aggregate Impact of College Expansion

Table 1.1 summarizes statistics related to changes in household income, education expenditure, and education attainment from 2002 to 2009. I restrict the sample to households with one child, since this is the most common family structure for urban

Chinese households. All of the following results are robust if I relax this restriction. For details on sample selection, see Appendix A.1.

Table 1.1: Descriptive Statistics (UHS)

Variable	2002	2009
Education expenditure (RMB)		
All households	1,345	1,575
All with positive expenditure	1,996	2,747
Disposable income (RMB)		
Households, all	22,334	42,038
Households, tercile 1	10,408	18,619
Households, tercile 2	19,078	35,244
Households, tercile 3	37,518	72,257
Variable	1993-1998	2001-2005
Percentage of college graduates		
Child, four-year institution	18.04	38.21
Child, three- and four-year institution	51.63	71.50
Parent, four-year institution	6.57	8.77
Parent, three- and four-year institution	30.24	25.95

Note: Data source: UHS (2002,2009). This table shows unweighted averages of selected characteristics. All RMB amounts are deflated to 2002 values. Sample restricted to urban households with an only child.

Household pre-college education expenditure and disposable income both increased rapidly over this period. In particular, average real disposable income increased by 188%, while real college tuition only increased by 51%. College, therefore, became substantially more affordable for Chinese families. Moreover, average education expenditure increased by 38% for households that reported positive spending on children's education. This pattern indicates that the share of education expenditure in household income declined during this period.

Next, I show how to derive the impact of college expansion on education attainment of children from the UHS.[8] As I stressed earlier, UHS2002 is the earliest dataset available to me, but the college expansion policy was implemented in 1999. Therefore, I can only infer the fraction of college-educated children who took the exam before

[8] In UHS, students who are currently in universities are classified as college-educated individuals.

the policy change. Specifically, when I calculate the percentage of college-educated children before college expansion, I only include households whose children were above age 22 (and below age 26) in 2002, since they took the College Entrance Examination between 1993 and 1998 and hence are unaffected by the college expansion program.

The last four rows of Table 1.1 show that as a result of the college expansion policy, the fraction of children who entered college between 2001 and 2005 increased by approximately 20 percentage points, relative to those who entered college between 1993 and 1998.[9] Furthermore, immediately after college expansion, over 70% of children went to three-year or four-year institutions. This demonstrates that college was no longer very selective in urban areas.

1.4.2 Education Expenditure and Parents' Characteristics.

The evidence presented in this subsection highlights two important features of pre-college educational expenditure on children. First, education investment is associated with the parents' socioeconomic background. For example, the light bars in Figure 1.4 (left panel) show that high-income parents (top income tercile) spent about RMB1,500 (144%) more on their children than low-income parents (bottom income tercile) in 2002. The light bars in the right panel show that college-educated parents spent approximately RMB860 (54%) more than non-college-educated parents in 2002. Second, the gap in education expenditure became larger between 2002 and 2009. High-income parents increased their education expenditure on children by 56% (vs. a 33% rise for low-income parents), and college-educated parents increased their education expenditure by 48% (vs. a 37% rise for non-college-educated parents).

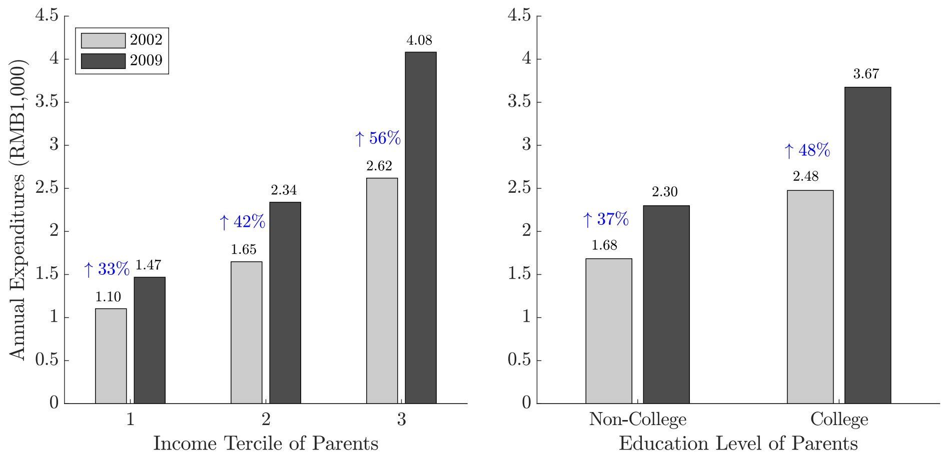
1.4.3 Education Expenditure and Developmental Stages.

Figure 1.5 displays pre-college education expenditure (in % of household income) in relation to the age of the child.[10] It increases from 6% (preschool stage) to 13%

[9]Since the dataset does not cover rural households, the numbers displayed in the table are not nationally representative.

[10]Since this chapter focuses on the pre-college educational investment decisions, I do not report the statistics for children above age 17. Choukhmane, Coeurdacier, and Jin (2017) use the data from CHIP2002 and plot a similar graph which contains the information about educational spending on

Figure 1.4: Education Expenditure by Parents' Characteristics



Note: Data source: UHS (2002,2009). Sample restricted to urban households with an only child.

(high school stage). Spending on tuition and extracurricular training increase the most rapidly as children age, especially for children above age 14. This is mainly because Chinese children receive a 9-year compulsory (almost free) education. Additionally, extracurricular training to prepare for the College Entrance Examination are incrementally important as children reach the high school stage.

Next, I estimate the stage-dependent effects of household income on pre-college education expenditure. Using the subscripts i and t to index the individual household and year, I run the following regression

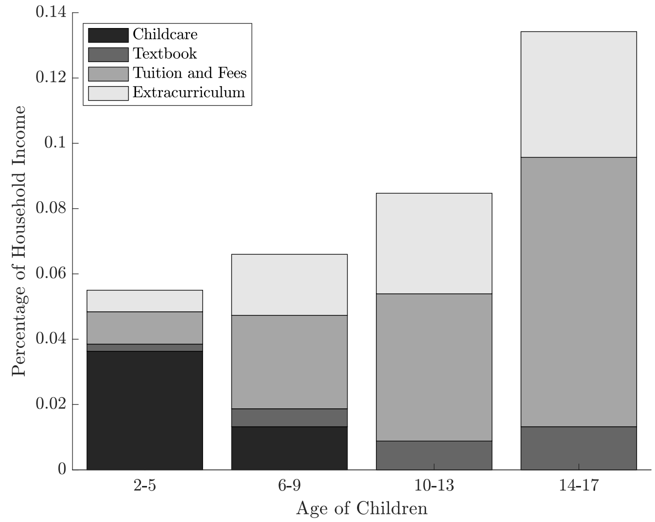
$$log(EXP_{i,t}) = \alpha + \beta log(INC_{i,t}) + Year_t + HH_i + \epsilon_{i,t}$$

respectively for each developmental stage j,[11] where INC is household disposable income, EXP is household education expenditure, fixed-effect $Year$ controls for time effects, HH controls for time-invariant household characteristics, and ϵ is the error

post-college children.

[11] Here, $j = 1$ corresponds to preschool stage (age 2-5), $j = 2$ corresponds to early elementary school stage (age 6-9), $j = 3$ corresponds to late elementary school stage (age 10-13), and $j = 4$ corresponds to high-school stage (age 14-17).

Figure 1.5: Education Expenditure by Children's Developmental Stage



Note: Data source: UHS (2002). Sample restricted to urban households with an only child.

term.[12] The regression coefficient β captures the impact of within-household deviations in disposable income.

Table 1.2 summarizes the estimation of β at stage j using various regression specifications. In the first two specifications, I construct a 2- and 3-year short-panel, respectively, and include year and household dummies. In the last specification, I run a cross-sectional regression using 2002 UHS data.

The coefficient of interest is β, which reports how household income impacts education spendings on children. The results presented in Table 1.2 show that education expenditure is more elastic to changes in household disposable income at early childhood developmental stages. For example, column (1) shows that from 2002 to 2004, a 1% increase in household income increases predicted education expenditure by approximately 0.75% at the first and second developmental stages, and by only 0.55% at the last stage. The results are robust in the 2-year panel and cross-sectional regressions, as shown in columns (2) and (3).

[12]For each household, I can observe its information for three consecutive years. If the child age jumps across two developmental stages during this time span, I drop them from the fixed-effect estimation.

Table 1.2: Effect of Household Income on Education Expenditure

Dep. variable: log-education expenditure			
	(1)	(2)	(3)
Indep. variable	2002-2004	2002-2003	2002
log-income (stage 1)	0.747***	0.953***	0.858***
	(0.282)	(0.214)	(0.073)
log-income (stage 2)	0.756***	0.557***	0.649***
	(0.140)	(0.130)	(0.047)
log-income (stage 3)	0.689***	0.645***	0.617***
	(0.118)	(0.117)	(0.040)
log-income (stage 4)	0.551***	0.457***	0.563***
	(0.128)	(0.107)	(0.047)
FE	Y	Y	N

*Note: Data source: UHS (2002-2004). Sample restricted to urban households with an only child. Standard errors are reported in parentheses. *,**,*** denotes statistical significance at 10, 5, and 1 percent, respectively.*

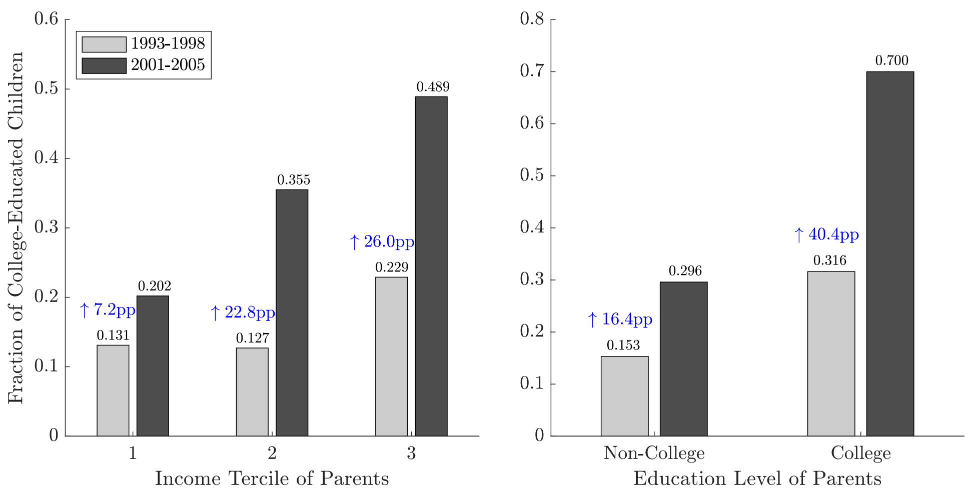
1.4.4 Education Outcomes and Parents' Characteristics

Figure 1.6 shows the education outcomes of children (proxied by the probability of earning a terminal degree from a four-year college) in relation to the parents' income and education level prior to the college expansion policy.[13] The light bars in the left graph show that the children of the high-income (top tercile) parents are about 10 percentage points more likely to earn a college degree than those of middle- and low-income (middle and bottom terciles) parents. The light bars in the right graph show that the children of college-educated parents are about 16 percentage points more likely to earn a college degree than those of non-college-educated parents.

After the college expansion program, it is notable that for middle- and high-income parents, their children's probability of attending college increases by over 23 to 26 percentage points (vs. an 8 percentage point rise for low-income parents). For college-educated parents, their children are 40 percentage points more likely to earn a college degree (vs. a 16 percentage point rise for non-college-educated parents).

[13] Here I am referring to individuals who took the College Entrance Examination between 1993 and 1998 (derived from UHS2002). For comparison, I also display the statistics for those who took the exam between 2001 and 2005 (derived from UHS2009).

Figure 1.6: College Attainment of Children by Parents' Characteristics



Note: Data source: UHS (2002, 2009). College is defined as four-year institutions. Sample restricted to urban households with an only child.

This empirical evidence suggests that children with high-income and college-educated parents benefit the most from the policy intervention, since their admission probability is substantially higher than before. For a robustness test in which I define college as three- and four-year institutions, see Appendix A.2.

The data demonstrate that changes in children's college attendance rate vary significantly across their parents' income and education groups. However, for exam takers who took the exam between 2001 and 2005, their parents had a short window during which they could change their parental investments in response to the policy implemented in 1999. Therefore, the empirical results may underestimate the aggregate and distributional impact of college expansion. Model-based policy analysis has a better predictive power for the long-run effect, since in that case, parents can take the new policy environment into account as soon as the child is born.

1.5 Conclusion

In this chapter, I perform an empirical analysis of China's college expansion policy. First, I estimate the impact of a substantial increase in the college-educated labor supply on the college wage premium. I find that the return to college education is stable within a decade after college expansion. Second, I investigate how college expansion has affected pre-college education expenditure on children and their educational outcomes. The main finding is that the magnitude of the effect depends crucially on parents' socioeconomic backgrounds. In particular, disadvantaged children, whose parents are at the lower end of the income and education groups, benefits the least from the college expansion policy. It is notable that the available data only cover household information between 2002 and 2009. As a result, how college expansion affects the college wage premium and the patterns of household education expenses in recent years are open questions for future research.

Chapter 2

The Impact of College Expansion on Human Capital Investment and Inequality

2.1 Introduction

Individuals living in developing countries face difficulties in gaining access to higher education due to the limited capacity of public college.[1] Since education attainment and skill accumulation are complementary, this situation can substantially distort intergenerational investment in human capital and lead to slow growth in labor productivity. Therefore, government intervention in the market for higher education is crucial to promote economic development.

Since 1999, China has implemented a large-scale public college expansion program. This policy has led to an additional three million students passing the College Entrance Examination and attending four-year colleges every year. Meanwhile, college becomes more affordable for households due to the rapid growth in disposable income. The number of exam takers has dramatically increased since the early 2000s, which reflects that an increasing fraction of population prefer going to college over

[1]Private institutions in developing countries are characterized by their poor quality of teaching and expensive tuition. As a result, public college is the only affordable channel through which people can acquire a high-quality college education.

immediately entering the labor force.

As the aggregate capacity of public college constrains college attendance and the exam-based selection scheme favors the test takers with high scores (human capital), pre-college parental investments[2] can relax the constraint at the individual level by raising children's probability of passing the test. If the college expansion policy can further reward children with high skills by increasing their admission chances, parents will have more incentives to make education expenditure on their children. The goal of this paper is to quantify how much college expansion affects long-run intergenerational human capital investment and to examine the impact of the policy change on the educational outcomes of children with different socioeconomic backgrounds. Moreover, this investigation also provides a framework to analyze the effects of alternative education policies, including government subsidies on childhood development.

To these ends, I build an overlapping-generations framework where altruistic parents invest in their children's skills before they go to college and make the decision on whether or not their children should take the College Entrance Examination. Specifically, I incorporate childhood development into an otherwise standard incomplete market model. Parents augment their children's human capital children through multiple-period skill investments according to a technology that features dynamic complementarity and self-productivity. A critical element of this model is that intergenerational skill investment can increase not only children's future labor efficiency but also their probability of passing the College Entrance Examination. To specify how each level of human capital (proxied by test score) is associated with the probability of college admission, I estimate an admission policy function that resembles the college selection scheme of China. I find that with a score below the average, a test taker has a very low probability of attending college. However, if the score is above the average, the probability of passing increases significantly with higher test scores. The nonlinear correlation between the admission probability and human capital plays an essential role in the analysis of the distributional effects of the college expansion program.

[2]Throughout this paper, pre-college parental investments can accumulate children's human capital according to a skill formation technology. Although parents also cover college tuition for their children, investing in college only enables children to earn the college wage rate (after they enter the labor force) rather than raise their human capital.

I estimate the model to match both macro and micro moments constructed using Chinese data. The crucial part is the estimation of skill formation technology, which combines the current-period child's skill, parent's skill, as well as monetary investment to produce the next-period child's human capital. The model requires me to specify how current-stage investment in children's education is complementary to that in the previous stage. I recover the parameters controlling the degrees of dynamic complementarity at different childhood developmental stages via indirect inference. Specifically, for each developmental stage, I first pin down the share of the child's skill in the production function by matching the corresponding average household education expenditure to income ratio. Then I design an auxiliary model to highlight data patterns on the stage-dependent effects of household income on education expenditure on children. The model parameters are chosen by matching model-predicted auxiliary coefficients to their empirical counterparts.

To quantify the long-run macroeconomic and distributional consequences of college expansion programs, I lower the tuition-to-income ratio by 22 percentage points, which reflects the college costs in 2015, and re-estimate an admission policy function using the post-reform data. Additionally, I feed in a skill-biased technological change that perfectly counterbalances the decline in college wage premium resulting from the general equilibrium effect. I find that the existing policy yields an education expenditure increase of 16.5% and ex ante welfare gains of 17.2%. Meanwhile, inequality in human capital and intergenerational persistence in education attainments rise significantly. To gain some insights on these unequal outcomes, I explore how changes in parental investments are correlated with the human capital and education groups of parents. I find that consistent with the short-run evidence displayed in the data, high-skill and college-educated parents' education expenditure are more elastic to the policy change following the college expansion in the long run. In turn, their children's human capital, as well as the college admission probability, increases more than in the case of disadvantaged children. As a result, parents with high human capital and a college degree are more likely to transmit their socioeconomic status to their children than before, which leads to a widening income gap between rich and poor and more persistent skill and schooling across generations.

To explore a more efficient way for the government to implement education policies, I use the calibrated model to conduct a counterfactual policy exercise. I analyze an economy in which the government implements a targeted early childhood intervention. This program subsidizes 60% of the education expenditure made by the parents of disadvantaged children whose ages are between 2 to 9. The expenditure is financed by raising college tuition. I find that this policy yields an education expenditure increase of 29.4% and ex ante welfare gains of 26.1%, both of which are significantly higher than the numbers under the existing policy. Furthermore, since the program exclusively targets disadvantaged children, it redistributes human capital and welfare gains to children of parents with low human capital. Consequently, the remediation policy can generate a substantial decline in inequality and intergenerational persistence, which suggests that policy makers should consider diverting a part of the government subsidy on college tuition to support early childhood development for disadvantaged children.

Related Literature. There is extensive literature that quantitatively evaluates the effects of higher education policies. Garriga and Keightley (2007), Meghir, Abbott, Gallipoli, and Violante (forthcoming) study the impact of various financial aid programs in the US under a general equilibrium context. Krueger and Ludwig (2016) focus on characterizing the optimal fiscal and education policy mix. Bohácek and Kapicka (2016) explore whether the variation in education and tax policies can explain differences in educational outcomes in the US and Europe. Kindermann (2012) proposes a reform that would transform the publicly funded college education system to a privately funded system. Among the papers that study higher education policies in developed economies, the public education sector can accommodate everyone who chooses to study in college. This paper complements this literature by examining the impact of education policies in China, where the capacity of public college constrains college attendance. The main issue of education reform is hence expanding the size of the college. Additionally, all of the literature mentioned above ignores the effect of education policies on parental investments. This paper endogenizes the skill formation process of children and studies the distributional impact of college expansion on children's development.

My work contributes to the literature which examines the impact of college expansion in China on *skill selection*. Ma (2014) quantitatively studies the impact of college expansion on college wage premiums for different age groups. In her model, whether or not an individual can go to college depends on the exogenous ability draw. In my model, a child's performance in the College Entrance Examination depends on the level of human capital accumulated by their parents. Through explicitly modeling the intergenerational transmission of skill, the richer model allows me to focus on *skill formation* and study how college expansion affects the educational outcomes of children whose parents differ in their socioeconomic background. Additionally, Feng (2019) develops a discrete college choice model, estimates a college admission probability function, and studies heterogeneous effects of college expansion on individuals in different cohorts.

There are two building blocks of my model. The first one is a heterogeneous-agent framework where individuals are facing uninsurable idiosyncratic earnings risk introduced by Bewley (1986), Huggett (1993), and Aiyagari (1994). The second is the framework of intergenerational linkage, beginning with the work of Becker and Tomes (1979). The model of this paper is most closely related to Daruich (2018), which incorporates intergenerational human capital investment and education choice into individuals' life-cycle. Relative to the prior work, this paper highlights a new channel that incentivizes parents to invest in children's education. That is, since the capacity of college constrains college attendance, skill accumulation can make college easier to get into by increasing children's college admission probability. With this mechanism in place, college expansion will significantly affect parental investments because it impacts the aggregate tightness of the capacity constraint.

The estimation of the skill formation function is essential in previous literature (e.g., Agostinelli and Wiswall, 2016; Cunha, Heckman, and Schennach, 2010; Cunha, 2013; Lee and Seshadri, 2019; Moschini, 2019; Daruich, 2018; Mullins, 2019; Caucutt and Lochner, forthcoming) since the technology specifies how parental investments map onto children's outcomes.[3] In this paper, I present a human capital production function consistent with two properties regarding childhood development: dy-

[3]As highlighted by several papers mentioned above, parental time is also an important input for developing skills of children. However, monetary investment is the only endogenous input in the skill formation technology.

namic complementarity and self-productivity. I estimate skill formation technology using Chinese household-level education expenditure data. The dataset highlights the empirical patterns on the effects of household income on education expenditure on children. An indirect inference approach is then put into use to pin down the stage-dependent dynamic complementarity parameters.

This paper also contributes to the recent literature which studies the Chinese economy by endogenizing human capital investment in a quantitative framework. Choukhmane, Coeurdacier, and Jin (2017) study the contribution of the 'one-child policy' to the rise in China's household saving rate and education investment in recent decades. Doesey, Li, and Yang (2019) use a model featuring endogenous human capital investment to examine the role of demographics and industrial policies in accounting for the rise of the savings rate and economic growth in China. Both papers focus on quantifying the linkage between the changing demographic structure and skill investment. Relative to their work, college expansion in my paper is the key driving force that leads to an increase in educational expenditure on children. Additionally, different from prior work, this paper focuses on the distributional consequences of the policy on human capital accumulation and welfare.

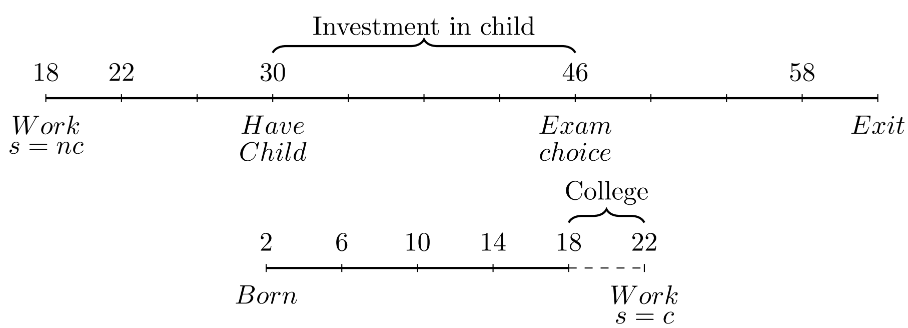
The rest of the paper is organized as follows. Section 2.2 lays out the life-cycle model. Section 2.3 describes the parameterization and model fit. Sections 2.4 present the quantitative results from the existing college expansion policy and counterfactual policies, respectively. Finally, Section 2.5 concludes.

2.2 Model

I study an overlapping-generations model in which parents, for altruistic purposes, choose intergenerational human capital investment and choose whether or not their children will take the College Entrance Examination. A skill formation technology maps the monetary investment to child development outcomes. Accumulating human capital can raise a child's future labor productivity as well as her probability of passing the test. Whether the child can earn a college degree depends not only on the endogenous education choice but also on the government admission policy because the public college has a limited capacity. Once the education outcome (whether to attend college) is realized, the individual's human capital becomes fixed for the rest of her life. Except for the intergenerational linkages through human capital investment, households solve a standard consumption-savings problem for maximizing lifetime utilities. I abstract from modeling the retirement stage. As a result, individuals exit the economy immediately after the end of the working stage. A representative firm combines capital, college labor, and non-college labor to produce the final consumption good.

2.2.1 Demographics and Timing

Figure 2.1: Timeline in the Model



Time is discrete, and one model period is four years. There is no mortality risk. There are $J = 11$ overlapping generations, each with a unit mass of households. The demographic structure is assumed to be uniform. Let j denote the model period[4] of parents (adults). Before entering the labor force, children live with their parents and do not make any economic decisions. Individuals become economically active at different stages, depending on their education level. College-educated individuals spend the first period (age 18-21) in college and start working as college labor in period 2. Non-college individuals enter the labor market in period 1. At the beginning of period 4, all of the individuals give birth to a child (age 2). From period 4 to 7, parents make monetary investments in their children's human capital. At period 8, they decide whether or not to support their children taking the College Entrance

[4]Model period j represent the stage of the life-cycle between ages $[14 + 4j, 17 + 4j]$.

Examination. Whether a child can attend college also depends on the result of the test. Parents pay tuition and living expenses for their children during their college stage. After their children become independent, parents continue to work until the end of period 11 (age 61).

2.2.2 Aggregate Production Function

An individual's education outcome is endogenously determined before she becomes independent. The education level s falls into the set $s \in \{nc, c\}$, where nc denotes non-college-educated individuals, and c denotes college-educated individuals. I assume that college and non-college-educated labor are imperfectly substitutable in production. Let H_s denote the aggregate effective labor of education level s, measured in efficiency units. The total labor efficiency units aggregate across education groups, which is given by

$$H = (\Phi(A_c H_c)^{\Omega} + (1 - \Phi)H_{nc}^{\Omega})^{\frac{1}{\Omega}},$$

where A_c captures a skill-biased change in productivity that directly affects the relative contribution of college-educated workers to output, $\frac{1}{1-\Omega}$ is the elasticity of substitution between non-college and college-educated labor, and Φ denotes the share of college educated labor in production. The college wage premium will be endogenously determined by the supply of college workers, conditional on $\Omega < 1$.

A representative firm combines the aggregate labor and physical capital to produce final output according to a Cobb-Douglas production technology

$$Y = F(K, H) = K^{\Lambda} H^{1-\Lambda} = K_t^{\Lambda}(\Phi(A_c H_c)^{\Omega} + (1 - \Phi)H_{nc}^{\Omega})^{\frac{1-\Lambda}{\Omega}}, \tag{2.1}$$

where Λ measures the capital share. The firm chooses two types of labor and capital to solve

$$\max_{H_c, H_{nc}, K} Y - w_c H_c - w_{nc} H_{nc} - (r + \xi + \delta)K, \tag{2.2}$$

where w_s is the wage per efficiency unit of labor of skill s, r is the capital rental rate, ξ is the intermediation cost in capital market,[5] and δ is the depreciation rate of capital.

[5]The intermediation cost captures the fact that the return to capital in China is puzzlingly

2.2.3 Preference

Individuals derive utility from consumption of all household members that are representable by a expected lifetime utility function

$$E_1 \sum_{j=1}^{J} \beta^{j-1} u(\frac{c_j}{1 + \mathbf{1_c} \zeta}), \tag{2.3}$$

where c_j is the total consumption in period j, $\mathbf{1_c}$ is an indicator function taking the value one during the period when the child is living with their parents,[6] and ζ is a parents equivalence parameter. Labor hours are assumed to be supplied inelastically. Expectations are taken with respect to the stochastic processes governing labor productivity risk.

Additionally, at the period $j = 8$, the child's expected lifetime utility enters the parental lifetime utility function with a weight ν, which measures the strength of parental altruism.

2.2.4 Human Capital Formation

Parents accumulate their children's human capital through multiple-period skill investments according to a technology that features dynamic complementarity (i.e., human capital produced at one stage can raise the investment at subsequent stages) and self-productivity (i.e., human capital produced at one stage is input in the next stage).

Let h_p denote the human capital of parents[7] and let $h_{j,c}$ denote the human capital stock of their child in period j, which is endogenously affected by parental skill investment for four model periods ($j \in [4, 7]$). Once an individual enters the labor force and becomes economically active, her human capital becomes fixed during the

high, whereas the deposit rate at State-owned banks are set to be low by the government. Song, Storesletten, and Zilibotti (2011) interprets this cost as the operational costs, red tape, etc.

[6]Note that college-educated children leave their families a period after the non-college-educated children in the same cohort, which implies that parents have to raise the children in college in period 8, which in turn increases the opportunity cost for supporting their children's college education.

[7]At the first three model periods, individuals do not have their children yet, but they are still regarded as parents in this model.

entire working stage.

I assume that every child is born with the same level of human capital endowment $\underline{h}$. The evolution of each child's skills $h_{j,c}$ over time is determined by a human capital production function. The next-period child's human capital $h_{j+1,c}$ depends on her parent's human capital h_p, her current stock of human capital $h_{j,c}$, and the parental investment m. I specify the technology of human capital formation as:

$$h_{j+1,c} = \psi h_p^w \left[\alpha_j h_{j,c}^{\rho_j} + (1 - \alpha_j) m_j^{\rho_j} \right]^{\frac{1-w}{\rho_j}}, \tag{2.4}$$

where ψ is an anchor that transforms the child's human capital into adult outcomes, w captures the contribution of parental human capital in the child's skill formation, α_j represents the share of current stock of the child's human capital, and ρ_j measures the complementarity between the investment in period $j-1$ and j. The technology parameters ρ_j and α_j can vary across investment stages, which is well appreciated in recent literature. Skills are persistent over generations because high-skill parents have more resources to invest in their children's human capital and they are more productive in educating their children.

2.2.5 Labor Earnings

An individual with education attainment s, human capital stock h_p , and idiosyncratic labor productivity shock ϵ earns a labor income

$$w_s \eta(h_p, \epsilon), \tag{2.5}$$

where w_s is the wage rate of type-s human capital, and $\eta(h_p, \epsilon)$ is an efficiency units function depending on individual's human capital and labor productivity shock. The wage rate is endogenously determined in a competitive labor market. There is no on-the-job human capital accumulation.

The idiosyncratic labor efficiency process $\eta(h_p, \epsilon)$ is specified as

$$log(\eta(h_p, \epsilon)) = \lambda log(h_p) + \bar{\epsilon} \tag{2.6}$$

$$\bar{\epsilon}' = \rho_\epsilon \bar{\epsilon} + z,\ \sigma_z \overset{iid}{\sim} N(0, \sigma_z)$$

where $\bar{\epsilon} = log(\epsilon)$,[8] and λ is a parameter controlling the wage-skill gradient.

2.2.6 Government Policies

Education policies. The government has two education policy tools. First, because the demand for public college is greater than its capacity, the government holds a College Entrance Examination to decide who is eligible for attending four-year colleges. As I discussed in Section 1.2 in Chapter 1, the probability of passing the test depends only on test scores. In this paper, I assume that test scores are perfectly correlated with test takers' stock of human capital. I specify that for a test taker with human capital h_c, $\chi(h_c)$ is the probability of admission, where $\chi(\cdot)$ is a strictly increasing admission function that will be estimated using micro-level admission data.

Second, I assume that a fraction θ of the college tuition is borne by the government. Suppose the per-student cost of college is κ. Then the tuition net of subsidy is $(1-\theta)\kappa$. The government can commit to subsidizing tuition for all the students who have passed the College Entrance Examination during their entire college stage.

Labor income tax. Labor income taxes are progressive. The total amount of labor income taxes paid takes the following form

$$T(y) = \bar{\tau}_y max(y - d, 0), \tag{2.7}$$

where y is labor income, d is the amount of income tax deduction, and $\bar{\tau}_y$ is the income tax rate applied to the taxable labor income.

2.2.7 Recursive Problems

Next, I lay out the dynamic individual problems at the different stages in the life cycle recursively.

[8] The productivity shock ϵ is mean-reverting and follows a Markov chain with states $\varepsilon = \{\epsilon_1, \epsilon_2, ..., \epsilon_M\}$ and transitions $\pi(\epsilon'|\epsilon) > 0$.

Problem at $j = 1, 2$. Right after their independence, before having children, individuals choose how much to consume c and how much to save a. Households are not allowed to borrow, so the next period asset (a') is non-negative. The value function of individuals of age j, with education level s, human capital stock h_p, labor productivity shock ϵ, asset a reads as

$$V_j^s(h_p, \epsilon, a) = \max_{c,a'} \left\{ u(c) + \beta \sum_{\epsilon'} \pi(\epsilon'|\epsilon) V_{j+1}^s(h_p, \epsilon', a') \right\} \tag{2.8}$$

subject to the budget constraint

$$c + a' = (1 + r)a + y - T(y)$$

$$y = w_s \eta(h_p, \epsilon), \;\; c \geq 0, \;\; a' \geq 0.$$

I assume that all of the individuals start their life with $a = 0$, which means there is no inter vivos financial wealth transfer from parent to child. The initial labor productivity is drawn from an invariant distribution $\pi(\epsilon)$. Note that college graduates start solving this dynamic problem in period 2 because they spend period 1 in college.

Problem at $j = 3$. In period 3, individuals solve the same problem as before. I lay out the problem separately because the parent will have a child in period 4, so the child's initial endowment of human capital $h'_c = \underline{h}$ enters the continuation value of the Bellman equation in period 3. The value function of individuals is given by

$$V_j^s(h_p, \epsilon, a) = \max_{c,a'} \left\{ u(c) + \beta \sum_{\epsilon'} \pi(\epsilon'|\epsilon) V_{j+1}^s(h_p, \epsilon', a', h'_c) \right\} \tag{2.9}$$

subject to the budget constraint

$$c + a' = (1 + r)a + y - T(y)$$

$$y = w_s \eta(h_p, \epsilon), \;\; c \geq 0, \;\; a' \geq 0.$$

Importantly, under this specification, children do not differ in their innate ability or initial endowment of human capital. As a result, all of the post-independence variation in human capital is due to the differences in the intensity of monetary investment and the parents' human capital.

Problem at $j = 4, 5, 6, 7$**.** At the beginning of period 4, the child is born and the state space of the parent is expanded to include the child's human capital h_c. During these four periods, in addition to the standard choices of consumption, savings, the altruistic parent also decides how much money m to invest in child's development of skill. Then using the technology specified in Subsection 2.2.4, the next-period human capital of child h_c' is produced by combining the current-period child's skill h_c, parent's human capital h_p, and education expenditure m. The dynamic problem becomes

$$V_j^s(h_p, \epsilon, a, h_c) = \max_{c,a',m} \left\{ u(\frac{c}{1+\zeta}) + \beta \sum_{\epsilon'} \pi(\epsilon'|\epsilon) V_{j+1}^s(h_p, \epsilon', a', h_c') \right\} \tag{2.10}$$

subject to the budget constraint

$$c + a' + m = (1+r)a + y - T(y)$$

$$y = w_s \eta(h_p, \epsilon),\ c \geq 0,\ a' \geq 0,\ m \geq 0$$

$$h_c' = \psi h_p^w \left[\alpha_j h_c^{\rho_j} + (1-\alpha_j) m_j^{\rho_j} \right]^{\frac{1-w}{\rho_j}}.$$

Notice that since children live with their parents during these periods, I use a consumption equivalence parameter ζ to capture the fact that parents should transfer some additional resources to child. Also, it borrowing against the current stock of human capital is not allowed, which implies that money investment must be non-negative.

Problem at $j = 8$**.** At period 8, the final education outcome of children is realized. A critical feature of the model is that parents will decide whether their children should take or skip the College Entrance Examination. If they choose to have their children take the exam, then their children can attend college as long as they pass the test. Additionally, I assume that taking the test requires an upfront cost κ_e paid by parents.

Her parents will also cover tuitions $(1-\theta)\kappa$ as well as living expenses (captured by ζ) during their children's college stage. If parents choose to have their children skip the exam, or their children fail the test, then the children will immediately leave their family and enter the labor market as non-college worker. I assume that the exam choice is irreversible, and that the College Entrance Examination can be taken only once.

I first lay out the dynamic problems solved by parents conditional on the exam choice being and the exam result being. Let $V_j^s(\cdot|c)$ denote the value of an individual with education level s if her child passes the exam and attends college. The maximization problem is given by

$$V_j^s(h_p,\epsilon,a,h_c|c) = \underset{c,a'}{max} \left\{ u(\frac{c}{1+\zeta}) + \beta \sum_{\epsilon'} \pi(\epsilon'|\epsilon) \underbrace{V_{j+1}^s(h_p,\epsilon',a')}_{parent's\ value} + \nu \underbrace{\mathbb{E}_{\epsilon'}[V_2^c(h_c,\epsilon',0)]}_{child's\ value} \right\} \tag{2.11}$$

subject to the budget constraint

$$c + a' + (1-\theta)\kappa + \kappa_e = (1+r)a + y - T(y)$$

$$y = w_s \eta(h_p,\epsilon),\ c \geq 0,\ a' \geq 0$$

where ζ captures the fact that college students still live with their parents during the college stage. The exam cost κ_e is in the parent's budget constraint because children must have passed the test before going to college. In additional, I assume that the exam cost only gives children the knowledge that is specific to the test. Consequently, children's human capital is not affected by whether or not their parents pay the upfront cost.

Notice that in the next period, the child will leave the family. As a result, her human capital h_c no longer appears in her parent's state space in period 9. In addition, the child's initial value function V_2^c enters the parent's value function at period 8. The superscript c indicates that the child is college labor, and the subscript $j=2$ implies that the child will not become independent until the next period since she will spend one more period in college. In turn, the labor productivity shock ϵ', which is drawn from an invariant distribution, will be realized in next period. The parameter ν

controls the strength of altruism.

Let $V_j^s(\cdot|nc)$ denotes the value of an individual with education level s if her child does not attend college. The maximization problem is given by

$$V_j^s(h_p, \epsilon, a, h_c|nc, \mathbf{1_e}) = \max_{c,a'} \left\{ u(c) + \beta \sum_{\epsilon'} \pi(\epsilon'|\epsilon) \underbrace{V_{j+1}^s(h_p, \epsilon', a')}_{parent's\ value} + \nu \underbrace{\mathbb{E}_\epsilon[V_1^{nc}(h_c, \epsilon, 0)]}_{child's\ value} \right\} \tag{2.12}$$

subject to the budget constraint

$$c + a' + \mathbf{1_e}\kappa_e = (1+r)a + y - T(y)$$

$$y = w_s \eta(h_p, \epsilon),\ c \geq 0,\ a' \geq 0$$

where $\mathbf{1_e}$ denotes an indicator function taking the value one if the child takes the College Entrance Examination.

The child's initial value function V_1^{nc} still enters the parent's value function at $j = 8$. The superscript nc indicates that the child is a non-college labor, and the subscript $j = 1$ implies that the child will become independent and enter the labor force immediately. As a result, the labor productivity shock ϵ is realized in the same period.

Next, I present a discrete choice problem in which parents decide whether to support their children to take the College Entrance Examination. A fraction of children will take the test following their parents' decision. Since public college has a limited capacity, the government has to use a rationing scheme to select college students from an admission pool. As discussed in Section 1.2 in Chapter 1, the admission system does not perfectly sort students into college according to their test scores. This feature will be captured by a reduced-form admission policy $\chi(h_c)$, which is a function of children's human capital h_c.

For a parent with education level s, before the exam outcome is realized, the ex ante value of supporting her child taking the exam $\widehat{V}_j^s$ is obtained by taking the expectation over the value of passing the exam $V_j^s(\cdot|c)$ and the value of failing in the exam $V_j^s(\cdot|nc)$, which is given by

$$\underbrace{\widehat{V}_j^s(h_p, \epsilon, a, h_c)}_{take\ exam} = \chi(h_c)\underbrace{V_j^s(h_p, \epsilon, a, h_c|c)}_{success} + (1 - \chi(h_c))\underbrace{V_j^s(h_p, \epsilon, a, h_c|nc, 1)}_{failure} \tag{2.13}$$

where $\mathbf{1_e} = 1$ indicates that her child took the College Entrance Examination but ended up with a failure result.

Let V_j^s denote the value of an individual who can choose between have their children skip the exam (enter the labor force), and have their children take the exam. The discrete choice problem is given by

$$V_j^s(h_p, \epsilon, a, h_c) = max\left\{\underbrace{V_j^s(h_p, \epsilon, a, h_c|nc, 0)}_{skip\ exam}, \underbrace{\widehat{V}_j^s(h_p, \epsilon, a, h_c)}_{take\ exam}\right\} \tag{2.14}$$

where $\mathbf{1_e} = 0$ indicates that the child skips the college entrance exam.

Note that by choosing to have their children skip the exam, parents can avoid paying the upfront cost of the test. As a result, the value of skipping the exam is strictly greater than the value of taking but failing the exam. However, every parent who chooses to have her child take the exam (strictly) prefers to support her child attending college than skipping the exam. Therefore, failing the exam will lead to a deviation from the optimal decision path. To increase the probability of passing the test, parents have incentives to invest in their children's human capital. This channel only exists in the environment where the college attainment is constrained by the capacity of the college.

Problem at $j = 9, 10, 11$. Starting from period 9 all of the children leave their family. Thus, before exiting the economy at period 11, parents only choose consumption and savings. The dynamic problem will be the same as the that in periods 1 and 2.

2.2.8 Definition of Equilibrium

Let $x_j \in X_j^s$ denote the vector of state variables of an individual in period j and completed education s. Let μ_j^s be the corresponding measures over Borel sigma-algebras defined using those state spaces. A stationary recursive competitive equilibrium for this economy is a collection of (i) value functions $\{V_j(x_j)\}$ and $\widehat{V}_8^s(x_8)$; (ii) policy functions for consumption and savings $\{c_j(x_j),\, a'_j(x_j)\}$, education expenditure $\{m_j(x_j)\}$ and exam choice $\{\mathbf{1_e}(x_8)\}$; (iii) aggregate capital and labor inputs $\{K, H_c, H_{nc}\}$; (iv) tax policy $\{\tau, d\}$ and admission policy χ; (v) measures for parents $\mu = \{\mu_j^s\}$, such that:

1. Given prices, the policy functions solve the dynamic programming problems described in Subsection 2.2.7 and $\{V_j(x_j)\}$ and $\widehat{V}_8^s(x_8)$ are the associated value functions;

2. Given prices, aggregate capital and labor inputs solve the representative firm's problem;

3. Labor market for each education group clears:

$$H_c = \sum_{j=2}^{11} \int_{X_j^c} \epsilon_j h_{c,j} d\mu_j^c$$

$$H_{nc} = \sum_{j=1}^{11} \int_{X_j^{nc}} \epsilon_j h_{nc,j} d\mu_j^{nc},$$

   where H_s denotes the aggregate effective labor supply of education level s.

4. Capital market clears:

$$K = \sum_{j=2}^{11} \int_{X_j^c} \epsilon_j a'_j(x_j) d\mu_j^c + \sum_{j=1}^{11} \int_{X_j^{nc}} \epsilon_j a'_j(x_j) d\mu_j^{nc},$$

   where the first term is the aggregate savings of college-educated parents, and the second term is the aggregate savings of non-college-educated parents.

5. Good market clears;

6. The distribution of μ is stationary:

$$\mu(x) = \int \Gamma(x) d\mu(x),$$

where $\Gamma(\cdot)$ denote the aggregate law of motion of $x = \{x_j\}$, which is derived from the individuals' policy functions.

2.3 Calibration

In this section I describe how I parametrize the model. Some parameters are calibrated externally or taken from other literature, others are jointly estimated from the simulation of the model. To do so, I numerically solve the decision rules of individuals, approximate the distribution of this economy, and then adjust parameters to minimize the distance between model moments and the data counterparts. After calibrating the model, I check the performance of the model by comparing the non-targeted model moments with the data.

2.3.1 Model Parameterization

The benchmark model is calibrated to the China data. The model period is four years. Individuals enter the economy at period 1 [age 18], give birth to child at period 4 [age 30], make college choice for their children at period 8 [age 46] and exit from the economy at the end of period 11 [age 61].

Preference. I specify the period utility over parent and child consumption as

$$u(c) = \frac{(\frac{c}{1+\mathbf{1_c}\zeta})^{1-\sigma}}{1-\sigma}.$$

I choose a coefficient of relative risk aversion of $\sigma = 1.50$, and an adult consumption equivalence scale $\zeta = 0.33$ following the standard literature.[9] Then the discount rate β is chosen to generate an annual real interest rate of 4%, and a capital-output ratio (in 1998) of 1.57, which is calculate by Bai, Hsieh, and Qian (2006). This requires an annual discount rate $\overline{\beta} = \beta^{1/4} = 0.97$. In addition, I choose ν to match that 29.6% of

[9]This paper implicitly assumes a two-parent and one-child family structure. The scales from Organization for Economic Cooperation and Development (OECD) assign a value of 1 for the first adult, and 0.5 for the subsequent adults. By setting $\zeta = 0.33$, I assume a child is equivalent to 0.5 of the first adult in terms of consumption expenditure following Doesey, Li, and Yang (2019).

Table 2.1: Model Parameters

Parameters Calibrated outside the Model		
Parameter		**Value**
Risk aversion	σ	1.50
Capital share in production	Λ	0.41
Labor elasticity of substitution	Ω	0.74
Skill-biased technology	A_c	1.00
Depreciation rate of physical capital	δ	0.11
Intermediation cost in financial sector	ξ	0.12
Government subsidy on college tuition	θ	0.78
Persistence of labor productivity shocks	ρ_z	0.86
Variance of labor productivity shocks	σ_z^2	0.06
Return to human capital	λ	0.51
College admission policy	$\chi(\cdot)$	see text
Parameters Calibrated (Jointly) Inside the Model		
Preference		
Annual discount rate	$\overline{\beta}$	0.97
Altruism parameter	ν	0.26
Aggregate production function		
Share of skill labor	Φ	0.41
Tuition and fees		
Tuitions paid by parents	$\overline{\kappa}$	0.62
Upfront cost of test	κ_e	0.04
Tax system		
Labor income tax deductibles	d	2.60
Labor tax rate	$\bar{\tau}_y$	0.22
Human capital formation technology		
Total factor productivity of skill formation	ψ	1.28
Self-productivity of child's human capital	$\alpha_4, \alpha_5, \alpha_6, \alpha_7$	see text
Complementarity parameter	$\rho_4, \rho_5, \rho_6, \rho_7$	see text
Parent's human capital share	ω	0.18

children whose parents are college-educated attend four-year colleges in 1998, which requires $\nu = 0.26$. In addition, $\mathbf{1_c}$ takes the value of one in period 4 to 7 for all parents, and in period 8 for parents whose children attend college.

Aggregate production function. I choose a capital share to be $\Lambda = 0.41$, following Bai and Qian (2010), which combines the China's labor share computed with GDP by income approach at provincial level into one series. The elasticity of substitution between college and non-college labor efficiency units is set to be $\Omega = 0.74$.[10] At the initial steady state equilibrium, I normalize the skill-biased technology parameter $A_c = 1$. The depreciation of physical capital is set to be $\delta = 0.11$, and the intermediation cost is set to be $\xi = 0.12$ following Bai, Hsieh, and Qian (2006).[11] The share parameter Φ is chosen to target the college wage premium of 0.50, which requires $\Phi = 0.41$.

Admission policy. My estimation strategy for college admission probability assumes that test scores can precisely reflect the test takers' human capital. Furthermore, it is the distance between a test taker's human capital and the average human capital of test takers that pins down her probability of admission.[12] When I solve the model and compute the stationary distribution, I use the method of linear interpolation to approximate the admission probability off the known data points.

In order to approximate how exam passing probability depends on the human capital of children ($\chi(h_c)$), I first normalize the raw scores by calculating their log difference from the mean score of the exam-taking year. This exercise is motivated by the consideration that the level of difficulty of the exam may vary across test-taking years. With the normalization, the same adjusted score will correspond to the equal probability of college admission in different years.

[10]The estimation strategy is following Katz and Murphy (1992). Related literature has estimated the elasticity of substitution between college and non-college labor in China (e.g., Ge and Yang, 2014; Feng, 2019).

[11]The cost is chosen so that the net rate of return to capital is 16% in China since the long-run real interest rate is 4%.

[12]As a result, before parents decide whether or not their children should take the test, they have internalized the distribution of human capital since the distribution matters for the probability of passing the test.

Next, I divide the scoring support into ten equal-length intervals and calculate the mean score for each interval. For the samples in each range, I compute the fraction of test takers who have a four-year college degree. I repeat this exercise for the test takers who took the College Entrance Examination between 1989 and 1998, and between 2008 and 2012, respectively. I separately estimate two functions because the college expansion policy was implemented in 1999. Therefore, I assume that the government has adopted a new admission policy after college expansion.[13] I provide more details on sample selection and score adjustment in Appendix B.1.1.

Figure 2.2 plots the admission probability of passing the College Entrance Examination against the normalized test score in the college entrance exam.[14] The figure displays that with a test score below the mean score, one has very little chance to pass the exam. Once the test score reaches the average, the probability of admission sharply increases.[15] This empirical observation suggests that the return to human capital investment is increasing at a faster rate within the sensitive region, where the admission chance grows more rapidly. Additionally, the college expansion policy gives test takers whose score is 0.1 to 0.2 log point above the average a significantly higher probability of attending college. However, the policy is unhelpful for the test takers whose score is below the average score.

College tuition. The tuition paid by parents for their children's college education $\overline{\kappa}_0 = (1-\theta)\kappa$ and the share of expenditure borne by the household $1-\theta$ in the benchmark model is chosen to match the tuition to average household income ratio, $\frac{\overline{\kappa}_0}{\overline{y}}$, and as a fraction of average per student costs of college education, $\frac{\overline{\kappa}}{\kappa}$.

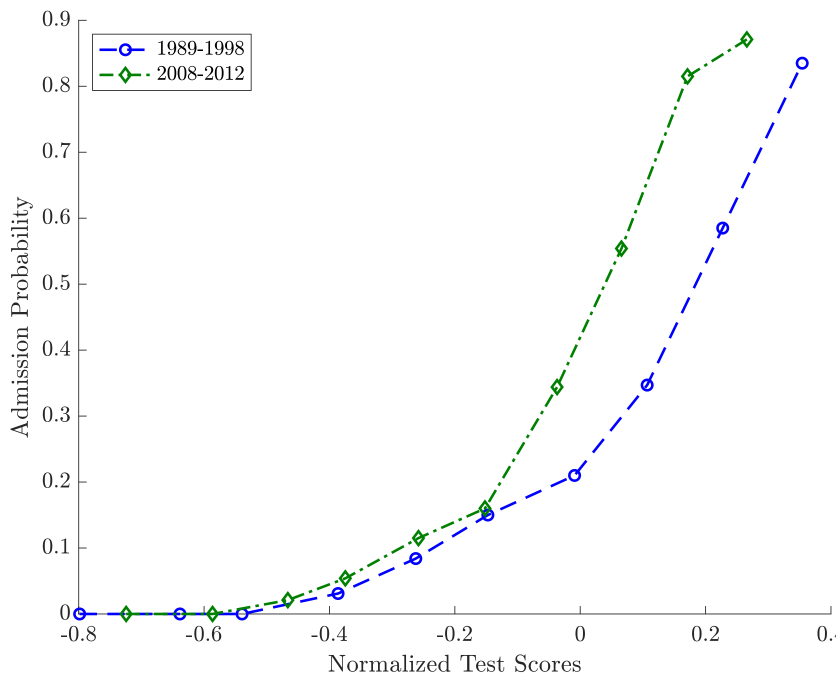
To calculate the corresponding numbers from the data, I turn to the *China Statistical Yearbook* (CSY) and the *China Statistical Yearbook of Education Fundings* (CSYEF). CSYEF reports that the average yearly tuition for a four-year college in

[13]I drop the observations on test takers who took the test between 1999 and 2007 because college in China has been gradually expanding. Since I am interested in long-run outcomes of college expansion, I need to ensure that the post-reform admission policy is estimated using the information on recent test takers.

[14]Since the admission policy function displays a strong non-linearity, I cannot adopt a linear probability model (Donovan and Herrington, 2019) to estimate the probability of passing the college entrance exam.

[15]Column (1) of Table B.2 in Appendix B.2 shows the normalized human capital (test scores) and the corresponding admission probability in the baseline economy.

Figure 2.2: College Entrance Examination Admission Policy Function



Note: Data source: CHIP2013. This figure plots the probability of passing the College Entrance Examination against the normalized test score. A circle or diamond marker represents the admission probability among individuals in a scoring bin. Blue dashed line and green dash-dot line reflects the admission policy function before (1989-1998) and after (2008-2012) the implementation of the college expansion policy, respectively.

1998-2001 is RMB3,114. I assume that miscellaneous fees (textbook, supplies, room, and transportation) tied to college is 30% of out-of-pocket tuition. According to CSY, the average household income during this time span is RMB10,719. Thus, I have

$$\frac{\overline{\kappa}_0 \times 1.30}{\overline{y}} = \frac{3,114 \times 1.30}{10,719} = 0.38$$

and the cost parameter $\overline{\kappa} = 0.62$ is calibrated at the equilibrium of the benchmark model.

Furthermore, CSYEF reports that the average yearly per student costs of college education in 1998-2001 is RMB13,963. Therefore,

$$(1-\theta) = \frac{\overline{\kappa}_0}{\kappa} = \frac{3,114}{13,963} = 0.22,$$

which requires $\theta = 0.78$.

Tax system. Labor income tax is the only tax in the model since it can distort college attendance. The tax function is assumed to be

$$T(y) = \bar{\tau}_y max(y-d, 0),$$

which means there are two parameters to be calibrated. In practice, I choose the income tax deductible $d = 2.58$ to capture the fact that the labor income tax only applies on 15% of workers. Then I choose the income tax rate $\bar{\tau}_y = 22.4\%$ to match the total labor income tax revenue to GDP ratio (1.5%).

Labor earnings. I run a fixed effect regression to control the cohort-invariant test takers' characteristics to estimate the impact of human capital on labor income, which is controlled by the parameter λ. I first filter out experience effects from the log wage observations in the CHIP2013. Here I assume that any residual unobserved error term is uncorrelated with human capital. Next following Hendricks and Schoellman (2014), I estimate an OLS regression of log individual wages on log test scores, a school dummy, and a cohort dummy. The estimation equation is given by

$$log(Income) = \lambda log(Score) + School + Cohort + \epsilon$$

where $Income$ is individual's labor income, $Score$ is individual's adjusted test score, $School$ is an indicator variable that takes a value of one if the individual is college-educated, $Cohort$ is the cohort dummy indicating the year of test, and λ captures the return to human capital (skill gradient).[16]

Table 2.2: Estimate Return to Skill

Dep. variable: log-wages		
Indep. variable		
Test score	0.512***	0.525***
	(0.083)	(0.083)
College education	0.228***	0.225***
	(0.034)	(0.033)
Cohort effect	Y	N
Observations	2,089	2,089
R-squared	0.111	0.06

Note: Data source: CHIP2013. The omitted school category is non-college graduate. Standard errors are reported in parentheses. *,**,*** *denotes statistical significance at 10, 5, and 1 percent, respectively.*

The estimating results are reported in Table 2.2. A one standard deviation rise in human capital (i.e., test score) raises log-wages by 51%. As a result, I set $\lambda = 0.51$.

The $AR(1)$ process has a yearly persistence of 0.86 and an yearly innovation variance of 0.06, which is consistent with estimation of Yu and Zhu (2013), and

[16] Recent literature, such as Meghir, Abbott, Gallipoli, and Violante (forthcoming) and Daruich (2018), has exploited a similar method by using the US Armed Forces Qualification Test (AFQT) score to proxy individual's skills. Different from this paper, they estimate the skill gradient separately for individuals with different educational backgrounds. This strategy is motivated by the fact that the return to skill is higher among college-educated individuals than among other groups. In other words, the education level and human capital investment are complementary. I do not adopt their approach because there is an apparent selection bias associated with the observations of test scores in CHIP2013. Since the College Entrance Examination is a knowledge-based test requiring a lengthy learning period, a large fraction of individuals with low human capital never takes the exam because the passing probability for them is extremely low. As a result, the estimation of skill gradient for non-college graduates will be biased since the sample does not include those who skip the exam.

İmrohoroğlu and Zhao (2018). Since one period is four years in my model, I can recover $\rho_z = 0.55$, and $\sigma_z = 0.42$. I follow Kopecky and Suen (2010) and use the method of Rouwenhorst (1995a) to approximate this process with a discrete Markov transition matrix.

Human capital formation. Following Cunha, Heckman, and Schennach (2010), I assume that child's next-period human capital depends on her current stock of human capital, parent's human capital, and parental investment. Also I assume that there is a CES aggregator that combines current human capital of child and investment made by her parent

$$X = \left[\alpha_j h_c^{\rho_j} + (1-\alpha_j) m^{\rho_j}\right]^{\frac{1}{\rho_j}}$$

where α_j indicates the share of self-productivity of child's human capital, and ρ_j represents elasticity of substitution at the developmental stage j.

Next, I assume X is combined with parent's human capital to produce next period child's human capital according to a Cobb-Douglas technology

$$h_c' = \psi h_p^{\omega} X^{1-\omega}$$

where the anchor parameter ψ and share parameter ω are independent from child's age.

My estimation strategy can be explained as follows. The household-level data available to me only provide detailed information about household education expenditure on their children. However, it does not allow me to track how parental investments are linked with children's outcomes over a long period. Therefore, I discipline the skill formation technology by connecting the parental characteristics, including their income and education levels, to household education expenditure. Furthermore, I choose the altruism parameter by connection children's terminal education attainments to their associated parents' education levels.

I choose a set of α_j to target the average education expenditure to household income ratio in period j, which requires $\alpha_4 = 0.60$, $\alpha_5 = 0.81$, $\alpha_6 = 0.91$, and $\alpha_7 = 0.95$. This estimation result reflects children's current-period human capital is more important as they age. In other words, it is more difficult for parents to raise their children's human capital using monetary investment at the later developmental stages.

Since the UHS dataset does not record any information about children's education outcomes during their early childhood, it is impossible to adopt the approach employed by Lee and Seshadri (2019), which recovers the dynamic complementarity parameters by directly estimating the skill formation technology. Instead, I estimate these parameters via indirect inference, where I design an auxiliary model to highlight data patterns that are key for identification.

The auxiliary model is displayed in Subsection 1.4.3 in Chapter 1, where I estimate the effects of household income on pre-college education expenditure for each developmental stage by running a set of fixed-effect regressions. To estimate the dynamic complementarity parameters, I repeatedly simulate the life-cycle model and search for ρ_j for four different stages respectively to ensure that the model-predicted effects of household income on education expenditure can match their data counterparts.

Next, I explain the identification strategy in an intuitive way. The crucial argument is that the stage-dependent effects of household income on pre-college education expenditure on children can inform me of the degrees of the complementarity between investments in period $j-1$ and j. Specifically, a more complementary relationship between current-period children's skills and education expenditure is associated with a stronger effect of household income on monetary investments. In Appendix B.2, I show precisely how this logic works in a two-period model before quantitatively characterizing how model-predicted regression coefficients are sensitive to the choice of ρ_j. Here I summarize the key reasoning steps.

First, with a more substitutable (complementary) relationship between the current stock of children's human capital and parental investment, the optimal investment in human capital is lower (higher) when the household income is low. However, as household income increases, the optimal human capital investment grows more rapidly (slowly) in the substitutable (complementary) case. Therefore, if I find in the developmental stage j that household education expenditure grows more significantly with the household income, it implies that the skill formation technology at this stage features a more substitutable (complementary) relationship between current-period skill of children and monetary investment. Putting this intuition into practice, the auxiliary regression will generate a larger (smaller) regression coefficient in the stage where the current human capital of children is more substitutable (complementary) to the parental investments.

Table 2.3: Key Moments: Model vs. China Data

Description	**China Data**	**Model**
Aggregates		
Capital-output ratio	1.57	1.57
Share of exam taker	0.17	0.17
College wage premium	0.50	0.50
Tuitions to income ratio	0.38	0.38
Taxation		
Frac. of labor income tax payer	0.15	0.12
Labor income tax revenue to GDP	0.02	0.02
Skill formation		
Avg. human capital (exam taker)	1.00	1.00
Interg. corr. of college education	0.30	0.29
Edu. exp. to income ratio at j	0.06, 0.07, 0.09, 0.13	0.05, 0.07, 0.09, 0.13
Reg. coeff. $log(m_j)$ on $log(y_j)$	0.74, 0.75, 0.68, 0.56	0.74, 075, 0.68, 0.57
Corr. coeff. between m and h_p	0.17	0.17

I estimate that $\rho_4 = 0.17$, $\rho_5 = -0.16$, $\rho_6 = -0.66$, and $\rho_7 = -1.19$. The main finding is that it is easier to shape children's skill through money investment at the early stage of the human capital development, because the elasticity of substitution determined by ρ_j is larger the younger the children. Meanwhile, high early childhood investment in human capital will induce a larger amount of investment at the late developmental stages due to the complementary effect. This finding is consistent with the estimation implemented by Cunha, Heckman, and Schennach (2010).

Parent's human capital share. I choose $\omega = 0.18$ to target the correlation coefficient between the parent's human capital[17] and education investment $corr(h_p, m) = 0.17$. With a high ω, high-skill parents can augment their children's human capital

[17] Here, I use parent's years of schooling to proxy the parent's skill.

with low monetary investments, which makes the two inputs (h_p and m) less correlated. Lastly, the anchor parameter is calibrated jointly with other parameters to ensure that the average human capital (exam taker) is normalized to 1, which requires $\psi = 1.28$.

Table 2.1 summarizes the parameters that I calibrate independently (top panel) and those that are calibrated jointly in equilibrium (bottom panel) to match the moments shown in Table 2.3.

2.3.2 Performance of the Benchmark Model

Before moving on to the education policy analysis, I discuss whether the parameterized model provides an acceptable description of the China economy along the dimensions relevant for the current analysis.

Table 2.4: Non-targeted Moments

	Data	Model	Source
Standard Deviation			
Log-income	0.60	0.53	UHS
Log-consumption	0.61	0.42	UHS
Log-skill of exam takers	0.20	0.17	CHIP
Avg. Education Expenditure			
Income tercile Q1	-0.47	-0.49	UHS
Income tercile Q2	-0.11	-0.05	UHS
Income tercile Q3	0.39	0.37	UHS
College-educated parents	0.33	0.40	UHS
Non-college-educated parents	-0.07	-0.02	UHS

Note: All of the model moments are computed at the steady state. All the data counterparts are computed using the moments obtained from UHS2002, except for the standard deviation of skills of test taker, which is computed using test takers information from CHIP2013.

Inequality. Since one of the main focuses of this paper is inequality, I first check if the estimated model can reproduce the qualitative features in those dimensions as shown in data. Table 2.4 reports various non-targeted moments generated from the baseline model.

First, the upper panel of Table 2.4 reports that the household income and consumption inequality measured in the standard deviation of log earnings is 0.60 and 0.61 in the data, respectively. The model produces a slightly lower income inequality, but a significantly lower consumption inequality. As pointed out in Ding and He (2018), one of the puzzling observations in Chinese micro-level data is that the consumption inequality closely tracks with income inequality over time.

Second, Table 2.4 displays that the standard deviation of log human capital of test takers (proxied by test scores) in China is 0.20. The model counterparts are slightly lower but still reasonably close to the empirical values. The model generates a lower dispersion in test scores because it does not capture that in the real world, a small number of children with zero probability of admission still take the College Entrance Examination by paying an upfront cost.[18]

Education expenditure. The next set of moments I need to check is how education expenditure vary across parents in different income and education groups. The lower panel Table 2.4 reports that households in the bottom income tercile spend 49% log points less than the average on education expenditure, and the model counterpart is 47%. It also reports that college-educated households spend 33% more than the average, and the model counterpart is 40%. Therefore, the simulated model does a good job of matching the variation of education expenditure across income and education groups.

Human capital distribution. To see whether the simulated model can reproduce the patterns of human capital distribution, I compare the model-generated distribution with the Chinese data. Table 2.5 reports the statistics reflecting the distribution of log test scores, which is used as a proxy for human capital.

In the data, a test taker within the top 5% of the human capital (h_c) distribution (among test takers) should at least have a test score of 27% better than the average. The model counterpart is 29%, which means model-generated human capital distribution of the top percentiles is quite close to the data. In the data, test takers with a

[18]This puzzle can be reconciled if I incorporate some uncertainties to the test performance, which means that the test score may not be perfectly correlated with children's human capital. In that case, some children with low human capital may set to gamble on the test.

Table 2.5: Human Capital (Test Scores) Distribution

	Test Scores of Top X%				
X:	50	20	10	5	1
China Data	0.04	0.17	0.23	0.27	0.38
Model	-0.08	0.09	0.20	0.29	0.41

Note: Data source: CHIP2013. The test scores are normalized by taking their log differences from the average score.

median score should have a human capital level of 4% better than the average. The model counterpart is -8%. This implies that the required human capital for being a top 50% test taker is below the data.

2.4 Policy Evaluations

With estimates of skill formation technology, the wage function, and the admission policy, I turn now to the impact of various policy environments. By feeding the existing college expansion policy into the calibrated model, I can compare the model-generated long-run household behaviors with the short-run evidence shown in the data. Furthermore, to better understand the mechanisms that contribute to the effects of college expansion on macro variables, I quantify the impact of each channel through a sequential decomposition. Finally, I propose a counterfactual policy and ask the following question: Can government expenditure on education be implemented in a more efficient way to improve social welfare and reduce inequality? To address this question, I divert a part of the government subsidy for college tuition to support early childhood development for disadvantaged children and compare the aggregate and distributional implications with those of the existing policy.

2.4.1 Descriptions of the Policies

This subsection describes how I incorporate the existing policy and the counterfactual policy in the calibrated model framework. Let $\mathbb{P} = \{0, 1, 2\}$ denote the policy introduced, with $\mathbb{P} = 0$ being the baseline economy, $\mathbb{P} = 1$ the economy with the current college expansion policy, and $\mathbb{P} = 2$ the counterfactual economy with the childhood education subsidy program.

The current college expansion policy. To evaluate the impacts of the current reform and provide a benchmark for the counterfactual experiment, I analyze the aggregate and distributional effects of the existing college expansion program ($\mathbb{P} = 1$). There are three main differences between the benchmark Chinese economy and the current reform economy: (i) due to rapid income growth, the tuition-to-income ratio declines dramatically; (ii) the government adopts a new admission policy function; and (iii) a skill-biased technological change increases the demand for college-educated workers.

To capture the decline in tuition-to-household-income ratio, I enter a new tuition parameter, $\overline{\kappa}_1 = 0.26$. As the average household income goes up due to college expansion, $\overline{\kappa}_1$ is endogenously pinned down to match the tuition-to-income ratio (0.14) in 2015. I assume that the share of college costs borne by the government is fixed at $\theta_1 = \theta = 0.78$. The per student costs of college in the model therefore is

$$\frac{\bar{\kappa}_1}{1-\theta_1} = \frac{0.26}{1-0.78} = 1.19,$$

and the amount of government spendings on college education under the current policy is

$$EX_1 = 1.19\theta_1 \int_{\mathbf{1_e}=1} \chi_1(h_c) d\mu_8,$$

where $\mathbf{1_e}$ denotes an indicator function taking the value one if the child takes the college entrance exam.

Furthermore, as shown in column (2) of Table B.2 in Appendix B.2, the government adopts a new admission policy function $\chi_1(h_c)$. Relative to the pre-reform economy, the new policy primarily increases the admission opportunity for test takers whose scores are above the average.

Finally, there is a skill-biased technological change that affects the demand side of labor. Of course, it is difficult to predict the magnitude of technical change in the long run. In this exercise, I choose $A_c = 1.54$ to ensure that the existing college expansion policy generates the same college wage premium (0.50) in the final steady state as in the baseline economy. Appendix B.3 reports the results from two robustness experiments, in which the long-run outcomes are affected by two levels of skill-biased technological changes.

The early childhood subsidy program. In this case, I analyze an economy in which the government implements a targeted early childhood intervention ($\mathbb{P} = 2$). The aim of this experiment is to explore a more efficient way for the government to implement education policies.

The subsidy targets children whose parents are in the bottom quartile of the distribution of income. I do not use the parent or child's human capital as an eligibility criterion, because in practice it could be the private information of individuals. However, since income level largely depends on parent human capital, I can still use this rule to identify disadvantaged families. In addition, the program only targets children at the first and second developmental stages ($j = 4, 5$). This is motivated by the fact that educational intervention at early developmental stages is more effective, since human capital investment is more complementary to children's human capital at the later stages. I assume that the government subsidizes 60% of the education expenditure made by the parents of disadvantaged children. The subsidizing program is financed by increasing college tuition. I also assume that the admission policy function and technological change are identical to those in $\mathbb{P} = 1$.

Let $\mathbf{1_g}$ denote an indicator function taking the value one if the parent is eligible for the child education subsidy. The budget constraint of parents becomes

$$c + a' + \mathbf{1_g} 0.4m + (1 - \mathbf{1_g})m = (1 + r)a + y - T(y).$$

I assume the government expenditure on college subsidy and early childhood subsidy equals the total amount of college subsidy under the existing education policy. To do so, I search for the out-of-pocket tuition $\bar{\kappa}_2$ that can balance the government budget in this economy. Since the tuition is adjusted, the new share of college costs borne by the government is

$$\theta_2 = 1 - \frac{\bar{\kappa}_2}{1.19}$$

where 1.19 is the per student cost of college.

The government expenditure are given by EX_2, where:

$$EX_2 = 0.6 \sum_{j=4}^{5} \int_{\mathbf{1_g}=1} m_j(x_j) d\mu_j + 1.19\theta_2 \int_{\mathbf{1_e}=1} \chi^1(h_c) d\mu_8,$$

where the first term aggregates the government spending on the early childhood development subsidy, and the second term aggregate the subsidy for college education with a new level of tuition in place.

In the steady state equilibrium, the new tuition is such that the government budget is balanced:

$$EX_2 = EX_1,$$

which requires $\bar{\kappa}_2 = 0.50$.

2.4.2 Results

When evaluating the aggregate impact of policies, I am interested in the following three outcomes in particular. First, how does human capital investment respond to the policy change? Second, how do education outcomes, including the human capital of children and the education level of children, change as the result of the policy change? Third, to what extent can the welfare of households improve due to the policy change? When analyzing the distributional effects of policies, my attention will be devoted to the distribution of the increase in human capital, college attainment, and welfare gains across children from different socioeconomic backgrounds.

The welfare changes at the individual level are expressed in terms of consumption-equivalent variation, which allows me to quantify the gains and losses experienced by different groups in the population. Specifically, for a parent whose human capital is h_p and education level is s, before any realization of income shocks, I compute the expected lifetime welfare for her child, which is denoted by $V_{\mathbb{P}}^{\tilde{s}}(\widetilde{h}_p)$.[19] The conditional welfare change of children in the economy $\mathbb{P}$ relative to the baseline economy can be

[19] Although $V_{\mathbb{P}}^{\tilde{s}}(\widetilde{h}_p)$ measures the ex-ante welfare of a child, the notation $\sim$ indicates that the state variable h_p and s reflect the human capital and education level of her parent.

expressed as:

$$\Delta W_{\mathbb{P}}^{\widetilde{s}}(\widetilde{h}_p) = \left[\frac{V_{\mathbb{P}}^{\widetilde{s}}(\widetilde{h}_p)}{V_0^{\widetilde{s}}(\widetilde{h}_p)}\right]^{\frac{1}{1-\sigma}} - 1. \tag{2.15}$$

In this way, I can compute the heterogenous impacts of policy on the welfare of children whose parents are different in their human capital h_p and education level s.

Next, I also calculate the aggregate-level welfare changes under the veil of ignorance by assuming that the planner weights every agent in the stationary distribution equally. The ex ante welfare changes in consumption-equivalent units are computed as follows:

$$\Delta W_{\mathbb{P}} = \left[\frac{\int V_{\mathbb{P}}^{s}(h_p) d\mu_{\mathbb{P}}^{s}}{\int V_0^{s}(h_p) d\mu_0^{s}}\right]^{\frac{1}{1-\sigma}} - 1. \tag{2.16}$$

The social welfare in the economy $\mathbb{P}$ is obtained by integrating over the stationary distribution of human capital and education levels of parents. The total social welfare changes come from two sources: (i) changes in the expected welfare at each state and (ii) changes in the distribution over different states due to policy changes.

Macro outcomes. In this subsection, I analyze the effects of the existing college expansion policy and the counterfactual childhood development subsidy program. I compare the aggregate outcomes in the stationary equilibria of these two economies with those in the benchmark, and report the results in Table 2.6.

With respect to the effects of the current policy, column (2) of Table 2.6 shows that aggregate quantities increase across the board. Starting with the most direct effect of the reform, due to the expansion in college capacity and decline in the tuition-to-income ratio, the fraction of test takers and college graduates increases by 17.1 and 10.1 percentage points,[20] respectively. Furthermore, the existing policy motivates parents to spend 16.5% more on their children's education. The 16.1% rise in aggregate human capital is due partly to the rise in pre-college parent investments

[20]In the data, the fraction of test takers and college graduates increased by 45% and 21%, respectively, in 2015, which implies that the existing college expansion policy and explain about half of the rise in the exam-taking rate and college attendance rate from 1998 to 2015. Other factors, including the changes in family structure, job-specific skill requirement, and college wage premium, can also affect exam choices and college attainments. However, this model does not take those driving forces into account.

Table 2.6: Aggregate Effects of Education Policies

	(1) Baseline	(2) Existing Policy	(3) Childhood Subsidy
	Level	*Change*	*Change*
(a). ***Aggregate***			
Test taker share	17.19%	17.1pp	20.0pp
College share	4.73%	10.1pp	11.1pp
College wage premium	0.50	0.0%	5.5%
Edu. expenditure	0.14	16.5%	29.4%
Human capital, all	0.72	16.1%	30.0%
Human capital, test takers	1.00	13.0%	14.0%
Labor income	1.62	17.9%	25.3%
Output	0.60	29.0%	44.1%
Welfare	-13.51	17.2%	26.1%
(b). ***Std. Deviation***			
Edu. expenditure	0.63	3.6p	-7.4p
Human capital	0.28	5.2p	-2.6p
Labor income	0.53	1.2p	-0.4p
(c). ***Persistence***			
Human capital	0.80	5.3p	-0.4p
College education	28.91%	25.0pp	18.5pp

Note: The table shows the baseline and simulated results related to the macroeconomic variables. Column (1) corresponds to the level in the baseline economy. Column (2) and (3) correspond to the (percentage point, percentage, or point) changes after implementing the existing and counterfactual policy relative to the baseline economy. The welfare in entry (a) is measured by consumption-equivalent units. All the variables in entry (b) are in log scale. The persistence in human capital in entry (c) is measured by computing the correlation coefficient between parents' and children's human capital (in log).

and partly to the parents' increased human capital, which causes them to develop their children's skills more efficiently. Finally, the reform leads to a 29.0% increase in output and a 17.2% improvement in ex ante welfare, which are primarily driven by the higher aggregate human capital and labor income, respectively.

Meanwhile, because the education expenditure becomes more dispersed (3.6 log points) than the baseline economy, the standard deviation in human capital and income increases by 5.2 and 1.2 log points, respectively. In addition, the correlation between parents' and children's human capital increases by 5.3 points. These results suggest that although the existing college expansion program generates substantial human capital and welfare gains, it also increases inequality and reduces intergenerational mobility across generations.

With respect to the effects induced by the childhood development subsidy program, column (3) of Table 2.6 shows that the counterfactual reform leads to additional gains in all of the aggregate quantities relative to the existing policy. In particular, the rise in the share of test takers increases from 17.1 to 20.0 percentage points. This change is the result of two opposing forces. First, college tuition increases by 92% to finance the childhood subsidy program, which renders college less appealing for poor parents. However, low-income parents, incentivized by the subsidy policy, increase their education expenditure on children. For disadvantaged children, since both their human capital and their exam-passing probability go up, their parents are more likely to choose to have their children take the exam.

Moreover, compared with the existing college expansion policy, the childhood subsidy program I proposed can also promote growth in aggregate human capital (from 16.1% to 30.0%); output (from 29.0% to 44.1%); and ex ante welfare (from 17.2% to 26.1%). More importantly, as the subsidy policy exclusively targets human capital investment in disadvantaged children, the standard deviation of education expenditure drops by 7.4 log points. Since parents with low human capital and a low education level are induced to spend more on their children's education, the dispersion in human capital and intergenerational correlation in human capital drops by 2.5 and 0.4 log points, respectively. These results suggest that supporting the childhood development of disadvantaged children can not only raise social welfare but also mitigate inequality and improve social mobility in the long run.

The existing college expansion policy affects aggregate variables through four main channels: (i) college becomes more affordable for parents, (ii) admission probability, given a human capital level, is higher, (iii) a general equilibrium effect moves prices, and (iv) skill-biased technological change affects the demand side. Although these four channels interact with each other and cannot be perfectly disentangled, this exercise aims to gain insight into their relative importance through a sequential decomposition. Table 2.7 reports a decomposition of the four effects on the change in macro variables with the current college expansion policy.

Table 2.7: Results Decomposition (with Existing Policy)

	Total chg.	**Due to:**	(1) Decline in tuition	(2) Rise in capacity	(3) G.E. effect	(4) Skill-biased tech. chg.
(a). ***Aggregate***						
Test takers share	17.1pp		-4.2pp	22.2pp	-17.9pp	17.0pp
College share	10.1pp		0.0pp	10.4pp	-7.9pp	7.5pp
Wage premium	0.00%		18.5%	-10.3%	-31.3%	23.1%
Edu. expenditure	16.5%		3.3%	9.5%	-13.1%	16.9%
Human capital	16.1%		3.1%	9.2%	-12.6%	16.5%
Labor income	17.9%		1.2%	7.4%	-7.7%	17.0%
Output	29.0%		3.4%	9.1%	-12.2%	28.8%
Welfare	17.2%		0.8%	6.2%	-5.6%	15.8%
(b). ***St. Dev.***						
Edu. expenditure	3.6p		1.5p	2.1p	-4.0p	4.0p
Human capital	5.2p		2.8p	3.5p	-7.5p	6.4p
Labor income	1.2p		0.5p	1.7p	-2.6p	1.6p
(c). ***Persistence***						
Human capital	5.3p		3.1p	3.1p	-7.9p	7.1p
College education	25.0pp		16.9pp	6.5pp	-26.1pp	24.5pp

Note: This table presents the results from the decomposition exercise. Column (1) reports the effects of a 22 percentage points drop in tuition-to-income *ratio, fixing the college capacity, equilibrium prices, and skill-biased technology. Column (2) reports the incremental effects from column (1) when the college capacity constraint is relaxed, while still fixing the prices and technology. Column (3) reports the incremental effects from column (2) when prices are adjusted, while the technology remains unchanged. Column (4) reports the incremental effects from column (3) when a calibrated skill-biased technological change is fed in to the model.*

Column (1) shows that a decline in the tuition-to-income ratio on its own (fixing college capacity[21], prices, and technology) would have little impact on most aggregate variables. In particular, the share of test takers goes down by 4.2 percentage points, even though college is significantly cheaper. The reason for this decrease can be explained as follows: If the college education supplies elastically, more affordable college can induce more parents to support their children in attending college. However, due to the college capacity constraint, an increase in demand for college only makes college admission more competitive. A lower probability of admission, in turn, leads to a lower return from exam-taking. As a result, more parents avoid paying the upfront cost (κ_e) by choosing to have their children skip the test.

Furthermore, the modest rise in aggregate human capital is mainly driven by a behavioral education expenditure response by wealthy parents. As the test becomes more selective than the baseline economy, rich parents must increase their parental investment to secure their children's college attendance. Finally, the college wage premium rises substantially by 18.5%. Under the partial equilibrium environment, the relative skill price remains unchanged. Therefore, the increase in the college wage premium is only accounted for by the increased in human capital sorting between college- and non-college individuals.

Column (2), together with column (1), presents the aggregate effects of college expansion with fixed prices and technology. The dramatic rise in the share of test takers (22 percentage points) is not surprising, given the substantial relaxation of the college capacity constraint. Moreover, a comparison of columns (1) and (2) clearly shows that the rise in aggregate quantities—of human capital, labor income, and welfare—is mainly due to the capacity expansion and not the lower tuition-to-income ratio. In addition, these two shocks are equally important in explaining the rise in inequality and intergenerational persistence in human capital.

Column (3) shows that if equilibrium prices are adjusted, most of the gains in aggregate variables will be offset by the general equilibrium effect. As the college wage premium falls by 31.3%, parents are disincentivized to invest in their children's

[21] Here, I adopt a counterfactual admission policy function $max(\chi_1(h_c) - \Xi, 0)$, where $\Xi = 0.066$ is endogenously determined to ensure that the share of college individuals is fixed. This is a reduced-form way to mimic a more selective admission process when college is more affordable.

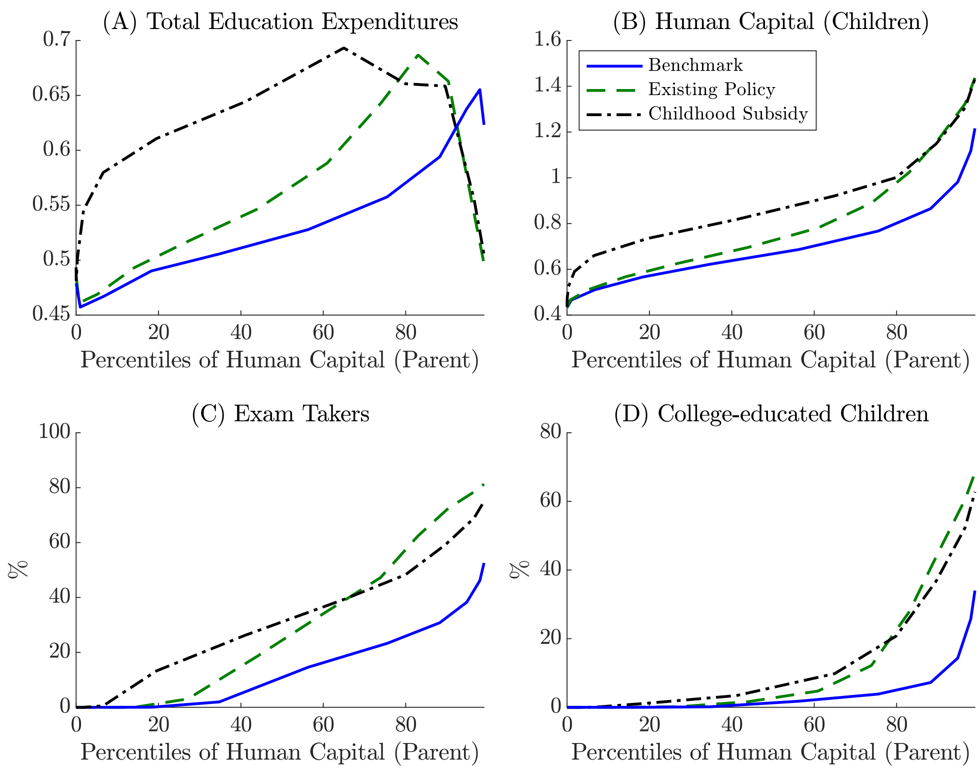
skill development and college education. Column (4) shows that with a skill-biased technological change that perfectly counterbalances the three effects that affects the college wage premium, the exam-taking rate and college attendance rate rise back to the levels with prices fixed. Furthermore, aggregate education expenditure and human capital are slightly higher than those under the partial equilibrium exercise. Lastly, due to the rising demand for labor inputs, the increase in skill prices leads to substantial gains in labor income and welfare.

Distributional effects. The aggregate statistics reveal that the current college expansion policy can contribute to rising inequality, while the childhood subsidy program can mitigate this effect. However, the channel through which the education policies affect inequality and intergenerational mobility is not clear. To illustrate the mechanism, in this subsection I show how changes in education investments and outcomes vary across parents who are heterogeneous in their human capital and education levels.

Figure 2.3 plots the simulated results related to parental investments and education outcomes against percentiles of parents' human capital. Specifically, Panels (A) and (B) of Figure 2.3 plot the average lifetime pre-college education expenditure and the average human capital of children, respectively, against percentiles of the distribution of parent human capital. Panels (C) and (D) of Figure 2.3 plot the fraction of the associated children who take the college entrance exam, and the fraction of associated children who pass the test, respectively, against percentiles of the distribution of parent human capital. The solid blue line displays the results in the baseline economy, the dashed green line displays the results under the current policy, and the dash-dot black line displays the results under the childhood development subsidy program.

Panel (A) of Figure 2.3 reveals that the existing college expansion policy (dashed green line) significantly raises the educational investment of parents whose human capital is above the 50th percentile. In contrast, parents whose human capital is below the median level only slightly increase their human capital investment on children. Consequently, as shown in Panel (B) of Figure 2.3, the increments in children's human capital that result from the current policy increase with the human capital of parents. Panel (C) of Figure 2.3 shows that since college is more affordable than in

Figure 2.3: Edu. Investment and Outcomes in Relation to Human Capital of Parents



Note: This figure presents how life-time education expenditure (Panel (A)), average human capital of children (Panel (B)), fraction of test takers (Panel (C), and fraction of college-educated children (Panel (D)) depend on parents' human capital. The horizontal axis corresponds to the human capital percentiles of parents.

the baseline economy, most parents (except for the bottom 20%) are more likely to choose to have their children take the exam. However, Panel (D) of Figure 2.3 reveals that the education outcome measured by the probability of college admission varies substantially across the human capital groups, with the children of low-skill parents gaining the least. The uneven outcomes can be explained as follows: The children of low-skill parents only have a slight gain in their human capital compared with the baseline economy. As a result, their admission possibility is still slim. The children of parents with high human capital, in contrast, take full advantage of the college expansion, since both their human capital and admission probability dramatically increases.

It is worth noting that the implications from the simulated model are consistent with the empirical evidence documented in Subsection 1.4.4 in Chapter 1. The quantitative exercise, as stated above, illustrates the channel through which the college expansion policy leads to heterogeneous impacts on children from different socioeconomic backgrounds. For disadvantaged children whose human capital (test score) is distant from the average of test takers, as shown in Figure 2.2, additional investments in human capital do not spur an immediate rise in the probability of admission. Furthermore, college expansion also does not change the situation.[22] Consequently, low-skill parents, facing the new admission policy function, are disincentivized to spend more on their children's education. In contrast, for high-skill parents, their children's human capital can reach the average level before the reform. College expansion rewards additional skill accumulation for children with above-average human capital by increasing their admission probability.

In the economy with a childhood subsidy (dash-dot black line), as shown in Panel (A) of Figure 2.3 , the key difference is at the bottom: Low-skill parents significantly increase their education expenditure on children. As a result, as shown in Panel (B) of Figure 2.3 , the increments in children's human capital are more evenly distributed across parents with different human capital. The college attendance rate of disadvantaged children, in turn, goes up relative to that in the economy with the current

[22]The key observation from the estimation of college admission policies in Subsection **??** is that only test takers whose scores are above the average have a significantly higher probability of passing the exam following college expansion.

policy in place. Meanwhile, Panel (C) of Figure 2.3 also shows that fewer children of high-skill parents take the exam, which is a result of the higher college tuition.

Table 2.8 show how education outcomes and welfare changes are distributed across children whose parents differ in their education levels. Column (1) corresponds to the baseline implications of the model. Columns (2) and (3) present the change in education outcomes and welfare due to introduction of the current college expansion policy and the counterfactual childhood subsidy program.

Table 2.8: Distributional Implications of Policies

	(1) Baseline		(2) Existing Policy		(3) Child Subsidy	
Parent with a college degree	No	Yes	No	Yes	No	Yes
	Level		*Change*		*Change*	
Child						
Test taker share	15.16%	58.01%	11.9pp	18.4pp	16.2pp	10.3pp
College share	3.53%	28.91%	4.5pp	25.0pp	6.3pp	18.5pp
Human capital	0.70	1.10	8.5%	15.2%	25.0%	13.9%
Welfare	-12.35	-11.76	2.8%	21.7%	13.4%	19.4%

Note: This table displays how children's education outcomes and welfare depend on the associated parents with different education levels. Column (1) corresponds to the initial steady state. Column (2) and (3) corresponds to the percentage points or percentage changes after implementing the existing and counterfactual policies relative to the baseline economy.

Column (2) of Table 2.8 shows that in the economy with the existing policy in place, the children of college-educated parents increase their college attendance rates, human capital, and welfare more than the children of non-college-educated parents. Therefore, the policy gives rise to more persistent schooling across generations. Column (3) of Table 2.8 shows that the childhood subsidy program redistributes the human capital and welfare gains away from children of college-educated parents to children of non-college-educated parents. The reason for this is in line with the previous explanations, since college-educated parents are associated with high human capital.

2.5 Conclusion

In this paper, I quantitatively investigate how China's college expansion program impacts parental investment and inequality in the long run. To this end, I present a heterogeneous-agent overlapping-generations model in which altruistic parents invest in their children's education, and estimate the model using Chinese household-level data. I use the model to examine the aggregate and distributional effects of the higher education reform. The main finding is that the increase in college attainment, human capital, and ex ante welfare are substantial but unevenly distributed, with disadvantaged children benefiting the least from the existing policy. The numerical exercise reveals that high-skill parents' education expenditure are more elastic to the policy change following the college expansion. As a result, their children can accumulate higher human capital, and hence are more likely to gain access to college, which leads to a widening income gap and more persistent schooling across generations. Next, I use the model to study the effects of an early childhood development program, which subsidizes 60% of the education expenditure by the eligible parents. The additional spending is financed by raising college tuition. I show that the remediation policy can generate substantial welfare gains and a decline in inequality relative to the existing policy, which suggests that government expenditure on education subsidies can be implemented more efficiently.

Chapter 3

Understanding the Secular Decline in New Business Creation

3.1 Introduction

A growing body of research documents a significant drop in the formation of new businesses in the United States since the early 1980s. This decline in the creation of new businesses is at the center of the decline in the overall dynamism experienced by the U.S. economy in the last last three decades, because startups and young firms contribute to job creation, productivity, and economic growth (Decker et al. (2014)).

Recent papers have sparked heated debate regarding reasons for the secular decline in new business creation. A possible explanation is that the cost of starting a firm is increasing as a result, for example, of the growth of occupational licensing (Kleiner and Krueger (2013)) or weaker anti-trust enforcement, which would otherwise erect entry barriers (Gutierrez and Philippon (2018)). Another possible reason is that shocks to firms' productivity have become more serially correlated over time than before, in the sense that it is less likely that an unproductive firm will become a productive one. This stems, for example, from better intellectual property protection (Akcigit and Ates (2019b)), which makes it harder for less productive firms to use ideas from highly productive, successful firms. Consequently, potential startups may not choose to enter the market, since they believe it is less likely that they will succeed. These two forces cannot be observed directly from the data; this requires for a framework, assisted by a set of relevant moments, in order to infer them indirectly. Moreover, the implications of these two forces can be vastly different. If the decline in new business creation is mainly due to higher entry cost, it essentially reduces overall welfare and total factor productivity (TFP). If, on the other hand, it is the fact that shocks to firms' productivity become more persistent over time accounts for the largest part of the decline, overall welfare and TFP can be even higher than before. The intuition is that more persistent shocks to productivity help undo the misallocation of production factors in the presence of financial friction through entrepreneurs' stronger self-financing motives, as emphasized by Buera and Shin (2011) and Moll (2014).

The goal of this paper is to identify and quantify the relative contributions of higher entry cost and higher persistence of shocks to the observed declines in new business creation, relying on a set of moments regarding business dynamism. More specifically, the two key moments we use are the dispersion of employment growth rate and the relative size of entrants. Our intuition is that if the decline in firm entry is due to a higher entry cost, entrants should become larger relative to incumbents. Likewise, if the decline in firm entry is due to higher persistence of productivity shocks, we should observe a lower dispersion of the employment growth rate; this is because higher persistence means that large firms continue to be large and small firms continue to be small. In the data, dispersion of the employment growth rate at both firm level and establishment level has dropped dramatically over the last three decades (Decker et al. (2016)), while the relative size of entrants remains fairly stable and has even increased slightly since the early 2000s (Hopenhayn et al. (2019)). This suggests that the decline in firm entry is likely to be driven by the two forces jointly.

To further test and examine these insights, we first develop a quantitative general equilibrium model of entrepreneurship that features occupational choices. In the model, an individual must decide in each period whether to be a worker or an entrepreneur conditional on their assets, productivity in running a business (i.e., entrepreneurial productivity), and productivity in working for someone else. A new business is created if an individual who was previously a worker chooses to become an entrepreneur. If a worker becomes an entrepreneur, she must pay a fixed entry cost. Each agent's entrepreneurial productivity and working productivity are two independent Markov processes disciplined by the data.

The two forces that contribute to the decline in new business creation we focus on in this paper manifest as an increase in the fixed entry cost and an increase in the persistence of entrepreneurial productivity shocks respectively. While it is straightforward that a higher fixed entry cost causes fewer workers to choose to become entrepreneurs, it is not self-evident that the higher persistence of entrepreneurial productivity shocks also leads to less entry. The reason is as follows. Given the level of assets and working productivity, only agents with relatively high entrepreneurial productivity choose to become an entrepreneur, so potential entrepreneurs, i.e., workers, are those with low entrepreneurial productivity. With more persistent entrepreneurial productivity shocks, potential entrants know that once they become entrepreneurs, they are more likely to remain in a state of low productivity; therefore, they are reluctant to enter the market.

We calibrate the model to the U.S. business sector under the assumption that it was at the steady state in the early 1980s to match several key moments, especially the entry rate, the employment share of entrants, dispersion of the employment growth rate, and the relative size of entrants. Based on our baseline calibration, entrants must pay an entry cost equal to their first year's average profit. The entry cost is also equal to around 79% of the average entrepreneurial income and six times that of the average labor income.

We then use this calibrated model to quantitatively infer which force—higher persistence of productivity shocks or higher entry cost—plays a more important role in driving the observed declines in new business creation. To achieve this goal, we perform our quantitative analysis in two steps. First, we increase the persistence of entrepreneurial productivity shocks and the entry cost in the model to match the decline in the employment share of entrants, [1] then check the movement of the other key moments (e.g., the dispersion of employment growth rate) we use to discipline model parameters. If one or more movements of the moments are not consistent with their empirical counterpart, we can at least say that the factor that drives the

[1] Alternatively, we can increase the persistence of entrepreneurial productivity shocks and the entry cost in the model to match the decline in entry rate of entrepreneurs, which makes no difference. We choose to match the decline in the employment share of entrants due to technical reasons, which will be explained in Section 3.5.

movement may not solely account for the decline in new business creation. Our finding is that after increasing the persistence of entrepreneurial productivity shocks while holding all other parameters fixed, dispersion of the employment growth rate declines (consistent with the data) and the relative size of entrants also declines (inconsistent with the data). If we increase the entry cost to match decline in the employment share of entrants while holding all other parameters fixed, dispersion of the employment growth rate increases (inconsistent with the data) and the relative size of entrants also increases (inconsistent with the data). This implies that the rising persistence of shocks or rising entry cost cannot account for all of the entire decline in the new business creation.

Second, we recalibrate the persistence of the entrepreneurial productivity process and the entry cost to match five moments during the 2010s simultaneously: the annual entry rate of entrepreneurs, the employment share of entrants, the entrepreneurial employment share, dispersion of the employment growth rate, and the relative size of entrants. While increasing the persistence of entrepreneurial productivity shocks and increasing the entry cost both contribute to the decline in entry rate as well as the employment share of startups, they yield opposite predictions regarding the other three moments. For example, higher persistence leads to a lower dispersion of the employment growth rate, but higher entry cost generates higher dispersion. Therefore, these five moments are balanced with each other, providing us with a new estimation on the persistence of shocks and entry cost in the 2010s.

We find that the persistence of productivity shocks and the entry cost both increase substantially. After decomposing the changes, we find that the relative contribution of higher entry cost is more than 1.5 times that of the higher persistence of idiosyncratic entrepreneurial productivity shocks to the decline in the entry rate of entrepreneurs, and around twice the decline in the employment share of startups. Moreover, the entry cost paid by start-ups in the 2010s becomes 1.15 times the average profit of entrants, 96.3% of the average entrepreneurial income, and 8.8 times the average labor income. This means that increases in the entry cost cause entrepreneurs to pay 15% more in terms of their first year's profit, 22% more in terms of the average entrepreneurial income, and 33% more in terms of the average labor income to start a business.

In terms of welfare and TFP, our quantitative results show that the increased entry cost and persistence of shocks calibrated to the 2010s jointly lead to a 2.8% decline in entrepreneurial TFP and a 2.0% decline in consumption-equivalent welfare. Moreover, higher entry cost alone reduces both entrepreneurial TFP and consumption-equivalent welfare, while higher persistence of productivity shocks alone generates a higher level of entrepreneurial TFP and consumption-equivalent welfare. These results are consistent with those of Buera and Shin (2011) and Moll (2014), who consider a model similar to ours (their model also features heterogeneous entrepreneurs and an imperfect capital rental market). That is, sufficiently persistent shocks imply that steady-state productivity losses and the welfare cost of market incompleteness are relatively small.

Our results do not mean—and are far from implying—that the increased entry barriers and higher persistence of idiosyncratic productivity shocks are the only two possible drivers of the observed decline in the creation of new businesses. However, our analysis, however, sheds light on the relative importance of the two factors in contributing to the declining firm entry and employment share of entrants. Identifying their relative importance is important, since although both higher entry cost and higher persistence of shocks lead to observed declines in new business creation, they have divergent impacts on TFP and welfare. Because our work suggests a more important role played by higher entry cost—which reduces TFP and welfare—this should be a concern for policy makers.

Finally, we study the implications of higher entry cost and higher persistence of shocks on how firms respond to a negative credit shock that mimics a financial crisis in transitional dynamics, based on our calibration results. Suppose there is a credit shock that suddenly tightens the collateral constraints of entrepreneurs and then recovers to the pre-crisis state. Our key finding is that given the path of credit shocks, the set of parameters with higher entry cost and higher persistence of shocks that are calibrated to the data from the 2010s generates a slower transition of the stock of entrepreneurs to the pre-crisis level. This result provides insights on the slow recovery from the Great Recession compared with the previous recessions. It is well-known that both the Great Recession and the 1980-1982 recession (or "Double Dip Recession") were accompanied by large drops in the number of firms, but the recovery in the number of firms has been much more sluggish since the Great Recession. The insights based on our results are that the entry barrier in the late 2000s is much larger than that in the early 1980s, which makes it harder for an entrepreneur who previously exited the market due to a credit crunch to re-enter the market.

Related Literature. This paper is related to a growing literature on the causes and consequences of the secular decline in firm creation and entrepreneurship observed in the United States since the early 1980s. Several papers have documented a decrease in the share of economic activity accounted for by small and new businesses in the United States (see, for example, Haltiwanger et al. (2012); Decker et al. (2014); and Pugsley and Sahin (2019), among others).

There is not a definitive explanation for the decline in new business creation, but the literature has proposed several potential candidates. For example, Hopenhayn et al. (2019) argue that the decline in the growth rate of the labor force participation observed in the data is at the heart of the decline in the formation of new businesses. Engbom (2019) examines how the aging of the U.S. population reduces individuals' incentives to start new firms. Salgado (2018) shows that skill-biased technical changes and the decrease in the cost of capital goods can account for a significant fraction of the decline in entrepreneurship. Akcigit and Ates (2019a) quantitatively investigate which force plays a dominant role in a group of candidates (i.e., lower effective corporate tax, higher R&D subsidy, higher entry cost, and lower knowledge diffusion from frontier firms and lagged ones) in explaining the decline in firm entry and the slowdown in the overall dynamism (e.g. increased concentration) of the U.S. economy. They conclude that the decline in knowledge diffusion is the most important driver, which may explain the higher persistence of productivity shocks we emphasized in our paper.

Our work is complementary to two papers, by Buera and Shin (2011) and Moll (2014), that feature models (i.e., a Bewley-Aiyagari-styled heterogeneous agent model with production and an imperfect capital rental market) quite similar to the one we study; they also focus on the persistence of idiosyncratic productivity shocks. Buera and Shin (2011) show that the overall welfare cost of market incompleteness can be increasing, decreasing, or even non-monotone in shock persistence, depending on the relative strengths of its two components: the cost of a lack of insurance and the cost of imperfect capital markets. The reason is that more persistent shocks are harder to self-insure but simultaneously lead to better allocation of production factors through entrepreneurs' self-financing. Based on similar logic, Moll (2014) argues that the persistence of idiosyncratic productivity shocks determines the size of steady-state productivity losses and shows that more persistent shocks lead to smaller steady-state losses but slower transitions. In our paper, we show that higher persistence of shocks hinders new business creation in the steady state, and leads to a quicker transition of firm entry and the employment share of entrants.

Finally, we join the literature that examines the reasons for lack of firm entry and the slow recovery of the number of firms after the Great Recession. Clementi et al. (2014); Khan and Thomas (2013); and Siemer (2014) develop a quantitative heterogeneous firm model that features borrowing constraints and showing that lack of entry is a consequence of credit crunches, since credit tightening directly affects small and young firms the most. The results of our work indicate that the slow recovery of the number of firms after the Great Recession may be due to a higher entry cost compared with the level in the early 1980s.

The paper is organized as follows. Section 3.2 briefly discusses the data we use in this paper. Section 3.3 describes the model set-up and defines a recursive competitive equilibrium. Section 3.4 discusses the calibration. In Section 3.5, we report the main results of this paper. Section 3.6 discusses the implications of the main results reported in Section 3.5 on firms' response to a credit shock that mimics a financial crisis. Section 3.7 concludes the paper.

3.2 Data

As emphasized in Decker et al. (2014), measuring entrepreneurship and its economic effects is difficult. There are two major strands of literature to follow. The first strand of literature (e.g. Decker et al. (2014), Haltiwanger et al. (2012)) uses firm-level data or establishment data to measure it and define entrepreneurs as a particular type of firms based on their age and size (in terms of number of employees). Since available government datasets on the U.S. firms do not have a specific entry for "entrepreneurs." but have traditionally contained information about the size and age of firms, some observers have written or spoken as if small and young businesses are synonymous with entrepreneurs. We also notice that there are several recent papers defining entrepreneurship based on the legal form of the business organizations (e.g. Bhandari and McGrattan (2019), Dyrda and Pugsley (2019)). For example, Dyrda and Pugsley (2019) defines entrepreneurial income as the income from pass-through entities (i.e. sole proprietorships, partnerships, and S corporate firms). The second strand of literature (e.g. Quadrini (2000), Cagetti and DeNardi (2006)) uses household-level data such as PSID and SCF and define entrepreneurs as a type of households based on whether they own a business or are self-employed. [2]

In this paper, we follow the first strand of literature on measuring entrepreneurship. We define entrepreneurs as establishments with less than 20 employees using data from the Business Dynamic Statistics (BDS). Our reasoning is as follows. Establishments with less than 20 employees are relatively small businesses. The reason for choosing 20 employees as a cutoff is that based on Dyrda and Pugsley (2019), the average size of establishment with legal form of sole proprietorship and partnership is around 6 employees, and by choosing 20 employees as a cutoff for defining entrepreneurship, we get the average size of entrepreneurs closer to 6.

The following are the definitions of the moments that we are going to use in this paper. We compute the annual entry rate of entrepreneurs as the number of establishment with age 0 and size smaller than 20 employees divided by the number of establishments with size smaller than 20 employees. We compute the employment share of startups as the total employment of establishments with age 0 and size smaller than 20 employees divided by the total employment of all the employer establishments in BDS for a specific year. We compute the entrepreneurial employment share as the total employment of establishments with size smaller than 20 employees divided by

[2] Even among papers which use household-level data to define entrepreneurs, there is little consensus about which households or individuals should be classified as such. For example, Evans and Leighton (1989) considers as entrepreneurs those that are self-employed, Hurst and Lusardi (2004) all those households that own a business, whereas Gentry and Hubbard (2004) defines as entrepreneurs all those business owners with businesses with a total market value of $5,000 or more. Quadrini (2000) considers both, business owners and self-employed as entrepreneurs. Cagetti and DeNardi (2006) define entrepreneurs as those self-employed business owners that have an active management in the firm. Salgado (2018) thus refer to four classifications of entrepreneurs that encompass the different alternatives considered in the literature.

the total employment of all the employer establishments in BDS for a specific year. The average size of entrant entrepreneurs relative to the incumbent entrepreneurs is computed as the average size of establishments with age 0 and size smaller than 20 employees divided by the average size of establishments with size smaller than 20 employees for a specific year. Finally, the dispersion of employment growth rate is computed as the standard deviation of the employment growth rate for all the continuing firms (i.e. $(l_{i,t} - l_{i,t-1})/[0.5 \times (l_{i,t} + l_{i,t-1})]$ where lit denotes the employment of firm i in year t). Since we do not have firm-level or establishment-level census data, we draw this moment from Decker et al. (2016) that uses Longitudinal Business Dynamics (LBD) data to compute the standard deviation of employment growth rate for all the employer establishments for the years 1980-2014. [3]

3.3 Model

We consider a model of entrepreneurship based on Buera et al. (2011) and Buera and Shin (2013) but augmented with an entry cost and a corporate production sector as in Quadrini (2000).

We model an economy populated by a continuum of individuals, who are heterogenous with respect to their wealth (or assets), previous occupational status (so that new entrepreneurs are different from incumbents), entrepreneurial productivity, and working productivity. In each period, an individual chooses whether to work for a wage or to operate an individual-specific technology (entrepreneurship). One entrepreneur can operate only one production unit (establishment) in a given period. Entrepreneurial ideas are inalienable, and there is no market for managers or entrepreneurial talent to be traded. If a previously worker becomes an entrepreneur, she needs to pay a fixed entry cost.

Output is produced by both entrepreneurs and a representative corporate firm. A zero-profit financial intermediary borrows from households with positive savings to

[3]We admit that there is discrepancy between this moment and the other moments used in this paper. The ideal moment should be the standard deviation of employment growth rate for all the continuing employer establishments with size smaller than 20 employees. However, since we do not have LBD data at hand, this is the best moment on dispersion of employment growth rate that we can use for now.

supply productive capital for entrepreneurs and the corporate sector.

3.3.1 Environment

Heterogeneity and Demographics. Consider an economy with a continuum of individuals of measure one. Individuals live infinitely and are heterogenous in their asset a_t, previous occupational status d_{t-1}, worker ability ϵ_t, and entrepreneurial productivity z_t. Both the worker ability and the entrepreneurial productivity follows a Markov process, and the two processes are independent to each other. There is no population growth and no aggregate uncertainty either.

Preferences. Individual preferences are described by the following expected utility function over sequences of consumption c_t:

$$U(C) = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t u(c_t) \right] \tag{3.1}$$

where β is the discount factor, which is smaller than one. The expectation is taken over the realizations of the worker ability ϵ_t and the entrepreneurial productivity z_t. We choose a period utility function that has a constant relative risk aversion. That is, $u(c_t) = \frac{c_t^{1-\sigma}-1}{1-\sigma}$.

Occupational Choice and Production Technology. At the beginning of each period, after the realization of shocks, an individual chooses whether to operate his own business or work for a wage (labor is indivisible). If the individual decides to be a worker, she receives an income of $w_t\epsilon_t$ where ϵ_t is an idiosyncratic, positively autocorrelated shock, and w_t is the market wage rate in period t. A worker cannot borrow but can save in a risk-free asset, at, with return r_t. If the individual chooses to be an entrepreneur, she gains access to a productive technology that uses her own entrepreneurial ability z_t, capital k_t, and labor l_t, based on a decreasing-return-to-scale technology:

$$z_t f(k_t, l_t) = z_t (k_t^{\alpha} l_t^{1-\alpha})^{\gamma} \tag{3.2}$$

where $\gamma < 1$ is the span-of-control parameter. A share γ of output goes to factor of inputs. Out of this, a fraction of α is going to capital and $1 - \alpha$ going to labor.

In reality, a large fraction of firms are not managed by households weighing the cost and benefit of running their own business or working in someone else's company. Therefore, as in Quadrini (2000) and Cagetti and DeNardi (2006), we model a second sector of production populated by a large number of homogeneous firms which we refer to as the non-entrepreneurial, or corporate sector. Firms in this sector are operating a constant returns to scale production technology given by

$$AF(K_{C,t}, L_{C,t}) = AK_{C,t}^{\theta} L_{C,t}^{1-\theta} \tag{3.3}$$

where A is the time-invariant corporate productivity, which will be normalized to 1, while $K_{C,t}$, $L_{C,t}$ are corporate capital and labor demand respectively. Corporate production does not involve fixed costs. Both sectors produce the same good, and in both sectors capital depreciates at the same rate.

Financial Market. Productive capital is the only asset in the economy. There is a perfectly competitive financial intermediary that receives deposits and rents out capital to entrepreneurs. The return on deposited assets, i.e. the interest rate in the economy, is r_t. The zero-profit condition of the intermediary implies that the rental price of capital is $r_t + \delta$, where δ is the depreciation rate.

3.3.2 Stationary Equilibrium

Recursive Problem of Individuals. At the beginning of the period, each individual is characterized by her asset a, working productivity ϵ, and entrepreneurial productivity z_t, previous occupational status d_-, where $d_- = 0$ identifies a worker and $d_- = 1$ an entrepreneur. Then, an individual solves the occupation choice problem given by

$$v(a, \epsilon, z, d_-) = \max_{d \in \{0,1\}} \left\{ (1-d) v^W(a, \epsilon, z, d_-) + d v^E(a, \epsilon, z, d_-) \right\}, \tag{3.4}$$

where v^W is the value of being a worker, v^E is the value of being an entrepreneur, and d denotes an individual's current-period occupation.

The problem solved by current-period workers is given by

$$v^W(a,\epsilon,z,d_-) = \underset{c,a'\geq 0}{max} \left\{ u(c) + \beta \sum_{\epsilon',z'} P(\epsilon',z'|\epsilon,z) v(a',\epsilon',z',d=0) \right\}, \tag{3.5}$$

subject to

$$c + a' = (1+r)a + w\epsilon,$$

and also to the laws of motion of ϵ_t and z_t, and the law of motion of the distribution of individuals over idiosyncratic states. Additionally, $P(\cdot|\cdot)$ is transition probabilities, v is continuation value, and $d=0$ indicates that the individual will enter next period as a worker before choosing a new occupation.

The problem solved by current-period entrepreneurs is given by

$$v^E(a,\epsilon,z,d_-) = \underset{c,a'\geq 0}{max} \left\{ u(c) + \beta \sum_{\epsilon',z'} P(\epsilon',z'|\epsilon,z) v(a',\epsilon',z',d=1) \right\}, \tag{3.6}$$

subject to

$$c + a' + \mathbb{I}(d_- = 0)\kappa = (1+r)a + \pi(a,z),$$

and also to the laws of motion of ϵ_t and z_t, and the law of motion of the distribution of individuals over idiosyncratic states. Additionally, $P(\cdot|\cdot)$ is transition probabilities, and v is continuation value, and $d=1$ indicates that the individual will enter next period as an entrepreneur before choosing a new occupation. The profit function is given by

$$\pi(a,z) = \underset{0\leq k\leq \lambda a, l\geq 0}{max} \left\{ zf(k,l) - wl - (r+\delta)k \right\}.$$

Here, $\mathbb{I}(d_- = 0)$ is an indicator function which is equal to 1 if the individual was a worker in the previous period, i.e. $d_- = 0$, and is equal to zero otherwise. This function captures the assumption that the fixed cost of creating a firm is paid only by those individuals transitioning from a worker to an entrepreneur.

Note that we focus on within-period borrowing, or capital rental for production purposes. We do not allow borrowing for inter-temporal consumption smoothing, which translates into $a' \geq 0$. Several papers have documented the importance of borrowing constraints to the decision to become an entrepreneur.[4]. Here, we assume that entrepreneurs' capital rental k is limited by a multiple of the collateral, i.e. $k \leq \lambda a$.[5]

Problem of Corporate Sector. The problem of the corporate (non-entrepreneurial) sector is simple and is given by

$$\pi_C = \max_{K_C, L_C \geq 0} \left\{ AF(K_C, L_C) - wL_C - (r+\delta)K_C \right\}. \tag{3.7}$$

Definition of Equilibrium. A stationary recursive competitive equilibrium is value functions v, v^E , and v^W; individual's policy functions c, a', and d; entrepreneur's factor demand k and l; corporate sector's factor demand K_C and L_C; prices r and w; and a distribution (μ) over individual wealth (a), working ability (ϵ), entrepreneurial ability (z), previous occupation status (d_-) such that

1. given prices, the policy functions—namely, c, a', d, k, l—solve dynamic programming problems associated with value functions v, v^E, v^W;

2. given prices, corporate sector's factor demand—namely, K_c and L_c—solve corporate firm's optimization problem;

3. the asset market clears

$$\int a'(a, \epsilon, z, d_-) d\mu = K_C + \int_{d(a,\epsilon,z,d_-)=1} k(a, \epsilon, z, d_-) d\mu; \tag{3.8}$$

[4]See, for instance, Evans and Jovanovic (1989), Quadrini (2000), Hurst and Lusardi (2004), or Cagetti and DeNardi (2006).

[5]Alternatively, we can have entrepreneurs own capital k and face a constraint on borrowing leverage, i.e. $b' \leq \frac{\lambda-1}{\lambda} k'$. Defining $b = k - a$, with the understanding that $b < 0$ denotes savings, and assuming that λ capital and debt (k, b) are chosen after the realizations of idiosyncratic shocks (ϵ, z) give us an equivalent problem to the one specified in our paper. This assumption that producer profits are a function solely of its net worth or wealth at, not of capital k and debt b in isolation, helps to reduce the dimension of the problem and simplifies the computation, which is widely used in the literature (e.g. Gavazza et al. (2018); Midrigan and Xu (2014)).

4. the labor market clears

$$\int_{d(a,\epsilon,z,d_-)=0} \epsilon d\mu = L_C + \int_{d(a,\epsilon,z,d_-)=1} l(a,\epsilon,z,d_-)d\mu; \tag{3.9}$$

5. the distribution of individuals over states (a, ϵ, z, d_-) are invariant, i.e.,

$$\mu(a,\epsilon,z,d_-) = \Psi(\mu(a,\epsilon,z,d_-)), \tag{3.10}$$

   where Ψ depends on optimal policy of a' and d as well as the law of motion of ϵ and z.

3.4 Calibration

We numerically solve the model by using non-linear methods, and find a stationary equilibrium where individual decisions are consistent with market clearing prices.[6] We begin with the subset of parameters calibrated externally, and then consider those estimated within the model. Calibrated parameters are chosen such that the model resembles the U.S. economy around early 1980s when the U.S. business dynamism starts to decline. Thus, data moments are averages over 1980-1985 unless otherwise specified.

3.4.1 Externally Calibrated Parameters

To maintain the tractability of the calibration, we take some parameters directly from the literature. The time period in this model is equal to a year. We take a standard value of 1.5 for the coefficient of risk aversion of the households' utility function and the span of control parameter of 0.79 following Buera et al. (2011). The capital share parameter of corporate firms' production function is set to be 0.35 matching the labor income share of corporate sector in early 1980s. For simplicity, we make the value of the capital share parameter of entrepreneurs equal to that of the corporate sector. Taking the scale of production γ into consideration leads to a capital share $\alpha\gamma = 0.28$,

[6] See Appendix for computation details.

which is close to the value used in the literature (e.g. Buera et al. (2011), Cagetti and DeNardi (2006)). The capital depreciation rate is set to be 6% based on the BEA fixed asset tables taking both physical capital and BEA-measured intangible capital (or IPP capital) into consideration.

The working productivity ϵ is assumed to follow an autoregressive process with normal innovations, $log\epsilon' = \rho_\epsilon log\epsilon + e_\epsilon$ with $e_\epsilon \sim N(0, \sigma_\epsilon)$. Since the main focus of this paper is on the producers' side, we take the parameters that govern the process of working productivity, i.e. $(\rho_\epsilon, \sigma_\epsilon)$ from Bhandari and McGrattan (2019), which is also consistent with the estimated wage processes of Low et al. (2010) for U.S. households in U.S. Census and the Survey of Income and Program Participation (SIPP). Table 3.1 summarizes these parameter values.

Table 3.1: Parameter values set externally

Parameter		**Value**	**Source/Target**
Curvature of utility function	σ	1.50	BKS 2011
Entrepreneur capital share	α	0.35	-
Entrepreneur scale of production	γ	0.79	BKS 2011
Corporate capital share	θ	0.35	Corp. labor income share
Persistence of ϵ shocks	ρ_ϵ	0.70	Bhandari and McGrattan 2019
SD of ϵ shocks	σ_ϵ	0.16	Bhandari and McGrattan 2019
Capital depreciation rate	δ	0.06	BEA fixed asset tables

3.4.2 Internally Calibrated Parameters

The entrepreneurial productivity z is assumed to follow a discretized version of an autoregressive process with normal innovations, $logz' = \rho_z logz + e_z$ with $e_z \sim N(0, \sigma_z)$. In particular, we approximate this autoregressive process with a 9-state Markov chain following the procedure of Rouwenhorst (1995b).[7] We have six parameters $(\beta, A, \rho_z, \sigma_z, \kappa, \lambda)$ left to be calibrated within the model. Table 3.2 lists the results. Even though every targeted moment is determined simultaneously by all parame-

[7]We choose the Rouwenhorst's method over the Tauchen's method (see Tauchen (1986)) since Rouwenhorst method has better performance in the case of highly persistent shocks.

ters, in what follows we discuss each of them in relation to the parameter for which, intuitively, that moment yields the most identification power.

Discount factor β is chosen such that the annual real interest rate is 4%. The productivity of the representative corporate firm A is calibrated to match the aggregate employment of all the entrepreneurs as a share of total employment (i.e. the sum of employment of both corporate sector and entrepreneurial sector).[8] We calibrate the collateral parameter λ to match the aggregate debt-to-value-added ratio for the non-corporate sector in the data.[9]

The rest three parameters $(\rho_z, \sigma_z, \kappa)$ are calibrated jointly to match three important moments that regards the dynamism of the U.S. economy in the early 1980s. The first one is the annual entry rate of entrepreneurs. In the model, the moment in period t is calculated as the number of entrants (i.e. entrepreneurs in period t who are workers in period $t-1$) as a share of total number of entrepreneurs in period t. Increasing the persistence of entrepreneurial productivity process ρ_z and increasing the fixed entry cost κ respectively both leads to a reduction in the entry rate of entrepreneurs. While it is straightforward that a higher κ renders less workers choose to become entrepreneurs, it is not self-evident that a higher ρ_z also leads to less entry. The reason is as follows. Given the level of assets and working productivity, only agents with relatively high entrepreneurial productivity choose to become an entrepreneur, so potential entrepreneurs, i.e. workers, are those with low entrepreneurial productivity. With more persistent entrepreneurial productivity shocks, potential entrants know that once they become entrepreneurs they are more likely to remain low productivity, so they choose not to enter the market. [10]

[8] We calibrate A to match the entrepreneurial employment share since we assume the mean of log of entrepreneurial productivity shocks z is zero. Alternatively, we can normalize A to one and calibrate the mean of log z to target the entrepreneurial employment share, which makes no difference.

[9] The data on debt is liability level of loans for non-financial non-corporate business sector, obtained from Z.1 Financial Accounts of the U.S. of the Board of Governors of the Federal Reserve System, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NNBLL.

[10] Due the general equilibrium (GE) effect, an increase in ρ_z leads to a higher equilibrium wage (since with more persistent shocks, entrepreneurs have stronger motivation to do self-financing to get rid of the collateral constraint so that they can choose capital and labor optimally, which increases labor demand), and a higher wage means being a worker becomes more attractive, so one may wonder whether it is mainly due to the GE effect or the reason specified above. Based on our computation,

The second moment is the standard deviation of employment growth rate for continuing establishments (excluding entrants and exiters). We draw this moment from Decker et al. (2016). Decker et al. (2016) uses LBD data and calculates an establishment i's employment growth rate in year t as $(l_{i,t} - l_{i,t-1}) / [0.5 \times (l_{i,t} + l_{i,t-1})]$. In the model, we are consistent with this definition to compute the moment of the standard deviation of employment growth rate for all the entrepreneurs. The third moment is the average size of entrants relative to the average size of all the entrepreneurs in the economy. Note that although we are not directly targeting the employment share of entrants, which is another important moment regarding business dynamism and features a secular decline in recent decades, since we are matching the entry rate, the employment share of entrepreneurs, and the relative size of entrants, then the employment share of entrants are automatically matched.[11] The employment share of entrants in the model is equal to 0.021 which is very closer to its empirical counterpart 0.022.

Table 3.2: Parameter values calibrated internally

Parameter		**Value**	**Moment**	**Data**	**Model**
Discount factor	β	0.943	Annual risk-free rate	0.040	0.040
Corporate productivity	A	1.326	Entrep. empl. share	0.272	0.272
Persistence of z shocks	ρ_z	0.915	Annual entry rate	0.125	0.125
SD of z shocks	σ_z	0.236	SD of empl. growth	0.634	0.633
Entry cost	κ	12.17	Rel. size of entrants	0.630	0.630
Collateral parameter	λ	5.431	Debt to GDP (entrep.)	1.355	1.357

we find that the reason specified above is the dominant one. The GE effect only slightly strengthen the results on the decline. Suppose we increase ρ_z from 0.915 to 0.940. With GE, the entry rate declines from 12.5% to 10.76%, while without GE, i.e. fixing the wage, the entry rate declines from 12.5% to 10.89%.

[11]More specifically, the equation {entry rate} $\times$ {startups relative size} = {employment share of startups} $\times$ {employment share of entrepreneurs} always holds. The reasons are as follows. The $LHS \equiv \frac{N_s}{N_e} \times \frac{l_s}{l_e} = \frac{L_s}{L_e} = \frac{L_s}{L} / \frac{L_e}{L} \equiv RHS$ where N_s denotes the number of startups, N_e denotes the number of entrepreneurs (so $\frac{N_s}{N_e}$ means the entry rate of entrepreneurs), l_s denotes the average size of startups, l_e denotes the average size of entrepreneurs (so $\frac{l_s}{l_e}$ means the relative size of entrants), L_s denotes the employment of startups, and L_s denotes the employment of entrepreneurs (so $\frac{L_s}{L}$ and $\frac{L_e}{L}$ mean the employment share of startups and the employment share of entrepreneurs respectively). This equation thus implies that if any three of the four moments are matched to the data perfectly, the rest one will be automatically matched.

Increasing ρ_z while fixing the unconditional distribution of the idiosyncratic productivity shocks reduces the standard deviation of employment growth rate as well as the relative size of entrants. Increasing κ raises both the relative size of entrants and also the standard deviation of employment growth rate. Thus, although an increase in the persistence of entrepreneurial productivity process ρ_z and the entry cost κ both contribute to a decline in entry rate, the other two moments, i.e. the dispersion of employment growth rate and the relative size of startups, can help us identify the parameters governing the productivity process and the entry cost parameter separately. Based on our baseline calibration, we obtain a ρ_z of 0.915. [12] Moreover, we find that the entry cost in early 1980s faced by firms equals the average income of entrants, 78.9% of the average entrepreneurial income, and six times of the average labor income.

3.5 Main Results

This section consists of three parts. In Subsection 3.5.1, we show that higher entry cost and more persistent productivity shocks cannot solely account for the decline in new business creation. In Subsection 3.5.2, we use the calibrated model from Section 3.4 to measure changes in entry cost and the persistence of shocks from the 1980s to 2010s. We then identify and quantify how changes in entry cost and the persistence of idiosyncratic productivity shocks contribute to the observed declines. Moreover, we check the implications of changes in these two factors on the aggregate productivity and welfare in Subsection 3.5.3 in terms of the creation of new businesses. In Subsection 3.5.4, we analyze the robustness of our main results.

[12] Although the persistence of idiosyncratic productivity shocks is considered an important parameter, there is no consensus on the estimated value of it. The calibrated value obtained in this paper is not far away from the existing literature that uses establishment-level or firm-level data to estimate ρ_z. For example, Cooper and Haltiwanger (2006) estimate it to be 0.981. Lee and Mukoyama (2015) estimate it be 0.843 or 0.956 depending on the specification used for estimation.

3.5.1 Understanding the Factors in Isolation

We first change the entry cost κ and the persistence of productivity shocks ρ_z (while fixing the unconditional distribution of shocks—i.e., fixing $\sigma_z/\sqrt{1-\rho_z^2}$ by adjusting the standard deviation σ_z, as in Buera and Buera and Shin (2011) and Moll (2014)) to match the decreased employment share of startups in the data for the 2010s respectively.[13] We increase ρ_z from the baseline value 0.915 to 0.976 and κ from 12.17 to 26.10 in order to match the overall decline in the employment share of startups. Table 3.3 summarizes the key results. It shows the observed change in each variable and compares them with their model counterparts in each experiment.

Table 3.3: Qualitative experiment results

	Data (1)		$\rho_z = 0.976$ (2)		$\kappa = 26.1$ (3)	
	Start	End	Start	End	Start	End
Entry rate	0.125	0.077	0.125	0.063	0.125	0.091
Empl. share of startups	0.022	**0.013**	0.022	**0.013**	0.022	**0.013**
Entrep. empl. share	0.272	0.250	0.272	0.532	0.272	0.159
SD of empl. growth rate	0.634	0.535	0.634	0.330	0.634	0.666
Relative size of entrants	0.630	0.635	0.630	0.386	0.630	0.905

A few observations stand out. First, despite the fact that an increase in the persistence of shocks leads to a lower entry rate of entrepreneurs and a lower standard deviation of the employment growth rate, both of which are consistent with the data qualitatively, changes in the entrepreneurial employment share and the relative size of entrants are not consistent with the data. Second, the directions of change in the entry rate and entrepreneurial employment share resulting from higher entry cost κ are consistent with the data. However, the higher entry cost generates an increase in

[13] Alternatively, we can increase κ and ρ_z to match the decreased entry rate of entrepreneurs respectively, but in that case, we find that we are not able to the increase in entry cost (column 3) to match the entire decline in firm entry. Even though we increase κ to a very large number, e.g. ten times of the value of κ in the initial steady state, the entry rate is stable around 0.082. In that case, only financially unconstrained agents with highest entrepreneurial productivity choose to become or keep being an entrepreneur. However, if we keep increasing κ, the entry rate will jump to zero from 0.082. We thus increase κ to match the decline in the employment share of startups in the data, making it comparable for the case of increased persistence of shocks.

the dispersion of the employment growth rate, which decreases in the data, and an increase in the relative size of entrants which is relatively stable in the data.

3.5.2 Identification and Decomposition

The results from the previous section imply that higher entry cost κ and higher persistence of shocks ρ_z should jointly account for the decline in new business creation (in terms of both the entry rate and employment share of entrants). Since we can observe neither κ nor ρ_z directly from the data, we can only infer the changes in the two factors from the relevant moments that may be the consequences of them. The moments we use for calibration give us some clue to separately identify and quantify how changes in these two factors contribute to the observed declines in the creation of new businesses. We thus conduct the following numerical exercise. We jointly recalibrate the persistence of idiosyncratic entrepreneurial productivity shocks ρ_z while fixing the unconditional distribution of shocks and fixed entry cost κ to match a set of moments in the data for the 2010s, including the (1) entry rate of entrepreneurs, (2) employment share of entrants, (3) relative size of entrants, (4) dispersion of the employment growth rate, and (5) entrepreneurial employment share. That is, we estimate two parameters to target five moments to exploit the power of "over-identification."

Table 3.4: Entry Cost and Persistence of Shocks

	Model (1980s)	Model (2010s)	Data (2010s)
Parameter			
ρ_z	0.915	0.940	–
κ	12.17	17.79	–
Moment			
(1) Entry rate	0.125	0.079	0.077
(2) Entrants empl. share	0.021	0.012	0.013
(3) Entrants relative size	0.630	0.610	0.630
(4) SD empl. growth rate	0.634	0.592	0.535
(5) Entrep. empl. share	0.272	0.250	0.250

Next, we discuss how we choose these moments strategically. The first two moments—i.e., entry rate and entrants' employment share—are main indicators of the creation of new businesses. Given the goal of this paper, we must include these two moments into the set for re-calibration. However, since higher persistence of shocks ρ_z and higher entry cost κ both lead to a lower employment share of entrants and a lower entry rate, these two moments provide no information on the relative contribution of higher κ and higher ρ_z to the decline in new business creation. Therefore, we add (3) relative size of entrants and (4) dispersion of the employment growth rate, which are informative moments in identifying κ and ρ_z in the baseline. To further discipline the change of κ and ρ_z, we add (5) entrepreneurial employment share, because higher ρ_z and higher κ have opposite impacts on this moment.[14] More specifically, a higher ρ_z leads to a higher entrepreneurial employment share, since it favors large, highly productive entrepreneurs—but higher κ leads to a lower entrepreneurial employment share, since it makes it harder for potential entrants to become entrepreneurs. After jointly recalibrating ρ_z and σ_z to match the chosen moments, we get $\rho_z = 0.940$ and $\kappa = 17.79$. The results are summarized in Table 3.4.

Table 3.5: Entry Cost in Real Terms

Entry cost to	Model (1980s)	Model (2010s)	Change
Entrants avg. profit	1.00	1.15	15%
Avg. entrep. profit	0.79	0.96	22%
Avg. labor income	6.00	8.80	47%

With the newly estimated persistence of shocks ρ_z and fixed entry cost κ, we find that the entry cost now becomes around 1.15 times the average income of entrants, 96.3% of the average entrepreneurial income, and around 8.8 times the average labor income. In contrast, for ρ_z and κ calibrated to the economy in the early 1980s, the entry cost is only 1 times the average income of entrants, 78.9% of the entrepreneurial income and 6 times the average labor income. We summarize the results in Table 3.5. This means that the entry cost not only increases in nominal value, but also causes potential entrants in the 2010s pay more, in real terms, to start a business than in

[14]Note that in the baseline calibration, we discipline the corporate productivity parameter A to match the entrepreneurial employment share, but in the case of re-calibration, we fix A at the baseline level.

the 1980s.

We then use the recalibrated parameters $\rho_z = 0.940$ and $\kappa = 17.79$ to perform the following decomposition in order to ascertain which force plays a relatively more important role in generating the decline in new business creation in terms of entry rate and the employment share of startups. We first fix the entry cost $\kappa = 12.17$, which is the calibration value in the initial steady state that captures the economy in the early 1980s. We then let the parameter for the persistence of shocks ρ_z equal 0.940, which is the newly calibrated value and captures the economy in the 2010s. This gives us results that can be used to compute the relative contribution of higher ρ_z to the decline in new business creation. Likewise, we follow the same procedure to compute the relative contribution of higher κ. More specifically, denoting a variable of interest by X, its value at time t when both channels move by X_t^2, and its hypothetical value when channel i is shut down by X_t^{2-i}, we can express the contribution of the channel i to the total deviation over the three decades as follows:

$$contribution_i = \frac{X^2_{2010s} - X^{2-i}_{2010s}}{X^2_{2010s} - X^2_{1980s}}$$

We summarize the paper's main results in Table 3.6. We find that the relative contribution of higher κ is more than 1.5 times that of higher ρ_z to the decline in the entry rate of entrepreneurs, and around twice the decline of the employment share of startups.

Table 3.6: Relative Contributions

	Higher κ		Higher ρ		Both
Entry rate	-2.85p.p.	(62.6%)	-1.72p.p.	(38.0%)	-4.60p.p.
Entrants empl. share	-0.57p.p.	(70.2%)	-0.28p.p.	(39.4%)	-0.94p.p.

Note: Percentage values in parentheses measure the share of the contribution from the specific channel to the total model-generated deviation between 1980s and 2010s.

3.5.3 TFP and Welfare

In this section, we examine the changes in entrepreneurial total factor productivity (TFP) and consumption-equivalent welfare induced by higher entry cost and more persistent entrepreneurial productivity shocks[15] and summarize the results in Table 3.7. Overall, compared with our baseline estimation, the increased entry cost and more persistent shocks faced by entrepreneurs in the 2010s lead to a 2.80% decline in entrepreneurial TFP and a 1.97% reduction in consumption-equivalent welfare. After decomposing the two factors that contribute to the decline in new business creation, we can see that higher entry cost alone reduces both entrepreneurial TFP and consumption-equivalent welfare, while higher persistence of productivity shocks alone generates a higher level of entrepreneurial TFP and consumption-equivalent welfare. This is because entrepreneurs can undo capital misallocation via self-financing: With persistent shocks, self-financing is an effective substitute for well-functioning capital rental markets in terms of allocating production factors, as emphasized by Buera and Shin (2011) and Moll (2014).

Table 3.7: TFP and Welfare

	Higher κ	Higher ρ	Both
Entrep. TFP	-5.04%	3.45%	-2.80%
Welfare	-1.76%	0.44%	-1.97%

Our results, whereby a higher entry cost and higher persistence of productivity shocks impact welfare and TFP differently, have important implications. If the decline in new business creation is mainly driven by higher persistence of shocks, this decline can be good in terms of welfare and TFP. If, on the other hand, the higher entry cost is a more dominant reason for the decline in new business creation, this should be a concern, since an increase in entry cost worsens aggregate productivity and overall welfare. Since our key finding of this paper suggests that higher entry cost plays a more important role in explaining the decline in new business creation, policymakers should take action to effectively reduce the entry barriers faced by potential startups.

[15] The TFP of the entrepreneurial sector is computed as the Solow residual:

$$TFP = \frac{\int_{d(a,\epsilon,z,d_-)=1} y\left(a,\epsilon,z,d_-\right) d\mu}{\left[\left(\int_{d(a,\epsilon,z,d_-)=1} l_t\left(a,\epsilon,z,d_-\right) d\mu\right)^{\alpha}\left(\int_{d_t(a,\epsilon,z,d_-)=1} k_t\left(a,\epsilon,z,d_-\right) d\mu\right)^{1-\alpha}\right]^{\gamma}}$$

3.5.4 Robustness

In this section, we analyze the robustness of our main finding regarding how we obtain the new estimation on entry cost κ and persistence of shocks ρ_z reported in subsection 3.5.2. Generally speaking, we obtain new estimation on κ and ρ_z to target five moments specified in Table 3.4 by searching an optimizer to minimize the distance between the moments generated from the model and their empirical counterparts given a specified weight matrix. Specifically, the vector of parameters Ψ is chosen to minimize the minimum-distance-estimator criterion function

$$f(\Psi) = (m_{data} - m_{model}(\Psi))^{'} W (m_{data} - m_{model}(\Psi)), \tag{3.11}$$

where m_{data}, m_{model} are the vectors of moments in the data and model, and W is a diagonal weighting matrix.[16] We give each moment an equal weight so that these moments are balanced to each other to give us new estimation on entry cost κ and persistence of shocks ρ_z jointly.

Next, we re-do this procedure by assuming alternative weighting matrices and objective functions for minimization. The first case we consider is to give entry rate and employment share of entrants a weight of five and give the rest three moments a weight of one.[17] The second case we consider is to use an alternative objective function that has been used by the existing literature (e.g. Acemoglu et al. (2018); Akcigit and Ates (2019b)) for calibration,[18] which is defined as

$$\sum_{k=1}^{N} \frac{|m_{data} - m_{model}(k)|}{\frac{1}{2}|m_{data}| + \frac{1}{2}|m_{model}(k)|} \tag{3.12}$$

[16]Since we only have a relatively small number of parameters calibrated within the model, we use a local search method rather than a combination of global stage and local search used in quantitative labor literature when the number of parameters calibrated within the model is large.

[17]We would always keep the weight equal for the two moments (1) dispersion of employment growth rate, and (2) entrants relative size. Since these two moments are major governors' of persistence of shocks and entry cost respectively, we do not want to give either of them more weight. Otherwise, the leading result on the relative contribution in the decline of new business creation will be biased towards either higher persistent of shocks or higher entry cost.

[18]Compared to the one used in our paper, i.e. equation (3.11), the objection function specified in equation (3.12) prioritizes the moments that are easier to match but sacrifices moments harder to match.

where k denotes each moments and N is the number of targets. In this case, we give each moment an equal weight. The third case we consider is to still use the objection function defined in equation (3.12) but give entry rate and employment share of entrants a weight of five and give the rest three moments a weight of one.

Table 3.8: Robustness Check

	Data (2010s)	Baseline	Case I	Case II	Case III
Parameter					
ρ_z	–	0.940	0.939	0.938	0.938
κ	–	17.79	17.81	17.42	17.24
Moment					
(1) Entry rate	0.077	0.079	0.079	0.081	0.082
(2) Entrants empl. share	0.013	0.012	0.012	0.012	0.013
(3) Entrants relative size	0.630	0.610	0.614	0.613	0.611
(4) SD empl. growth rate	0.535	0.592	0.594	0.597	0.597
(5) Entrep. empl. share	0.250	0.250	0.249	0.250	0.251

We report the results on the estimation of κ and ρ_z in alternative ways in Table 3.8. The case that gives moment (1) and (2) more weight is labelled as "Case I", the case that uses the objective function in (3.12) and give each moments an equal weight is labelled as "Case II", and the case that uses the objective function in (3.12) and give moment (1) and (2) more weight is labelled as "Case III". We can see that the new estimation on ρ_z and κ in both cases are very close to the one used in this paper, labelled as "Main" in Table 3.8. In any case, our conclusion that the relative contribution of higher entry cost is roughly 1.5 to 2 times as large as that of higher persistence of shocks in explaining the observed declines in new business creation will not be changed.

3.6 Impact of Credit Shocks

Our results in Section 3.5 implies that higher entry cost plays a relatively more important role in explaining the decline in firm entry as well as the employment share of entrants in the recent three decades. In this section, we want to use the two sets of parameters --- persistence of entrepreneurial productivity shocks ρ_z and fixed entry cost κ --- to study how changes in persistence of shocks and entry cost affect the entry and the stock of entrepreneurs in response to a credit shock that mimics a financial crisis.

We simulate the aggregate dynamics of the model tightening the collateral constraint λ_t that is calibrated to generate a decline in the ratio of debt to the value-added,

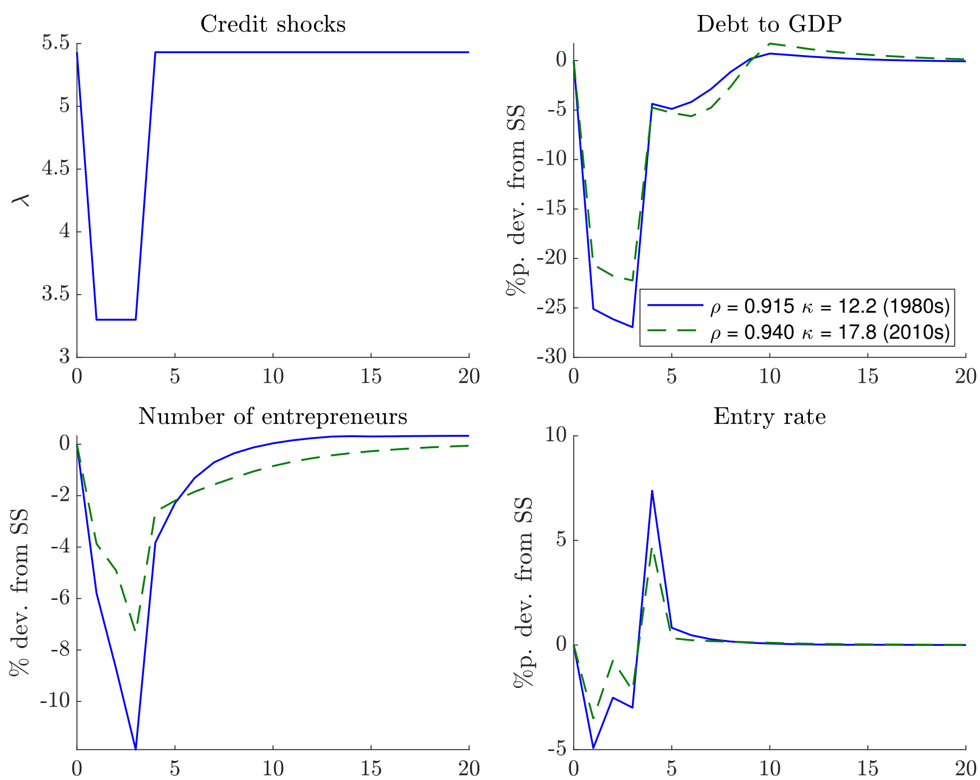
$$\frac{\int max\left\{k_t\left(a, \epsilon, z, d_{-}\right) - a, 0\right\} d\mu_t}{\int y_t\left(a, \epsilon, z, d_{-}\right) d\mu_t}.$$

We reduce the value of λ_t for the first three periods such that the largest decline in the debt-to-value-added ratio the model is able to generate is around 25 percentage points. This is consistent with the magnitude of the largest decline in the debt-to-value-added ratio for the non-corporate business sector in the U.S. economy during the Great Recession. After the three periods of negative credit shocks, we assume that λ_t goes back to its pre-crisis level immediately.[19] To be clear, the initial contraction in λ_t is a completely unexpected event, but its deterministic path after the initial drop is perfectly known. The first two panels of Figure 1 shows the path of the credit shocks fed into the model and the resulting evolution of the ratio of debt to value-added for different sets of persistence of shocks and entry cost (ρ_z, κ) The first set ($\rho_z = 0.915$, $\kappa = 12.2$) is our baseline calibration that targets moments in the early 1980s. The second set ($\rho_z = 0.940$, $\kappa = 17.8$) is our re-calibration results that targets moments in 2010s.

Since the results from previous section suggest that (1) entrepreneurs in 2010s face higher entry cost than firms in 1980s, and (2) entrepreneurs' productivity shocks become more persistent in 2010s than 1980s, we would like to know if these changes are going to lead to different results on the aggregate dynamics of firms in response to the credit shocks defined above. Thus, we compare the results on transitional dynamics of entry rate of entrepreneurs, the stock of entrepreneurs, and several important macro variables for the two sets of parameters on persistence of shocks ρ_z and entry cost κ.

[19] We define the path of credit shocks in this way to simulate a financial crisis because we want to show that the recovery speed of firm entry and the stock of firms depend on the values of ρ_z and κ. Alternatively, we can let λ_t gradually recover and eventually converge to its pre-crisis level as in Buera et al. (2015). In that case, the slow recovery of firm entry and the stock of firms will be mostly driven by the slow recovery of λ_t.

Figure 3.1: Transition Dynamics: Entrepreneurs' Dynamics

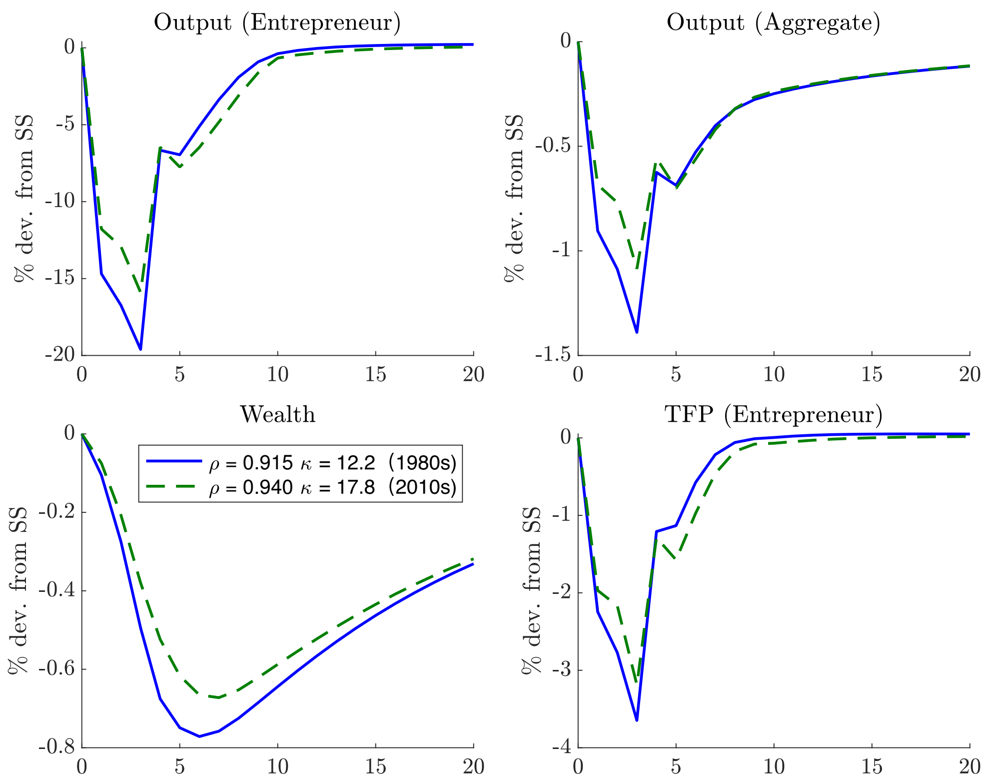


The one that captures 1980s is represented by the blue solid line, and the one that captures 2010s is represented by the green dashed line. Our key finding is reported in the third panel of Figure 3.1. When entrepreneurs in the economy face higher persistence of shocks and higher entry cost that captures the conditions in 2010s, the number of entrepreneurs declines less but recovers slower. The behavior of entry rate is less volatile in the case of 2010s, meaning it declines less but also overshoots less.

To explain these patterns more clearly, we check how changes in ρ_z and κ separately affect the transitional dynamics of entry and the stock of entrepreneurs. We find that when only κ increases to the level of 2010s, both the entry rate and the number of entrepreneurs decline less but recover slower. The reason is that when entry cost is very high, it is harder for incumbent entrepreneurs to exit the market since they know if they exit, they are harder to re-enter the market. When only ρ_z increases to the level of 2010s, both the entry rate and the number of entrepreneurs decline more but recover faster. With more persistent shocks, entrepreneurs have a stronger motivation to do self-financing thus saving more. This makes interest rate decline less in response to the negative credit shock. Consequently, entrepreneurs' profits drop a lot, while the decline in equilibrium wage due to negative credit shocks is relatively modest. Therefore, the decline in the entry and the stock of entrepreneurs is larger when persistence of shocks is higher. Likewise, when shocks are more persistent, agents with high productivity shocks that are previously exit the market due to the negative credit shock will enter the market immediately as credit condition goes back to the pre-crisis level. This renders a quicker recovery. When both ρ_z and κ increase to our estimated level that captures the condition faced by firms in 2010s, the pattern is more similar to the one when only κ rises. This implies that the increase in the fixed entry cost is the dominant force to explain the different patterns of transitional dynamics of entry rate and the stock of entrepreneurs in response to a negative credit shock that mimics a financial crisis.

The results above provide some insights on the comparison of 1980-1982 recession ("Double-Dip Recession") and the Great recession in terms of the number of firms. We know that both the Double-Dip Recession and the Great Recession experience a dramatic drop in the number of firms, but the recovery in the stock of firms from the Great Recession is slower. Our results indicate that higher entry cost faced by potential startups may be an important reason for the phenomena.

Figure 3.2: Transition Dynamics: Macro Variables



We also check the aggregate dynamics (under perfect foresight) of several important macro variables including output, total wealth (capital stock), and total factor productivity (TFP) driven by credit shocks given different values of persistence shocks ρ_z and entry cost κ. We report the results in Figure 3.2. We can see that changes in ρ_z and κ do not make a significant difference on the transitional dynamics of these macro variables. The output produced by entrepreneurs declines less and recovers slightly slower in the case of higher persistence of shocks and higher entry cost. So do the aggregate output, total wealth, and TFP of the entrepreneurial sector. Our results on the decline in aggregate output resulting from credit crunch are consistent with Shourideh and Zetlin-Jones (2017) that casts doubts on the ability of credit shocks to generate significant economic fluctuations.[20] Since our model features a corporate sector which is not subject to a credit constraint,[21] after calibrating our model to match the employment share of entrepreneurs and corporates as well as the debt-to-value-added ratio for non-corporate sector, our model also generates a modest decline in total output, as the second panel of Figure 3.2 shows.

3.7 Conclusion

In this paper, we propose a general equilibrium model of entrepreneurship to separately identify and quantify how changes in entry cost and persistence of idiosyncratic productivity shocks contribute to the observed declines in the creation of new businesses. We show that entrepreneurs face more persistent productivity shocks and higher entry cost to start up a business in the 2010s than in the 1980s. We find that the relative contribution of higher entry cost is 1.5 times larger than that of higher persistence of entrepreneurial productivity shocks in accounting for the decline in the entry rate of entrepreneurs, and twice as large in accounting for the decline in the employment share of new entrants. Our results suggest that higher entry barriers potentially play a more important role in explaining the secular decline in the new business creation experienced by the U.S. economy since the early 1980s. We also find that higher persistence of shocks and higher entry cost have different impacts, respectively, on TFP and welfare, which implies the importance of differentiating the two types of shocks that contribute to the decline in firm creation.

Given the above results, we study the implications of changes in entry cost and persistence of entrepreneurial productivity shocks on the aggregate dynamics of entry and the stock of entrepreneurs following a credit crunch. The key finding is that with higher persistence of entrepreneurial productivity shocks and the higher entry

[20] Shourideh and Zetlin-Jones (2017) develops a general equilibrium model of heterogeneous firms with borrowing collateral constraints, which are the same as the ones in our paper. The authors find that when the model is calibrated to match the observed financing patterns that roughly 80\% of investment by private firms is financed externally compared to 20% for public firms, a large negative credit shock which generates the decline in aggregate debt-to-assets observed following the Great Recession can only lead to roughly a 1% decline in the aggregate GDP.

[21] Our assumption that corporate firms are not borrowing constrained is consistent with the existing literature (see, for example, Dyrda and Pugsley (2019); Shourideh and Zetlin-Jones (2017) .

cost that captures the conditions faced by entrepreneurs in the 2010s, the number of entrepreneurs declines less but recovers more slowly. This sheds light on the more sluggish recovery in terms of the number of firms during and after the Great Recession compared with the 1980-1982 recession: The entry barrier in the late 2000s is much larger than that in the early 1980s which makes it harder for an entrepreneur who previously exited the market due to a credit crunch to re-enter it.

The findings of this paper also present a direction for not only future research but also policy design. Our results show that both the entry cost to start a firm and the persistence of productivity shocks are higher than before, which are quantitatively powerful in explaining the decline in new business creation. In our framework, we assume the two factors are independent of each other. However, it is likely that higher entry cost and higher persistence of shocks are in fact linked. For example, with more persistent productivity shocks, the highly productive incumbents will gain more market power, which may erect entry barriers for potential startups. Therefore, future research should be devoted to understanding not only the underlying reasons for both higher entry cost and higher persistence of shocks, but also the potential connections between them. In terms of policy, our results suggest that the appropriate response in terms of encouraging new business creation and reviving business dynamism in the U.S. economy should focus more on reducing entry barriers. We leave for future research the design of policies aimed at effectively reducing entry barriers.

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Appendix A

Appendix to Chapter 1

A.1 Data

A.1.1 Education Expenditure

The household-level data on education expenditure are used to construct empirical evidence on how parental investments are associated with parents' characteristics, with children's developmental stages, and with household income in Section 1.4.1. The data comes from 2002-2009 waves of the Urban Household Survey (UHS).

Sample selection. First, I classify household members into three categories: child (age 0 to 23), young adult (age 24 to 59), and old adult (above age 59). Given the assumption on the household structure in the model, I start with all the households with one child and one or more young adults. Given that I study education expenditure for childhood development, I restrict the sample to households with a child whose age is between 2 and 17. Since parents invest in their children's education until the end of the high-school stage in the model environment, I drop the households with an employed child.

A.1.2 College Wage Premium

I use three survey data to estimate China's college wage premium. They are 2002-2009 waves of the Urban Household Survey (UHS), 1999, 2002, 2007, 2008, 2013 waves of the Chinese Household Income Project (CHIP), and 2005 wave of 1% Population Survey.

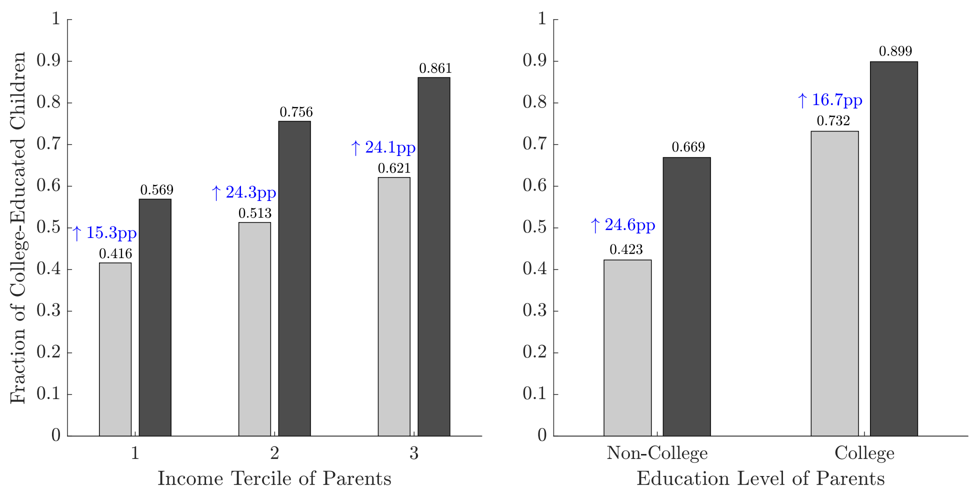
Sample selection. First, I only keep all individuals who currently have a job and earn positive wages. Next, I drop all individuals whose age is above 59. Then, I drop all observations whose working experience is either negative or above 50 years. I also drop all observations whose years of education do not match their education level. Finally, following standard literature, I restrict the sample to individuals working for wages, which means self-employed individuals or business owners are excluded from the sample.

A.2 Additional Results

The empirical evidence in Subsection 1.4.4 displays that the changes in children's four-year college attendance rate following college expansion vary significantly across the parents' income and education groups. Here, I re-define college as three- and four-year institutions. Since three-year colleges in China mainly accept students with low test scores, as discussed in Section 1.2, the college admission will be considerably less competitive under the new definition. As a result, whether or not children attend college mainly reflects their college choices instead of mirroring children's human capital.

Figure A.1 shows that, in contrast to the previous results, the changes in children's college attainments vary modestly across income and education groups. In particular, for non-college-educated parents, their children are 25 percentage points more likely to earn a college degree (vs. a 17 percentage point rise for college-educated parents). These patterns suggest that college expansion has universally increased the three- and four-year college attendance rates for children with different socioeconomic backgrounds. One of the key driving forces is the decline in tuition-to-income ratio, which makes college more affordable for children from low-income families.

Figure A.1: College Attainment of Children by Parents' Characteristics



Note: Data source: UHS (2002, 2009). College is defined as three- and four-year institutions. Sample restricted to urban households with an only child.

Nevertheless, this result does not contradict my main empirical conclusion. Although children with low-income and non-college-educated parents are more likely to go to college after college expansion, due to their low human capital, they will find it difficult to be admitted by four-year institutions, which are more prestigious and lead to much higher education returns than three-year institutions. Therefore, it is still interesting to study the unequal education outcomes across socioeconomic groups owing to college expansion.

Appendix B

Appendix to Chapter 2

B.1 Data

B.1.1 Test Scores

To inspect to what extent the probability of passing the College Entrance Examination depends on children's skill and to what extent wages are associated with human capital, I construct a dataset derived from the 2013 *Chinese Household Income Project* (CHIP2013) survey. This cross-sectional survey follows a nationally representative sample of over 18,000 households, and 64,000 individuals living in urban and rural areas of China. It collects detailed information on a range of economic and demographic indicators. In particular, one crucial feature of the survey is the availability of test score (in the college entrance exam) data.

Sample selection. I start with all the individuals for whom I can observe test scores. I only keep the individuals who took either social science-oriented or natural science-oriented exams.[1] I drop individuals who took the College Entrance Exam-

[1] Some test takers took the uni-category exam or took the special exam for students with arts or sports talent. Due to the complexity of interpreting the observed scores, I drop them from the sample.

ination in Jiangsu province,[2] and drop individuals who took the test before 1989.[3] I restrict the sample to individuals who at least complete junior high school before taking the College Entrance Examination. Furthermore, I restrict the sample to individuals who took the College Entrance Examination between the ages of 16 and 22. For the individuals who took the College Entrance Examination between 1989 and 1992, I convert their raw scores to scaled scores consistent with the current scoring system.[4] Finally, I drop all the individuals whose test score is below 100 or above 700.[5]

Descriptive statistics. Table B.1 displays summary statistics on variables that are useful for the empirical analysis of estimating the admission policy function and return to skill. The average exam scores are almost identical before and after the college expansion despite the rapid changes in the human capital distribution of test takers.[6] This fact suggests that the same test score does not necessarily imply the same skill if test takers took the exam in different years, which may lead to a biased estimation of return to human capital.

Additionally, although the dataset records information on rural households, the rural test takers who took the exam between 1989 and 1998 are underrepresented in the sample. Consequently, the actual national admission rate of four-year college before college expansion is substantially below the number (34%) shown in the table.

[2]The College Entrance Examination in Jiangsu province uses a different scoring system from other provinces. As a result, it is difficult to convert the raw scores to the scaled scores for individuals who took the test in Jiangsu province.

[3]China resumed the National Higher Education Entrance Examination in 1977. However, the scoring and admission system in the early years can be different from the status quo. So for estimating the admission policy function before the reform, I only keep the individuals who took the exam between 1989 and 1998.

[4]In the current scoring system, the full score is 750. However, between 1989 and 1992, the full score could be either 640 or 710 depending on the orientation of test takers.

[5]These scores are extremely rare in the college entrance exam. Individuals are likely to misreport their test scores in this case.

[6]There are at least two driving forces. First, since the tuition-to-income ratio is declining, and admission possibility is rising, more individuals with low human capital may decide to take the test. This force will lower the average student quality in the national admission pool. Second, the same situations can also incentivize more intergenerational human capital investment, which can improve the average student quality in the admission pool.

Table B.1: Descriptive Statistics (College Entrance Exam)

Variable	All years	1989-1998	2008-2012
Raw test score (out of 750)			
Mean	469.35	474.73	471.70
Standard deviation	85.05	88.73	79.57
Percentage of college admission	40.80	34.14	43.75
Variable	All years	1989-1998	1999-2008
Annual disposable income (in RMB)			
All	43,771.00	49,846.26	40,403.39
College graduates	51,797.95	61,141.90	47,118.22
No-college graduates	37,635.54	42,145.84	34,939.09
Working experience	11.52	18.67	7.56

Note: Data source: CHIP2013. This table shows unweighted averages of selected characteristics. College is defined as four-year institutions. The fraction of test takers who enters the four-year college shown in table only reflects the situation in sample.

B.1.2 Admission Probability

This appendix shows the admission policy function that maps the human capital of children h_c onto the probability of passing the College Entrance Examination $\chi(h_c)$. Note that the human capital shown in Table B.2 has been normalized by its log difference from the average human capital of test takers.

B.2 Identifying Dynamic Complementarity Parameters

B.2.1 Description of Environment

Consider a single-parent and single-child problem. In the morning, the parent whose human capital is (h_p) chooses her consumption (c_p) and human capital investment (education expenditure) on her child (m). Parent's income depends on human capital as follows

$$y = h^\gamma$$

Table B.2: Estimation of Exam Admission Probability

(1) Baseline		(2) Existing Policy		(3) Fixed Capacity	
h_c	$\chi(h_c)$	h_c	$\chi(h_c)$	h_c	$\chi(h_c)$
-0.80	0.00	-0.72	0.00	-0.72	0.00
-0.64	0.00	-0.59	0.00	-0.59	0.00
-0.54	0.00	-0.47	0.02	-0.47	0.00
-0.39	0.03	-0.37	0.05	-0.37	0.01
-0.26	0.08	-0.26	0.12	-0.26	0.05
-0.15	0.15	-0.15	0.16	-0.15	0.07
-0.01	0.21	-0.04	0.34	-0.04	0.08
0.11	0.35	0.07	0.55	0.07	0.14
0.23	0.59	0.17	0.82	0.17	0.36
0.35	0.84	0.27	0.87	0.27	0.80

Note: Data source: CHIP2013. This table presents the estimated results of admission policy function. The test scores are normalized by taking their (log) difference from the the average test score. The probability of admission is estimated using the observations on individuals' test scores and education outcomes (whether or not they have eared a four-year college degree). Column (1) corresponds to the estimation for the baseline economy, which reflects the pre-reform admission policy. Only individuals who took the College Entrance Examination between 1989 and 1998 are in the sample to obtain the policy function. Column (2) corresponds to the estimation for the post-reform admission policy. Only the individuals who took the College Entrance Examination between 2008 and 2012 are in the sample to obtain the policy function. Column (3) displays a counterfactual admission policy function when the tuition-to-income ratio declines but the capacity constraint of college is not relaxed.

where γ controls the return to human capital. So the budget constraint of the parent reads as

$$c_p + m = h_p^{\gamma}.$$

Her child is endowed with human capital (h_1) in the morning. The following technology combines the human capital endowment (h_1), the parent's human capital (h_p), and parental investments (m) to produce new human capital h_2.

$$h_2 = h_p^{\omega}[\alpha h_1^{\rho} + (1-\alpha)m^{\rho}]^{\frac{1-\omega}{\rho}},$$

where ω controls the share of the parent's human capital in skill production, α controls the share of the child's current human capital in producing the new human capital, and σ controls the elasticity of substitution between the child's endowment of human capital and monetary investment.

In the evening, the child earns income depending on her human capital (h_2). The child will consume everything she has. So the budget constraint reads as

$$c_c = h_2^{\gamma}.$$

The altruistic parent is the one who makes consumption and investment decisions. She cares about her child's consumption in the evening. The preference of the parent is given by

$$log(c_p) + \nu log(c_c)$$

where ν captures the degrees of altruism.

B.2.2 Household Problem

The household solves the following problem based on the description in the previous subsection

$$\max_{c_p, m} \; log(c_p) + \nu log(c_c)$$

$$s.t. \; c_c = [\alpha h_1^{\rho} + (1-\alpha)(y_p - c_p)^{\rho}]^{\frac{\gamma}{\rho}}.$$

I solve this problem using the standard algorithm. The solution can be characterized by the following Euler equation

$$\underbrace{\frac{1}{c_p}}_{\substack{\textit{marginal}\\ \textit{return to } c_p}} = \underbrace{\nu\gamma(1-\alpha)(1-\omega)\frac{(h_p^\gamma - c_p)^{\rho-1}}{\alpha h_1^\rho + (1-\alpha)(h_p^\gamma - c_p)^\rho}}_{\substack{\textit{marginal}\\ \textit{return to } m}},$$

which implies that the parent at optimality should equalize the marginal return to her own consumption, and marginal return to human capital investment in her child.

B.2.3 Analytical Solution

Cobb-Douglas $\rho = 0$. There Euler equation is simplified as

$$\frac{1}{h_p^\gamma - m} = \nu\gamma(1-\alpha)(1-\omega)\frac{1}{m}.$$

Then, the relationship between parent's income h_p^γ and human capital investment m can be written as

$$m = \underbrace{\frac{\nu\gamma(1-\alpha)(1-\omega)}{1+\nu\gamma(1-\alpha)(1-\omega)}}_{\textit{slope}} h_p^\gamma.$$

Perfect substitute $\rho = 1$. There Euler equation can be simplified as

$$\frac{1}{h_p^\gamma - m} = \nu\gamma(1-\alpha)(1-\omega)\frac{1}{\alpha h_1 + (1-\alpha)m}.$$

Then, the relationship between the parent's income h_p^γ and human capital investment m can be written as

$$m = \underbrace{\frac{\nu\gamma(1-\alpha)(1-\omega)}{1+\nu\gamma(1-\alpha)(1-\omega)-\alpha}}_{\textit{slope}} h_p^\gamma - \frac{\alpha h_1}{1+\nu\gamma(1-\alpha)(1-\omega)-\alpha}.$$

Link to calibration. It is clear that if the current child's human capital is more substitutable to parental investments, the household income (h_p^γ) will have a stronger effect on education expenditure (m). The magnitude of difference (in effect of income on education expenditure) between the Cobb-Douglas world and the perfect-substitute world is determined by children's human capital share (α). As a result, when I estimate ρ, I should first pin down α and other parameters. Next, I can simulate my model and internally search for the parameter ρ through matching model-predicted auxiliary coefficients to the data counterparts.

B.2.4 Link to the Full Model

In the quantitative life-cycle model, decisions on education expenditure will be complicated by the heterogeneity in the current-period human capital of children and financial wealth. However, the following numerical exercise shows that the full model's implications on the effects of income on parental investments are consistent with those implied by the static problem.

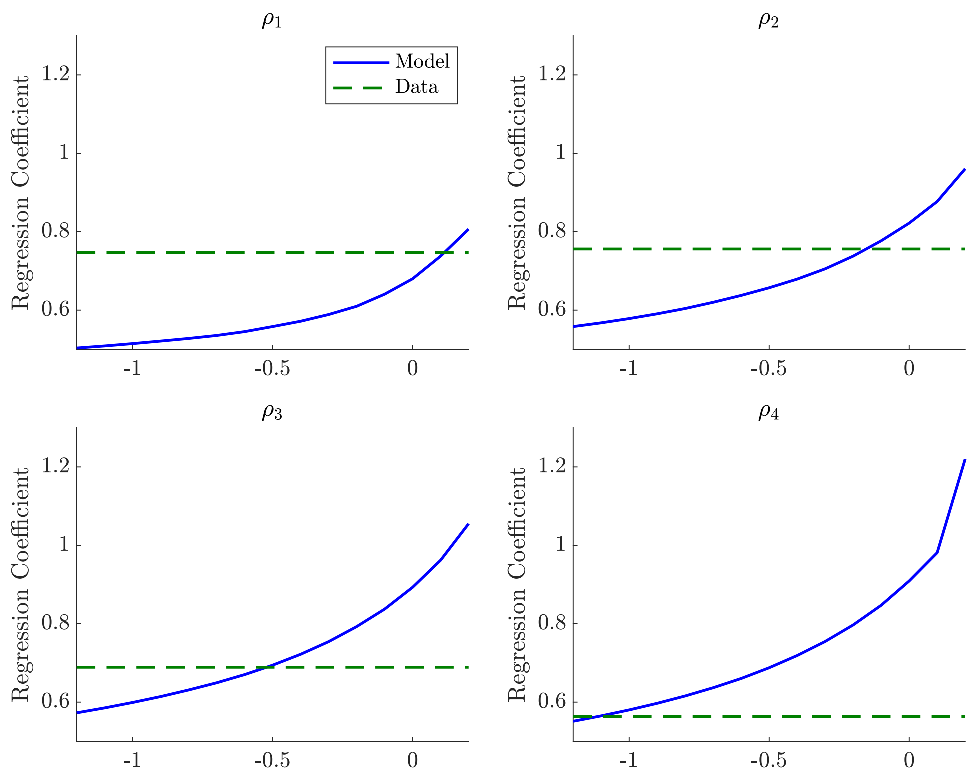
Figure B.1 plots the data- and model-predicted effects of household income on education expenditure on children. I plot the coefficients for each childhood developmental stage, respectively. The green dashed lines are obtained from the estimation results (first column) as displayed in Subsection 1.4.3. The blue solids lines are obtained from repeatedly simulating the model by varying the dynamic complementarity parameters ρ_j.[7] It is clear that a more substitutable relationship between current-period children's human capital and parental investments implies a stronger effect of household income on education expenditure. With this feature in place, I can search for the four parameters that minimize the weighted distance between model-predicted coefficients and their data counterparts.

B.3 Additional Results

In Subsection 2.4.2, I have examined the macroeconomic effects of the existing college expansion policy. In this exercise, I choose the parameter controlling the skill-biased technical change $A_c = 1.54$ to ensure that the current policy generates the same college

[7] To obtain this figure, for each panel, I only vary one parameter each time and fix other parameters. In my calibration exercise, this set of parameters are jointly determined.

Figure B.1: Calibration of Dynamic Complementarity Parameters



Note: Each graph is associated to the calibration of a dynamic complementarity parameter, ρ_j, where j corresponds to a child development stage. The solid blue line shows how effect of household income on education expenditure is sensitive to changes in ρ_j in the model, and the dashed green line shows the associated regression coefficient obtained from the data. The intersection points give the calibrated value of ρ_j.

wage premium (0.50) at the final steady state as the baseline economy. This appendix repeats the current college reform with two robustness experiments that include: (i) raising the technology parameter to $A_c = 1.67$; (ii) lowering the technology parameter to $A_c = 1.33$, and reports the aggregate and distributional results in Table B.3 and Figure B.2, respectively.

Table B.3: Robustness: Skill-Biased Technological Change

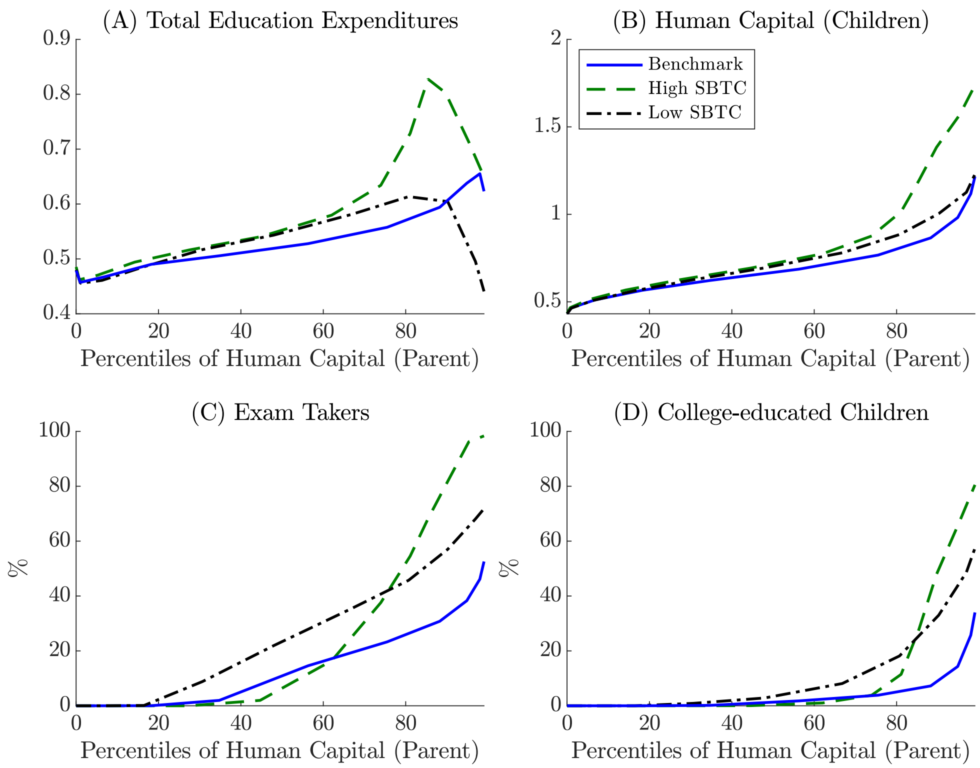
	(1) Baseline	(2) Current Policy	(3) High SBTC	(4) Low SBTC
	Level	*Change*	*Change*	*Change*
(a). ***Aggregate***				
Test taker share	17.19%	17.1pp	10.8pp	13.1pp
College share	4.73%	10.1pp	7.6pp	8.2pp
College wage premium	0.50	0.0%	30.0%	-15.0%
Edu. expenditure	0.14	16.5%	21.5%	8.4%
Human capital, all	0.72	16.1%	21.3%	8.1%
Human capital, test takers	1.00	13.0%	35.4%	2.0%
Labor income	1.62	17.9%	20.8%	10.7%
Output	0.60	29.0%	37.6%	15.3%
Welfare	-13.51	17.2%	18.5%	10.8%
(b). ***Std. Deviation***				
Edu. expenditure	0.63	3.6p	5.9p	1.6p
Human capital	0.28	5.2p	9.9p	1.3p
Labor income	0.53	1.2p	2.7p	0.3p
(c). ***Persistence***				
Human capital	0.80	5.3p	8.9p	1.4p
College education	28.91%	25.0pp	37.7pp	14.7pp

Note: Column (1) displays the macroeconomic variables generated from the baseline estimation. Column (2) shows the (percentage point, percentage, or point) changes owing to the existing college expansion policy. The two robustness experiments are as follows: Column (3) reports the results from an economy where a skill-biased technological growth leads to a 30% increase in the college wage premium; Column (4) reports the results from an economy where a skill-biased technological growth leads to a 15% drop in the college wage premium.

I highlight two particularly interesting results. First, although the education expenditure and labor income rise more significantly than the standard case with a high-level skill-biased technological change, the share of test takers as well as college graduates are lower than the economy with a standard technical progress. This result comes from the fact that the average human capital of test takers increases by 35.4% with a high-level growth in skill-biased technology (vs. 13.0% with a standard growth in technology). As I discussed in Subsection 2.3.1, the admission probability is determined by the difference between an individual's test score and the average score of test takers. Consequently, as shown in Panel (C), Figure B.2, the children of low-skill parents face more difficulties getting into the college since their skill levels are more distant from the average level. Since it is costly to take the College Entrance Examination, this situation will discourage low-skill parents from having their children take the test.

Second, the changes in inequality and intergenerational persistence depend on the degrees of skill-biased improvement in technology, which can lead to different levels of college wage premium. With a higher college wage premium, as shown in Panel (A), Figure B.2, only high-skill parents substantially spend more on their children's education. For low-skill parents, although the higher college wage premium incentivizes parental investments, the marginal cost for them to do so is large due to their budget limits. As a result, as shown in Panel (B) and (D), only the children from rich families have significant rises in human capital and college attendance rate, which implies more unequal outcomes owing to college expansion with a more substantial improvement in skill-biased technology.

Figure B.2: Robustness: Impact of Skill-Biased Technical Changes on Distribution



Note: This figure presents how life-time education expenditure (Panel (A)), average human capital of children (Panel (B)), fraction of test takers (Panel (C)), and fraction of college-educated children (Panel (D)) depend on parents' human capital. The horizontal axis corresponds to the human capital percentiles of parents. The blue solid line shows the results in the benchmark ($A_c = 1.54$) , the green dashed line shows the results under the existing college expansion policy with a high-level skill-biased technological change ($A_c = 1.67$), and the blacked dash-dot line shows the results under the existing college expansion policy with a low-level skill-biased technological change ($A_c = 1.33$).

Appendix C

Appendix to Chapter 3

C.1 Computational Algorithm

In this computational appendix we first lay out the solution method for the household problem described in Section 3.3. Then, we discuss the algorithm for computing the transition dynamics.

C.1.1 Household Problem

In this subsection, we first describe the general solution algorithm for finding steady-state equilibrium. Next, we lay out an efficient method for solving the recursive equilibria.

Computing stationary equilibrium. We have three nested fixed point problems. First, we have to solve market clearing wage ($\overline{w}$) and interest ($\bar{r}$) rate. Second, we have to compute an approximation of the stationary distributions $\overline{\mu}^W$ and $\overline{\mu}^E$ over financial asset a, working productivity ϵ, and entrepreneurial talent z for each occupation. Third, we have to compute a fixed point in (expected) continuation values $\bar{v}^1$ (containing entry option) and $\bar{v}^2$ (containing exit option).[1] The iteration is then as follows:

[1]We provide detailed information on what function to approximate in Appendix C.1.1.

1. Guess an initial wage rate, w_0, initial distributions, μ_0^W and μ_0^E, and initial (expected) value functions v_0^1 and v_0^2. The initial interest rate can be obtained by the following equation:

$$r_0 = \frac{\theta(A(1-\theta))^{\frac{1}{\theta}}}{1-\theta} w_0^{\frac{\theta-1}{\theta}} - \delta$$

2. In price iteration i, given prices w_i and r_i, the loop as follows

   (a) In iteration k, solving the household problem requires finding the fixed point in value functions. We apply the collocation method to approximate the expected continuation values, and use golden-search approach to solve saving decisions. For each idiosyncratic state, entry decision can be obtained by comparing the value of entry with the value of being a worker and exit decision can be solved by comparing the value of exit with the value of being an entrepreneur.

   (b) We implement both value function iteration and Broyden's algorithm to update a finite set of coefficients that can define the value functions. The root-finding problem stops if the convergence criterion $max\{\| v_{k+1}^1 - v_k^1 \|, \| v_{k+1}^2 - v_k^2 \|\} < \zeta$ is satisfied. Otherwise, repeat step $2(a)$ with the updated coefficients.

   (c) Solve saving, entry, and exit decision rules on a finer grid. Create big transition matrix[2] using saving policy functions and exogenous transitions matrix $P(z'|z)$ and $P(\epsilon'|\epsilon)$.

   (d) Start from the initial distribution μ_0^W and μ_0^E. In iteration j, updating distributions by applying big transition matrix, entry, and exit decisions on existing ones.

   (e) Iteration stops if the convergence criterion $max\{\| \mu_{j+1}^W - \mu_j^W \|, \| \mu_{j+1}^E - \mu_j^E \|\} < \zeta$ is satisfied. Otherwise, repeat step $2(d)$ with the updated distributions.

[2] Here, we use Young (2010) method that is a discrete approximation to the law of motion of the distribution of agents over states.

(f) Aggregate across all households and compute aggregate labor supply, L^W, asset supply, A, entrepreneur's capital demand, K^E. Capital for corporate sector can be obtained by $K^C = A - K^E$. If $K^C < 0$, then go to step 1 and guess a new price. Then, aggregate labor for corporate sector can be calculated as follows:

$$L^C = \frac{1-\theta}{\theta}\frac{r_i+\delta}{w_i}K^C$$

3. Check if the convergence criterion $\| L^W - L^C - L^E \| < \zeta$ is satisfied. If yes, *STOP*. Otherwise, update wage rate $w_{i+1} = w_i - \phi(L^W - L^C - L^E)$, where ϕ controls the adjustment speed, and then go back to step 2.

Computing recursive equilibria. This subsection describes how to use Mongey (2015) algorithm to compute the recursive equilibria. This approach accelerates computation speed by adapting Judd et al. (2017) method on pre-computation of expectation functions to collocation method for approximating value functions. Moreover, Miranda and Fackler (2002) toolbox allows us to efficiently find optimal policies using vectorized golden-section search and solve fixed point problems using Broyden's algorithm.

The continuous and discrete choice problem described in the model section can be solved by approximating two expected continuation values as follows

$$v^1(s) = \sum_{\epsilon',z'} P(\epsilon',z'|\epsilon,z) max\{v^W(s'),v^F(s')\},$$

$$v^2(s) = \sum_{\epsilon',z'} P(\epsilon',z'|\epsilon,z) max\{v^W(s'),v^E(s')\},$$

where $v^1(s)$ nests a worker's entry decision and $v^2(s)$ nests an entrepreneur's exit decision,[3] and the state vector is $s = [a,\epsilon,z]$.[4] Note that we have $N_a = 100$ asset grid points, $N_\epsilon = 9$ working productivity shock grid points, and $N_z = 9$ entrepreneurial

[3] v^W and v^F in the continuation value v^1 correspond to the options the individuals whose $d_- = 0$ have: staying in the worker sector, or switching to the entrepreneur sector, respectively. v^W and v^E in the continuation value v^2 correspond to the options the individuals whose $d_- = 1$ have: switching to the worker sector, or staying in the entrepreneur sector, respectively.

[4] For computational purpose, $s = [\mathbf{i}_{N_z\times N_\epsilon}\otimes a, \mathbf{i}_{N_z}\otimes\epsilon\otimes\mathbf{i}_{N_a}, z\otimes\mathbf{i}_{N_\epsilon\times N_a}]$, where $\otimes$ is a symbol of tensor product and $\mathbf{i}_N$ is a N-by-1 matrix of ones.

productivity shock grid points. In total, there are $N = N_a \times N_\epsilon \times N_z = 8,100$ states.

We now replace the functions we want to approximate with interpolants

$$v^1(s_i) = \sum_{j=1}^{N} \phi(s_i)c_j^1 = \Phi(s)c^1,$$

$$v^2(s_i) = \sum_{j=1}^{N} \phi(s_i)c_j^2 = \Phi(s)c^2,$$

where ϕ is a basis function, c^1 and c^2 are vectors of coefficients, and $s_i \in s$ is a collocation node. If we substitute these interpolants into the original system of functional equations we have N system of equations with N unknowns as follows

$$\Phi(s)c^1 = (P \otimes \mathbf{I}_{N_a})[(1 - I^f(s))\odot\Phi(s)c^W + I^f(s)\odot\Phi(s)c^F],$$

$$\Phi(s)c^2 = (P \otimes \mathbf{I}_{N_a})[I^e(s)\odot\Phi(s)c^W + (1 - I^e(s))\odot\Phi(s)c^F],$$

where $P \otimes \mathbf{I}_{N_a}$ is a pre-computed expectation matrix, $I^f(s)$ and $I^e(s)$ captures the entry and exit decisions at s, respectively, and $\Phi(s)c^W$, $\Phi(s)c^E$, and $\Phi(s)c^F$ are values associated with worker, entrepreneur, and entrant, respectively. Note that they can be rewritten as follows

$$\Phi(s)c^W = max\Big\{u(w\epsilon + (1+r)a - a'(s)) + \beta\Phi([a'(s), \epsilon, z])c^1\Big\},$$

$$\Phi(s)c^E = max\Big\{u(\pi(s) + (1+r)a - a'(s)) + \beta\Phi([a'(s), \epsilon, z])c^2\Big\},$$

$$\Phi(s)c^F = max\Big\{u(\pi(s) + (1+r)a - a'(s) - \kappa) + \beta\Phi([a'(s), \epsilon, z])c^2\Big\}.$$

We can solve for c^1 and c^2 by applying either value function iteration or Broyden's (Quasi-Newton) algorithm. In practice, we start with two sets of initial guess, c_0^1 and c_0^2. Then, we iterate on the following system for two times

$$c_{k+1}^1 = \Phi(s)^{-1}(P \otimes \mathbf{I}_{N_a})[(1 - I^f(s))\odot\Phi(s)c^W + I^f(s)\odot\Phi(s)c^F],$$

$$c_{k+1}^2 = \Phi(s)^{-1}(P \otimes \mathbf{I}_{N_a})[I^e(s)\odot\Phi(s)c^W + (1 - I^e(s))\odot\Phi(s)c^F].$$

Next, we rewrite the problem the system of equations as root-finding problem as follows

$$g(c^1, c^2) = \Phi(s)c^1 - (P \otimes \mathbf{I}_{N_a})[(1 - I^f(s))\odot\Phi(s)c^W + I^f(s)\odot\Phi(s)c^F],$$

$$g(c^1, c^2) = \Phi(s)c^2 - (P \otimes \mathbf{I}_{N_a})[I^e(s)\odot\Phi(s)c^W + (1 - I^e(s))\odot\Phi(s)c^F].$$

The Jacobian of this problem is

$$D(c^1, c^2) = \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix},$$

where

$$Q_{11} = \Phi(s) - \beta(P \otimes \mathbf{I}_{N_a})[(1 - I^f(s))\odot\Phi([a'(s), \epsilon, z])],$$

$$Q_{12} = -\beta(P \otimes \mathbf{I}_{N_a})[I^f(s)\odot\Phi([a'(s), \epsilon, z])],$$

$$Q_{21} = -\beta(P \otimes \mathbf{I}_{N_a})[I^e(s)\odot\Phi([a'(s), \epsilon, z])],$$

$$Q_{22} = \Phi(s) - \beta(P \otimes \mathbf{I}_{N_a})[(1 - I^e(s))\odot\Phi([a'(s), \epsilon, z])].$$

Finally, we have the updating scheme

$$\begin{bmatrix} c^1_{k+1} \\ c^2_{k+1} \end{bmatrix} = \begin{bmatrix} c^1_k \\ c^2_k \end{bmatrix} - D(c^1, c^2)^{-1} \begin{bmatrix} g(c^1_k, c^2_k) \\ g(c^1_k, c^2_k) \end{bmatrix},$$

where $D(c^1, c^2)^{-1}$ is the inverse of the Jacobian.

C.1.2 Transition Dynamics

In this subsection, we describe the algorithm for computing the transition dynamics discussed in Section 3.6.

1. Solve the steady-state equilibrium. Save the (expected) continuation values v^W_T, v^E_T , v^F_T as well as stationary distribution μ^W_0 and μ^E_0.[5]

[5] Since the credit shocks only last for 3 periods and then recover to pre-crisis level immediately, the initial and final value functions (as well as distributions) are identical as long as T is large.

2. Guess a sequence of wages $\mathbf{w_0} = \{w_1, w_2, ..., w_T\}$ and compute the associated sequence of interest rates $\mathbf{r_0} = \{r_1, r_2, ..., r_T\}$. Moreover, construct a sequence of credit shocks $\Lambda = \{\lambda_1, \lambda_2, ..., \lambda_T\}$. We set $T = 300$.

3. Given the sequences of prices and credit shocks, we start from the final (expected) continuation values and iterate backward from $t = T$ to $t = 1$. We also solve the decision rules for optimal saving, entry (I_t^f), and exit (I_t^e).

4. For each period t, solve saving, entry, and exit decision rules on a finer grid and construct big transition matrix Q_t^W, Q_t^E, and Q_t^F using saving policy functions and exogenous transitions matrices.

5. Starting from μ_0^W and μ_0^E, the distribution of individuals over their asset, working productivity, entrepreneurial productivity, and occupation during transition will evolve as follows

$$\mu_{t+1}^E = Q_t^{E'}((1 - I_t^e)\mu_t^E) + Q_t^{F'}(I_t^f \mu_t^W),$$

$$\mu_{t+1}^W = Q_t^{W'}((1 - I_t^f)\mu_t^W) + Q_t^{W'}(I_t^e \mu_t^E).$$

6. For each t, aggregate across all individuals and compute aggregate labor supply, L_t^W, asset supply, A_t, entrepreneur's capital demand, K_t^E, corporate sector capital demand K_t^C, and corporate sector labor demand L_t^C.

7. Check if the convergence criterion $\parallel L_t^W - L_t^C - L_t^E \parallel < \zeta$ is satisfied. If yes, *STOP*. Otherwise, update wage rate $w_{t+1} = w_t - \phi_t(L_t^W - L_t^C - L_t^E)$ and their associated r_t for each t. Then, reconstruct $\mathbf{w_{k+1}}$ and $\mathbf{r_{k+1}}$ and go back to step 3.