What's Driving the Decline in Entrepreneurship?*

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Abstract

Why has there been a steady decline in entrepreneurship in the US in recent decades? This paper addresses this question from an occupational choice perspective with new empirical facts about trends in peoples' labor market choices and the size of the businesses of entrepreneurs over time, interpreted with a dynamic occupational choice model. By using changes in entrepreneurship along multiple dimensions and the structure of the model, the contribution of a range of forces to the changes in entrepreneurship from 1987 to 2015 are estimated. Increasing entry costs are found to explain most of the decline in the share of people who are entrepreneurs and most of the decline in the entry rate of firms. Skill-biased technical change has tilted entrepreneurship towards less educated people, but this change to the economy has had little impact on the level of entrepreneurship. Empirical evidence suggests that the rise in entry costs is coming from both increasing regulation and changes in technology.

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1 Introduction

The US is famous for providing an environment that fosters entrepreneurship and for its high degree of competition that ensures that the best firms flourish. Research supports the idea that entrepreneurship plays an important role in the economy by identifying its relevance for growth, job creation, income and wealth inequality, and economic mobility.[1] Entrepreneurship also receives considerable policy attention. It is discussed extensively by politicians and in the media, and the federal government has a department—the Small Business Administration—whose mission is to support small businesses. In light of this, research documenting that measures of entrepreneurship in the US have declined in recent decades (e.g. Davis et al., 2006; Decker et al., 2014a,b; Pugsley and Sahin, 2014) have generated considerable concern.[2]

The purpose of this paper is to address the question, why has there been a decline in entrepreneurship? Answering this question is important for two reasons. First it is a step towards understanding the economic consequences of this trend because different explanations will have different implications. For example, if the decline in entrepreneurship is due to regulations impeding business creation then the consequences are likely to be worse than if changes in technology have made it optimal to have fewer, but larger, firms. Second, different causes will have different policy implications. Identifying the cause is necessary for determining whether any policy response is appropriate and, if so, what.[3]

This paper evaluates four potential explanations for the decline in entrepreneurship: skill-biased technical change causing changes in wages that impact peoples' choices about whether to be an employee or entrepreneur; changes in regulations that have increased the fixed and/or entry costs of business; changes in technology that have also increased these costs; and changes in technology that have increased the productivity of larger businesses relative to smaller ones. The analysis uses both data and a dynamic general equilibrium model of occupational choice. The main result is that increasing entry costs are found, both theoretically and quantiatively, to be the strongest explanation for the declines in the share of people who are entrepreneurs and the entry rate into entrepreneurship. Increasing productivity of large, non-entrepreneurial firms, mattters little for these moments, but has driven most of the reallocation of labor away from entrepreneur business. Skill-biased technical change also can't explain the changes in these moments, but has tiled entrepreneurship towards less educated people. Finally the paper provides empirical evidence suggesting that the rise in entry and fixed costs is due to both increasing regulation and changes in technology.

For the empirical analysis I study the entrepreneurial decisions of people in the US using data

[1]For growth of the economy see, for example, Luttmer (2011); Acemoglu et al. (2013); Akcigit and Kerr (2015). For job creation see Haltiwanger et al. (2013); Adelino et al. (2016). For inequality and economic mobility see, for example, Quadrini (2000) and Cagetti and De Nardi (2006).

[2]For discussion of this trend in leading media outlets see Weissmann (2012); Casselman (2014); The Economist (2014); Harrison (2015).

[3]For discussion of the decrease in firm entry by a policy maker see Yellen (2014).

from the Current Population Survey for 1987 to 2015. An entrepreneur is defined as a person who owns and actively manages a business with at least 10 employees. The starting point for the empirical analysis is that the entrepreneurship rate (the share of the labor force who are entrepreneurs) has declined by 26% from 1987 to 2015, a similar to decline to what we have seen for the firm entry rate (see Decker et al., 2014a,b; Pugsley and Sahin, 2014). This holds even after controlling for many changes in the composition of the economy and is not driven by a small number of sectors; it's a broad trend.

The paper documents two new facts. First, the decrease in entrepreneurship has been larger for higher education groups. For example, for people with less than a high school education the entrepreneurship rate has decreased by 2.4%, while for people with more than a college education it has decreased by 35%. This tells us that at least part of the force driving changes in entrepreneurship is not skill neutral. Skill-biased technical change is therefore a natural candidate explanation because this force has pushed up the wages of high skill people and could explain why fewer of them are choosing to be entrepreneurs.

The second fact is that the size distribution of entrepreneur firms has been stable over time. A declining entrepreneurship rate and stable size distribution imply that the share of economic activity that entrepreneurs account for has declined. This motivates the consideration of explanations for the decline in entrepreneurship that disadvantage entrepreneurs relative to larger non-entrepreneur firms (e.g. public firms). Three such theories have been prominent in debates about declining entrepreneurship. One is that there have been changes in regulations that have increased the fixed and/or entry costs of businesses, disproportionately affecting smaller firms.[4] Regulations that are commonly discussed as having this effect include increases in occupational licensing, increasing complexity of the tax system and zoning restrictions.[5] Fixed costs could also have increased for technological reasons, for example because of the increasing use of IT technology (see Aghion et al., 2019; Hsieh and Rossi-Hansberg, 2019; De Ridder, 2019). The third theory is that there have been changes in technology that have given the largest firms in the economy a productivity advantage, resulting in production becoming increasingly concentrated amongst them.[6] I'll call this the superstar firms hypothesis, adopting the language of Autor et al. (2017) who study the effects of this kind of change to the economy on the labor share. The second and third theories could, of course, be related. To the extent that they are the analysis will be able to separately assess the effects of the cost and productivity changes.

[4]See Decker et al. (2014a), Davis and Haltiwanger (2014) and Davis (2017) for discussions of this explanation.

[5]The motivation for the discussion of occupational licensing is Kleiner (2015) who shows that the prevalence of occupational licenses has increased over time. Hsieh and Moretti (2017) argue that zoning restrictions have contributed to high property prices in major economic centers like New York and the Bay Area. While they do not study the effect of this on entrepreneurship, the increase in property prices will increases the upfront cost of any business that needs physical space.

[6]See Davis and Haltiwanger (2014) for discussion of this idea. While it is beyond the scope of this paper to assess why exactly this has occurred—I model it in a general way—ideas include that new technologies have enabled people to better compare prices and qualities which advantages the most productive firms, or larger firms are better placed to take advantage of new technologies because of their size or better access to financing.

The second part of the paper uses a model to evaluate whether the theories suggested by the data can explain the decline in entrepreneurship. The model is a dynamic general equilibrium model of occupational choice. Agents have an ability to do either low or high skill work and also an entrepreneurial productivity. Each period they choose whether to be out of the labor force, work as an employee or run a firm as an entrepreneur. There is also a non-entrepreneurial sector. All businesses use the same production technology, which has fixed and entry costs associated with it, and takes capital and the two types of labor as inputs. The model is used to quantitatively assess the four candidate explanations for the decline in entrepreneurship from 1987 to 2015. The analysis focuses on explaining the decline in the share of people who are entrepreneurs, the deceline in the etnry rate into entrepreneurship, and the reallocation of labor from the entrepreneurial to the non-entrepreneurial sector. Skill-biased technical change is modelled through changes in capital prices, closely following existing literature (e.g. Krusell et al., 2000; Autor et al., 2003), the superstar firm hypothesesis is modeled with an increase in the relative productivity of non-entrepreneur firms, and fixed and entry costs are also allowed to change.

The core of the analysis focuses on understanding how each force affects the occupational choices of agents, and quantitatively assessing how these effects match up with the data. From a theoretical perspective, increasing entry costs are a clean fit for the data. They make entrepreneurship less profitable, so fewer people choose this occupation and the share of employment at entrepreneurial firms declines. Higher entry costs also drive a wedge between the threshold for entering this occupation and leaving it, because a person who closes their business will face higher costs of starting again. This pushes the entry and exit rates down. When this mechanism is evaluated quantitatively, it can generate all of the decline in the entry rate that we have seen in the data, and a large share of the decline in the share of people who are entrepreneurs.

The mechanism through which increasing productivity of superstar firms affects entrepreneurs is by increasing the demand for labor, and pushing up wages. This causes fewer people to choose to be entrepreneurs and, conditional on being an entrepreneur, people employ less labor. Both of these changes cause a reallocation of labor towards non-entrepreneurial firms. The data tells us how much of this flow should come from the intensive and extensive margins—and the problem for this explanation is that is generates far too much change on the intensive rather than the extensive margin. Quantitatively I find that this change to the economy accounts for most of the reallocation of labor to the non-entrepreneurial sector, but is not quantitatively very relevant for the other moments of entrepreneurship.

Increasing fixed costs are very similar in theory to increasing entry costs, with one key exception. While increasing entry costs drive a wedge between the thresholds for starting a business and closing it, increasing fixed costs push them closer together. The reason for this is that the marginal entrepreneur who is already operating a business is less profitable than the marginal entrepreneur starting a business, because only the latter needs to cover entry costs. An increase in fixed costs therefore affects the marginal incumbent entrepreneur more, and makes the problems of these agents more similar. This results in more entry and exit from entrepreneurship. This is an issue for the fixed cost explanation, because the entry rate has gone down, not up, in the data. The quantitative analysis finds that increasing fixed costs have played a role in pushing the share of people who are entrepreneurs down, but has not been relevant for the other changes in the data.

For skill-biased technical change, when there are improvements in capital technology that increase the demand for high skill labor, it pushes the high skill wage up. All else being equal this would cause entrepreneurship to decline for this group. However, the technological improvements that drive these wage changes benefit the people using the production technology—entrepreneurs. So there is an increase in the value of entrepreneurship that offsets the wage effect. The quantitative results show that given the size of the improvement in capital technology and the change in the high skill wage that is observed in the data, the overall effect is to actually make the high skilled more likely to be entrepreneurs. This effect is even stronger for the low skilled since their wage has increased far less in the data than that of the high skilled, making entrepreneurship even more attractive. Overall, skill-biased technical change is important for explaining why the relative entrepreneurship rate for high skilled compared to low skilled people has decreased; but it can't explain the decline in the aggregate level of entrepreneurship.

In the final exercise the paper provides empirical guidance on how the increase in entry and fixed costs should be interpreted. Two theories that have been put forward for the change in these costs are that they are the result of increasing regulation or that they are the result of technological changes driven by the increasing use of IT technology that have increased fixed component of firms costs. To test these theories the relationship across industries between the change in entrepreneurship and changes in regulations and IT technology are studied. The results provide support for both channels contributing to the rise in these costs.

Contribution to the literature Evidence of declining entrepreneurship has been documented in a number of recent papers (see Davis et al., 2006; Decker et al., 2014a,b; Pugsley and Sahin, 2014; Hyatt and Spletzer, 2013). This research primarily focuses on measuring entrepreneurship with the firm entry rate and uses firm microdata to study the phenomenon. I approach the data from a slightly different angle, using data on individuals and measuring entrepreneurship with the share of people who are self-employed with businesses with at least one employee. An advantage of this data is that it provides information about the owner-managers of businesses that is not available in the firm data. This allows me to document new facts about the decline in entrepreneurship and to use rich data to calibrate the model and assess potential explanations for the decline in entrepreneurship.

Guzman and Stern (2016) argue that evidence of declining entrepreneurship focuses on the quantity, but that once you adjust for quality entrepreneurship may not have declined. They argue that the growth potential of cohorts of new firms (measured using the probability that a firm is acquired or makes an IPO within six years of founding) has not had a downward trend over time, however they find that firms have become less likely to realize this potential. This paper uses different data and provides another angle on this. If the quantity of entrepreneurs has declined over time but their quality has increased to offset this then we should see evidence of the quality distribution of entrepreneurs improving over time. If we measure quality with firm size, a measure that focuses less on the far right tail than Guzman and Stern's (2016), then the CPS data indicates that quality has been stable over time since the size distribution of entrepreneur firms is quite stable.

The main contribution of the paper is to further our understanding of what has caused the decrease in entrepreneurship. There are other papers that have also tackled this question. Several papers have considered demographic explanations. Karahan et al. (2016) and Hopenhayn et al. (2018) quantitatively evaluate the effect of a decreasing labor force growth rate on the firm entry rate. Kopecky (2017) evaluates the effects of the aging of the population and increases in life expectancy on entry into entrepreneurship. In a contemporaneous paper Salgado (2019) also studies the effect of skill-biased technical change on entrepreneurship. Aghion et al. (2019) and De Ridder (2019) develop theories for a number of macroeconomic trends including declining entry based on improvements in IT technology allowing firms to operate with higher fixed costs and lower variable costs. Gutierrez et al. (2019) argue that increasing regulations are a key driver of declining firm entry. The present paper contributes to this line of research by studying a number of potential explanations in a unified framework.

Two other papers that are closely related, but study slightly different questions are Davis and Haltiwanger (2016) and Decker et al. (2017). The first studies the effect of the housing market and credit constraints on business creation, however it focuses on fluctuations in the short and medium term rather than long run trends. The second focuses on the dynamism of firms post-entry and assesses whether decreasing dynamism is the result of a decrease in the variance of shocks that firms face or a decrease in the responsiveness of firms to shocks.

This paper also contributes to the literature on skill-biased and routine-biased technical change (see, for example, Krusell et al., 2000; Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013). This literature has primarily focused on the effect of changes in technology on the distribution of wages and the occupational distribution of employees. The research that is most closely related to this paper is recent work using macro models to quantitatively evaluate the effects of technical change (vom Lehn, 2015; Eden and Gaggl, 2016; Lee and Shin, 2016; Burstein et al., 2016; Giannone, 2017; Cortes et al., 2016). This paper extends this line of research by showing that not only does technical change cause a shift in employment towards higher skills and drives up the relative wages of higher skill workers, but it also affects entrepreneurship by shifting the composition of entrepreneurs towards those with less education.

From a technical perspective the model in the paper is related to existing macroeconomic models of entrepreneurship. Models with similar features have been used to study questions in a variety of areas including inequality (Quadrini, 2000; Cagetti and De Nardi, 2006; Lee, 2015), taxation (Kitao, 2008; Cagetti and De Nardi, 2009; Scheuer, 2014) and credit shocks (Bassetto et al., 2015; Buera et al., 2015; Buera and Moll, 2015). This paper studies a different question to existing research by focusing on understanding long run changes in entrepreneurship.

The remainder of the paper is structured as follows. Section 2 provides empirical evidence. The model is presented in Section 3 and calibrated in Section 5. Section 6 contains the results, Section 7 provides empirical guidance on the interpretation of the results and the conclusion is in Section 8.

2 Empirics

This section documents how the share of the labor force engaged in entrepreneurial activity and the composition of entrepreneurs have evolved over the last three decades. I use this evidence to identify theories for the decline in entrepreneurship that are consistent with the data, which I will evaluate with a model in the remainder of the paper.

2.1 Data description

I use data from the Current Population Survey (CPS) from the Bureau of Labor Statistics (BLS). This is a sample of the civilian non-institutionalized population.[7] For the majority of the analysis I use data from the Annual Social and Economic Supplement (the March supplement) for 1988–2016 and focus on the population of people aged 25–65 who are not working in the agriculture or government sectors.[8] This provides cross-sectional samples taken in March each year that, once weighted, are representative of this population. The surveys ask respondents about their employment experience in the previous year, so the data covers the years 1987–2015. The sample size ranges from 63,019 to 105,283 individuals with an average of 87,292. I restrict attention to ages 25–65 to reduce the effect of changes in education and retirement decisions over time.[9] I exclude the agriculture sector from the analysis since there has been a significant decline in the self-employment rate in this sector over time and I want to eliminate concern that any of the results are driven by this.

For the empirical analysis I define an entrepreneur to be a person who is self-employed and has at least 10 employees in their business. The paper focuses on classifying people according to their main job in the calendar year prior to when each survey was conducted, since the March supplement provides information on income and firm size for these jobs that will be used in this

[7]The CPS includes some people who are in the armed forces. I exclude these for my analysis.

[8]The data has been accessed from the Integrated Public Use Microdata Series (Flood et al., 2015), commonly known as IPUMS.

[9]I also show in the Appendix that changes in the decisions of people in the sample who are in education does not drive any of the results.

Firm size (employees)	*Self-employed (000's)*	*Firms (000's)*
<10	9,320.8	19,063.5
10–99	1,087.1	1,050.4
100–499	136.3	76.7
500–999	26.0	8.1
1000+	134.9	9.6

Table 1: **Size distribution of self-employed businesses and firms, 1997.** The Self-employed column is the number of self-employed people with businesses in each size category in the US, estimated using the full CPS sample and population data from the BLS. The Firms column is the number of firms in each size category computed using the Business Dynamics Statistics and Non-employer Statistics from the Census Bureau.

paper.[10] The CPS classifies peoples' main jobs into five categories depending on who the work was for: government; private for profit company; non profit organization including tax exempt and charitable organization; self-employed; working in a family business.[11] In defining an entrepreneur I place a size threshold on their business to focus attention on the most economically significant businesses and avoid concern that any of the results are driven by very small businesses. I choose a threshold of 10 employees since this is the smallest threshold (other than zero) that is available for most of the sample period (it is available for 1991–2015). All results hold without the size threshold and I will present some of these.[12]

To give a sense of what component of the economy self-employed people account for Table 1 presents information on the size distribution of the businesses of the self-employed and the size distribution of all firms in the economy for 1997. The main point that I wish to make is that self-employed people run businesses across the size distribution, not just small businesses. The *Self-employed* column provides the number of self-employed people with businesses in five size categories, measured with the number of employees, while the *Firms* column provides the number of firms in the whole economy in these categories. These numbers show three things. First, many of the smallest businesses (<10 employees) are not associated with a self-employed person: there are over 19 million firms with less 10 employees in the economy, but only 9.3 million self-employed people with such businesses. Assuming that the self-employed have one business each, which the data supports,[13] there are 9.7 million small businesses not associated with a self-employed person.

[10] A person's main job is their longest job in the previous year.

[11] In recent years the wording of the question that determines this has been: were you employed by government, by a PRIVATE company, a nonprofit organization, or were you self-employed or working in a family business? (Capitalization in original.)

[12] The remainder are in the Appendix and otherwise available upon request.

[13] In 1992 there was 1.07 owners per business for businesses with less that 10 employees in the US. Assuming that most of these owners work in their business as their main job, which seems reasonable for small business, this supports that there is approximately one self-employed person per business in this size category. This data is from the 1992 Characteristics of Business Owners Survey from the Census Bureau. This data provides the number of sole proprietorships, partnerships and S corporations, and the number of owners of these businesses, by firm size. I use 1992 data since this is the closest year to 1997 with this information (the survey was discontinued after 1992).

This is due to a large number of people owning business but not working in them the majority of their time. Second, self-employed people account for most medium sized businesses (10–99 employees). In this size category there is an average of 1.35 owners per firm so the self-employed account for 805,259 out of the 1.05 million firms.[14] Third, for large businesses (100+ employees) there are many more self-employed people than firms: 134,900 compared to 9,600. While I don't have an estimate of the number of owners per firm in this category these numbers indicate that there are many self-employed people running large businesses.[15]

The sample period of 1987–2015 has been chosen to ensure that self-employment can be measured consistently over time. The CPS does have data prior to 1987 on self-employment, but for this period the BLS only reported people as self-employed if their business was not incorporated. From 1987 onward people with incorporated businesses have been counted as self-employed as well. The exclusion of people with incorporated businesses from self-employment prior to 1987 is likely to downwardly bias the trend in self-employment since people have been increasingly likely to incorporate their businesses over time. Since the share of people who are self-employed is a critical moment for the analysis, I exclude the pre-1987 data.[16] One additional point regarding the consistency of the data over time is that in 1994 the CPS questionnaire and data collection methods were updated (see Polivka and Miller, 1998). For the variables that I am using the substance of the questions remained the same, however there are jumps in some series as a result of the changes. I smooth these out by assuming that a series x_t is equal for 1993 and 1994 and that $x_t = (x_t/x_{1994}) \times x_{1993}$ for $t > 1994$. In figures I indicate this by a break in a series from 1993 to 1994.

2.2 Aggregate entrepreneurship rate

I define the aggregate entrepreneurship rate to be the share of the labor force who are entrepreneurs. I use the labor force as the numerator rather than the population to abstract from the effect of changes in labor force participation over time. I define the self-employment rate analogously. These two rates are presented in Figure 1. The entrepreneurship rate (right hand axis) has declined from 1.56% to 1.16%, a 26% decrease, while the self-employment rate (left hand axis) has declined from 11.4% to 9.4%, a decrease of 18%. Both rates have cyclical fluctuations but downward trends.

C corporations are omitted from this dataset so I am assuming that they account for a negligible number of the businesses owned by self-employed people in this size category.

[14] The number of owners per firm is computed in the same way as for firms with less than 10 employees.

[15] The Survey of Business Owners provides an estimate of the number of owners per firm for sole proprietorships, partnerships and S corporations in this size category. C corporations are omitted. I don't use this number since it would imply more firms than is possible. The omission of C corporations appears important for large firms.

[16] In their analysis of entrepreneurs Levine and Rubinstein (2017) distinguish between people with incorporated and unincorporated businesses arguing that incorporation is a signal for entrepreneurial quality. In this paper I don't do analysis dividing the sample by the legal form of businesses since I am focusing on trends over time and the data shows that there is a trend towards incorporation over time so that this division is not stable.

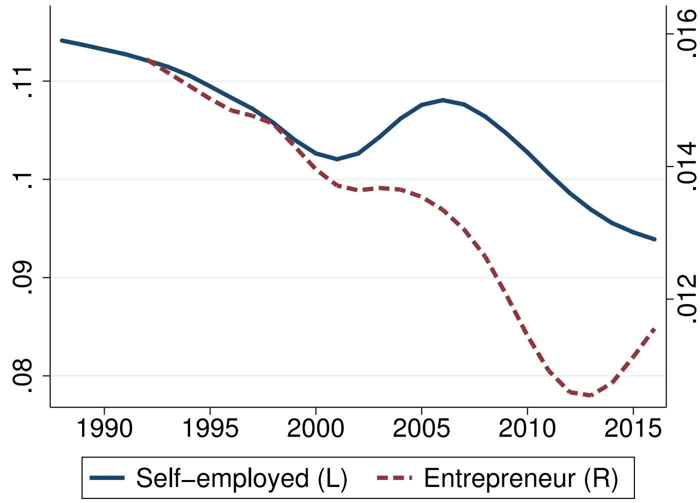


Figure 1: **Entrepreneurship and self-employment rates.** The self-employment and entrepreneurship rates are the shares of the labor force who are self-employed and entrepreneurs, respectively. The scale for the self-employment rate is on the left axis and the for the entrepreneurship rate it is on the right axis. Both series are smoothed using a HP filter with smoothing parameter equal to 6.25.

The fact that the Great Recession is in the latter part of the sample may bias the trend downwards a little, but including the post-2007 data has the advantage of providing a longer sample to work with. There are also three reasons why including the post-2007 data should not be a large concern. First, the downward trend is evident in the data prior to 2007 so the post-2007 data is not essential for establishing this. Second, the data includes seven years of observations after the end of the Great Recession so the economy has had considerable time to return to the trend level of entrepreneurship. Third, I have done similar analysis for 1983 to 1995 using the Survey of Income and Program Participation from the Census Bureau and found the same trend. These results are in the appendix.

A natural question to ask at this point is whether the downward trend in entrepreneurship is due to changes in the composition of the economy, or whether the trend is being driven by a partcular industry. Analysis in the appendix shows that changes in the composition of the economy along sector, age, education, gender and geographic measures actually have had a positive effect on the entrepreneurship rate between 1991 and 2015. So accounting for these factors actually makes the decline in entrepreneurship *larger* then it appears in the raw data. Regarding within sector changes, the largest decline has been in the wholesale and retail trade sector, however there has been declines in all other sector too and these other sector acount for about 50% of the decline in the aggregate. Thus the trend is broad-based.

2.3 Changes in entrepreneurship by education

The second main fact is about how the decrease in the entrepreneurship rate has differed across the education distribution. For this analysis I divide the sample into five groups according to the highest level of education that each person has completed: less than high school (<HS), high school (HS), some college education but less than a bachelor's degree (some college), a bachelor's degree (college) and more education than a bachelor's degree (>college). I look at changes in the entrepreneurship rate by education group from 1991 to 2015. Figure 2(a) shows that the entrepreneurship rate is higher for more educated people throughout the period of analysis and appears to be decreasing more rapidly. To compare the changes in entrepreneurship rates across these groups panel (b) presents the percentage change in the average entrepreneurship rate for 1991–92 to the average for 2014–15 for each group. I take averages at the end points to smooth out year to year volatility. It shows a clear pattern of larger decreases in the entrepreneurship rate for higher education levels. At less than a high school education the decrease is 2.4% while for more than a college education the decrease is 33.9%.

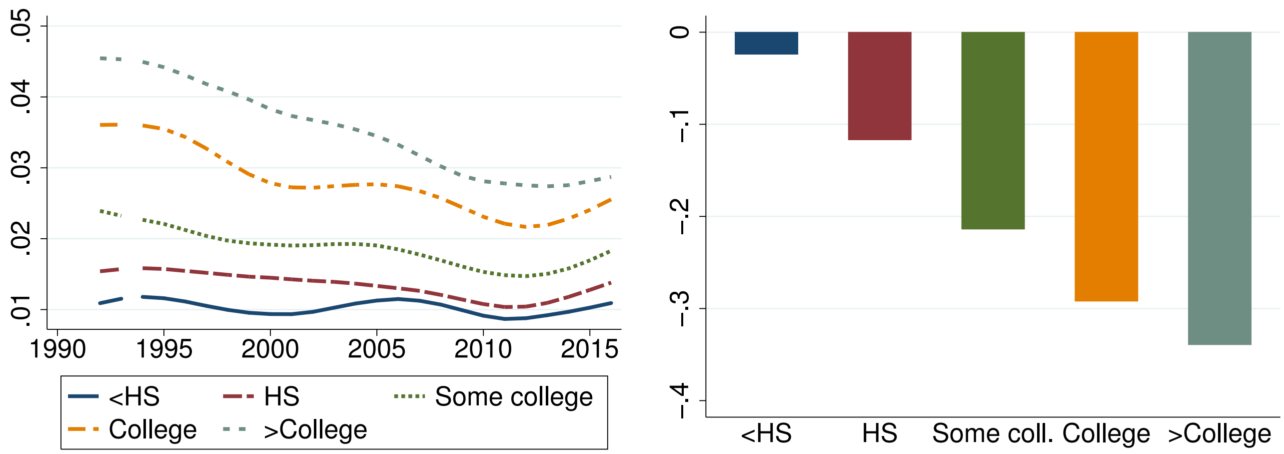
As far as my knowledge extends this is a new fact. Unlike previous evidence of declining entrepreneurship this evidence suggests that at least part of the force driving changes in entrepreneurship is not skill neutral. In this paper I will consider the relevance of skill-biased technical change for these trends. There are a number of reasons for focusing on this. First, this force has heterogeneous effects by skill and there is evidence that it has caused an increase in the wages of higher skill workers relative to those of lower skill workers (e.g. Krusell et al., 2000). All else being equal, this provides a basis upon which higher skill workers could have more incentive to leave entrepreneurship. This suggests that there could be a link between skill-biased technical change and the changes in entrepreneurship that have occurred, and this paper will evaluate this link in detail. Second, we know that this force has affected the economy over the relevant period (e.g. Autor et al., 2003; Acemoglu and Autor, 2011; Eden and Gaggl, 2016). Third, there are well developed theories and measures of technical change which provide a foundation for evaluating its contribution to the trends I am studying.

2.4 Entrepreneur firm size

The third fact is that the size distribution of entrepreneur firms has been quite stable over time. Figure 3 presents the share of self-employed people with firms in different size categories for 1991–2015.[17] It shows that the shares in each category have been approximately flat over time. There is an uptick in the share of the self-employed with businesses with 500–999 employees at the end of the sample, but this is only in the last three years and so does not establish a long run upward trend.

This fact has two important implications. First it means that the decline in entrepreneur-

[17] I omit 1987–90 since the size categories are different for this period.



(a) Entrepreneurship rate, 1991–2015

(b) Percentage change, 1991/92–2014/15

Figure 2: **Entrepreneurship rate by education and percentage change.** Panel (a) is the share of the labor force for each education level who are entrepreneurs. These series are smoothed with a HP filter with smoothing parameter equal to 6.25. Panel (b) is the the percentage change in the entrepreneurship rate from the average for 1991–92 to the average for 2014–15 for each education group. These calculations use the unsmoothed series.

ship has not been concentrated amongst the smallest businesses that are likely to have the least economic impact. The trend appears to apply to businesses evenly across the size distribution. Second, the fact that the size distribution has been fairly stable and the share of the labor force who are self-employed has decreased indicates that over time there has been a shift in economic activity towards firms that aren't run by a self-employed people. I will call these non-entrepreneur firms.

This evidence suggests that we should consider explanations for the decline in entrepreneurship that disadvantages entrepreneurs relative to larger non-entrepreneur firms (e.g. public firms). This paper considers three such theories. One idea is that level of regulation has increased and because regualtions have a large fixed cost of compliance they have burdened smaller businesses more.[18] Regulations that are commonly discussed as having this effect include increases in occupational licensing, weaker enforcement of anti-trust laws and zoning restrictions.[19] The second idea is that changes in technology have increased the fixed cost component of production, generating an advantage for larger firms (see Aghion et al., 2019; Hsieh and Rossi-Hansberg, 2019; De Ridder, 2019). The third idea is that there have been other changes in technology that have advantaged the largest firms in the economy and resulted in production becoming increasingly concentrated

[18] See Decker et al. (2014a), Davis and Haltiwanger (2014) and Davis (2017) for discussions of this explanation.

[19] The motivation for the discussion of occupational licensing is Kleiner (2015) who shows that the prevalence of occupational licenses has increased over time. Hsieh and Moretti (2017) argue that zoning restrictions have contributed to high property prices in major economic centers like New York and the Bay Area. While they do not study the effect of this on entrepreneurship, the increase in property prices will increases the upfront cost of any business that needs physical space.

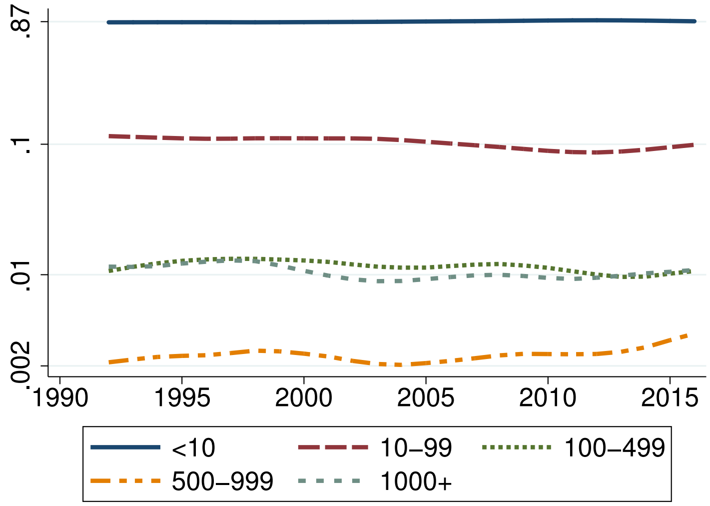


Figure 3: **Size distribution of businesses of self-employed.** The scale of the y-axis is logarithmic. Each series is HP filtered with smoothing parameter equal to 6.25.

amongst them.[20] I'll call this the superstar firms hypothesis, adopting the language of Autor et al. (2017) who study the effects of this on the labor share. While it is beyond the scope of this paper to assess why exactly this has occurred, ideas include that new technologies have enabled people to better compare prices and quantities, which advantages the most productive firms, or larger firms are better placed to take advantage of new technologies because of their size or better access to financing. I will include these explanations in the model I build to evaluate why the entrepreneurship rate has declined.

3 Model

The model is a dynamic occupational choice model. It is designed to capture the theories for the decline in entrepreneurship that have been discussed, and it will be used to evaluate them.

3.1 Environment

Time is discrete and infinite, and there is a unit mass of agents. When an agent is born it has a type, high or low skill, which is fixed for life. With probability θ_h an agent is a high type, and otherwise she is a low type. An agent that is a high type draws a productivity z_h for doing high skill work at birth, and if she is low type then she draws a productivity for low skill work z_l. Each agent also receives an entrepreneurial productivity z_e at birth. Therefore all agents will be endowed with one worker productivity, z_l or z_h, and an entrepreneur productivity z_e. To simplify notation going forward, let $\mathbf{z} = [z_l, z_h, z_e]$ be the productivity vector of an agent, with

[20] See Davis and Haltiwanger (2014) for discussion of this idea.

$z_l = 0$ for high types and $z_h = 0$ for low types. At birth this productivity vector is drawn from a distribution $G(\mathbf{z})$. It then evolves stochastically over time according to a Markov chain, $G(\mathbf{z}'|\mathbf{z})$. The distribution for initial draws, $G(\mathbf{z})$, is the stationary distribution of the Markov chain. Agents discount the future at rate β and each agent dies at the end of each period with probability δ. An agent that dies is replaced by a new agent at the start of the next period.

For the quantitative exercise later in the paper, θ_h and the productivity distributions will be allowed to depend on an agent's education level so that the model can be mapped to the data. Education will be taken as given. The model will therefore have a distinction between skill and education. This will allow people with different education levels to perform the same job. For example, people with and without college educations can all be plumbers. The education dimension of the model is suppressed now for simplicity, and will be introduced when the model is taken to the data.

Each period agents must choose whether to work and what kind of work to do: their *occupational choice*. If an agent chooses not to work she receives b units of consumption, which can be thought of as the output of home production, consumption-equivalent units of leisure, or a combination of both. If an agent has low skill productivity $z_l > 0$ then she can work as a low skill employee. She will provide z_l efficiency units of low skill labor and earn income $z_l w_l$, where w_l is the low skill wage per efficiency unit. If an agent has high skill productivity $z_h > 0$, then she can work as a high skill worker and earn $z_h w_h$, with these variables interpreted analogously to z_l and w_l. Finally agents can choose to be entrepreneurs. If an agent was not an entrepreneur last period then she needs to pay an entry cost ψ_e. Then each period of entrepreneurship the agent pays a fixed operating cost, ψ, and can run a production technology $f(z_e, k_o, k_i, \ell_l, \ell_h)$. It is assumed that being an entrepreneur is a full-time occupation so that an entrepreneur can't also be an employee. As an entrepreneur the agent hires inputs to produce and keeps the profits from the operation. There are four inputs. The two types of capital, k_o and k_i, can be rented at rate r_o and r_i, respectively. The two labor inputs are high and low skill labor measured in efficiency units, ℓ_l and ℓ_h, which have prices w_l and w_h.

The objective of each agent is to maximize the present discounted value of utility. The utility function is $u(c)$, satisfying $u'(c) > 0$, $u''(c) < 0$ and $\lim_{c \to 0} u'(c) = \infty$. There is no saving, so agents consume what they earn each period. Saving is abstracted from since its not central to the mechanisms being studied.

There is also a non-entrepreneurial sector, modeled by a representative non-entrepreneur firm. It has productivity z_f and produces using the technology $f(z_f, k_o, k_i, \ell_l, \ell_h)$, which has the same functional form as the technology that entrepreneurs use.[21] This firm should be thought of as representing large firms in the economy, such as public firms, that don't have an owner who runs

[21] It would be equivalent to have a continuum of non-entrepreneurs with a distribution of productivities. For the function that is used (see below), such a distribution of firms would aggregate up into a representative firm with exactly the form being used.

them. In contrast to entrepreneurial firms, the productivities of non-entrepreneurial firms are assumed to be intrinsic to the firm, embodied in the ideas and institutional structures that have been developed over time rather than being attached to an owner-manager. The representative non-entrepreneur firm is owned equally by all agents and is operated to maximize the present discounted value of profits.

3.2 Production technology

The production technology builds on existing research on technical change. The core idea that I adopt from this research is that improvements in capital technology over time have allowed capital to substitute for lower skill labor, and that this technology has also made higher skill workers more productive (Krusell et al., 2000; Autor et al., 2003; Autor and Dorn, 2013). A classic example of this is a manufacturing facility which can use better machines to replace production line workers, but then needs more engineers to operate, maintain and manage them. A more modern example is a company like Google which, amongst other things, provides information services that were previously provided by workers such as travel agents and call center employees. Google needs few low skill employees to provide these services but needs a lot of computer scientists.

The functional form for the production technology is

$$f(z, k_o, k_i, \ell_l, \ell_h) = z k_o^{\eta} \Big[\phi \ell_h^{\gamma} + (1-\phi)(\lambda k_i^{\tau} + (1-\lambda)\ell_l^{\tau})^{\frac{\gamma}{\tau}}\Big]^{\frac{\alpha}{\gamma}}, \tag{1}$$

where $\eta, \phi, \lambda, \alpha \in (0, 1)$; $\alpha + \eta < 1$; and $\tau, \gamma < 1$. The nested CES structure follows other papers that study the effects of technical change quantitatively (Krusell et al., 2000; vom Lehn, 2015; Eden and Gaggl, 2016). The main difference here is the use of a decreasing returns to scale technology since this paper studies production at the firm, rather than the aggregate, level and needs a distribution of firms. The productivity of the firm z is z_e for an entrepreneur and z_f for the non-entrepreneur sector. There are two types of labor, low skill ℓ_l and high skill ℓ_h, both measured in efficiency units. k_i and k_o are two types of capital. k_i is the type of capital that drives technical change. Its degree of substitutability/complementarity with low and high skill labor are determined by τ and γ, respectively. There are no restrictions on whether, and the degree to which, these inputs are substitutes or complements, allowing the data to determine this when the model is calibrated. When I take the model to the data I will measure k_i with information and communication technology, as others have (e.g. Eden and Gaggl, 2016; Cortes et al., 2016), so I will call this IT capital. The rationale for this measure is that it is improvements in IT technology that are driving technical change. The fourth production input is k_o, which is all other capital. This is combined with the other inputs in Cobb-Douglas form. This input in necessary for taking the model to the data but will not play a key role in the results.

3.3 Optimization problems and equilibrium

Let $\epsilon \in \{0,1\}$ be an indicator for whether an agent was an entrepreneur in the previous period. The value function of an agent at the start of a period is denoted $V(\mathbf{z},\epsilon)$.[22] The value functions for being out of the labor force, a low skill employee, a high skill employee, and an entrepreneur are, respectively:

$$\begin{aligned}
V_{\text{olf}}(\mathbf{z},\epsilon) &= u(b+\pi_f)+\beta(1-\delta)\mathbb{E}[V(\mathbf{z}',0)|\mathbf{z}], && (2)\\
V_{\text{l}}(\mathbf{z},\epsilon) &= u(z_l w_l+\pi_f)+\beta(1-\delta)\mathbb{E}[V(\mathbf{z}',0)|\mathbf{z}], && (3)\\
V_{\text{h}}(\mathbf{z},\epsilon) &= u(z_h w_h+\pi_f)+\beta(1-\delta)\mathbb{E}[V(\mathbf{z}',0)|\mathbf{z}], && (4)\\
V_{\text{e}}(\mathbf{z},\epsilon) &= u(\pi(z_e,\epsilon)+\pi_f)+\beta(1-\delta)\mathbb{E}[V(\mathbf{z}',1)|\mathbf{z}], && (5)
\end{aligned}$$

where π_f is the profit of the non-entrepreneur sector and the profit of an entrepreneur is

$$\pi(z_e,\epsilon) = \max_{\{k_o,k_i,\ell_l,\ell_h\}} \big\{ f(z_e,k_o,k_i,\ell_l,\ell_h) - w_l\ell_l - w_h\ell_h - r_ok_o - r_ik_i - \mathbb{1}_\epsilon(0)\psi_e - \psi \big\}.$$

$\mathbb{1}_A(a)$ is the indicator function for whether variable A is equal to value a. The optimal choice for input x is

$$x(z_e) = \Gamma_x z_e^{\frac{1}{1-\alpha-\eta}} \tag{6}$$

and the profit function is:

$$\pi_e(z_e,\epsilon) = \Gamma_\pi z_e^{\frac{1}{1-\alpha-\eta}} - \mathbb{1}_\epsilon(0)\psi_e - \psi,$$

where the Γ's are functions of parameters and prices provided in the Appendix. Let the output of a firm be denoted $y(z_e)$.

Denote the set of possible occupations $\mathcal{O} = \{\text{olf}, l, h, e\}$ where the notation corresponds to the subscripts on the relevant value functions. The value function satisfies:

$$V(\mathbf{z},\epsilon) = \max_{x\in\mathcal{O}} V_x(\mathbf{z},\epsilon).$$

and the occupational choice is

$$\mathcal{o}(\mathbf{z},\epsilon) = \arg\max_{x\in\mathcal{O}} V_x(\mathbf{z},\epsilon). \tag{7}$$

The production problem for the representative non-entrepreneur firm is

$$\pi_f = \max_{\{k_o,k_i,\ell_l,\ell_h\}} \big\{ f(z_f,k_o,k_i,\ell_l,\ell_h) - w_l\ell_l - w_h\ell_h - r_ok_o - r_ik_i \big\},$$

which yields the same functions for input choices and output as for entrepreneur firms, $x(z_f)$ and

[22] The value function of course depends on the aggregate state as well. Since the focus will be on the stationary equilibrium in which the aggregate state is constant, this state variable is suppressed.

$y(z_f)$, and the profit is

$$\pi_f = \Gamma_\pi z_f^{\frac{1}{1-\alpha-\eta}}.$$

Agents in the model are distributed over the states $(\mathbf{z}, \epsilon)$. Let the state state space, which is the Cartesian product $\mathbb{R}^3_+ \times \{0,1\}$, be denoted by J and let the σ-algebra Σ_J be defined as $B_{\mathbb{R}^3_+} \otimes P(\{0,1\})$ where $B_{\mathbb{R}^3_+}$ is the Borel σ-algebra of $\mathbb{R}^3_+$ and $P(\{0,1\})$ is the power set of $\{0,1\}$. Let the typical subset of Σ_J be denoted by $\mathcal{Z} \times \mathcal{E}$. With this notation, the transition function for the distribution of agents, $Q : J \times \Sigma_J \to [0,1]$, can be expressed as:

$$Q((\mathbf{z}, \epsilon), \mathcal{Z} \times \mathcal{E}) = (1-\delta)\big[\big(1 - \mathbb{1}_s(e)\big)\mathbb{1}_{\mathcal{E}}(0) + \mathbb{1}_s(e)\mathbb{1}_{\mathcal{E}}(1)\big] \int_{\mathcal{Z}} g(\mathbf{z}'|\mathbf{z})d\mathbf{z}' + \delta \mathbb{1}_{\mathcal{E}}(0) \int_{\mathcal{Z}} g(\mathbf{z}')d\mathbf{z}',$$

where $g(\mathbf{z}'|\mathbf{z})$ and $g(\mathbf{z})$ are the probability density functions of $G(\mathbf{z}'|\mathbf{z})$ and $G(\mathbf{z})$ respectively. The indicator function for the set $\mathcal{E}$, $\mathbb{1}_{\mathcal{E}}(x)$, indicates whether element x is in set $\mathcal{E}$. To understand this formula, recall that with probability $1-\delta$ an agent survives to the next period. If they are not an entrepreneur this period ($\not{o} \neq e$) then $\epsilon' = 0$, and if they are then $\epsilon' = 1$. Their productivity vector evolves according to $G(\mathbf{z}'|\mathbf{z})$. With probability δ an agent will die. In this case they will be replaced by a new agent next period who will have $\epsilon = 0$ and will draw her productivities from $G(\mathbf{z})$. A stationary distribution of agents is a function $H : \Sigma_J \to [0,1]$, such that for all $\mathcal{Z} \times \mathcal{E} \in \Sigma_J$

$$H(\mathcal{Z} \times \mathcal{E}) = \int_J Q((\mathbf{z}, \epsilon), \mathcal{Z} \times \mathcal{E}) dH. \tag{8}$$

There are three markets that need to clear: the markets for low skill labor, high skill labor and the market for the final good. For a stationary distribution of agents H, the market clearing conditions are:

$$\int_J \mathbb{1}_s(l) z_l \, dH = \int_J \mathbb{1}_s(e)\ell_l(z_e)\, dH + \ell_l(z_f), \tag{9}$$

$$\int_J \mathbb{1}_s(h) z_h \, dH = \int_J \mathbb{1}_s(e)\ell_h(z_e)\, dH + \ell_h(z_f), \tag{10}$$

$$\begin{aligned} &\int_J \mathbb{1}_s(e)\Big(\pi_e(z_e,\epsilon) + w_l\ell_l(z_e) + w_h\ell_h(z_e) + r_o k_o(z_e) + r_i k_i(z_e) + \mathbb{1}_\epsilon(0)\psi_e + \psi\Big)\, dH \\ &\qquad + \pi_f(z_f) + r_o k_o(z_f) + r_i k_i(z_f) = \int_J \mathbb{1}_s(e) y(z_e)\, dH + y(z_f). \end{aligned} \tag{11}$$

The analysis will focus on the stationary equlibrium of the model, which is defined as follows.

Equilibrium *A stationary equilibrium is a pair of wages* $\{w_l, w_h\}$*; a function for occupational choices* $\not{o}(z_l, z_h, z_e, \epsilon)$*; production input decisions for entrepreneurs and non-entrepreneur firms* $\{\ell_l(z), \ell_h(z), k_o(z), k_i(z)\}$ *with* $z = z_e$ *for entrepreneurs and* $z = z_f$ *for non-entrepreneurs; and a distribution* H *of agents over idiosyncratic states such that:*

- *the production input decisions of entrepreneurs and non-entrepreneur firms satisfy* (6)*;*

- *occupational choices satisfy* (7)*;*
- *the distribution of agents H satisfies* (8)*; and*
- *the markets for low skill labor, high skill labor and the final good clear in accordance with equations* (9)*,* (10) *and* (11)*.*

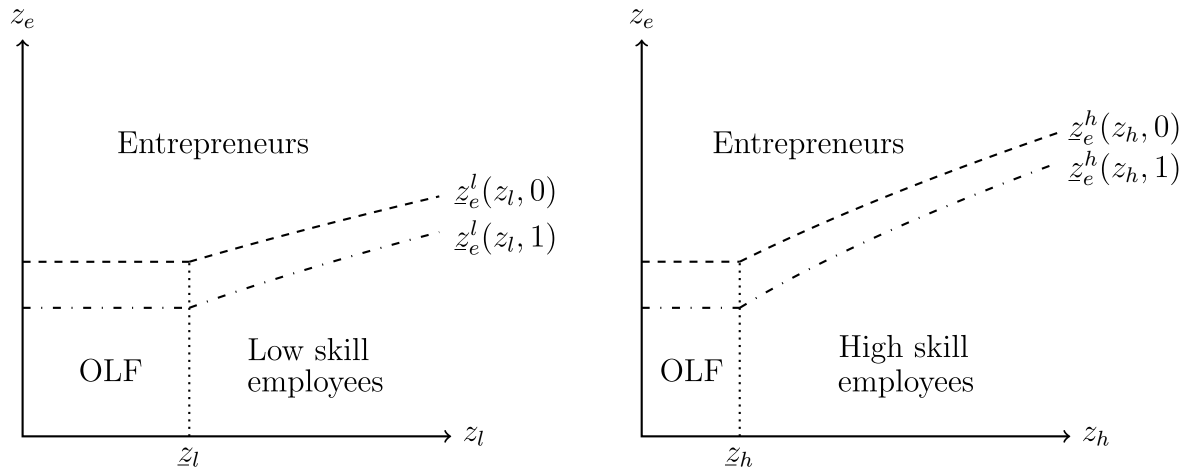
4 Sources of declining entrepreneurship

This section discusses how skill-biased technical change, increasing productivity of non-entrepreneurs, and increasing fixed and entry costs affect entrepreneurship in the model. Recall that the motivation for considering increasing non-entrepreneur productivity is evidence that large firms in the economy have become more productive over time, while increasing fixed and entry costs aim to capture changes in the regulatory environment and technological changes affecting these components of costs. The objective is to explain the mechanisms that link these changes in the economy to occupational choice decisions, and to use this theory to explain how changes in key parameters of the model can be identified. For this purpose a simplified single period model will be used in order to provide the main intuition with sharper analysis than would be possible with the full model.

4.1 Occupational sorting in a simplified model

Consider a version of the model which has a single period. Agents are either low or high skill, and each is endowed with a vector of productivities $\mathbf{z}$. Agents choose their occupation and the payoffs are given by equations (2)–(5) with $\beta = 0$. To maintain the effect of the entry cost on the occupation decision, it is assumed that a fraction of agents have $\epsilon = 1$ so that they don't have to pay the entry cost to be entrepreneurs and the remainder of agents do face this cost ($\epsilon = 0$). Agents with $\epsilon = 1$ can be thought of as being endowed with a business, while other agents have to set one up if they want to be an entrepreneur.

Figure 4 presents the occupational choice policies of agents in the simple model. First consider low types whose occupational choices are presented in panel (a). The productivity of an agent when working as an employee is along the horizontal axis and their productivity as an entrepreneur is along the vertical axis. For low levels of z_e agents will either work as an employee or chose to be out of the labor force. Since the value of being a low skill employee is increasing in z_l and the value of being out of the labor force is constant, there is a threshold ($\underline{z}_l = b/w_l$) above which agents choose to work and otherwise they do not. Moving vertically up the figure, there are two thresholds that separate agents who are entrepreneurs from those who are out of the labor force or working as employees. These thresholds are a function of the employee productivity of an agent, z_l, and whether she is endowed with a business, ϵ. The higher of these, $\underline{z}_e^l(z_l, 0)$, is the threshold for agents who are not endowed with a business ($\epsilon = 0$). In general, agents with higher entrepreneurial productivity are more likely to be entrepreneurs. For low values of z_l the threshold is flat because



(a) Low skill types (b) High skill types

Figure 4: **Equilibrium occupational choices.** $\underline{z}_e^s(z_s, \epsilon)$ is the threshold value of z_e above which agents of skill type $s \in \{l, h\}$, worker productivity z_s, and business endowment state ϵ, choose to be an entrepreneur. $\underline{z}_s$ is the minimum employee productivity level for which an agent of skill type s could choose to be an employee.

the outside option to entrepreneurship is being out of the labor force, and this has the same value for everyone. For $z_l > \underline{z}_l$ this threshold is increasing in the level of z_l because agents with higher z_l earn more as employees and therefore need to make higher profits as entrepreneurs in order to choose that profession. The threshold is concave because the return to being an employee is linear in z_l while the return to being an entrepreneur is convex in z_e. The second threshold, $\underline{z}_e^l(z_l, 1)$, is for agents who are endowed with a business ($\epsilon = 1$). These agents choose to be entrepreneurs for lower values of z_e because they do not need to pay the entry cost. In the dynamic model, $\underline{z}_e^l(z_l, 0)$ corresponds to the threshold for entering entrepreneurship, while $\underline{z}_e^l(z_l, 1)$ corresponds to the exit threshold.

For high skill types the tradeoffs are the same except that the value of being an employee is $z_h w_h$ instead of $z_l w_l$. The two panels in Figure 4 are drawn to depict a case in which z_l and z_h have the same range and $w_h > w_l$. This illustrates two points. The first is that since high skill agents earn more for a given productivity they will choose to be out of the labor force for a smaller range of productivities. That is, $\underline{z}_h = b/w_h < \underline{z}_l$. Second, for a given employee productivity, the z_e threshold for being an entrepreneur is higher for high skill types because they earn more as employees: $\underline{z}_e^h(x, 1) > \underline{z}_e^l(x, 1)$ and $\underline{z}_e^h(x, 0) > \underline{z}_e^l(x, 0)$ for all $x > \underline{z}_h$. The functional form for the entrepreneurship boundaries for an agent with skill type $s \in \{l, h\}$ is:

$$\underline{z}_e^s(z_s, \epsilon) = \begin{cases} \left(\dfrac{b + \psi + \mathbb{1}_\epsilon(0)\psi_e}{\Gamma_\pi}\right)^{1-\alpha-\eta} & \text{for } z_s \in [0, \underline{z}_s], \\ \left(\dfrac{z_s w_s + \psi + \mathbb{1}_\epsilon(0)\psi_e}{\Gamma_\pi}\right)^{1-\alpha-\eta} & \text{for } z_s > \underline{z}_s. \end{cases} \tag{12}$$

It should also be noted that the size of the regions in Figure 4 should not be interpreted as indicating the relative shares of the occupation categories. This depends on the thresholds depicted as well as the distribution of agents over the productivity space.

4.2 Skill-biased technical change

The force driving skill-biased technical change in the model is a decrease in the rental rate of IT capital, r_i. As is well understood from the technical change literature this will affect the equilibrium wages of high and low skill workers, with the changes depending on the values of the two elasticity of substitution parameters for the production function. For the period being studied, the main change in wages was an increase in the high skill wage. So this analysis focuses on the effect of increasing r_i and decreasing w_h on occupational choices.

The following proposition characterizes the effects of these changes on the decisions of agents whether to be entrepreneurs or not. Derivatives that are conditional on $\mathbf{w}$ hold the wages fixed. Otherwise they express equilibrium relationships. All proofs are in the Appendix.

Proposition 1. *The effects of changes in the IT capital rental rate and the high skill wage on the entrepreneur thresholds are as follows.*

(a) For all $s \in \{l, h\}$, $\epsilon \in \{0, 1\}$ and $z_s > 0$,

$$\left.\frac{\partial \underline{z}_e^s(z_s,\epsilon)}{\partial r_i}\right|_{\mathbf{w}} > 0 \quad \text{and} \quad \frac{\partial \underline{z}_e^s(z_s,\epsilon)}{\partial w_h} > 0.$$

(b) If $w_h > w_l$, then for all $z_s > \underline{z}_h$ and $\epsilon \in \{0, 1\}$,

$$\left.\frac{\partial \underline{z}_e^h(z_s,\epsilon)}{\partial r_i}\right|_{\mathbf{w}} > \left.\frac{\partial \underline{z}_e^l(z_s,\epsilon)}{\partial r_i}\right|_{\mathbf{w}} \quad \text{and} \quad \frac{\partial \underline{z}_e^h(z_s,\epsilon)}{\partial w_h} > \frac{\partial \underline{z}_e^l(z_s,\epsilon)}{\partial w_h}.$$

(c) For all $s \in \{l, h\}$ and $z_s > 0$,

$$\left.\frac{\partial [\underline{z}_e^s(z_s,0) - \underline{z}_e^s(z_s,1)]}{\partial r_i}\right|_{\mathbf{w}} > 0.$$

Parts (a) and (b) of this proposition tell us about the effects of skill-biased technical change on the share of agents who are entrepreneurs. If we were to consider a pure increase in w_h (no change in r_i), these results have clear implications for how entrepreneurship decisions change. The entrepreneurship thresholds, $\underline{z}_e^s(z_s,\epsilon)$ for $\epsilon \in \{0, 1\}$, will increase for both skill types, and the increases will be larger for high skill types. This will decrease the share of agents of each skill type who are entrepreneurs. Whether the decrease is larger for high skill types will depend on the shape of the distributions of low and high skill agents in the productivity space. If the mass of agents distributed near the entrepreneurship threshold is similar for the two skill types, then the entrepreneurship share for high skill agents will decrease more. This indicates how an increasing high skill wage could generate these patterns, which were documented in the data in Section 2.

The fact that this change in the high skill wage is being driven by a declining rental rate for IT capital complicates the analysis. This change increases the profit of an entrepreneur because it is a decline in an input price. This decreases all entrepreneurship thresholds and thereby increases the entrepreneurship share for both skill types. This effect offsets the decline in entrepreneurship shares due to the increase in the high skill wage.

In the static model, the analog of the entry rate is the share of entrepreneurs who were not endowed with a business, i.e. those with $\epsilon = 1$. For the purposes of this section I will call this the "entry rate." A key factor affecting this is the size of the wedge between the productivity thresholds for running a business for people with and without an endowed business. As this wedge decreases, the entry rate will tend to increase.[23] For an agent with skill type s and $z_s > \underline{z}_s$, this wedge is

$$\underline{z}_e^s(z_s, 0) - \underline{z}_e^s(z_s, 1) = \left(\frac{1}{\Gamma_\pi}\right)^{1-\alpha-\eta} \left([z_s w_s + \psi + \psi_e]^{1-\alpha-\eta} - [z_s w_s + \psi]^{1-\alpha-\eta} \right). \tag{13}$$

A decrease in r_i has two types of effects on this wedge. It changes the profitability of entrepreneurs, which shows up in the Γ_π term. The direct effect of decreasing r_i is to increase profitability. This decreases the wedge because, if entrepreneurs are more profitable, then the entry cost is less relevant to them. This is the effect captured in part (c) of the proposition and it pushes in the opposite direction of what has occurred in the data. To the extent that the falling IT capital price increases the high skill wage, it will decrease entrepreneur profits and offset this effect. This price change has a second effect for high skill agents, captured by the $z_s w_s$ terms when $s = h$. This effect is that an increase in the high skill wage pushes up the productivity threshold for being an entrepreneur because the outside option is better. This means than in equilibrium high skill entrepreneurs are more profitable, so that the entry cost is less relevant to them and the wedge decreases.

The third dimension of entrepreneurship under consideration is the share of employment at entrepreneur firms. This depends on the share of people who are entrepreneurs, and the amount of labor that each entrepreneur hires. As just mentioned, the direct effect of a fall in the price of IT capital is to increase the share of people who are entrepreneurs, which tends to increase the share of employment at entrepreneur firms. The effect on the employment level of each firms depends on the elasticity of substitution parameters. To the extent that demand of high skill labor, as a complementary input to IT capital, increases, firms will grow larger. If low skill labor is substitutable for IT capital then this will decrease the size of firms.

The overall message of this analysis is that while there are good theoretical reasons for expecting skill-biased technical change to decrease the relative entrepreneurship rate of high skill agents, there are competing forces determining the changes in other moments of entrepreneurship that need to be determined quantitatively. Section 5 and 6 will take up this task.

[23] The observed change will also depend on the direction and size of the changes in these thresholds, and the shape of the distribution over the state space.

4.3 Non-entrepreneur productivity

The expansion of non-entrepreneur firms is modeled through an increases in their productivity, z_f. The effects of this on the entrepreneur thresholds and the labor demand of entrepreneurs is characterized by Proposition 2.

Proposition 2. *An increase in non-entrepreneur productivity affects the entrepreneur thresholds and labor demands as follows.*

(a) For all $s \in \{l, h\}$, $\epsilon \in \{0, 1\}$ and $z_s > 0$,

$$\frac{\partial \underline{z}_e^s(z_s, \epsilon)}{\partial z_f} > 0.$$

(b) If $1 - \gamma$ is sufficiently large, then for all $s \in \{l, h\}$ and $z_e > 0$,

$$\frac{\partial \ell_s(z_e)}{\partial z_f} < 0.$$

This proposition says that an increase in non-entrepreneur productivity causes the entrepreneur thresholds to increase, so that the entrepreneur share decreases for both skill types. Conditional on being an entrepreneur, demand for both types of labor falls. All of these effects occur because of how the change in productivity affects wages. When productivity of the non-entrepreneur sector increases, its demand for both types of labor increases, pushing up wages. This makes entrepreneurship less profitable, so that the entrepreneur thresholds increase and fewer agents choose to be entrepreneurs. Amongst agents who still choose to be entrepreneurs, demand for labor decreases because the wages are higher.[24]

For present purposes, the useful insight from this is that increasing non-entrepreneur productivity is going to affect both the share of agents who are entrepreneurs, and the share of employment in the economy that they account for. Both of these moment are available from the data presented in Section 2, so the strength of this channel for explaining the changes in entrepreneurship can be evaluated against this moments. This will be part of the quantitative strategy.

The increase in non-entrepreneur productivity doesn't have a clear qualitative effect on the entry rate of entrepreneurs. This can be seen with equation (13). On one hand, the increase in wages that this change generates decreases the profits of entrepreneurs (captured by the Γ_π term in the equation). This increases the wedge between the two entrepreneur thresholds. On the other hand, the increase in wages pushes up the outside option, so that the marginal entrepreneur is more profitable and the entry cost matters less to them.

[24]The restriction on γ in the proposition implies that low and high skill labor is not too substitutable. This ensures that when one of the wages increases, the increase in demand for the other type of labor is not too strong.

4.4 Fixed and entry costs

The effects of increasing fixed and entry costs on the agents' choices are as follows.

Proposition 3. *Increases in fixed and entry costs have the following effects on the entrepreneur thresholds and labor demand.*

(a) *For all* $s \in \{l, h\}$, $\epsilon \in \{0, 1\}$ *and* $z_s > 0$,

$$\left.\frac{\partial \underline{z}_e^s(z_s, \epsilon)}{\partial \psi}\right|_{\mathbf{w}} > 0.$$

(b) *For all* $s \in \{l, h\}$ *and* $z_s > 0$,

$$\left.\frac{\partial [\underline{z}_e^s(z_s, 0) - \underline{z}_e^s(z_s, 1)]}{\partial \psi}\right|_{\mathbf{w}} < 0.$$

(c) *For all* $s \in \{l, h\}$ *and* $z_s > 0$,

$$\left.\frac{\partial \underline{z}_e^s(z_s, 0)}{\partial \psi_e}\right|_{\mathbf{w}} > 0 \text{ and } \frac{\partial \underline{z}_e^s(z_s, 1)}{\partial \psi_e} < 0.$$

(d) *If* $1 - \gamma$ *is sufficiently large, then for all* $s \in \{l, h\}$ *and* $z_e > 0$,

$$\frac{\partial \ell_s(z_e)}{\partial \psi} > 0 \text{ and } \frac{\partial \ell_s(z_e)}{\partial \psi_e} > 0.$$

The direct effect (holding wages fixed) of increasing fixed costs on the entrepreneur thresholds is to increase them. Higher fixed costs decrease the payoff from being an entrepreneur, so only more profitable entrenpreneurs will keep choosing this profession. The magnitude of this effect for the marginal entrepeneurs who have to start a business, and those who are already endowed with one, differ. Condition on skill type and employee productivity, the marginal entrepreneur starting a new business needs to be more productive and profitable than the marginal entrepreneur who is endowed with a business. The fixed cost therefore effects the marginal entrepreneur who is endowed with a business more, so the entrepreneur threshold for this type of agent increases more than for agents starting new businesses. Thus, the wedge between these two thresholds decreases, as stated in part (b) of the Proposition. This will tend to decrease the entry rate, subject to the same caveats about the importance of the shape of the distribution of agents across the state space that were discussed earlier.

An increase in the entry cost has some qualitatively different effects. For entrepreneurs who need to start a business the effect is the same as for an increase in fixed costs: the threshold for becoming an entrepreneur increases. Holding wages fixed, there is no effect on the occupational choice of agents endowed with a business. In equilibrium though, the decline in the number of entrepreneurs pushes wages down, increasing the payofff of this occupation and pushing the entrepreneur threshold down for agents endowed with a business. These forces increase the wedge between the entrepreneur thresholds for agents who are endowed with a business and those who aren't, which can decrease the entry rate. The differing effects on the occupational choices of agents endowed with businesses is the key distinction between the effects of increasing fixed and entry costs.

Most of the discussion of fixed and entry costs so far has put general equilibrium effects through wages to the side. By decreasing demand for labor, higher fixed and entry costs push wages down. This complicates the analysis of the effect on entrepreneur thresholds by changing the value of the outside option to entrepreneurship. When wages are lower, agents need to make a lower return on entrepreneurship to choose this occupation. This works against upward pressure that rising fixed and entry costs have on the entrepreneur thresholds. The quantitative analysis will show that for the estimated parameters values these general equilibrium effects are not strong enough to overturn the forces exphasized here.

The last part of Proposition 3 addresses the effect of changes in fixed and entry costs on the size of entrepreneurial firms. Conditional on productivity, entrepreneurs will employ more people after these cost changes. This is because both of these changes cause labor demand to decrease, as discussed above, so labor prices fall.

4.5 Parameter identification

The analysis so far in this section has explained the qualitative effects of changes to the economy on entrepreneurial decisions. As well as providing theoretical guidance for the quantitative results to come, this analysis is the basis for identifying a number of parameter changes. This is useful since, while there is empirical work measuring the change in the rental rate of capital over time in a way that corresponds to r_i in the model, measuring the changes in fixed costs, entry costs and non-entrepreneurial productivity are more difficult. The approach will be to infer these parameter changes from other moments of the data.

The foundation for this inference comes from Propositions 2 and 3. The idea for the inference is that the three parameters in question have independent effects on three of the policy functions of agents—the entrepreneur thresholds for agents endowed with a business $\underline{z}_e^x(z_x, 1)$, the thresholds for agents without a business $\underline{z}_e^x(z_x, 0)$, and the the labor policy functions $l_x(z_x)$—and that these map to independent changes in three moments of the data. Since some of the qualitative analysis is in partial equilibrium, this strategy depends on general equilibrium effects not qualitatively changing the relationships outlined. This will be confirmed in the quantitative section.

The first step for the inference is to see the independent movement in the model objects. Table 2 summarizes the directions of the effects of relevant parameter changes. While increases in all three parameters cause a decline in the share of agents who are entrepreneurs through an increase in the entrepreneur threshold for agents who aren't endowed with a business, the effects on the other policies vary. Increasing non-entrepreneur productivity and fixed costs push up the entrepreneur thresholds for all agents, however their effects on the size of firms on the intensive

x	$\frac{\partial \underline{z}_e^s(z_s,0)}{\partial x}$	$\frac{\partial \underline{z}_e^s(z_s,1)}{\partial x}$	$\frac{l_s(z_e)}{\partial x}$
z_f	> 0	> 0	< 0
ψ	$> 0^*$	$> 0^*$	> 0
ψ_e	$> 0^*$	< 0	> 0

* Denotes derivative conditional on $\mathbf{w}$

Table 2: **Summary of effects of parameter changes on agent policies.** $s \in \{l, h\}$ denotes the skill type.

margin differ. Increasing non-entrepreneur productivity pushes up wages causing entrepreneur firms to shrink, while increasing fixed costs have the opposite effect. An increase in entry costs is also distinguished from an increase in non-entrepreneur productivity by differing effects on the size of firms. Again, the culprit is that these two changes have opposite effects on labor demand and wages. Distinguishing between changes in fixed and entry costs hinges on their differing effects on the entrepreneur threshold for agents who are endowed with businesses. Higher fixed costs push this threshold up, while higher entry costs push it down through the equilibrium effect on wages.

To connect the parameter changes to the data, three moments are used: the share of agents who are entrepreneurs (the entrepreneur share), the share of employment at entrepreneur firms, and the share of firms run by agents who did not have a firm initially (the entry rate). To understand how these moments pin down the parameters in question, start with the mapping between the fixed cost and non-entrepreneur productivity, and the entrepreneur employment share and entrepreneur share. An increase in non-entrepreneur productivity pushes the entrepreneur share down. An increase in the fixed cost has this effect too, but the two parameter changes differ in their effects on the employment choices of firms. Employment decreases as a result of increasing non-entrepreneur productivity, but increases when fixed costs rise. Therefore, for a given change in the entrepreneur share, these two forces will have different implications for the change in the share of employment at entrepreneur firms.

The distinction between increases in fixed and entry costs comes from their effects on the entry rate. While both of these parameter changes decrease the entrepreneur share for agents who are not endowed with a business, for those who are endowed with a business this share increases when entry costs rise, but falls when fixed costs rise. So these two parameters can be determined by these two shares. An alternative pair of moments that contain the same information is the share of all agents who are entrepreneurs, and the share of entrepreneurs who did not have a business initially—the entry rate. This is the formulation of the moments that will be used from the data.

5 Calibration

To quantitatively evaluate the effects of the proposed theories on entrepreneurship, the model needs to be taken to the data. The details of this are presented in this section. I start by explaining how the model is mapped to the data, which involves adding some additional structure to the model from Section 3, defining moments in the model and data, and explaining some aspects of moment measurement. Once this mapping is clear, I explain the calibration strategy and present the calibrated model.

5.1 Additional structure for taking model to data

To take the model to the data it is necessary to specify the definitions of skills and entrepreneurs in the data, add education heterogeneity to the model, make adjustments to the data so that it is comparable to the model, and make functional form assumptions for the productivity distributions.

Data The main dataset that is used for the calibration is the CPS March supplement, which was introduce in Section 2. The sample is the same as the main sample for the analysis in that section: people aged 25–65 not working in the agriculture or government sectors. The main moments that are used are from the occupation distribution and the income distribution. The main considerations in computing these moments are outlined below, with full details in the Appendix.

Skills The model has two types of skills, high and low. In the data I divide people who work as employees into high and low skill based on the occupation classification scheme from Acemoglu and Autor (2011). This scheme divides occupations into four categories according what types of tasks the occupation is most intensive in: non-routine cognitive, routine cognitive, routine manual or non-routine manual tasks.[25] For a detailed discussion of these categories see Autor et al. (2003) and Acemoglu and Autor (2011). Briefly, routine tasks are repetitive tasks that could be summarized by a set of instructions that a machine could follow. They are cognitive if they require mostly mental effort (e.g. book-keeping) while they are manual if they require mostly physical effort (e.g. production line assembly). Non-routine tasks are difficult to get a machine to do with a set of instructions. Cognitive non-routine tasks include research, marketing activities and managerial tasks. Manual non-routine tasks include many low skill service jobs. In terms of relative wages, non-routine manual occupations earn the lowest wages, followed by routine occupations and then non-routine cognitive occupations. I therefore use non-routine cognitive occupations as high skill occupations and the rest as low skill occupations.

[25]Under this classification managerial, professional and technical occupations are non-routine cognitive; sales, clerical and administrative support occupations are routine cognitive; production, craft, repair and operative occupations are routine manual; and service occupations are non-routine manual.

There is a line of research on routine-biased technical change that distinguishes between non-routine manual occupations and routine occupations (e.g. Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014; Jaimovich and Siu, 2014; vom Lehn, 2015; Cortes et al., 2016; Lee and Shin, 2016). The rationale for this is that employment and wages in non-routine manual jobs has increased relative to that of routine manual jobs in recent decades, although much less than the relative wages of non-routine cognitive occupations have increased. This paper abstracts from the difference between non-routine manual and routine occupations by grouping them together since the key force under my theory is the increase in demand for high skill employees as technology changes, rather than the differential effects amongst low skill workers who are all worse off relative to the high skilled. Adding an additional employee type would clutter the analysis without adding much.

Education levels A key moment of the data from Section 2 is that the decrease in the entrepreneurship rate has differed across the education distribution. To incorporate education in the model I assume that there are two education levels: non-college (people who have not completed a four year college degree) and college (people who have completed at least a four year college degree), denoted by N and C respectively. In the model each agent is endowed with an education level and these draws are made to match the education shares in the data. The share of agents with a non-college education is denoted ω. Education will matter by affecting the probability of being a high skill type, θ_h^ξ for $\xi \in \{N, C\}$, the distribution from which initial productivities is drawn $G^\xi(\mathbf{z})$, and the law of motion for poductivities $G^\xi(\mathbf{z}'|\mathbf{z})$.

Empirical occupation distribution To map the occupation distribution in the model to the data, there are a few details to take care of. In the model an entrepreneur is a person who spends their time managing a firm with employees, so in the data I define an entrepreneur as a self-employed person (which means that they spend the majority of their working hours in self-employment) with at least one employee. The CPS does not distinguish exactly between self-employed people with and without employees, but by using the information on the size distribution of these firms that is provided, the share of people who are self-employed with at least one employee can be estimated. For the share of agents who are out of the labor force, a complication is that in the early part of the period being studied female labor force participation was increasing for reasons outside the model. To correct for this I adjust the 1988 data with an estimate for what the female labor force participation rate would have been under the conditions that prevailed from the late 1990s onwards. The final component of the occupation distribution is the share of people who are low and high skill, which can be taken directly from the data using the definitions of these skill groups outlined above. These distributions are constructed for each education level and summing them, weighted by the relevant education shares, gives the aggregate distribution. Full details of the construction of these distributions are in the Appendix.

Functional forms The worker productivity of agent j with education level $\xi \in \{N, C\}$ and skill level $s \in \{l, h\}$ is assumed to be $z_{s,j,t} = \exp(\tilde{z}_{s,j,t})$, with $\tilde{z}_{s,j,t}$ following the AR(1) process

$$\tilde{z}_{s,j,t} = \mu_s^\xi + \rho_{lh}\tilde{z}_{s,j,t-1} + \sigma_s^\xi \varepsilon_{s,j,t}$$

with $\varepsilon_{s,j,t} \sim N(0,1)$. The specification for entrepreneur productivity for this agent is

$$z_{e,j,t} = \zeta \exp(\mu_{e,j,t} + \tilde{z}_{e,j,t}).$$

ζ is simply a scaling term that will be useful for simulating changes in the productivity level for all entrepreneurs. The second term in the parenthesis follows a standard AR(1) process

$$\tilde{z}_{e,j,t} = \rho_e \tilde{z}_{e,j,t-1} + \sigma_e^\xi \varepsilon_{e,j,t}$$

with $\varepsilon_{e,j,t} \sim N(0,1)$ being independent of $\varepsilon_{s,j,t}$.[26] The correlation between worker and entrepreneur productivity comes through the term $\mu_{e,j,t}$, which is a function of agent j's contemporaneous worker productivity:

$$\mu_{e,j,t} = \bar{\mu}_e^\xi + \chi^\xi \left(\frac{\tilde{z}_{s,j,t} - \mathbb{E}^\xi[\tilde{z}_s]}{\mathbb{V}^\xi[\tilde{z}_s]^{\frac{1}{2}}} \right),$$

where $\mathbb{E}^\xi[\tilde{z}_s]$ and $\mathbb{V}^\xi[\tilde{z}_s]$ are the unconditional expected value and variance, respectively, of $\tilde{z}_s$ for agents with education level ξ. This specification allows mean entrepreneur productivity to differ across education levels through the $\bar{\mu}_e^\xi$ term, and the strength and direction of the correlation between worker and entrepreneur productivity is controlled by χ^ξ, which is also dependent on education. The final term is the deviation of an agent's worker productivity from its mean value, in units of the relevant standard deviation. This specification standardizes the effect of worker productivity on entrepreneur productivity for low and high skill agents so that the effect of changes in low or high skill productivity on entrepreneurial productivity is not affected by the scale or dispersion on these variables.

The utility function is assumed to have constant relative risk aversion form: $u(c) = c^{1-\nu}/(1-\nu)$, with $\nu > 0$ and $\nu \neq 1$.

5.2 Quantitative strategy and calibration

For the quantitative exercise I calibrate the model to the 1987 data and adjust select parameters, calibrated to the 2015 data, to simulate changes to the economy over this period. The parameters that change from 1987 to 2015 are:

1. the share of agents who have not completed college, ω;
2. the out of labor force value, b;

[26] The innovations $\varepsilon_{s,j,t}$ and $\varepsilon_{e,j,t}$ are also indepenendent across agents and over time.

3. the level of entrepreneur productivity, ζ;
4. capital rental rates, r_o and r_i;
5. non-entrepreneur productivity, z_f;
6. entry and fixed costs, ψ_e and ψ.

The first three parameters change for consistency with the data. The education distribution has changed significantly over time, which matters for the skill distribution. As is well known, the out of labor force share has been increasing, which the model can match with an increasing value of this activity. The level of entrepreneur productivity increases because of productivity growth, and the non-IT capital rental rate, r_o, increases as measured in the data. The remaining parameters are adjusted to simulated the forces that this paper is focused on: r_i is the capital rental rates that drive skill-biased technical change. The change in z_f is simulating increasing productivity of non-entrepreneur firms. The changes in fixed and entry costs capture both the effects of more regulation and technological effects on these cost. Parameter values are determined as follows.

1987 parameters The share of the population without a college education can be computed with the CPS and is 77.90% in 1987.[27] The death rate is set to a value of 0.025 to achieve an expected working life of 40 years. Given this value, β is chosen so that the effective annual discount rate is 4%. The CRRA parameter is set to 2.0. The value for the parameter controlling the persistence of employee productivity is given a value of 0.95, in accordance with the estimate of Storesletten et al. (2004). The returns to scale of the production function are given by $\alpha + \eta$. Atkeson and Kehoe (2005) provide an extensive discussion of returns to scale and settle on a value of 0.85, which is used here as well. For the rental rates of IT and non-IT capital the estimates of Eden and Gaggl (2016) are used. For productivities, the average productivity of low skill workers, high skill workers and entrepreneurs can be normalized for one of the education levels. I make this normalization for non-college agents, setting μ_l^N and μ_h^N so that average low and high skill productivities for this group are equal to 1. $\bar{\mu}_e^N$ is normalized to zero. ζ can also be normalized for 1987 and is set to one.

All but one of the remaining 1987 parameters are calibrated internally. While the parameters are determined jointly by simulated method of moments, the approximate mapping between the moments and parameters is as follows. The consumption level for agents who are out of the labor force is set to target the out of labor force share. The production function parameters η, ϕ and λ affect the demand for the various production inputs. To determine their values I use moments related to division of income amongst inputs: the share of income going to employees (from the BEA),[28] the ratio of the average high skill income to average low skill income from the CPS,[29] and the IT share of capital (from the BEA detailed fixed assets tables). The productivity

[27] A college education is defined as having completed at least a bachelor's degree.

[28] The is value added by industry, which is available at https://www.bea.gov/industry/gdpbyind_data.htm (accessed 21 March 2017).

[29] Since there is no variation in hours worked in the model, moments of the empirical income distributions are

level of the non-entrepreneur sector z_f, the fixed cost ψ, and the entry cost ψ_e are pinned down using the identification strategy outlined in Section 4. Regarding the moments used for this, the share of employment at entrepreneur firms is estimated using data from the CPS and BDS, and the share of agents who are entrepreneurs comes from the CPS. To estimate the entry rate into entrepreneurship, the entry rate of firms in the BDS is used since, as discussed earlier, self-employed people account for a large share of firms. Additional details for these moments are provided in the Appendix.

Parameters relating to skill shares and productivities remain. The share of agents who are high skill conditional on education, θ_h^ξ for $\xi \in \{N, C\}$, is chosen to target the share of people in the relevant education group who work in high skilled occupations. The parameters that determine the level of low and high skill productivity for college educated agents, μ_l^C and μ_h^C, are chosen to target the ratio of average income for college and non-college people in each of these skill groups. The level of entrepreneur productivity for college agents, $\bar{\mu}_e^C$, determines the share of college agents who are entrepreneurs. χ^ξ affects the correlation between worker and entrepreneur productivity for agents with education level ξ. A higher correlation increases the productivity of entrepreneurs, so this parameter is chosen to target the ratio of average entrepreneur to average high skill employee income for this education level. There are six standard deviation parameters: for each education level there is one for each skill level and one for entrepreneurship. These determine the coefficient of variation of income for people in the corresponding occupation-education group. The persistence of entrepreneur income shocks affects the persistence of income for these people. From the data I use the estimate of the fraction of continuing entrepreneurs who remain in the same decile of the entrepreneur income distribution from one year to the next (37.5%), from DeBacker et al. (2018).

2015 parameters The share of agents without a college education, ω, and the capital rental rates, r_o and r_i, are taken directly from the data, using the same sources as for 1987. The consumption level of agents who are out of the labor force, the level of non-entrepreneur productivity, and the fixed and entry costs are all calibrated internally using the 2015 values of the same moments as are used for 1987.

The remaining parameters are the two elasticity of substitution parameters (τ and γ), which take the same value for both years, and the level of entrepreneur productivity ζ for 2015. These parameters are key for determining how the wages of low and high skill workers change from 1987 to 2015. Getting these changes right is crucial for the analysis since wages are fundamental for the tradeoff between being a worker and an entrepreneur. To calibrate these parameters, I fix one of the elasticity of substitution parameters, γ, with guidance from the literature and use the other two parameters to target the change in average real income of low skill workers and high skill workers from 1987 to 2015. Since the CPS omits non-wage income, I adjust the growth rates from that source using data on non-wage compensation from the Bureau of Labor Statistics' Employer

computed using average hourly income for each person. Full details of income calculations are in the appendix.

Costs of Employee Compensation dataset. Using similar production functions to in the present model, Krusell et al. (2000) and vom Lehn (2015) have estimated the elasticity of substitution between high skill workers, defined on the basis of education or occupation, and capital equipment, generating estimates of 0.67 and 0.13 respectively.[30] γ is set to achieve an elasticity of substitution in the middle of this range (0.4).

5.3 Calibrated model

The parameters, their values and the calibration procedure are summarized in Table 3. The data and model values of the calibration targets are in Table 4. Overall the model fits the data well. Despite the high dimensionality of the calibration problem, all of the targeted moments have similar values in the model and the data. The moments presented in Table 4 illustrate some of the differences by skill and education. College educated people do better along many dimensions. They are much more likely to be high skill workers than non-college educate people (60% compared to 13%) and high skill workers earn more (45% more on average compared to low skill). They also earn more conditional on skill: the average high skill college educated worker earns 29% more than the average high skill non-college worker, and for low skill workers this education premium is 40%. The model captures this with different means of the productivity distributions for the two education levels.

The parameters controlling the correlation between worker and entrepreneur productivities are estimated to be small, postive for college-educated agents and negative for non-college. The implied correlations between z_s, $s \in \{l, h\}$, and z_e for non-college and college agents are -0.31 and 0.23, respectively.[31] Recall that these parameters are primarily determined by the relative level of entrepreneur income and worker income. The negative correlation between worker and entrepreneur productivity for non-college educated agents is driven by the income premium for entrepreneurs in this education group being relatively low. From the perspective of the model, this implies that it is relatively low productivity people in this education group who choose to be entrepreneurs. In terms of the quantitative importance of worker productivity in determining entrepreneur productivity, its role is modest. For the four education-skill groups, variation in worker productivity only accounts for 5.0–13.4% of the variance of entrepreneur productivity.[32]

The estimated elasticity of substitution between low skill labor and IT capital ($\frac{1}{1-\tau}$) is 2.56. As a point of comparison, Krusell et al. (2000) estimate the elasticity of substitution between capital

[30] In Krusell et al. (2000) the group of workers that most closely corresponds to the high skilled is those with a college education, which that paper labels "skilled." In vom Lehn (2015) the corresponding category of people perform "abstract" occupations, which are defined in a very similar way to high skilled occupations in this paper. While the production functions in those papers are not identical to one presently in use, they provide elasticity of substitution estimates to guide the choice of γ.

[31] For a given education level, there are small differences between the correlation of z_e with z_l and z_h, but they're very small. For college educated agents, for example, the correlations are 0.231 and 0.237.

[32] These shares are computed by comparing the counterfactual variance in z_e if χ_n or $\chi_c = 0$ with the variance in the full model.

Parameter	*Value*		*Remark*
	1987	2015	
ω	0.779	0.651	Non-college share of agents from CPS
β	0.985		
ν	2.0		
δ	0.025		Expected working life of 40 years
ρ_{lh}	0.95		Storesletten et al. (2004)
γ	-1.5		Guided by Krusell et al. (2000) and vom Lehn (2015)
$\alpha + \eta$	0.85		Atkeson and Kehoe (2005)
r_o	0.082	0.121	Eden and Gaggl (2016)
r_i	0.169	0.071	Eden and Gaggl (2016)
μ_l^N	-0.008		Normalized so that $E[z_l^N] = 1$
μ_h^N	-0.008		Normalized so that $E[z_h^N] = 1$
$\bar{\mu}_e^N$	0.0		Normalization

(a) Externally calibrated and normalized parameters

Parameter	*Value*		*Target*
	1987	2015	
b	0.303	0.415	Out of labor force share
η	0.235		Employee share of income
ϕ	0.140		Low to high skill average incomes
λ	0.203		IT share of capital
τ	0.610		1987–2015 growth of average low skill income
z_f	1.134	1.344	Entrepreneur employment share, entrepreneur share & entry rate
ψ	0.122	0.296	
ψ_e	0.272	1.012	
θ_h^N	0.151		Share of non-college educated doing high skill work
θ_h^C	0.650		Share of college educated doing high skill work
μ_l^C	0.008		College to non-college average low skill income
μ_h^C	0.009		College to non-college average high skill income
$\bar{\mu}_e^C$	0.159		Entrepreneurship rate for college educated
ζ	1.0	1.123	2015 value: 1987–2015 growth of average high skill income
χ^N	-0.083		Entrepreneur to high skill average income, non-college
χ^C	0.058		Entrepreneur to high skill average income, non-college
σ_l^N	0.173		Std. of low skill income for non-college educated
σ_l^C	0.211		Std. of low skill income for college educated
σ_h^N	0.181		Std. of high skill income for non-college educated
σ_h^C	0.176		Std. of high skill income for college educated
σ_e^N	0.036		Std. of entrepreneur income for non-college educated
σ_e^C	0.035		Std. of entrepreneur income for college educated
ρ_e	0.986		Persistence of entrepreneur income

(b) Internally calibrated parameters

Table 3: **Parameter values.** 2015 values are the same as 1987 values unless stated otherwise. Where necessary, parameter values are rounded to three decimal places.

Moment	Model	Data
Income moments, 1987		
Entrepreneur:high skill averages, non-college	1.32	1.36
Entrepreneur:high skill averages, college	1.89	1.82
High skill:low skill averages	1.49	1.45
College:non-college low skill averages	1.42	1.40
College:non-college high skill averages	1.31	1.29
CV, low skill non-college	0.51	0.51
CV, low skill college	0.69	0.67
CV, high skill non-college	0.58	0.60
CV, high skill college	0.60	0.61
CV, entrepreneurs non-college	0.91	0.96
CV, entrepreneurs college	0.91	0.94
Entrepreneur income persistence	38.6%	37.5%
Occupation distribution, 1987		
Out of labor force share	14.8%	15.1%
High skill share, non-college	13.1%	13.1%
High skill share, college	59.0%	60.0%
Entrepreneur share	5.3%	5.1%
Entrepreneur share, college	7.1%	7.3%
Other moments, 1987		
Employee share of income	54.6%	52.5%
IT share of capital	10.2%	10.1%
Entrepreneur share of employment	50.4%	50.0%
Entry rate of entrepreneurs	11.4%	11.7%
2015 moments		
1987–2015 growth of average low skill income	18.6%	16.6%
1987–2015 growth of average high skill income	44.3%	44.3%
2015:1987 out of labor force share	1.65	1.66
2015:1987 entrepreneur share	0.70	0.71
2015:1987 entrepreneur share of employment	0.80	0.80
2015:1987 entry rate of entrepreneurs	0.72	0.72

Table 4: **Calibration moments.** Colons denote ratios. For example, 'High skill:low skill averages' for income is the ratio of high skill to low skill average income. CV stands for the coefficient of variation. Entrepreneur income persistence is the share of continuing entrepreneurs who remain in the same decile of the entrepreneur income distribution from one year to the next. Income growth rates are for real income. Full details of how the data moments are computed are in the Appendix.

equipment and low education labor to be 1.67. Since the capital and labor inputs in this paper are defined more specifically to capture their substitutability, a higher elasticity of substitution makes sense. vom Lehn (2015) estimates the elasticity of substitution between routine labor and capital equipment at 1.39. While the labor input in this paper and vom Lehn (2015) are slightly different, the higher value that I estimate suggests that IT capital is more subsitutable for lower skill labor inputs than capital equipment in general. To put the estimates of entry and fixed costs for 1987 in perspective, they imply that it costs 25% of the median annual operating profit (sales less labor and capital costs) of entrepreneur firms to enter, and 11% to cover fixed costs. Fixed costs are estimated to have increased by a factor of 2.4 from 1987 to 2015, and entry costs by a factor of 3.7.

6 Quantitative results

To assess the ability of skill-biased technical change, increases in fixed and entry costs, and increasing non-entrepreneur productivity to explain the decline in entrepreneurship, the analysis proceeds in two steps. First I quantify the theory from Section 4 to assess the ability of each force to explain the data on its own. This analysis provides an assessment of each force independent of the particular magnitude that has been estimated in the calibration or from the data. It also provides intuition for the second exercise, which is to use the parameter estimates for 2015 to analyze the forces jointly and explain their relative importance in accounting for the changes in the data from 1987 to 2015.

6.1 Individual forces

Skill-biased technical change Figure 5 analyses the effects of skill-biased technical change in partial and general equilibrium. The starting point for these exercises is the 1987 calibration of the model. In the left panel the effects of changing r_i, holding wages fixed, are presented. In the middle panel w_h changes holding the other wage fixed, and in the right panel, r_i changes with wages adjusting so that the model is in equilibrium. In the panel with r_i changing the horizontal axis is flipped so that, as you go to the right, r_i decreases, as it has in the data. In all panels the changes in four moments are presented: the share of agents who are entrepreneurs, the entry rate, the share of employment at entrepeneur firms, and the ratio of the shares of college and non-college agents who are entrepreneurs. All of these moments decrease in the data, so a downward sloping line means that the relevant moment is moving in the same direction as in the data. The magnitude of the vertical axis is normalized so that a value of -1 means that the percentage change in the moment in the model is equal to the percentage change in the same moment in the data from 1987 to 2015.

The main results are in the right hand panel, which presents the effect of decreasing the IT capital price in general equilbrium. We see that, relative to the data, this force primarily affects

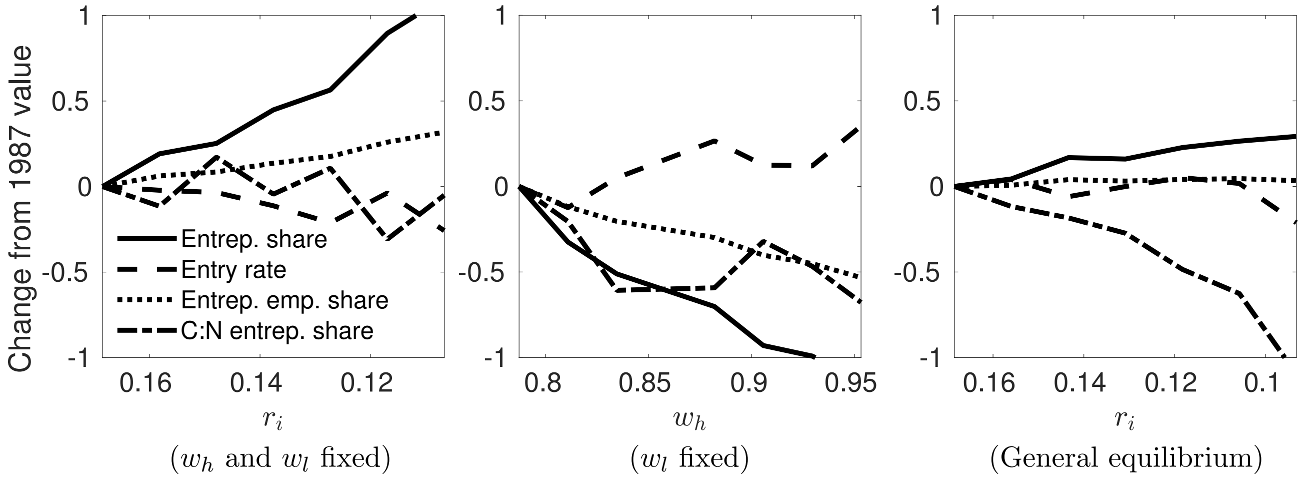


Figure 5: **Comparative statics for skill-biased technical change.** Parameter values are set to their 1987 values. In the left panel r_i is changed holding all other parameters and wages fixed. In the middle, only w_h changes. On the right, r_i changes and wages adjust so that that the model is in equilibrium. Four moments are plotted—the entrepreneurship share, the entry rate, the share of employment at entrepreneur firms, and the ratio of the entrepreneurship shares of college and non-college agents—and the vertical axis is normalized so that a magnitude of one means that the percentage change in the moment is the same as in the data from 1987 to 2015. E.g. A value of -1 for the entry rate means that the entry rate has declined, and the magnitude of this change is the same as the 1987 to 2015 change in the data.

the ratio of the college to non-college entrepreneur shares, and has modest effects on the other three moments of entreprenership. The theory from Section 4 told us that both decreasing r_i and increasing w_h would decrease the entrepreneurship rate more for high skill agents than low skill ones, as long as the distributions of low and high skill agents around the entrepreneurship thresholds are not too different. The results confirm that this caveat is satisfied. Note that the Figure uses the relative entrepreneurship rates of *college* and *non-college* agents, rather than of *high* and *low skill* agents, in order to be comparable to the data. These two moments are closely related since the high skill share of college agents is much higher than for non-college agents, at 65% and 15% respectively (Table 3). The results in the left and middle panels show that the decrease in r_i on its own only affects this moment modestly, and that most of the effect in coming from the increase in the high skill wage.[33]

The second feature of the general equilibrium results for r_i is that the effects on the entrepreneur share, the entry rate, and the share of employment at entrepreneur firms are modest. For a change in r_i that generates all of the change in the ratio of the college to non-college entrepreneur shares, these other moments either move in the wrong direction (the entrepreneur share), hardly change (the employment share are entrepreneur firms) or exhibit a fraction of the change in the data (the entry rate). The theory helps us understand why this is. For the entrepreneur share the decreasing IT capital rental rate and increasing high skill wage have opposing effects, as confirmed in the left

[33] To help with using the results from the graph for w_h to understand the magnitudes in the left side of panel b, w_h changes from 0.79 to 1.07 as r_i changes from 0.1685 to 0.0932 in that graph.

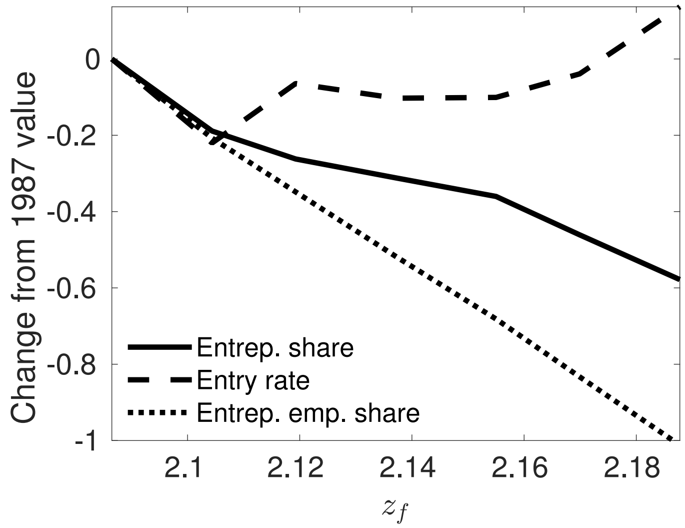


Figure 6: **Comparative statics for non-entrepreneur productivity.** Parameter values are set to their 1987 values and non-entrepreneur productivity changes as described by the horizontal axis value. Three moments are plotted—the entrepreneurship share, the entry rate and the share of employment in the entrepreneur sector—and the vertical axis is normalized so that a magnitude of one means that the percentage change in the moment is the same as in the data from 1987 to 2015. E.g. A value of -1 for the entry rate means that the entry rate has declined, and the magnitude of this change is the same as the 1987 to 2015 change in the data.

and middle panels of the figure. Quantitatively, the direct effect coming from the rental rate is stronger than the effect from the change in the equilibrium wage, so that overall the entrepreneur share increases. The entry rate decreases modestly thanks to the decreasing IT capital rental rate—as suggested by Proposition 1(c)—but the increasing high skill wage partially offsets this. For the share of employment at entrepreneur firms, there is virtually no change. This is due to the effects of the changes in r_i and w_h effectively cancelling each other out.

The overall message is that skill-biased technical change is a relevant force for undestanding the change in the relative entrepreneurship rates of higher and lower education agents, but does not appear relevant for understanding the change in the aggregate level of entrepreneurship.

Non-entrepreneur productivity Figure 6 presents the effects of decreasing z_f on moments of entrepreneurship. The setup for the figure is the same as for Figure 5. The vertical axis represents the change in each moment from its 1987 value with the magnitude normalized so that a value of minus one indicates that the moment has decreased by the same percentage amount as in the data from 1987 to 2015. Recall from Proposition 2 that the theory told us that increasing non-entrepreneur productivity would decrease the entrepreneur share and the employment share of entrepreneurs, and that the effect on the entry rate was ambiguous because of opposing effects from increasing wages. Figure 6 shows that these opposing effects on the entry rate essentially cancel each other out, so that the entry rate moves little in response to increasing non-entrepreneur productivity. For the other moments we see the predicted negative effects. Quantitatively the effect on the share of employment at entrepreneur firm is larger than the effect on the entrepreneur

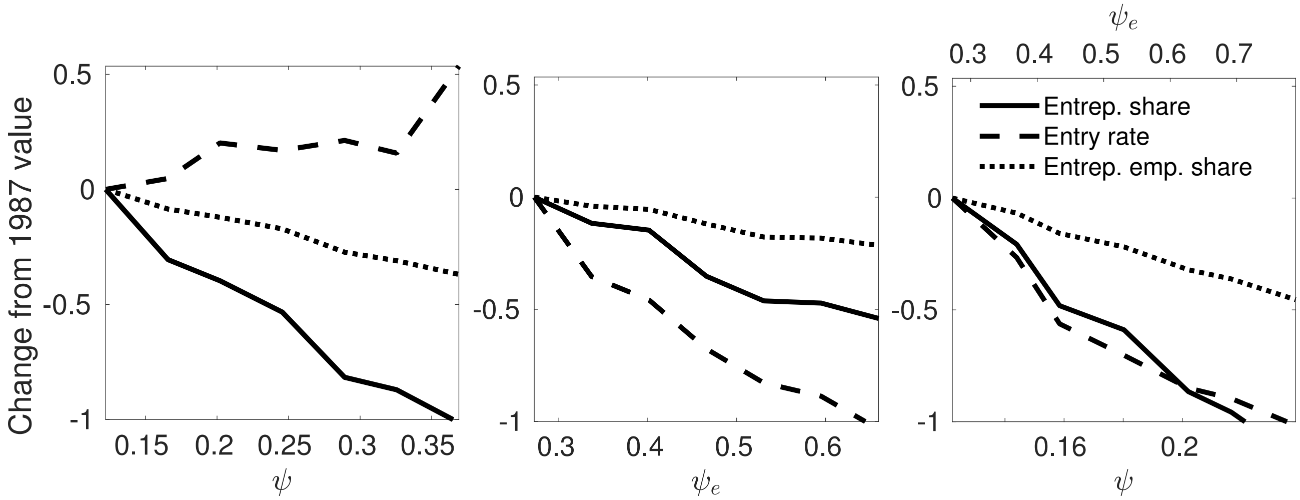


Figure 7: **Comparative statics for fixed and entry costs.** Parameter values are set to their 1987 values and only fixed and entry costs vary, as described by the horizontal axis value. In the left panel only ψ changes, in the middle panel only ψ_e, and in the right panel both. Three moments are plotted—the entrepreneurship share, the entry rate and the share of employment in the entrepreneur sector—and the vertical axis is normalized so that a magnitude of one means that the percentage change in the moment is the same as in the data from 1987 to 2015. E.g. A value of -1 for the entry rate means that the entry rate has declined, and the magnitude of this change is the same as the 1987 to 2015 change in the data.

share. When this force generates all of the reallocation of employment away from entrepreneurs, the decline in entrepreneur share is about 60% as large as in the data. Another way of putting this is that, relative to the data, increasing non-entrepreneur productivity causes entrepreneur firms to shrink too much, rather than decreasing the number of them.

Given these results, the biggest issue for this explanation for the decline in entrepreneurship is its inability to generate a decline in the entry rate. For this theory to be relevant, there would need to be a different force that pushes the entry rate down, while not generating declines in the entrepreneur share and the employment share of entrepreneurs that are large relative to the data.

Fixed and entry costs For the effects of increasing fixed and entry costs, see Figure 7. The left panel is for fixed costs, the middle panel for entry costs, and in the right panel both increase. The theory indicated that in partial equilibrium rising fixed costs should decrease the entrepreneur share and increase the entry rate—the quantitative results confirm that these effects hold in general equilibrium. Falling wages offset these effects, but only partially. The effect on the share of employment at entrepreneur firms was qualitatively ambiguous, but quantitatively we see that this moment declines. This is because increasing fixed costs have a strong negative effect on the entrepreneur share, which pushes down the employment share of entrepreneurs, and this is only partially offset by entrepreneurs having more employees, conditional on operating.

For entry costs, the main ambiguity from the theory was how an increase would affect the share of agents who are entrepreneurs. The theory indicated that the entrepreneur threshold would increase for agents who need to start a business and decrease for those who already have a business. Quantitatively the first force is dominant, so that the entrepreneur share decreases, as it has in the data. This change also pushes down the share of employment at entrepreneur firms. We know from the theory that this force is offset by entrepreneurs employing more workers, conditional on operating, but this offsetting force is only partial. The entry rate is also decreasing in the entry cost, as indicated by the theory, and this is the moment that changes the most, relative to the data.

Overall rising entry costs can push all three moments down, although the magnitudes of the relative changes are different to in the data. If fixed and entry costs are increased simultaneously, with the relative increases the same as has been estimated with the model for 1987 to 2015, the effects are plotted in the right panel of Figure 7. Together these changes can generate declines in the entrepreneur share and the entry rate that are quantitatively similar to the data. The decline in the entrepreneur employment share is about half as large as in the data. This indicates that these changes to the economy can account for most of the decline in entrepreneurship in the data. In the full quantitative exercise, rising non-entrepreneur productivity, which has a particularly strong effects on the entrepreneur employment share, accounts for the remainder.

Before moving onto the full exercise for 2015, there is one additional note on parameter identification to make. In Section 4 the strategy for identifying non-entrepreneur productivity, fixed costs and entry costs was discussed. Table 2 summarized how these parameters have independent effects on the two entrepreneur thresholds and labor demand of entrepreneur firms, conditional on operating. Figures 6 and 7 confirm that this independence holds when these characteristics of the model are translated into the three moments that are plotted. Comparing Figure 6 and the left panel of Figure 7, it is clear that changes in fixed costs and non-entrepreneur productivity have very different relative effects on the entrepreneur share and the entrepreneur share of employment. Fixed costs have a stronger effect on the former, while non-entrepreneur productivity has a stronger effect on the latter. Entry costs have different effects than both of these because it moves the entry rate in the opposite direction.

6.2 Joint effects

The assess the full array of changes in the model from 1987 to 2015, there are four parameters to consider, in addition to those discussed so far. The education level changes, consistent with the increase in the attainment of college education in the data, entrepreneur productivity increases to allow the economy to match wage changes, the value of being out of the labor force changes to fit the evolution of the share of people in this state, and the rental rate of non-IT capital changes, per the data. I'll call these parameters the *secondary parameters* and the parameters that are the main focus—fixed costs, entry costs, non-entrepreneur productivity and the rental rate of IT capital—the *primary parameters*. The approach for studying the joint effects of these changes to the economy is to start by changing the secondary parameters from their 1987 to 2015 values.

	Prod. growth	Education	OLF value	r_o	2015
Entrepreneur share	1.05	1.10	1.03	0.95	0.71
Entry rate	0.99	0.92	0.92	0.92	0.72
Entrepreneur emp. share	1.01	1.08	1.07	1.06	0.80
College:non-college entrep. share	0.97	1.05	1.16	1.29	0.85
OLF share	0.87	0.70	1.23	1.55	1.66
w_l	1.14	1.33	1.34	1.21	–
w_h	1.24	0.95	0.94	0.79	–
Av. low skill income	1.13	1.31	1.40	1.29	1.166
Av. high skill income	1.22	1.01	1.05	0.93	1.443

Table 5: **Effects of changes in productivity, education and the out of labor force value, and SBTC.** All moments are presented relative to their 1987 values. For the *Productivity growth* column ζ is changed to its 2015 value and z_f, ψ, ψ_e and b are scaled by the the same percentage amount. For the next three columns, several parameters are changed to their 2015 values additively. For *Education* ω is changed to its 2015 value, for *OLF value* b is also changed to its 2015 value, and finally r_i and r_o are changed to their 2015 values as well in the *SBTC* column. The 2015 column provides moment values for 2015 relative to 1987 from the data.

I'll then take that economy as the *baseline*, and assess the contribution of each of the primary parameters in moving the economy to 2015.

The effects of the changes to the secondary parameters on several moments of the model are presented in Table 5. There are four types of parameter changes, which are done in sequence, in a cumulative way. The first column shows just the effects of productivity growth, the second column shows the effects of productivity growth and the change in education, etc. For comparison, the final column of the table shows values for 2015 from the data. All values are presented relative to their 1987 values (i.e. 1.20 means a 20% increase).

The parameter changes in the education, out of labor force value and r_o columns are straightforward. They involve changing the share of agents with a non-college education (ω), the out of labor force value (b) and the non-IT capital rental rate from their 1987 to 2015 values (refer back to Table 3 for these). The parameter changes in productivity growth column are slightly more involved. The objective in this column is to account for the effects of general productivity growth in the economy. To this end, the main parameter that changes is ξ, which changes the productivity level of all entrepreneurs by the same factor. To simulate a general rise in productivity, rather than just for entrepreneurs, I increase z_f and the out of labor force value by the same factor. I also scale fixed costs and entry costs by the same factor so that their relevance is not diminished. All of these parameters change beyond this scaling to reach their 2015 values, and those changes are assessed later.

Start by focusing on the cumulative effect of these parameter changes in the r_o column. At best, they account for a modest amount of the changes in entrepreneurship moments in the data. They are most relevant for understanding the change in the entry rate, accounting for

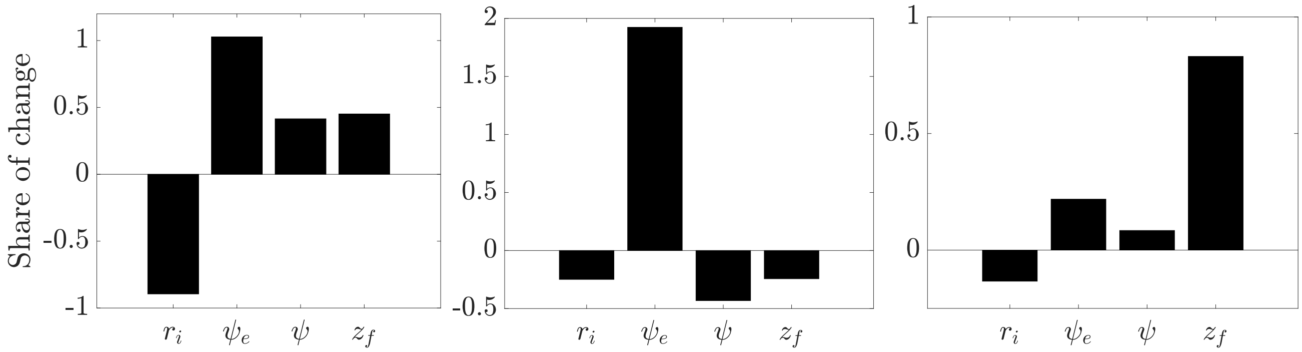
29% (eight out of 28 percentage points) of the change from 1987 to 2015. This is entirely due to the increasing education level of the population. Higher educated people exhibit less entry and exit from entrepreneurship, so a shift in the composition of the population towards them decreases the entry rate. There are several reasons for these differences by education. Looking back at the parameters of the model in Table 3, college agents have a lower standard deviation of productivity innovations for high skill wok and entrepreneurship. They also have a higher correlation between productivity as an employee and an entrepreneur. This means that when entrepreneur productivity increases, for example, which could cause entry into entrepreneurship, this force is offset by the value of employment increasing.

Changing education also explains why the secondary parameter changes cause the entrepreneur share of employment to increase. College educated people have a higher entrepreneurship rate than the non-college educated, so increasing education pushes up the entrepreneurship rate. With more people being entrepreneurs, the share of employment that their firms account for increases. This change goes against the trend int his moment in the data, increasing the gap for the primary parameters to explain.

The secondary parameter changes push the entrepreneur share down slightly, and the ratio of college to non-college entrepreneurship rates up substantially. The main forces driving these changes are the increasing out of labor force value and the increasing cost of non-IT capital. The former attracts people directly out of entrepreneurship and also pulls people away from being workers. The second effect drives up wages and drives down profits, adding to the decline in the entrepreneur share. The first effect is particularly strong for non-college educated entrepreneurs, because their profits are lower on average. This force therefore pushes up the relative entrepreneurship rate of the college educated. As for the increase in the rental rate of non-IT capital, it also pushes profits down, causing the entrepreneur share to fall. This effect is particularly strong for non-college educated people because, on average, their profits are lower so they're more likely to switch to being out of the labor force when profits fall.

The out of labor force share increases significantly with the parameter changes in Table 5, almost fully accounting for the change in the data from 1987 to 2015. Productivity growth and increasing education work against this trend by pushing up the wages of low skill people, and increasing the share of high skill agents (who earn more on average). The increases in the out of labor force value and the non-IT capital rental rate have sufficiently strong effects to offset these, and account for most of the increase in the out of labor force share in the data. The connection between this moment and the out of labor force value is straightforward, and this change accounts for 53% of the increase in the out of labor force share that is needed to match the 2015 data, once the countervailing effects of productivity growth and increasing education are accounted for. The increasing cost of non-IT capital is also quantitatively important, accounting for 34%. This effect primarily operates through the negative impact on wages.

As a final comment on the results for the secondary parameters, the last two columns show



(a) Entrepreneur share (b) Entry rate (c) Entrep. employment share

Figure 8: **Effects of changes to the economy on entrepreneurship.** Each panel decomposes the change in a moment from its value in the baseline scenario to its 2015 value. The baseline scenario is the 1987 parameters with the adjustments for productivity growth, education, the out of labor force value, and the rental rate of non-IT capital described in Table 5. In panel (a), for example, and value of 0.4 for ψ_e means that the increase in the entry cost accounts for 40% of the change in the entrepreneur share from the baseline scenario to 2015.

that these changes work against the increase in the relative income of high skill employees. The gaps to the 2015 data are almost accounted for by skill-biased technical change (the declining cost of IT capital). This comes from the negative effect that this has on low skill wages due the substitutability between this type of capital and low skill labor, and the positive effect on high skill wages due to complementarity.

Let's now turn to the effects of the primary parameters on moments of entrepreneurship. The approach is to take the economy after the changes to productivity growth, education, the out of labor force value and the rental rate of non-IT capital described in Table 5, and study the roles of each of the primary parameters from this baseline. The focus will be on how moments of entrepreneurship change from this baseline to 2015, and the quantitative relevance of each of the primary parameters for this. The sequencing of the parameter changes is: the non-IT capital rental rate, the entry cost, the fixed cost, and non-entrepreneur productivity. While the ordering of these changes does matter for the exact estimates, the main messages are robust to alternative orderings.[34]

Figures 8 and 9 present results on the contributions of the primary parameters in accounting for the changes in the main entrepreneurship moments. The scale of the vertical axis in all panels is the share of the change in the relevant moment from the baseline outlined above, to 2015, accounted for by a parameter change. Start by focusing on the quantitative effects of skill-biased technical change. As suggested by the analysis of this change to the economy in isolation, its main role is to shift entrepreneurship towards lower education agents. From Figure 9, it can account for 75% of the change in the ratio of the entrepreneurship rates of college and non-college educated agents from the baseline economy to 2015. Its other significant effect on entrepreneurship

[34]See Appendix for additional details on how the results vary for alternative orderings.

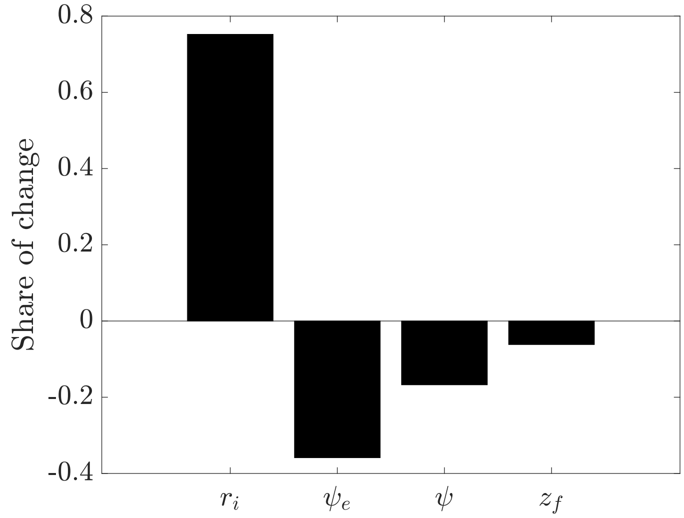


Figure 9: **Effects of changes to the economy on the ratio of college to non-college entrepreneur shares.** This figure presents the change in the ratio of the college to non-college entrepreneur share from its value in the baseline scenario to its 2015 model value. The baseline scenario is the 1987 parameters with the adjustments for productivity growth, education, the out of labor force value, and the rental rate of non-IT capital described in Table 5. The 2015 model value is the 1987 model value multiplied by the 2015 data value, divided by the 1987 data value. A value of 0.4 for r_i, for example, means that the decrease in r_i accounts for 40% of the change in the ratio of the college to non-college entrepreneur shares from the baseline scenario to 2015.

is to increase the entrepreneur share, which goes against the trend in the data (Figure 8a). This confirms that this force is relevant for understanding the change in the education composition of entrepreneurs, but not for explaining the aggregate level of entrepreneurship.

The increasing entry cost is primarily important for generating the decrease in the entry rate (Figure 8a), as was clear from the analysis of the primary parameters in isolation. Since the other changes to the economy go against the decrease in the entry rate, this force needs to generate about twice the decline that is in the data to make up for this. The increase in the entry cost is also the most quantitatively important factor in accounting for the decline in the entrepreneur share (Figure 8a). For this moment though, the increases in the fixed cost and non-entrepreneur productivity are also quantitatively relevant. Their effects are about half as large as the effect of the entry cost.

The analysis of the increase in entry and fixed costs in isolation indicated that their weakness for explaining the data is that they leave the entrepreneurial sector too large. They cause the share of people who are entrepreneurs to decline, but entrepreneurial firms have too many workers. Increasing non-entrepreneur productivity addresses this, accounting for 83% of the decline in the share of employment at entrepreneur firms.

To summarize, the results indicate that there have been a range of changes to the economy between 1987 and 2015 that have been relevant for understanding changes in entrepreneurship. There are three main messages. First, for understanding the declines in the entry rate into entrepreneurship and the share of people who are entrepreneurs, increasing entry costs are the main factor. Increasing fixed costs and non-entrepreneur productivity play a secondary role in explaining the decline in the second moment. Second, increasing non-entrepreneur productivity accounts for most of the shift in employment out of the entrepreneur sector. Third, skill-biased technical change accounts for a large share of the shift in entrepreneurship towards less educated people, but this force is not relevant for understanding the decline in the aggregate level of entrepreneurship.

7 Interpreting cost changes

The quantitative results have indicated that increases in both fixed and entry costs have contributed to the declines in the entrepreneurship share and the entry rate in the US economy, with increasing entry costs being particularly important. As discussed earlier, two potential explanations for the increase in these costs are that the level of regulation in the economy has increased or that changes in production technologies have caused the fixed and entry components of firms' costs to rise. This section uses cross-sectional empirical evidence to shed light on the plausibility of these explanations. The main finding is that there is evidence supporting both theories.

At the outset it should be noted that the objective is to assess cross industry correlations, conditional on control variables, to determine whether these correlations are consistent with the two proposed explanations for the increase in fixed costs. While causal evidence of the effect of changes in IT technology and regulations would be valuable, tackling the identification challenge associated with such evidence is beyond the scope of this paper.

7.1 Data and methodology

The strategy for the analysis is to assess the relationship across industries between changes in entrepreneurship and measure of changes in regulations and technologies that could have driven the fixed and entry costs up. To implement this, detailed industry level measures of entrepreneurship, regulations and technologies are needed, all with a long enough time series to facilitate the evaluation of changes over time.

To measure entrepreneurship I use the share of workers in an industry who are self-employed from the CPS. This data was described in Section 2 and I use the same data for 1987–2015 here. Unlike in Section 2 I do not restrict attention to self-employed people with at least 10 employees because at the industry level this would leave too few observations to construct reliable entrepreneurship rates.

To quantify changes in regulations at the industry level I use two measures. The first is the measure of Federal regulations at the industry level from the RegData dataset, constructed from the Code of Federal Regulations by McLaughlin and Sherouse (2018). The idea for this dataset is to take the Code of Federal Regulations, which contains all federal level regulations in the U.S., and separate it into its parts. For each part, textual analysis is performed to determine a relevance weight for the part for each industry, and the number of restrictions in the part. For each industry, a measure of regulation for each year is constructed by multiplying the relevance of each part by the number of restrictions in it, and then summing over parts. This provides a time series of the level of regulation for each industry.

The second measure of regulation is based on CPS occupation data. I construct a proxy for the level of industry regulations by computing the share of employees in regulation-related occupations. These are occupations in which people are likely to be performing tasks related to regulatory compliance, such as legal, human resources, accounting and auditing occupations. The full list of occupations that I classify as regulation-related is in the Appendix.

For changes in technology that could drive the increase in fixed and entry costs I focus on a particular theory for why these costs may have increased. This theory is that improvements in IT technology have allowed firms to adopt technologies with higher upfront costs and lower marginal costs (see Aghion et al., 2019; Hsieh and Rossi-Hansberg, 2019; De Ridder, 2019). Under this theory several technology related measures should be positively related to the rise in fixed and entry costs, and, if this is driving entrepreneurship down, then they should be negatively related to changes in entrepreneurship. In particular I focus on four measures for which data is available. First using data from the BEA detailed fixed assets tables I compute two measures of the IT capital intensity of each industry over time. The first is the the nominal value of the IT capital stock relative to nominal value added, and the second is the real value of the IT capital stock (in 2012 dollars) per employee.[35]

The third and fourth measures are based on the occupation composition of each industry. For the third measure I identify occupations in the CPS data that are IT related and compute the share of employees in each industry in these occupations. The idea is that if an industry is adopting more IT technology over time then it should also have more employees in these occupations. The fourth measure is the share of employees in non-routine cognitive occuaptions.[36] There is a long literature (e.g. Krusell et al., 2000; Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013) arguing that these occupations are complementary to IT capital such that we should see more employees in these occupations when more IT capital is in use.

To assess the relationship between changes in entrepreneurship and changes in regulations and fixed costs across industries I use the following regression:

$$\Delta \log e_{jt} = \alpha + \boldsymbol{\beta}_1' \boldsymbol{\Delta x}_{jt} + \boldsymbol{\beta}_2' \boldsymbol{\Delta y}_{jt} + \varepsilon_{jt} \tag{14}$$

where $\Delta \log e_{jt}$ is the change in the log of the entrepreneurship rate from an earlier period (specified shortly) to period t for industry j, $\boldsymbol{\Delta x}_{jt}$ is vector of changes in IT and regulation measures (in most regressions it will just have one element), and $\boldsymbol{\Delta y}_{jt}$ is a vector of changes in control variables.

[35] Value added by industry is also from the BEA and the number of employees in each industry is from the CPS.

[36] The occupation classification scheme from Acemoglu and Autor (2011) is used for this.

Since I am studying long run changes in the economy I would ideally use changes in each variable over the full sample period, from 1988 to 2016. However, this would provide just one observation per industry and give the analysis low statistical power. Therefore I divide the sample into 3 periods: 1988–89 to 1999/2000, 1999/2000 to 2005/06, and 2005/06 to 2014/15. At each start and end point I average each variable over two years to smooth randomness in the data. These periods have been chosen so that each one starts and ends just before a business cycle peak to reduce the risk of higher frequency fluctuations contaminating the results. Of course the data does not contain another peak after 2007, so the last years of the dataset are used for the final point. The control variables are the changes in the average age of people working in each industry, the share who are males, the share who have a college degree and the share who live in a metropolitan area.

The analysis requires consistent definitions of industries across datasets. The industry defintions from the BEA detailed fixed assets tables are used (a combination and two and three digit ISI codes) and industry codes from other datasets are harmonized with these.[37] This results in a maximum of 144 observations.[38] RegData provides information for fewer industries so any analysis including that data has fewer observations.

7.2 Results

The results of the analysis are presented in Tables 6 and 7. Table 6 presents results for the measures of changes in IT technology. I take one measure of IT technology at a time and regress the changes in it on changes in the self-employment rate, with and without the control variables. The main result is that the coefficients on all of these variables are estimated to be negative, consistent with the idea that increasing use of IT technology has driven up fixed and entry costs, and pushed entrepreneurship down. As expected with a small number of observations, the statistical power of the results is low, however the coefficient on the change in the the share of employees in IT occupations is significant at the 1% level and the coefficient on the log change in real IT capital per employee has a p-value of 11%. The magnitudes of the coefficients are also economically meaningful. An increase in the share of employees in an industry in IT occupations of one percentage point would imply a 7% decline in the self-employment rate in that industry. A 1% increase in the amount of IT capital per employee would imply an 0.1% decline in the self-employment rate.

Table 7 presents results for measures of changes in regulations. Again, the coefficients on the regulation variables are estimated to be negative in all regressions, implying that consistent with the proposed theory more regulation negatively affects the self-employment rate. In terms of significance in the regressions with controls, the coefficient on the log change in the number of regulations is significant at the 10% level and the coefficient on the change in the share of

[37] See the Appendix for details.

[38] Some regressions have fewer observations because some industry years have small cell counts that don't allow all varaibles to be estimated.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IT employment share	-5.437^{**}	-7.022^{***}						
	(2.165)	(2.353)						
NR cognitive emp. share			-0.348	-1.194				
			(0.814)	(1.037)				
log(IT capital per employee)					-0.075	-0.109		
					(0.065)	(0.069)		
IT capital/Value-added							-0.051	-0.072
							(0.380)	(0.388)
Average age		0.018		0.053		0.054		0.041
		(0.044)		(0.042)		(0.042)		(0.041)
College share		0.958		0.606		0.023		-0.125
		(1.126)		(1.241)		(1.051)		(1.066)
Male share		0.426		0.094		-0.054		0.231
		(1.004)		(0.993)		(0.997)		(0.996)
Metropolitan share		2.223		1.601		1.534		1.282
		(1.149)		(1.048)		(1.018)		(1.014)
Constant	-0.001	-0.101	-0.011	-0.116	0.022	-0.063	-0.018	-0.098
	(0.039)	(0.082)	(0.042)	(0.080)	(0.052)	(0.081)	(0.038)	(0.079)
Observations	139	139	144	144	144	144	144	144
R^2	0.044	0.083	0.001	0.027	0.009	0.035	0.000	0.018
Adjusted R^2	0.037	0.048	-0.006	-0.008	0.002	0.001	-0.007	-0.018

Table 6: **Regression results for IT technology measures.** The regression is specified in equation (14). The unit of observation is industry-time. Each industry has observations for three time periods: 1988–89 to 1999/2000, 1999/2000 to 2005/06, and 2005/06 to 2015/16. Variables are averaged over the two years at the start and end of each period. *IT employment share* is the share of employees in an industry in IT related occupations and *NR cognitive emp. share* is the share in non-routine cognitive occupations. *IT capital per emplpyee* is the real value of the IT capital stock (2012 dollars) in an industry divided by the number of workers. *IT capital/Value-added* is the nominal value of the IT capital stock divided by nominal value-added. *College share*, *male share* and *metropolitan share* and the shares of workers who have a college degree, are male, and live in a metropolitan area, respectively. *Average age* is the average age of workers. 'Workers' in an industry includes employees and the self-employed. Standard errors are in parentheses. *** and ** denote statistically significant differences from 0 at the 1% and 5% levels, respectively.

employees in regulation-related professions has a p-value of 11%.

Having found correlations in the data to support both theories, the final exercise is to assess whether these hold simultaneously or whether one disappears once the other is controlled for. This analysis is performed in column 5 of Table 7. I take the measures of regulatory change and IT technology change that had the most power on their own and include them both in the same regression. The coefficients on both variables remain negative and have similar significance levels: 11% for the regulations measure and 5% for the IT technology measure. In terms of magnitudes the regulations coefficient is virtually the same as when the variable is used on its own (column 2) while the coefficient on the IT employment share decreases by 30% from -7.0 to -4.9.

Overall the data provides support for both of the proposed theories for the rise in fixed and entry costs: that they are a result of increasing regulation and changes in IT technology.

	(1)	(2)	(3)	(4)	(5)
log(Regulations)	-0.276^{**}	-0.254^{*}			-0.230
	(0.138)	(0.144)			(0.144)
Regulatory employment share			-2.344	-2.587	
			(1.561)	(1.616)	
IT employment share					-4.919^{*}
					(2.506)
Average age		0.004		0.037	-0.027
		(0.048)		(0.042)	(0.052)
College share		-0.704		0.082	0.309
		(1.230)		(1.091)	(1.410)
Male share		0.345		-0.037	0.653
		(1.086)		(1.022)	(1.120)
Metropolitan share		1.700		1.560	2.944^{**}
		(1.084)		(1.080)	(1.295)
Constant	0.055	0.032	-0.014	-0.097	0.028
	(0.056)	(0.093)	(0.039)	(0.080)	(0.100)
Observations	102	102	140	140	98
R^2	0.038	0.063	0.016	0.037	0.119
Adjusted R^2	0.039	0.014	0.009	0.002	0.061

Table 7: **Regression results for regulation measures.** The regression is specified in equation (14). The unit of observation is industry-time. Each industry has observations for three time periods: 1988–89 to 1999/2000, 1999/2000 to 2005/06, and 2005/06 to 2015/16. Variables are averaged over the two years at the start and end of each period. *Regulations* is a measure of the number of regulations from RegData. *Regulatory employment share* is the share of workers in an industry who are regulation-related occupations. The control variables are defined in the notes to Table 6. Standard errors are in parentheses. ** and * denote statistically significant differences from 0 at the 5% and 10% levels, respectively.

8 Conclusion

This paper has studied why entrepreneurship in the US has declined over the last three decades, assessing four potential explanations: skill-biased technical change, increases in regulation, changes in technology that shifted costs to fixed and entry costs, and changes in technology that have increased the relative productivity of the largest firms.

Using a dynamic model of occupational choice calibrated to detailed data on occupations and income distributions I have evaluated these explanations. I find that the key driver of the decline in entrepreneurship is increases in fixed and entry costs. This conclusion stems from three results. First, skill-biased technical change creates a reallocation of entrepreneurship towards less educated people, but cannot explain the decline in the aggregate level of entrepreneurship. Second, for a given shift in economic activity towards non-entrepreneur firms an increase in fixed and entry costs generates a larger decline in entrepreneurship than an increase in the relative productivity of non-entrepreneur firms. Given the magnitudes of the decline in entrepreneurship and the shift towards non-entrepreneur firms in the data, the model tells us that an increase in fixed and entry costs must have driven most of the decline in entrepreneurship. If productivity gains by superstar firms were the main force then given the amount of economic activity that has shifted to non-entrepreneur firms we would have seen a much smaller decrease in entrepreneurship. Third, there needs to have been an increase in fixed and entry costs, not just one of them, in order to explain both the decline in the share of people who are entrepreneurs and the decline in the firm entry rate.

Finally the paper has empirically assessed whether cross-industry data suggests that the rise in fixed costs is due to increasing regulation or changes in technology. The results indicate that both forces have contributed to this change.

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A Additional details for Section 2

A.1 Survey of Income and Program Participation data

As an additional check that the downward trend in the entrepreneurship rate is robust to omitting the Great Recession from the sample I have computed the change in the entrepreneurship rate from 1983 to 1995 using the Survey of Income and Program Participation (SIPP) from the Census Bureau. This dataset is slightly different to the CPS so I will describe the sample, how I define an entrepreneur and then provide the results. Note that 1983 is the year after a recession trough while 1995 is four years after a recession trough so the cyclicality of the entrepreneurship rate should work against any decline over this period.

The SIPP is a nationally representative survey of US households that started in late 1983 and has been conducted regularly since. Using weights that are provided a nationally representative sample of individuals can be constructed. In general the survey has an overlapping panel structure, although changes to the survey over time mean that there are breaks. The panels typically last a few years (the duration has varied over time) with each household being interviewed every 4 months. Each round of interviews is referred to as a 'wave' and the interviews are conducted over four months, until it is time to start the next wave. For my analysis I use the interviews conducted in October 1983–January 1984 (wave 1 of the 1984 panel) and October 1995–January 1996 (wave 9 of the 1993 panel). I will refer to these as the 1983 and 1995 data. There is SIPP data after 1996, however the survey changed and it is not possible to construct a consistent measure of entrepreneurship across this change.

For the analysis of the entrepreneurship rate I have used two samples. Men and women aged at least 18, and men aged 24–65 who are not in education. I define an entrepreneur as a person who works at least 15 hours per week in self-employment, expects their business to generate at least $1,000 in revenue in the next 12 months and has at least one employee other than owner and co-owners in the same household.[39] For the first sample I find that the entrepreneurship rate (share of the labor force who are entrepreneurs) decreases from 5.38% in 1983 to 4.62% in 1995, a decrease of 14%. For the second sample I find a decrease from 9.40% to 7.67%, a decrease of 18.4%.

A.2 Composition changes

In this section I will show that the decline in entrepreneurship is not driven by changes in the composition of the population or the economy over time and is not a result of changes in one sector. To evaluate whether changes in composition are driving the result I compute the entrepreneurship rate holding the composition of the economy fixed along several dimensions. Specifically, the entrepreneurship rate in year t can be written as

$$e_t = \sum_{g \in \mathcal{G}} \omega_{g,t} e_{g,t}$$

where $\mathcal{G}$ is a partition of the labor force, $\omega_{g,t}$ is the share of the sample in subset $g \in \mathcal{G}$ and $e_{g,t}$ is the share of that subset who are entrepreneurs. Holding the composition fixed with respect to

[39] I am updating the sample and entrepreneur definitions so that they match those used in the CPS data. The results will be in a future draft.

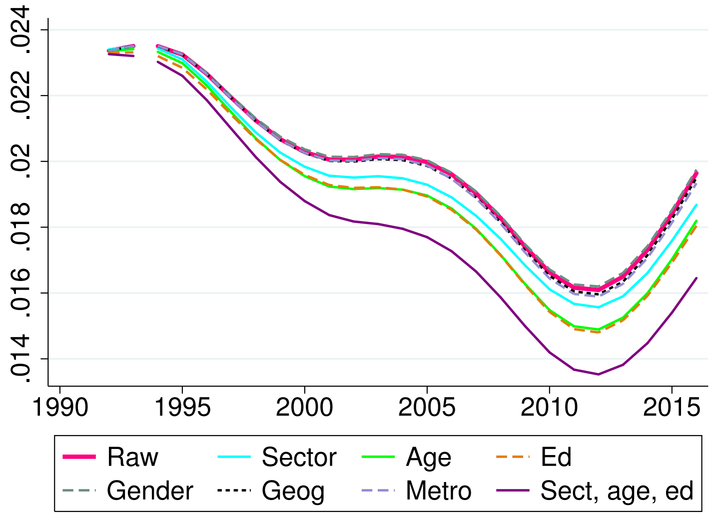


Figure 10: **Entrepreneurship rate with composition controls.** The *Raw* line is the entrepreneurship rate without any composition control. For the remaining lines the composition of the labor force along various dimensions is held fixed at its 1992 distribution, per equation (15). The subsets of the labor force that are used for each of the lines are as follows. *Sector:* 11 major non-agricultural non-government sectors from the 1990 Census Industrial Classification System. *Age:* age groups 25–35, 36–45, 46–55 and 56–65. *Ed:* less than a high school education, completed high school, some college, completed college and more than college. *Gender:* male and female. *Geog:* nine Census divisions. *Metro:* metropolitan and non-metropolitan areas. *Sect, age, ed:* Cartesian product of three sectoral groups (manufacturing, services and others), four age groups (25–35, 36–45, 46–55 and 56–65) and two education groups (less than college and at least college). All series are smoother with a HP filter with smoothing parameter equal to 6.25.

partition $\mathcal{G}$ the entrepreneurship rate in year t is

$$e_{\mathcal{G},t} \equiv \sum_{g \in \mathcal{G}} \omega_{g,1992} e_{g,t}. \tag{15}$$

This equation keeps the share of each subset of the economy fixed while allowing the entrepreneurship rate within each subset to vary.

I perform this exercise to control for composition along six dimensions individually and also do the exercise controlling for several of these dimensions jointly. These dimensions are the sector, age, education, gender, geographic and metropolitan/non-metropolitan distributions. To control for the sector distribution $\mathcal{G}$ is composed of the 11 major non-agricultural non-government sectors from the 1990 Census Industrial Classification System;[40] for age $\mathcal{G}$ has four categories: 25–35, 36–45, 46–55 and 56–65; for education $\mathcal{G}$ is composed of five categories for the highest level of education a person has completed: less than high school, high school, some college education but less than a bachelor's degree, a bachelor's degree and more education than a bachelor's degree; for gender $\mathcal{G}$ is male and female; for geographic distribution $\mathcal{G}$ is the nine Census divisions; and to control for the metropolitan and non-metropolitan shares of the labor force $\mathcal{G}$ has these two categories.

[40]These sectors are mining; construction; manufacturing; transportation, communication and public utilities; wholesale trade; retail; finance, insurance and real estate; business and repair services; personal services; entertainment and recreation services; and professional services.

Sector	1992 share	Entrepreneurship rate '92–'94	'14–'16	% change	% of total change
Mining, Con. and TCU	15.3	2.8	2.6	−4.3	3.2
Manufacturing	19.8	1.3	1.2	−9.1	4.2
Wholesale and retail trade	19.0	3.8	2.3	−43.0	54.5
FIRE	7.4	2.7	1.8	−34.4	11.9
Professional services	27.5	1.9	1.5	−20.4	18.9
Other services	11.0	3.4	3.0	−11.3	7.3

Table 8: **Entrepreneurship rate by sector.** The columns contain: (1) share of employed people (employees and self-employed) in each sector in 1992; (2)–(3) the average share of employed people in each sector who are entrepreneurs for 1992–94 and 2014–16, respectively; (4) percentage change in these rates from 1992–94 to 2014–16; (5) each sector's share of the total change in the entrepreneurship rate when the sector distribution is held fixed at 1988.

The results for $e_{\mathcal{G},t}$ for each of these composition controls are presented in Figure 10. They show that the decrease in the entrepreneurship rate is either virtually unchanged or larger when each of these composition controls is imposed. This implies that changes in composition are not what is causing the decrease in the entrepreneurship rate and, in fact, the decrease in the entrepreneurship rate would be larger without changes in composition. Due to sample size limitations I can't control for all of the changes in composition jointly, but I have taken the three dimensions that matter most (age, sector and education) and controlled for these jointly. To ensure that cell sizes are large enough for this exercise I use three sectors (manufacturing, services and all others), two education groups (less than college and at least college) and all four age categories. $\mathcal{G}$ is the Cartesian product of these sets. The resulting $e_{\mathcal{G},t}$ series is presented in Figure 10 and labeled Sect, age, ed. The decrease in the entrepreneurship rate is larger again under these joint controls, emphasizing that composition changes not are causing this decline, they are working against it.

To establish that the decline in the entrepreneurship rate is not driven by one sector Table 8 presents details of the change in the entrepreneurship rate by sector and the contribution of each sector to the aggregate change. To increase cell sizes I group the mining, construction and transportation, communication and public utilities sectors together and the business and repair services, personal services, and entertainment and recreation services sectors. To smooth out year-to-year volatility in the data I take averages of the entrepreneurship rate in the first three and last three years of the sample. The table shows that there was a decline in the entrepreneurship rate in all sectors, with the largest declines in wholesale and retail trade, FIRE and professional services. The last column of the table presents the share of the decrease in the aggregate entrepreneurship rate that each sector accounts for when the sectoral composition of the economy is held fixed. For sector g this is

$$\frac{\omega_{g,1992}(\bar{e}_{g,2015} - \bar{e}_{g,1993})}{\bar{e}_{\mathcal{G},2015} - \bar{e}_{\mathcal{G},1993}}$$

where the partition $\mathcal{G}$ is the set of sectors being used and $\bar{x}_t \equiv (x_{t-1} + x_t + x_{t+1})/3$ for any variable x_t. The results show that all sectors contribute to the decline, with the largest contributions coming from retail and wholesale trade, FIRE and services.

A.3 Additional details on composition changes

In the previous section I showed that changes in the composition of the economy have generally worked against the decrease in the entrepreneurship rate. In this section I provide additional details for the composition changes that have had the largest effect on the entrepreneurship rate: changes in the sectoral, education and age compositions.

Figure 11(a) shows how the sectoral distribution has evolved over time. The main change is that the share of employed people who are in services has been steadily increasing while the share in manufacturing has been decreasing. This has worked against the decrease in the entrepreneurship rate since, as panel (b) shows, the of people in the services sector who are entrepreneurs is larger than the share in manufacturing.

Panels (c) and (d) show the illustrate the effects of changes in the education distribution. Over time the share of people with a college or more than a college education has increased, while the shares in all lower education categories have decreased. Since more educated people have higher entrepreneurship rates—see panel (d)—this change has pushed the entrepreneurship rate down.

The effects of the changes in the the age distribution are demonstrated by Figures 11(e) and (f). While the change in the share of the labor force in each age category has not been monotone, in general there has been an aging of the population. This has has pushed the entrepreneurship rate upwards since the entrepreneurship rate is increasing in age. Note that the entrepreneurship rate is increasing in age rather than having the familiar hump shape because I use the labor force as the denominator. If we looked at the share of *people* in age groups who are entrepreneurs then we would see a hump shape in age.

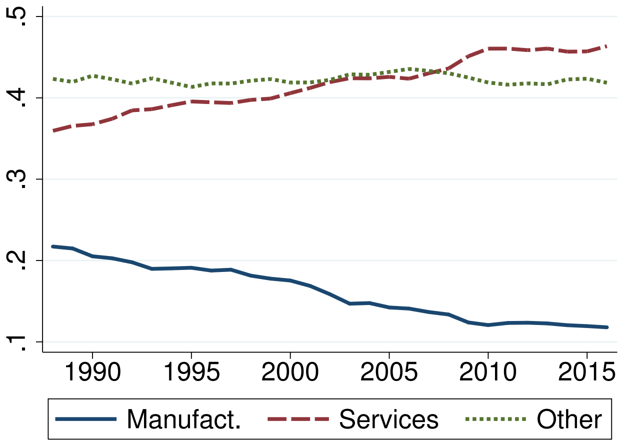
Finally Figure 12 presents the effects of composition controls for the self-employment rate instead of the entrepreneurship rate. The methodology is exactly the same as for Figure 10 in the body of the paper. The figure shows that the effects of controlling for composition are qualitatively the same as for the entrepreneurship rate.

B Additional details for the model

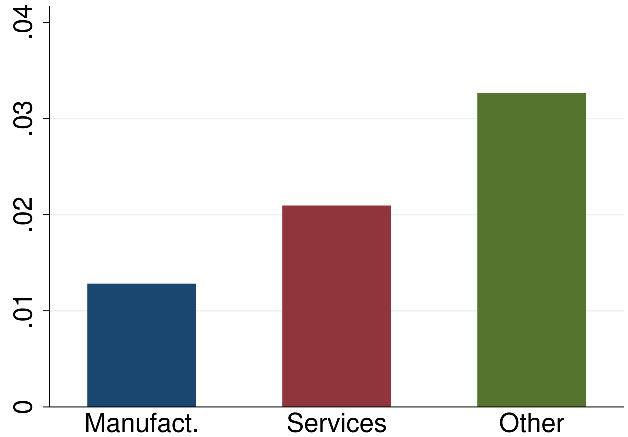
B.1 Optimal input choices and value function for entrepreneurs

The Γ functions for the optimal input choices and the profit function for entrepreneurs are:

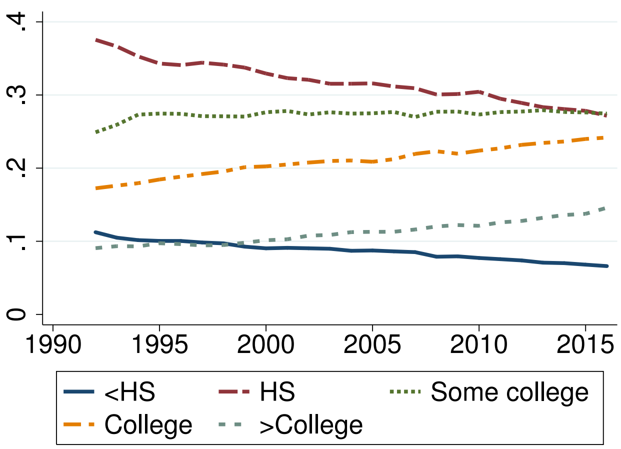
$$
\begin{aligned}
\Gamma_{k_o}(\Lambda) &= \left[\left(\frac{\eta}{r_o}\right)^{1-\alpha} D_3^{\alpha}\right]^{\frac{1}{1-\eta-\alpha}} \left(\phi + (1-\phi) D_1^{\frac{\gamma}{1-\gamma}} D_2^{\frac{\gamma(1-\tau)}{\tau(1-\gamma)}}\right)^{\frac{\alpha(1-\alpha)}{\gamma(1-\eta-\alpha)}}, \\
\Gamma_{\ell_h}(\Lambda) &= D_3^{\frac{1}{1-\alpha}} \Gamma_{k_o}^{\frac{\eta}{1-\alpha}}, \\
\Gamma_{\ell_l}(\Lambda) &= \left(D_1 D_2^{\frac{\gamma-\tau}{\tau}}\right)^{\frac{1}{1-\gamma}} \Gamma_{\ell_h}, \\
\Gamma_{k_i}(\Lambda) &= \left[\left(\frac{\lambda}{1-\lambda}\right)\left(\frac{w_l a^{\tau}}{r_i}\right)\right]^{\frac{1}{1-\tau}} \Gamma_{\ell_l}, \\
\Gamma_{\pi}(\Lambda) &= \Gamma_{k_o}^{\eta}\left[\phi \Gamma_{\ell_h}^{\gamma} + (1-\phi)\Big(\lambda (a\Gamma_{k_i})^{\tau} + (1-\lambda)\Gamma_{\ell_l}^{\tau}\Big)^{\frac{\gamma}{\tau}}\right]^{\frac{\alpha}{\gamma}} \\
&\quad - \Gamma_{k_o} r_o - \Gamma_{k_i} r_i - \Gamma_{\ell_h} w_h - \Gamma_{\ell_l} w_l,
\end{aligned}
$$



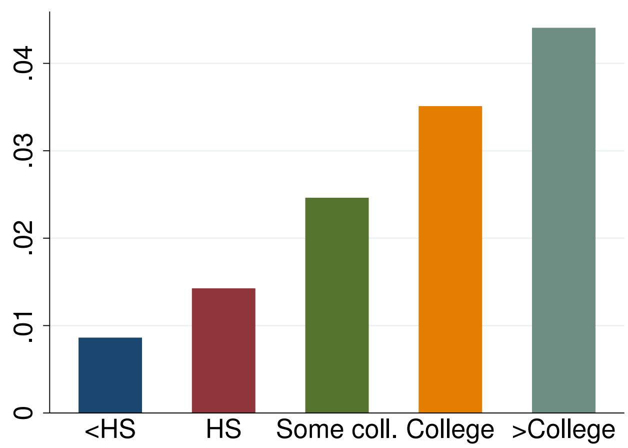
(a) Sectoral distribution



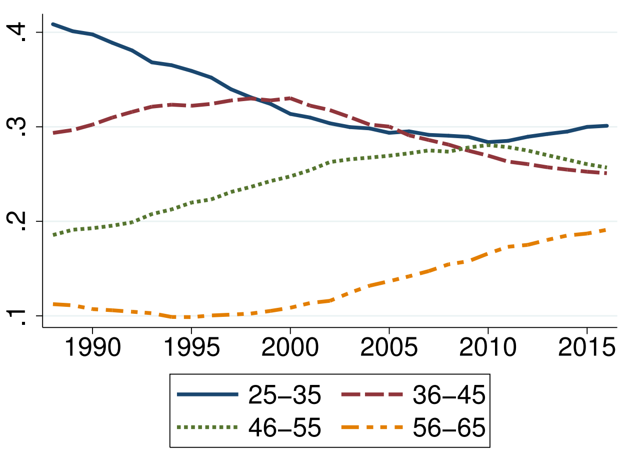
(b) Entrepreneurship rates by sector, 1992



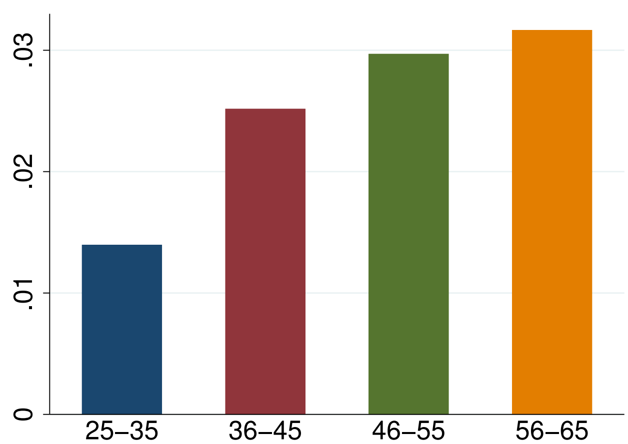
(c) Education distribution



(d) Entrepreneurship rates by education, 1992



(e) Age distribution



(f) Entrepreneurship rates by age, 1992

Figure 11: **Details of sectoral, education and age composition changes** The sectoral distribution is the share of the labor force in manufacturing, services (including business and repair services, personal services, entertainment and recreation services, and professional and related services) and all other sectors. The entrepreneurship rates by sector are the share of people working in each sector who are entrepreneurs. The education and age distributions are the share of the labor force in each education and age group, respectively.

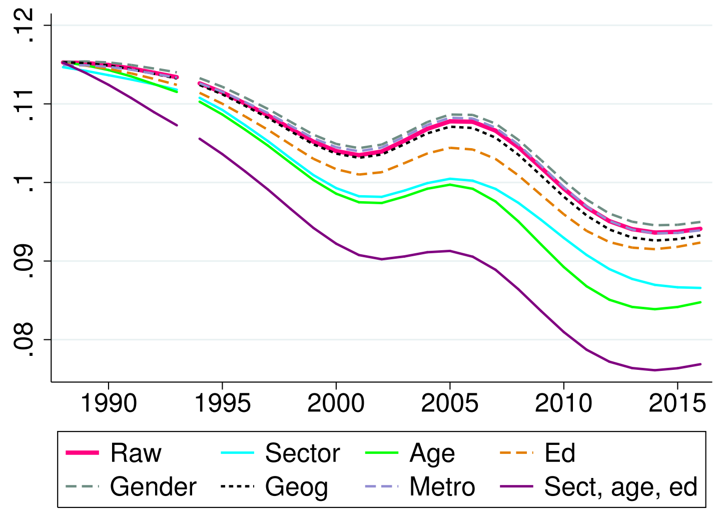


Figure 12: **Self-employment rate with composition controls.** The *Raw* line is the self-employment rate without any composition control. For the remaining lines the composition of the labor force along various dimensions is held fixed at its 1988 distribution, per equation (15). The subsets of the labor force that are used for each of the lines are as follows. *Sector:* 11 major non-agricultural non-government sectors from the 1990 Census Industrial Classification System. *Age:* age groups 25–35, 36–45, 46–55 and 56–65. *Ed:* less than a high school education, completed high school, some college, completed college and more than college. *Gender:* male and female. *Geog:* nine Census divisions. *Metro:* metropolitan and non-metropolitan areas. *Sect, age, ed:* Cartesian product of three sectoral groups (manufacturing, services and others), four age groups (25–35, 36–45, 46–55 and 56–65) and two education groups (less than college and at least college). All series are smoothed with a HP filter with smoothing parameter equal to 6.25.

where

$$D_1 = \Big(\frac{1-\phi}{\phi}\Big)\Big(\frac{w_h}{w_l}\Big)(1-\lambda),$$

$$D_2 = \lambda\Big[\Big(\frac{\lambda}{1-\lambda}\Big)\Big(\frac{w_l a}{r_i}\Big)\Big]^{\frac{\tau}{1-\tau}} + 1 - \lambda,$$

$$D_3 = \frac{\alpha\phi}{w_h}\Big(\phi + (1-\phi)D_1^{\frac{\gamma}{1-\gamma}} D_2^{\frac{\gamma(1-\tau)}{\tau(1-\gamma)}}\Big)^{\frac{\alpha-\gamma}{\gamma}}.$$

B.2 Proofs of propositions

To be completed.

C Empirical details for the quantitative exercise

C.1 Entrepreneur share

In the model an entrepreneur is a person who owns and manages a business with employees. In the data I define these people to be the self-employed with employees. This creates a challenge for the data. The size information provided in the CPS does not separate self-employed people with

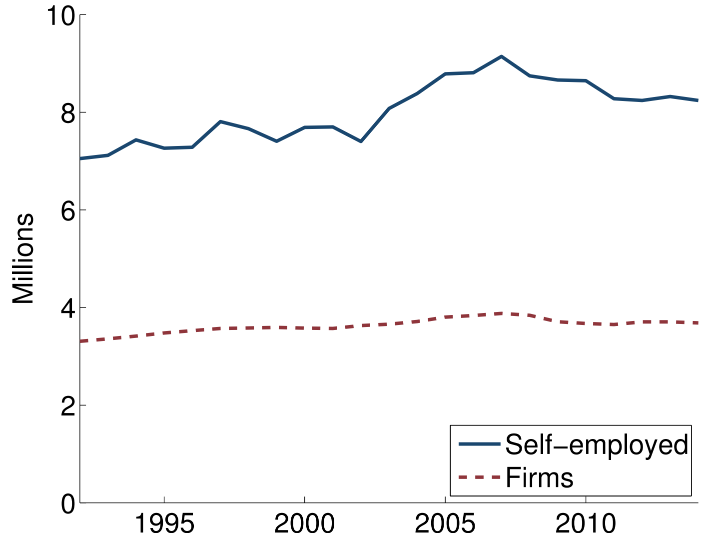


Figure 13: **Numbers of self-employed people with <10 employees and firms with 1–9 employees.** The *self-employed* series is the number of people aged 16+ in the US who are self-employed, are not in agriculture, and whose businesses have <10 employees. The *firms* series is the number of non-agriculture firms in the US with 1–9 employees.

businesses with no employees from those that have a small number of employees. For 1992–2016 the smallest size category is <10 employees and for 1988–91 it is <25 employees. To estimate the share of the self-employed in the <10 category who have employees I take the following approach. For 1992–2014 there are two steps. First, data from the Business Dynamics Statistics (BDS) from the Census Bureau provides information on the number of firms in various size categories on an annual basis up to 2014, including firms with 1–9 employees.[41] Since these are small firms I assume that they each are owned and run by one person, so that they are each associated with one self-employed person.[42] This gives me an estimate of the number of self-employed people with businesses with 1–9 employees each year. I exclude the agriculture sector from the data, just as I did in the empirical analysis in Section 2.

Second, using the CPS data I estimate the number of people in the population who are self-employed with non-agricultural businesses in a range of size categories.[43] The population for this analysis is the civilian non-institutional population aged 16 years and over, rather than the restricted population that I used for the empirical analysis, since the self-employment estimates

[41]This is an annual dataset going back to 1977 that provides information on the *population* of private sector firms in the US which have at least one employee. The information includes the number of firms in a range of size bins, with size measured with the number of employees. When I compute the number of firms with 1–9 employees I omit those in the agriculture sector since I don't count self-employed people in agriculture when I measure entrepreneurship in the CPS data.

[42]Some evidence to support this approach come from the data for businesses with 10–99 employees. The CPS provides an estimate of the number of self-employed people with businesses of this size and the BDS provides the number of firms of this size in the economy. For 1992–2014 there is an average of 1.09 self-employed people per firm. Assuming that having multiple owner-managers is less common for smaller businesses, the number of self-employed per firm for businesses with 1–9 employees should be less than this.

[43]The CPS data provides estimates of the share of the population who are self-employed with businesses in a number of size categories and I multiply these by the size of the population that the weighted CPS sample represents to estimate the number of self-employed people with businesses in each size category in the US. The size of the population that the CPS sample represents come from the BLS.

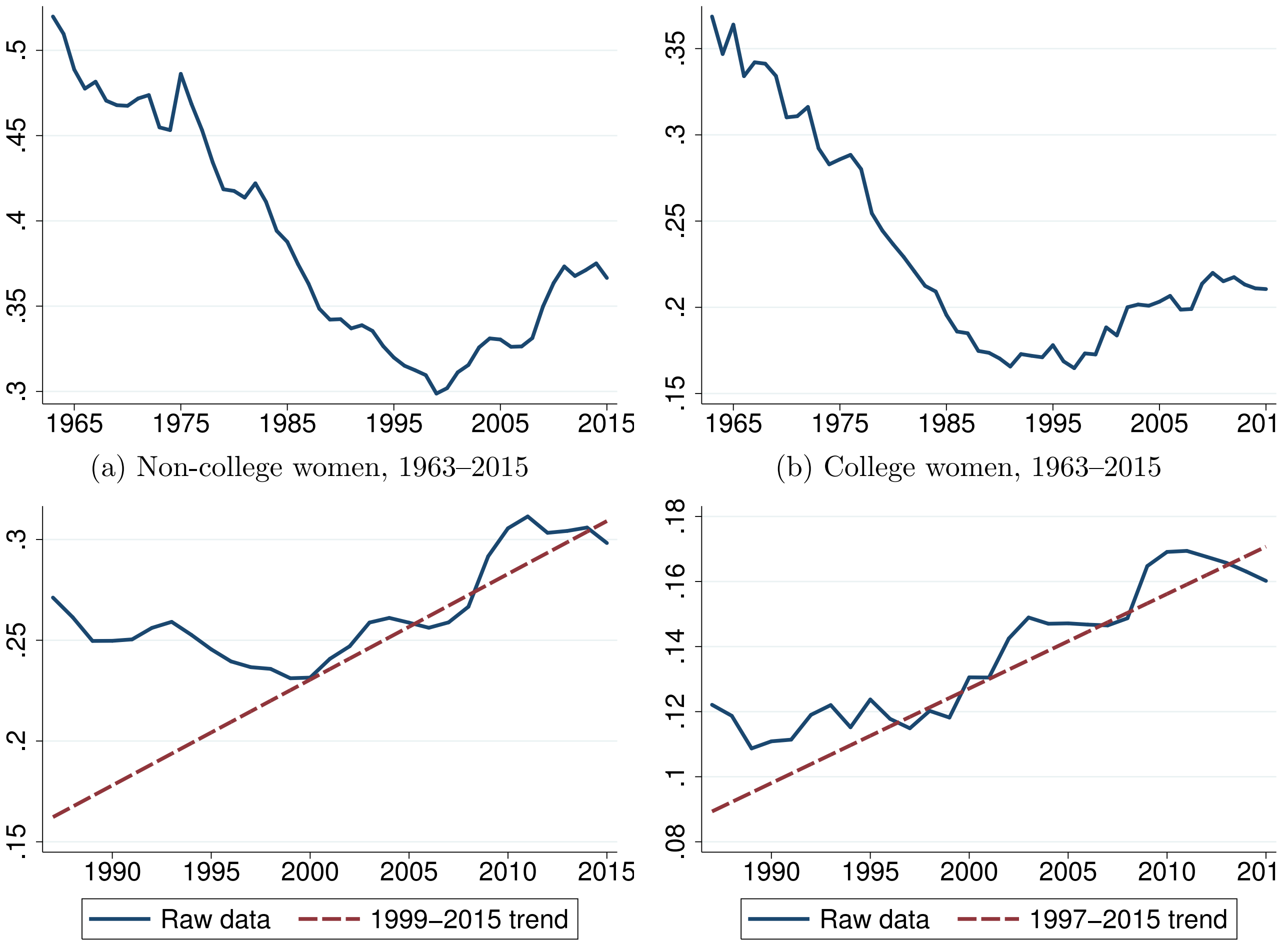
need to be for the whole population to be comparable to the BDS data. The estimate for the number of people in the US who are self-employed with less than 10 employees and the number of firms with 1–9 employees are presented in Figure 13. Both series grow steadily over time and the ratio of the number of firms to self-employed people is fairly stable, starting at 0.47 and ending at 0.45. I use the estimate of the number of self-employed people with 1–9 employees from the BDS data to divide the number of self-employed people with <10 employees in the CPS data into those with 0 employees and those with 1–9 employees. This provides the information necessary to compute the share of self-employed people with <10 employees who have at least one employee. Finally I assume that this share also holds for the restricted sample that I am studying (ages 25–65) and for both of the education levels I use.[44] This allows me to then compute the number of entrepreneurs in the data for each education level. When comparing model and data I omit self-employed people with no employees from the data so that the two are comparable.

For 1988–91 the size categories for small firms in the BDS and CPS don't match up. Since the size distribution of self-employed businesses is quite stable over time (see Figure 3) I estimate the share of people who are self-employed with at least one employee for each education level by taking the share who are self-employed each year and multiplying it by the average share of the self-employed who have employees for 1992–1994 for the relevant education level. For 2015 and 2016 BDS data on the number of firms with 1–9 employees is not yet available. I assume that the share of the self-employed with less than 10 employees who have at least one employee equals to the average of this moment for 2012–14.

C.2 Out of labor force share

A second challenge with matching up the occupation distributions in the model and data arises because of changes in female labor force participation over time. As is well known there was a strong and steady increase in the female labor force participation rate throughout at least the second half of the last century and this rate leveled off in the mid to late 1990s. Since my analysis starts in 1988 and I do not model gender this creates a disjunction between the model and the data. I deal with this by making adjustments to the data so that the two are comparable. The approach is as follows. I start with the out of labor force shares for women in my sample with non-college and college educations. For each education level there is a strong downward trend from when the CPS starts in 1962 until the late 1990s when both out of labor force shares start to rise. For non-college women the turning point is 1999, while for college educated women it is 1997 (see panels a and b of Figure 14). I assume that after these turning points the force generating the long run increase in female labor participation has ended. I therefore interpret the data after the turning points as representing the effect of other forces operating in the economy. To estimate what the data would have looked like prior to the turning points without the trend increase in female labor force participation I take the series for men and women combined for each education level, estimate the trend in the out of labor force share from the turning point (1999 for non-college and 1997 for college) to 2016, and then extrapolate the trend back to 1988. For both education groups the out of labor force share is approximately linear after the turning points, so I use a linear trend. See panels (c) and (d) of Figure 14.

[44] Ideally I would compute this share for each education group separately, but the data does not provide the information necessary to do this.



(a) Non-college women, 1963–2015

(b) College women, 1963–2015

(c) Non-college men and women, 1987–2015

(d) College men and women, 1987–2015

Figure 14: **Out of labor force share by education level** Panels (a) and (b) present the out of labor force share for women with the two education levels for 1963–2015. Panels (c) and (d) present the out of labor force shares for men and women for the two education levels for 1987–2015. These panels also show linear trends for 1999–2015 and 1997–2015, respectively, extrapolated back to 1987.

C.3 Occupation distribution

To complete the occupational distribution for each education level I also need estimates of the shares of low and high skill employees. The low and high skill employee shares can be measured directly from the CPS data. Since I don't have unemployed people in the model I treat them as employees and use the occupation of their last job to determine their skill type.[45] This gives me estimates of the occupation distribution for each education level, consisting of the shares of people who are out of the labor force, low skill employees, high skill employees and entrepreneurs.[46]

[45]There is a small number of unemployed people who don't have an occupation reported in the CPS. To deal with this I scale up the shares of low and high skill employees in the data so that their relative sizes are constant and these two shares sum to the share of people who are employed and unemployed in the data.

[46]Putting together the shares of people in each education group who are out of labor force, low skill employees, high skill employees and entrepreneurs does not produce a distribution that sums to one since I have estimated the out of labor force share and dropped self-employed people without employees from the data. To correct this I scale up the low skill employee, high skill employee and entrepreneur shares so that their relative sizes are constant and

	Non-college		*College*	
	1988	2016	1988	2016
Out of labor force	20.5	29.3	11.7	16.8
Low skill	62.4	53.1	22.3	20.1
High skill	12.2	13.7	57.8	57.5
Entrepreneur	4.8	3.8	8.2	5.5

Table 9: **Occupation distributions from data.** There are the occupation distributions for college and non-college agents for 1988 and 2016 after I adjust the out of labor force shares to remove the effect of increasing female labor force participation prior to 1999 and remove self-employed people without employees from the data.

To compute the aggregate occupation distribution I sum the two distributions conditional on education, weighting them by the shares of people with and without a college education. The final empirical occupation distributions that are used in the paper are presented in Table 9.

C.4 1987 income moments

The calibration moments require computing the mean and coefficient of variation of income for low skill people, high skill people and entrepreneurs, within each education group. These moments are computed using the March CPS, which provides data on income earned in the previous calendar year. The ensure a clean sample that is analogous to the model I restrict the sample to people who worked full time in the previous year (at least 50 weeks and an average of at least 40 hours per week), earned nearly all of their income (at least 99%) from their main job, and did not make a loss on a business. Since the model does not allow for variation in hours worked, I use average hourly income rather than total income. To compute each person's average hourly income I take their income earned from their main job and divide it by the number of weeks he or she worked multiplied by his or her usual hours worked per week. Once the average hourly income is constructed for each person, it is straighforward to compute means and coefficients of variation for each relevant subsample. For the rest of this section "income" should be taken to refer to average hourly income.

There are three additional issues with the income data that are addressed. First is top coding. While there is income top coding in the CPS data, replacement values are available to maintain the top of the income distribution while protecting the anonymity of respondents. The repalcement values for the 1988 March CPS have been taken from the CPS IPUMS website[47]. Second, there is evidence that self-employed people underreport their income in the Panel Study of Income Dynamics, another income survey in the US. Hurst et al. (2014) estimate an underreporting rate of 25%. To adjust for this I scale up the income of entrepreneurs by a factor of 1/0.75.

The third issue arises because the CPS does not provide information on the exact number of employees of each self-employed person. Thus it is necessary to estimate moments for the group of people who are defined as entrepreneurs in the model—self-employed people with at least one employee. I use the CPS data for 1991 for this purpose since, as described in Section 2 of the paper, it has more detailed information on the size of small firms than the data for 1987. I combine the 1991 estimates with information for 1987 to get estimates for that year, as I

the total share of people who are working equal one minus the out of labor force share.

[47] , accessed 4 May 2020

describe in detail below. For the coefficient of variation I use the data for 1991 to compute this moment of entrepreneur income for the two education groups for all self-employed people, and self-employed people with at least 10 employees. These moments are very similar, so the exact employment threshold doesn't appear to affect this moment very much. Therefore to estimate the 1987 coefficient of variation for entrepreneur income, I just use the value of this moment for all self-employed.

For average entrepreneur income the general approach is to use the data to estimate upper and lower bounds for this moment for each education group, and use this range to guide the choice of value. The details of the procedure are, using the data for 1991 unless stated otherwise:

- Compute average income of the self-employed, for each of the two education groups, conditional on three employment levels: any number of employees, < 10 employees and ≥ 10 employees.
- Take the estimate of the share of people who are self-employed with 0–10 employees who have at least one employee from the work done to estimate the share of people who are entrepreneurs (see discussion above). This value is 42.03% for 1991.
- Construct a lower bound for the average income of self-employed people with at least one employee, conditional on education, using a weighted average of the average income of the self-employed with < 10 employees and the average income of the self-employed with at least 10 employees:
$$\frac{(0.4203 \times shr^{\xi}_{<10})inc^{\xi}_{<10} + shr^{\xi}_{\geq 10}inc^{\xi}_{\geq 10}}{(0.4203 \times shr^{\xi}_{<10}) + shr^{\xi}_{\geq 10}}$$
where shr^{ξ}_{x} is the share of the self-employed with education level $\xi \in \{N, C\}$ in size category x and inc^{ξ}_{x} is the average income of self-employed in this education-size category.
- Construct an upper bound for the average income of self-employed people with at least one employee, conditional on education, in a similar way:
$$\frac{(0.4203 \times shr^{\xi}_{<10})inc^{\xi}_{10\text{–}24} + shr^{\xi}_{\geq 10}inc^{\xi}_{\geq 10}}{(0.4203 \times shr^{\xi}_{<10}) + shr^{\xi}_{\geq 10}}.$$
The difference for the upper bound is that the average income of the self-employed with 10–24 employees is being used to put an upper bound on the income of the self-employed with 1–10 employees.
- The last step is to use these lower and upper bounds for 1991 to estimate such bounds for 1987. To do this I compute the value of the lower and upper bounds for 1991 relative to the mean income of all self-employed for 1991, conditional on education. I then scale the 1988 mean income for all self-employed, conditional on educations, by these factors to get upper and lower bounds for 1987.

The resulting estimated ranges for mean (hourly) income of the self-employed in 1987 are: \$14.19–20.47 for non-college educated people and \$27.62–32.43 for the college educated. For calibration purposes I use the midpoints of these ranges.

C.5 1987–2015 income growth

Two of the key moments for the calibration are the growth of average real income for low and high skill agents from 1987 to 2015. A limitation of using the CPS data for these moments is that it does not include non-wage compensation, the growth of which has differed across skill levels over time. To adjust for this data from the BLS' Employer Costs of Employee Compensation (ECEC) survey is used. This dataset provides information going back to 1986 on compensation costs for employers by employee occupation and breaks the cost of compensation down into different components.[48] Particularly relevant for the purposes of this paper is that it separates wage and salary costs (which I'll call wages for brevity) from other forms of compensation. The data is annual up to 2001 and uses payroll data that includes March 12$^{\text{th}}$ each year. From 2002 onwards the data is quarterly and I use the observation for the first quarter of each year to match up with the timing of the annual data.

The approach to adjusting the growth in the average income for each skill level from 1987 to 2015 from the CPS data to account for growth in non-wage compensation follows three steps.

1. Using the CPS compute the average hourly income for low and high skill workers for 1987 and 2015. The sample for this is the main sample for the calibration, described in the paper. Put the 2015 values in 1987 dollars using the Personal Consumption Expenditures Index from the BEA. The ratio of 2015 to 1987 average hourly wages for low and high skill workers are 1.1303 and 1.3362, respectively.
2. For each skill level use the ECEC data to compute the ratio of 2015 to 1987 average hourly wages and average hourly total compensation, for the two skill levels. These ratios are presented in Table 10.
3. Use the ratio of compensation growth to wage growth to scale up the wage growth numbers from the CPS to account for non-wage compensation. For example, the estimated ratio of 2015 to 1987 average hourly total compensation for low skilled employes is $1.1303 \times (2.080/2.017) = 1.166$. This procedure assumes that the growth of compensation relative to wages is the same for my CPS sample as for the ECEC sample.

The one detail that has been omitted so far is how to compute the growth in average wages and total compensation for each skill level in step two. The ECEC data is by occupation so start by allocating each occupation to a skill level using the division described in Section 5.1 of the paper.[49] There is a change in the occupation classification system that the data uses from 2003 to 2004 so there is discontinuity in the data between these years. Next compute the average wage and average total compensation for each skill for 1987, 2003, 2004 and 2015. This requires aggregating the data across occupations. To do this weight each occupation by the share of the CPS sample in that occupation in the relevant year. In doing this I use the same occupation classification system from the CPS as the ECEC data uses. Note that some service occupations are not covered by the ECEC so I place zero weight on these occupations and scale up the other weights proportionally so that the total weights equal one.[50] Compute the ratios of the 2003 to 1987, and the 2015 to 2004, values of the average wage for each skill level, and do the same for average total compensation.

[48] The data used in this paper come from ECEC Table 9 for 1987–2003 and Table 15 for 2004–15.

[49] For one occupation group (Construction, extraction, farming, fishing and forestry) the data is missing for 2004 to 2006. I impute values for average compensation and average wages for this occupation by assuming that their growth rates from 2004 to 2007 were equal to their average growth rates from 2007 to 2015. The occupational crosswalk used for the mapping between CPS and ECEC occupations is available on request.

[50] One mismatch between the CPS sample and the ECEC data arises because the ECEC data for 2004–15 groups construction and extraction occupations with farming, fishing and forestry, which I exclude from the CPS sample. To deal with this I assume that the relative growth rates of compensation and wages are the same for these two types of occupations.

	Low skill	*High skill*
Wage growth	2.017	2.405
Compensation growth	2.080	2.597

Table 10: **Gross wage and compensation growth by skill, 1987–2015.** This table presents the gross growth rate of average wage and salary income and average total compensation for low skill employees and high skill employees for 1987 to 2015. 2.00 means that the relevant variable grew by 100%. The data is from the Employer Cost of Employee Compensation dataset from the BLS.

Finally multiply each 2003 to 1987 ratio by the corresponding 2015 to 2004 ratio to get estimates of the 2015 to 1987 ratios.

C.6 Entrepreneur employment share

The share of employment in the entrepreneur sector is estimated using data from the BDS and CPS. For 1987 the idea is to create a mapping from self-employed people in the CPS to establishments in the BDS, since the BDS provides richer information on size. Since the BDS covers the universe of private sector employer firms in the US, I use the full CPS sample for these calculations so that the coverage of the two datasets matches up, rather than restricting the sample based on age. From the CPS the public and agricultural sectors are omitted, as is the case for all of the analysis, and the agriculture sector is omitted from the BDS as well. The BDS does not include the public sector. For the mapping between the CPS and BDS I assume that each self-employed person in the CPS accounts for one establishment in the BDS at a firm in the same size class as the self-employed person's firm. Some support for this assumption is that for 1992 the number of owners per firm at firms with 10–99 employees was similar to the number of establishments per firm, at 1.35 and 1.23 respectively.[51] From a theoretical perspective the idea is that there is one person responsible for each establishment, who is also an owner. This would be the case, for example, under a partnership or franchise structure where each member of the partnership or franchise operates a location for the business. To give a sense of the implication of this for large firms, it implies that in 1992 self-employed people operated 17.2% of establishments of firms with at least 1000 employees.

This mapping provides an estimate of the share of establishments in each firm size class in the BDS that are run by self-employed people. To translate the establishment share into an estimate of the employment share of the self-employed I assume that within firm size classes in the BDS, each establishment is equal to the average size.[52] Since the size classes of firms used in the CPS change over time, they do not line up exactly with the BDS size classes in every year. However, they do line up for 1991, which is close to the start of the period of analysis. For this year the estimated share of employment at firms of the self-employed is 49.5%. Based on this, in the calibration for 1987 I use a share of employment at entrepreneur firms of 50%.

To provide some context for this estimate, using the Longitudinal Business Database from the Census Bureau and Computstat, Davis et al. (2006) estimate that privately held firms accounted for 75% of private sector employment in 1990. This value should be higher than the estimate just

[51] See Section 2 in the main text for a discussion of the value for owners per firm.

[52] For example, if there were 100 establishments at firms with 10–24 employees in the BDS and the total employment of firms in this size class was 1500, then the average establishment size would be 15.

outlined since not every privately held firm will have a self-employed person operating it. For example, there may be large privately owned firms who are managed on a day-to-day basis by employed managers and executives, and therefore won't have a self-employed person under the CPS definition. Given this, an estimate of 50% seems reasonable.

For 2015 the estimate is based on the fact that the size distribution of firms of the self-employed was stable over the period of analysis (see Figure 3). This implies that the percentage change in the share of employment at entrepreneur firms (firms of self-employed people with employees) equaled the percentage change in the share of the labor force who were entrepreneurs. After making adjustments for female labor force participation (discussed above), I estimate that this share declined by 20.1%. This implies a entrepreneur share of employment of 40.0% in 2015. As further validation of the methodology that I adopted for computing this employment share in 2015, I have repeated the calculations for 2015 and get a share of 39.0%. The fact that the two methodologies provide very similar answers supports the use of these estimates.

C.7 Entry rate

Since the March CPS provides annual cross-sectional samples that change each year, it is not suitable for measuring the entry rate of people into entrepreneurship. To estimate this moment I therefore make use of the BDS. Despite the BDS including non-entrepreneur firms, this doesn't create an issue for computing the entry rate. The reason for this is that we know from the data presented in Section 2 that the vast majority of firms with less than 100 employees are run by a single self-employed person, and that there is about one self-employed person for each of these firms. These firms also account for virtually all new firms in the BDS each year, and virtually all firms of all ages. For example, in 1987 firms with less than 100 employees account for 99.8% of new firms and 98.1% of all firms. Therefore the entry rate in the BDS is very similar to the rate of firm creation by entrepreneurs. The one issue that this doesn't address is that there could be entrepreneurs who close one firm and start another within a year. To the extent that this occurs, the BDS entry rate will overestimate the entry rate of people into entrepreneurship. While this could affect the level of the entry rate, the more important assumption for the purposes of the analysis in this paper is that the difference between these rates does not change over time, so that the trend in the firm entry rate is a good measure of the trend in the entrepreneurship entry rate.

The BDS data is collected for the pay period that includes March 12 each year. Therefore the best estimate of the entry rate for calendar year t is the entry rate between March in year t and March in year $t+1$ in the BDS. The formula for the entry rate is:

$$\text{entry}(t) = \frac{\text{entrants}(t+1)}{0.5(\text{firms}(t) + \text{firms}(t+1))},$$

where entry(t) is the entry rate in year t, entrants(t) is the number of entrants in the BDS in year t, and firms(t) is the total number of firms in the BDS in that year.[53]

[53] I keep the agriculture sector in the data for this analysis since the total number of firms increases when the data is split by sector—presumably some firms are being counted in two sectors. Repeating the calculations excluding this sector produces virtually identical results.

D Additional results

To be completed: additional results on how the sequencing of parameter changes affects the quantitative results.

E Additional details for Section 7

E.1 Industries

To be completed: Explain the industries that I use and the mappings of Census and NAICS industries to the BEA indsutries.

E.2 Regulation and IT related occupations

Table 11 lists the occupation that are treates as regulation-related for the purposes of the analysis in Section 7. The occupations that are treated as IT related are listed in Table **??**. The occupation codes are from the 1990 Census Bureau Occupational Classification System.

Code	Occupation
	Regulation-related occupations
008	Human resources and labor relations managers
023	Accountants and auditors
027	Personnel, HR, training, and labor relations specialists
035	Construction inspectors
036	Inspectors and compliance officers, outside construction
178	Lawyers
234	Legal assistants, paralegals, legal support, etc
328	Human resources clerks, except payroll and timekeeping
337	Bookkeepers and accounting and auditing clerks
375	Insurance adjusters, examiners, and investigators
376	Customer service reps, investigators and adjusters, except insurance
796	Production checkers and inspectors
	IT-related occupations
044–059	Engineers
064–068	Mathematical and computer scientists
069–083	Natural scientists (Physicists and astronomers, chemists etc.)
213–223	Engineering and related technologists and technicians
224–225	Science technicians
229	Computer software developers
233	Programmers of numerically controlled machine tools
308	Computer and peripheral equipment operators
525	Repairers of data processing equipment

Table 11: **Regulation-related occupations** This table listed the occupations from the 1990 Census Bureau Occupational Classification System that are treated as regualtion-related or IT-based in the analysis.