What's Driving the Decline in Entrepreneurship?[*]

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Abstract

Recent research shows that entrepreneurial activity has been declining in the US in recent decades. Given the role of entrepreneurship in theories of growth, job creation and economic mobility this has generated considerable concern. This paper investigates why entrepreneurship has declined. It documents that (1) the decline in entrepreneurship has been more pronounced for higher education levels, implying that at least part of the force driving the changes is not skill-neutral, and (2) the size distribution of entrepreneur businesses has been quite stable. Together with a decline in the entrepreneurship rate the second fact implies a shift of economic activity towards non-entrepreneur firms. Guided by this evidence I evaluate explanations for the decline in entrepreneurship based on skill-biased technical change, increases in the fixed costs of businesses which could be due to technological change or increases in regulations, and changes in technology that have benefited large non-entrepreneur firms. I do this using a general equilibrium model of occupational choice calibrated with a rich set of moments on occupations, income distributions and firm size distributions. I find that an increase in fixed costs explains most of the decline in the aggregate entrepreneurship rate and that skill-biased technical change can fully account for the larger decrease in entrepreneurship for more educated people when combined with the other forces.

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 importance for understanding the growth of the economy, the creation of jobs, income and wealth inequality, as well as economic mobility.[1] Entrepreneurship also receives considerable policy attention through ubiquitous political and media discussion, and from the Small Business Administration, the federal government department who's 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., 2007; 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 the economy. For example, if the the decline in entrepreneurship is due to regulations impeding business creation then the consequences are likely to be worse then if this change is an efficient response to changes in technology. Second, understanding the cause of the decrease in firm entry is important for formulating policy responses. Different causes will have different policy implications so identifying the cause is important for policy makers interested in this trend.[3]

To evaluate why entrepreneurship has declined I start with the data. In addition to documenting the decline in entrepreneurship I show that the decline has been larger for more educated people and that there has been a shift in economic activity away from entrepreneurs. Based on the empirical evidence I argue that three theories for the decline in entrepreneurship appear relevant: skill-biased technical change, an increase in fixed costs of entrepreneurs due to more regulation or technological reasons, and the superstar firm hypothesis which posits that technology changes have advantaged the largest firms. I then use a general equilibrium model of occupational choice along with the data to distinguish between these explanations and evaluate their contributions. I find that an increase in the fixed costs of entrepreneur businesses can generate most of the decrease in entrepreneurship and that skill-biased technical change can fully account for the larger decrease in entrepreneurship for more educated people when combined with the other forces.

For the empirical analysis I study the entrepreneurial decisions of people in the US using data from the Current Population Survey for 1988 to 2016. The idea for who an entrepreneur in this

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[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 the firm entry by a policy maker see Yellen (2014).

paper is a person who owns and actively manages a business which has employees and, due the information available in the data, for the empirical analysis a person must have 10 employees to be an entrepreneur. I focus on businesses with employees to avoid the risk of results being driven by very small businesses with little economic impact. The starting point for the empirical analysis is that the entrepreneurship rate (the share of the labor force who are entrepreneurs) has declined by 16% from 1988 to 2016. There have been a number of changes in the composition of the population and economy over this period—such as changes in the sectoral, age, education, gender, and geographic composition—which could explain this trend, but I show that none of these explain any significant fraction of it. In fact, most of these composition changes work against the trend. I also evaluate whether this trend is due to a particular sector in the economy, but find that this is not the case. Wholesale and retail exhibit the largest declines in entrepreneurship, but there are declines in most other sectors as well, and wholesale and retail trade only account for about half of the aggregate decline. These facts indicate that we should focus on explanations that apply to the economy broadly.

The second main fact is that 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 13%, while for people with more than a college education it has decreased by 35%. As far as I am aware this has not been documented before. This fact means that as well as entrepreneurship declining, there has been a shift in the composition of entrepreneurs towards those with smaller businesses and lower profits, suggesting lower productivity.[4] It also tells us that at least part of the force driving changes in entrepreneurship is not skill neutral. Such explanations have not received attention in the literature so far. When I quantitatively evaluate explanations for the decline in entrepreneurship in the second part of the paper, I consider skill-biased technical change. The rationale is that this force has affected the economy over the relevant period and has heterogeneous effects by skill. In particular it causes the relative wage of high skill workers to increase which, all else being equal, will increase their relative incentive to be employees rather than entrepreneurs.

The third main fact is that the size distribution of entrepreneur firms has been quite stable over time. A declining entrepreneurship rate and stable size distribution imply that the share of economic activity that entrepreneurs account for must have declined. Therefore explanations for the decline in entrepreneurship that disadvantage entrepreneurs relative to larger non-entrepreneur firms (e.g. public firms) must be considered. Two such theories have been prominent in debates about declining entrepreneurship. One theory is that there have been changes in regulations that have increased the fixed costs of businesses, disproportionately affecting smaller firms.[5] Regulations that are commonly discussed as having this effect include increases in occupational licensing,

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[4]In the nomenclature of Levine and Rubinstein (2017), the decline in entrepreneurship is concentrated amongst the 'smart' (I don't have a measure of the other dimension of entrepreneur characteristics that they focus on, illicit behavior).

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

increasing complexity of the tax system and zoning restrictions.[6] Fixed costs could also have increased for technological reasons. The other theory is that there have been changes in technology that have facilitated the expansion of the largest firms in the economy, resulting in production becoming increasingly concentrated amongst them.[7] 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—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.

I also use the data to address some alternative explanations for declining entrepreneurship based on changes in demographics. Karahan et al. (2016) argue that the decrease in the labor force growth rate explains at least part of the decline in the firm entry rate. I argue that there have been changes in entrepreneurship beyond what this theory can explain because it implies a constant share of the labor force are entrepreneurs in the long run while the data shows that this share has been decreasing.[8] A second demographic theory is based on the aging of the population and increasing life expectancy (Kopecky, 2017). This theory implies that changes in the age composition generate some of the decrease in entrepreneurship and that the decline in entrepreneurship should be more pronounced for older people, but I don't find either of these in the data.[9] A third theory is based on the idea that an older population makes it more difficult more people to accumulate experience which would help them be entrepreneurs (Liang et al., 2014). I show that while this theory predicts a larger decrease in entrepreneurship for people in the middle of the age distribution, in the data the decline has been similar for all ages.

In the second part of the paper I use a model to evaluate the ability of skill-biased technical change, changes in fixed costs and the superstar firm hypothesis to explain the changes in entrepreneurship that I have documented in the data. The model is a general equilibrium model of occupational choice. Agents are born as either low or high skill types and some receive an entrepreneurial idea. Each agent chooses between being out of the labor force (and receiving a fixed value), working as an employee using their low or high skill, or being an entrepreneur (if they have

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[6]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.

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

[8]Their model is a Hopenhayn (1992) style model in which firms are not attached to a particular owner-manager. The implication for the entrepreneur share of the labor force is based on the assumption of a constant number of entrepreneurs per firm in the model.

[9]Kopecky (2017) and this paper use different measures of entrepreneurship due to different data sources. He focuses on the firm entry rate using firm data while I use the share of the population who are entrepreneurs using individual level data. The change in the age composition is a more powerful explanation for the decline in the firm entry rate, although he finds that it is still not the most important factor because these demographic changes are too slow to explain much of what has occurred.

an idea). To capture the fact that we observe different distributions of occupations, wages and entrepreneurs for different education levels, the distributions of skills and entrepreneurial ideas are conditional on education. Production is performed by entrepreneurs operating their businesses and there are also non-entrepreneur businesses. Both types of businesses use the same production technology which takes capital and the two types of labor as inputs. In equilibrium wages adjust so that agents sort into the four occupations—out of the labor force, low skill employment, high skill employment and entrepreneurship—and markets clear.

Skill-biased technical change is modeled through the production technology. The key idea, which follows the technical change literature (e.g. Krusell et al., 2000; Autor et al., 2003), is that improvements in technology have resulted in a shift in demand for labor away from low skill workers and towards high skill workers. This is due to new types of capital being able to substitute for low skill workers and, at the same time, make high skill workers more productive. To model the superstar firms hypothesis I increase the productivity of non-entrepreneur businesses relative to entrepreneur businesses.

I use the model with the data to quantitatively evaluate the role of each force for explaining the decline in entrepreneurship from 1988 to 2016. The model is calibrated to the data for 1988 using moments of occupational choices, incomes and the size distribution of businesses. The experiments I run focus on changes in four parameters to simulate changes in the economy from 1988 to 2016. First I allow the education distribution of the population to change exactly as it has in the data, which affects the supply of skills. Second I change the productivity of capital to simulate skill-biased technical change, using a measure of this from the literature (Eden and Gaggl, 2016). Third I increase the fixed cost of businesses and fourth I increase the productivity of non-entrepreneur firms relative to entrepreneur firms. These two changes are pinned down by targeting the change in the aggregate entrepreneurship rate and the change in the share of the economy accounted for by non-entrepreneurs. This approach means that the model matches the decrease in the aggregate entrepreneurship rate by design, but the following are endogenous: the contribution of each force to this change; the change in relative entrepreneurship rates across the education distribution; and the change in the size distribution of businesses.

There are three main results. The first is that if the only change to the economy from 1988 to 2016 was the change in the education distribution, then the entrepreneurship rate would have increased. This is because with an increase in education the supply of high skill workers goes up, pushing the high skill wage down. This lowers an input cost for entrepreneurs and makes working as an employee less attractive for high skill types, leading to more entrepreneurship.

The second result is that the key force generating the decrease in the aggregate entrepreneurship rate is the increase in the fixed cost of entrepreneurs. There are two reasons for this. First, skill-biased technical change generates a change in the composition of entrepreneurs by education, but only decreases the aggregate entrepreneurship rate by a small amount. The reason for this is that this force increases the wages of high skill workers and decreases the wages of low skill workers.

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This results in high skill people switching from being entrepreneurs to employees, but most of this effect is offset by low skill people switching into entrepreneurship when their wages fall.

This leaves the increase in the fixed cost and the increase in the relative productivity of non-entrepreneur firms to explain the decrease in the entrepreneurship rate. Their relative contributions are pinned down by requiring that the model match the change in the non-entrepreneur share of the economy as well as the change in the aggregate entrepreneurship rate. When the relative productivity of non-entrepreneur firms increases production shifts towards those firms. This happens through entrepreneurs decreasing the size of their firms and some of them exiting. Most of the change is on the intensive margin, which means that given the size of the increase in the non-entrepreneur share of the economy, the entrepreneurship rate does not decrease that much. On its own this force accounts for 15% of the decline in the entrepreneurship rate. In contrast, when the fixed cost of a business increases the change in entrepreneurial production is mostly on the extensive margin. The least productive businesses exit while those that operate make virtually the same decisions (there are small changes due to small changes in wages). This means that for a given increase in the non-entrepreneur share of the economy, an increase in the fixed cost generates a much larger decrease in the entrepreneurship rate. Given the change in the entrepreneurship rate and the change in the non-entrepreneur share of the economy that has occurred, the model estimates that most of the decline in entrepreneurship is due to the increase in the fixed cost.

The results for the size distribution of entrepreneur businesses provide additional support for this explanation. I find that for the estimated changes in the fixed cost and the relative productivity of non-entrepreneur businesses the size distribution of entrepreneur businesses is quite stable, as it is in the data. While the increase in the fixed cost pushes the size distribution to the right by causing the smallest firms to exit, the increase in the relative productivity of non-entrepreneur businesses offsets this by causing entrepreneur businesses to shrink. So while it is the increase in the fixed cost that is key to explaining the decrease in the entrepreneurship rate, both forces play a role in explaining the stable size distribution.

These results provide evidence for the theory that increases in fixed costs have caused much of the decrease in entrepreneurship. The causes of the increase in fixed costs matters for whether its effects are efficient are not. To the extent that the increase is due to technological reasons, the effects are efficient in the model. In contrast, to the extent that the increase in due to regulatory reasons there are inefficiencies. Assuming that the entire increase in fixed costs is due to regulations the losses for the economy are 3.4% of aggregate consumption, with 80% of this due to the direct costs and the remainder due to resulting production inefficiency. Determining the cause of the increase in fixed costs is an important direction for future research.

The third result is that the model generates a larger decline in entrepreneurship for more educated people, with the magnitude of the decline for each education group almost exactly matching the data. Recall that while the quantitative strategy matches the decline in the aggregate

entrepreneurship rate by design, the different effects by education are endogenous. Skill-biased technical change is the force that drives this heterogeneity. Since more educated people are more likely to be high skill, more of them are attracted out of entrepreneurship by increasing high skill wages. In contrast less educated people are more likely to be low skill and have less incentive to leave entrepreneurship because of decreasing low skill wages. While at face value the shift in entrepreneurship towards less educated people may seem like a negative development, this explanation implies that it is an efficient response to the change in technology.

Contribution to the literature   Evidence of declining entrepreneurship has been documented in a number of recent papers (see Davis et al., 2007; 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 evaluate demographic explanations for it in a way that firm level data does not facilitate. A limitation of the data I use is that it is repeated cross-sections rather than a panel, so I study how the stock of entrepreneurs has changed over time rather than how entry into entrepreneurship has changed. In principle the decline in the stock could be driven by a decrease in entry or increase in exit. Given that the firm level data says that entry has declined over time while exit has been fairly flat, it seems likely that the decrease is due to changes on the entry margin.

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. Only a handful of other papers have addressed this question so far. Karahan et al. (2016) quantitatively evaluate the effect of a decreasing labor force growth rate on the firm entry rate. As I've already discussed I argue that my facts show that there is

a decline in entrepreneurship beyond what the mechanism in that paper can explain. Kopecky (2017) evaluates the effects of the aging of the population and increases in life expectancy on entry into entrepreneurship. The main mechanisms in that paper are that aging decreases the rate of entry into entrepreneurship because older people are less likely to start businesses and increasing life expectancy causes fewer older people to start businesses because they don't want to risk their savings close to retirement. In contrast to that paper I am studying the stock of entrepreneurship and find that the aging of the population does not cause the entrepreneurship rate to decrease through the first mechanism. The second mechanism implies that the decrease in entrepreneurship should be larger for older people, but I find similar declines across the age distribution. While Liang et al. (2014) do not study the decline in entrepreneurship in the US directly, they have a theory links demographics to the entrepreneurship rate that could explain what has occurred. However, as already mentioned, I find that the data does not support a key prediction of this theory.

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 4. Section 5 contains the results and the conclusion is in Section 6.

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 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.[10] 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. The data has been accessed from the Integrated Public Use Microdata Series (Flood et al., 2015), commonly known as IPUMS. This gives me cross-sectional samples taken in March each year that, once weighted, are representative of this population. 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.[11] 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 my 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. To be classified as self-employed a person must satisfy two requirements. First they must identify as self-employed in response to the question, 'Last week, were you employed by government, by a private company, a nonprofit organization, or were you self-employed?'[12] Second, if they have multiple sources of employment then they are only classified as self-employed if self-employment is the job that they spend the most hours doing. So self-employment captures people who own a business and work in that business as their main form of employment. 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 1992–2016). All results hold without the size threshold and I will present some of these.[13]

To give a sense of what component of the economy self-employed people account for Table 1

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

[11]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.

[12]This is the question that has been asked since 1994. Prior to 1994 the question was phrased slightly differently. Respondents were asked to say whether they were: an employee of a PRIVATE company, business or individual for wages, salary or commission; a FEDERAL government employee; a STATE government employee; a LOCAL government employee; self-employed in OWN business, professional practice or farm; working WITHOUT PAY in

Firm size (employees)	Self-employed (000's)	Firms (000's)
<10	8,838.4	19,063.5
10–99	1,239.7	1,050.4
100–499	258.9	76.7
500–999	66.8	8.1
1000+	478.9	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.

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 8.8 million self-employed people with such businesses. Assuming that the self-employed have one business each, which the data supports,[14] there are 10.2 million small businesses not associated with a self-employed person. This is due to a large number of people having businesses that not their main job so they are not classified as self-employed in the CPS. 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 918,000 out of the 1.05 million firms.[15] Third, for large businesses (100+ employees) there are many more self-employed people than firms: 805,000 compared to 94,000. 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.[16]

a family business or farm; or NEVER WORKED. (Capitalization in the original questionnaire.)

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

[14]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 also spend the majority of their working time in their business, 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). 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.

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

[16]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.

The sample period of 1988–2016 has been chosen to ensure that self-employment can be measured consistently over time. The CPS does have data prior to 1988 on self-employment, but for this period the BLS only reported people as self-employed if their business was not incorporated. From 1988 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 1998 is likely to downwardly bias the trend in the 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-1988 data.[17] 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 2.34% to 1.96%, a 16% decrease, while the self-employment rate (left hand axis) has declined from 11.5% to 9.4%, a decrease of 18%. Both rates have cyclical fluctuations but exhibit a similar downward trend.

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.

Before moving onto other features of the data I will show that this trend is not driven by changes in the composition of the population or the economy over time and is not a result of changes in

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[17]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.
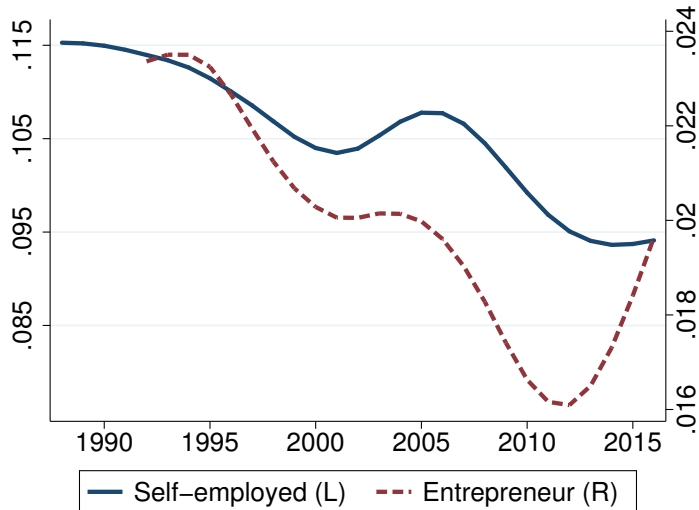
Figure 1: **Entrepreneurship and self-employment rates.** The self-employment and entrepreneur-ship rates are the shares of the labor force who are self-employed and entrepreneurs, respectively. The scale for the self-employment rate is on the left axis and the for the entrepreneurship rate it is on the right axis. Both series are smoothed using a HP filter with smoothing parameter equal to 6.25.

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

$$e_{\mathcal{G},t} \equiv \sum_{g \in \mathcal{G}} \omega_{g,1992} e_{g,t}. \tag{1}$$

This equation keeps the share of each subset of the economy fixed while allowing the entrepreneur-ship 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;[18] for age $\mathcal{G}$ has four categories: 25–35,

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[18]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; entertain-ment and recreation services; and professional services.
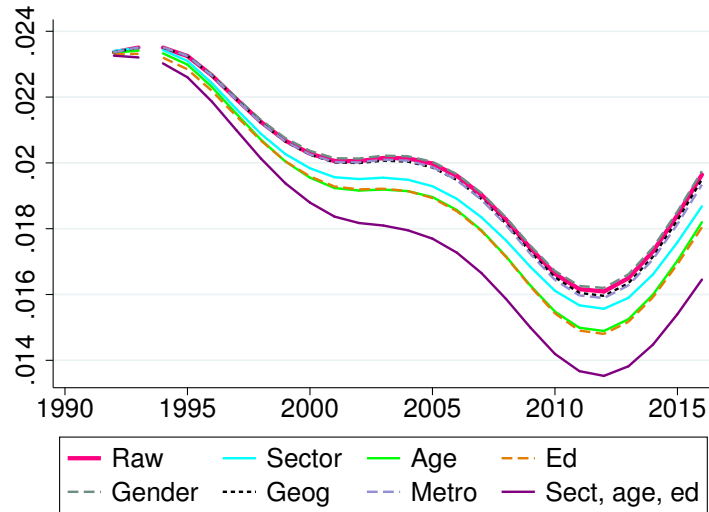
Figure 2: **Entrepreneurship rate with composition controls.** The *Raw* line is the entrepreneurship rate without any composition control. For the remaining lines the composition of the labor force along various dimensions is held fixed at its 1992 distribution, per equation (1). The subsets of the 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.

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.

The results for $e_{\mathcal{G},t}$ for each of these composition controls are presented in Figure 2. 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 2 and labeled Sect, age, ed. The decrease in the entrepreneurship rate is larger again under these joint controls, emphasizing

12

| Sector | 1992 | Entrepreneurship rate | | | % of total |
	share	'92–'94	'14–'16	% change	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 2: **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.

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 2 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.

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 1992 to 2016. Figure 3(a) shows that the

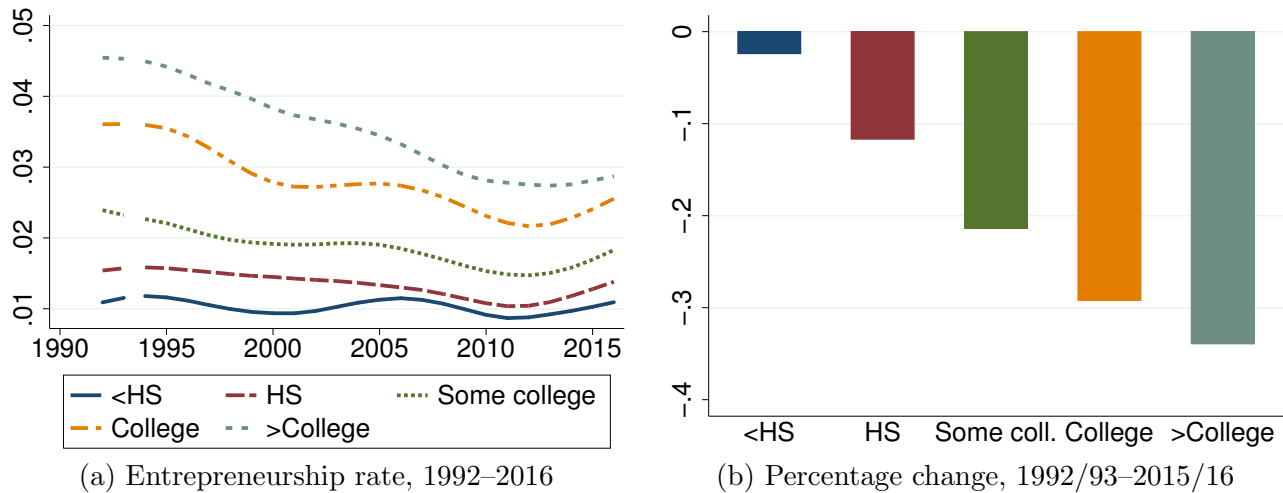(a) Entrepreneurship rate, 1992–2016   (b) Percentage change, 1992/93–2015/16

Figure 3: 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 1992–93 to the average for 2015–16 for each education group. These calculations use the unsmoothed series.

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 1992–93 to the average for 2015–16 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 333.9%.

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.
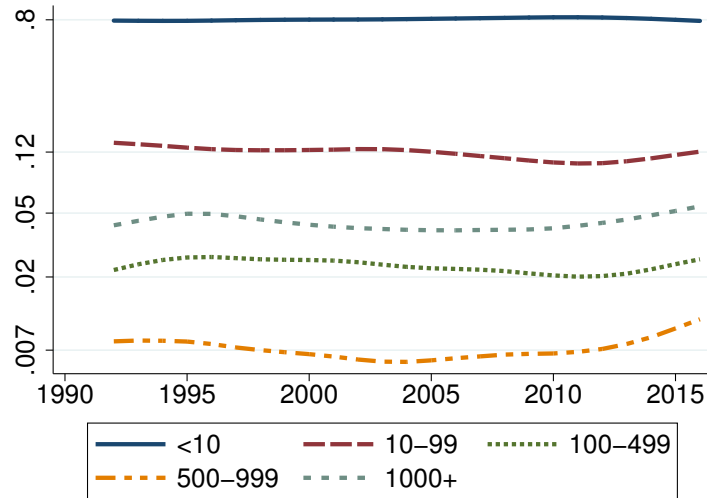
Figure 4: **Size distribution of businesses of self-employed.** The scale of the y-axis is logarithmic. Each series is HP filtered with smoothing parameter equal to 6.25.

2.4 Entrepreneur firm size

The third fact is that the size distribution of entrepreneur firms has been quite stable over time. Figure 4 presents the share of self-employed people with firms in different size categories for 1992–2016.[19] 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 entrepreneurship 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 disadvantage entrepreneurs relative to larger non-entrepreneur firms (e.g. public firms). Two theories that fit this description have been prominent in debates about declining entrepreneurship. One idea is that there have been changes in regulations that have increased the fixed costs of businesses.[20] Regulations that are commonly discussed as having this effect include increases in occupational licensing, weaker enforcement of anti-trust laws and zoning restrictions.[21] Fixed

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[19]I omit 1988–91 since the size categories are different for this period.

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

[21]The motivation for the discussion of occupational licensing is Kleiner (2015) who shows that the prevalence

costs could also have increased for technological reasons. The other idea is that there have been changes in technology that have advantaged the largest firms in the economy and resulted in production becoming increasingly concentrated amongst them.[22] 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.

2.5 Demographic explanations

In the recent literature studying the cause of the decline in the entrepreneurship demographic explanations have been prominent. There are two papers that directly study the effect of demographic changes on entrepreneurship in the US and a third that proposes a theory linking the entrepreneurship rate to demographics more generally. The first two papers focus on the firm entry rate rather than the share of the labor force who are entrepreneurs, but have implications for this measure of entrepreneurship as well. Karahan et al. (2016) study the decline in the firm entry rate and argue that part of the cause for this is a decrease in the growth rate of the labor force. Their idea is that in the long run in a Hopenhayn (1992) model, changes in labor supply result in changes in the number of firms rather than the size of firms, so when the labor force grows more slowly the firm entry rate decreases. The data presented in this paper shows that there are changes occurring beyond what this theory explains. While the theory does not tie firms to individual owners, if we assume that there is a constant number of entrepreneurs per firm then the entrepreneurship rate would be constant in the long run.

The second theory is that aging of the population and increases in life expectancy have caused the decrease in entrepreneurship. Kopecky (2017) argues that the aging of the population decreases entry into entrepreneurship because older people are less likely to start businesses, and increasing life expectancy causes fewer older people to start businesses because they don't want to risk their savings close to retirement. The evidence from the CPS does not favor these channels.[23] The results discussed earlier in this section and presented in Figure 2 show that when the age distribution of the population is held fixed over time the decrease in the entrepreneurship rate is

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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.

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

[23]One caveat to these remarks is that this composition channel is more powerful if you restrict attention to entrepreneurs with young firms, as Kopecky (2017) does, since the entrepreneurship rate is likely to decrease more with age under this definition.

(a) Entrepreneurship rate, 1992–2016
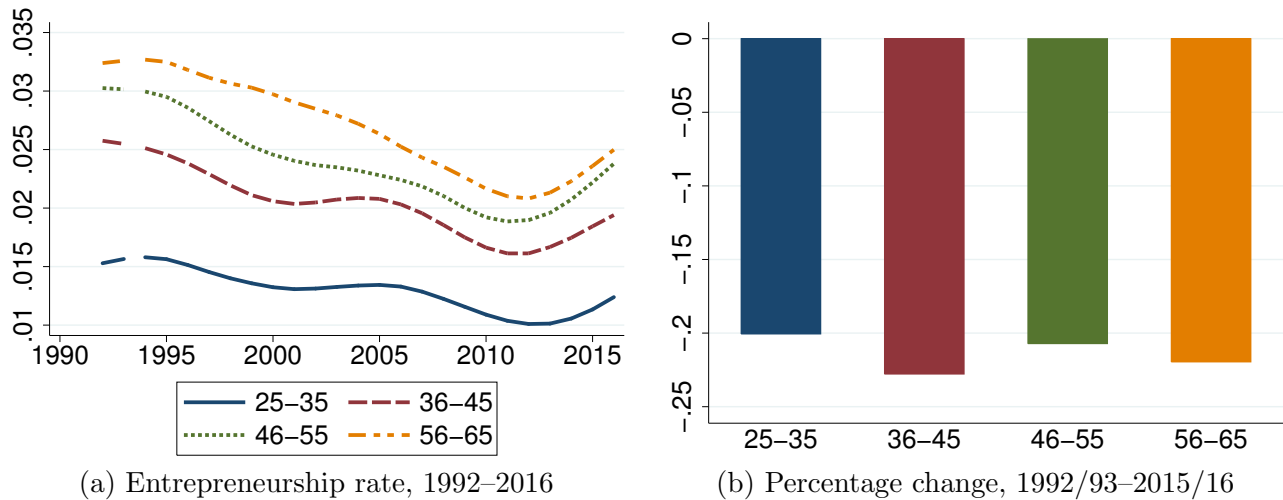
(b) Percentage change, 1992/93–2015/16

Figure 5: Entrepreneurship rate by age and percentage change. Panel (a) is the share of the labor force for each age group who are entrepreneurs. These series are smoothed with a HP filter with smoothing parameter equal to 6.25. Panel (b) is the percentage change in the entrepreneurship rate from the average for 1992–93 to the average for 2015–16 for each age group. These calculations use the unsmoothed series.

actually a little larger than it would otherwise have been.[24] The decrease in the entrepreneurship rate is therefore a result of changes conditional on age, rather than being due to composition effects. The data also shows that the decrease in entrepreneurship has been similar across the age distribution, rather than being larger for older age groups. Figure 5 presents the entrepreneurship rates by education and the percentage changes in them from 1992/93 to 2015/16. For each education group the entrepreneurship rate has declined by virtually the same percentage (20–23%). Additional details about changes in the age distribution and the entrepreneurship rate by age are presented in the Appendix.

The third paper linking entrepreneurship to demographics is Liang et al. (2014). This paper proposes a theory under which entrepreneurial ability depends on creativity and drive, which decline in age, and experience which comes from working in increasingly senior roles. When the population ages it takes longer for people to accumulate experience because the increasing share of older people in the population makes it more difficult to be promoted. This pushes the entrepreneurship rate down at all ages. The theory also predicts that the decrease in entrepreneurship will be largest somewhere in the middle of the age distribution. This is because young people have little experience whether the population is older or not so a change in the age distribution does not affect their entrepreneurial ability. For the oldest people in the population, they have had enough time to advance to the most senior employment positions regardless of the age distri-

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[24]The story is more complex than whether the population has become older or younger because the propensity to be an entrepreneur is hump shaped in age. As the population has aged there are fewer young people who are relatively unlikely to be entrepreneurs, more middle aged people who have a relatively high likelihood of being an entrepreneur and more old people who are less likely to be entrepreneurs. Overall the forces increasing entrepreneurship are larger for 1992 to 2016.

bution, so their experience and ability are also not affected. Figure 5 shows that for the period that this paper studies the prediction that the decline in entrepreneurship is largest for an age in the middle of the distribution does not hold. The decline in entrepreneurship is similar across the age distribution. Therefore this is not the explanation for the decline in entrepreneurship in the US in recent decades.

3 Model

In this section I present an occupational choice model. The model is designed to capture the three theories for the decline in entrepreneurship that I have discussed—skill-biased technical change, increasing fixed costs and the superstar firm hypothesis—and will be used to quantitatively evaluate them in the remainder of the paper.

3.1 Environment

There is a single period and a unit mass of agents. The objective of each agent is to maximize utility from end of period consumption $u(c)$, where $u'(c) > 0$. There won't be any uncertainty when agents make their decisions so the curvature of the utility function does not matter. Each agent is either a high skill or low skill type. With probability θ_h an agent is a high type, and otherwise she is a low type. An agent that is high skill draws a productivity z_h for doing high skill work from a distribution $G_h(z_h)$ and if she is low type then she draws a productivity for low skill work z_l from $G_l(z_l)$. Each agent also receives an entrepreneurial idea with probability θ_e and if this occurs then the productivity of the idea, z_e, is drawn from $G_e(z_e)$. Therefore all agents will be endowed with one worker productivity, z_l or z_h, and some agents will also have an entrepreneur productivity z_e.

Each agent must choose whether to work and what kind of work to do. I will refer to these decisions as the *occupational choice*. There are four options and each agent will be able to choose between a subset of them, depending on her set of productivities. All agents have the option to not work and will get b units of utility, which can be thought of as the value of leisure or home production. If an agent has a low skill productivity z_l 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 a high skill productivity z_h 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. If an agent has an entrepreneurial productivity then she also has the option of paying a fixed cost δ to setup a business which allows her to manage a production technology $f(z_e, k_o, k_i, \ell_l, \ell_h)$. I assume that implementing an entrepreneurial idea requires all of an agent's time so that agents with an idea must choose between entrepreneurship and working as an employee. As an entrepreneur the agent hires inputs to produce and keeps the profits from the operation. There are four inputs. Two types of capital, k_o and k_i, that can be produced using the final good at a ratio of one-ti-one

and depreciate fully after production. I will discuss these capital inputs in detail in a moment. I normalize the price of the final good, and therefore the prices of the two capital inputs, to one. 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. I will discuss the functional form for the production technology shortly.

There is also a fixed mass of non-entrepreneur firms, m. Each of these firms has a productivity z_f drawn from a distribution $G_f(z_f)$ and produce using the technology $f(z_f, k_o, k_i, \ell_l, \ell_h)$, which has the same function form as the technology that entrepreneurs use. The technology is run to maximize profit. These firms represent large firms, such as public firms, that don't have an owner who runs them. Their productivities 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. These firms are owned equally by all agents who receive their 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 there have been improvements in capital technology over time that 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

$$f(z, k_o, k_i, \ell_l, \ell_h) = z k_o^\eta \left[\phi \ell_h^\gamma + (1 - \phi)(\lambda(a k_i)^\rho + (1 - \lambda)\ell_l^\rho)^{\frac{\gamma}{\rho}} \right]^{\frac{\alpha}{\gamma}}, \tag{2}$$

where $\eta, \phi, \lambda, \alpha \in (0, 1)$; $\alpha + \eta < 1$; $\rho, \gamma < 1$; and $a > 0$. 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 that I use a decreasing returns to scale technology since I am studying production at the firm rather than the aggregate level and want a distribution of firms. The productivity of the firm z is z_e for an entrepreneur and z_f for a non-entrepreneur firm. 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 ρ and γ, respectively. I place 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 the values of being out of the labor force, a low skill worker with productivity z_l and a high skill worker with productivity z_h be denoted by $v_{\text{olf}} = b$, $v_l(z_l, w_l) = z_l w_l$ and $v_h(z_h, w_h) = z_h w_h$, respectively. The operating profit for an entrepreneur is

$$\pi_e(z_e, w_l, w_h) = \max_{\{k_o, k_i, \ell_l, \ell_h\}} \{f(z_e, k_o, k_i, \ell_l, \ell_h) - w_l \ell_l - w_h \ell_h - k_o - k_i\}. \tag{3}$$

The optimal inputs are

$$k_o(z_e, w_l, w_h) = \Gamma_{k_o}(w_l, w_h) z_e^{\frac{1}{1-\alpha-\eta}}, \tag{4}$$

$$\ell_h(z_e, w_l, w_h) = \Gamma_{\ell_h}(w_l, w_h) z_e^{\frac{1}{1-\alpha-\eta}}, \tag{5}$$

$$\ell_l(z_e, w_l, w_h) = \Gamma_{\ell_l}(w_l, w_h) z_e^{\frac{1}{1-\alpha-\eta}}, \tag{6}$$

$$k_i(z_e, w_l, w_h) = \Gamma_{k_i}(w_l, w_h) z_e^{\frac{1}{1-\alpha-\eta}}, \tag{7}$$

where the functional forms for the four Γ terms are given in the appendix. Let the net output of a firm be denoted by $y(z_e, w_l, w_h) \equiv f(z_e, k_o, k_i, \ell_l, \ell_h) - k_o - k_i$. The value of being an entrepreneur can be expressed as

$$v_e(z_e, w_l, w_h) = \Gamma_e(w_l, w_h) z_e^{\frac{1}{1-\alpha-\eta}} - \delta \tag{8}$$

with the functional form for Γ_e given in the appendix.

Denote the set of possible occupations by $\mathcal{S} = \{\text{olf}, l, h, e\}$ where the notation corresponds to the subscripts on the relevant value functions. If an agent does not receive a productivity draw for z_l, z_h or z_e then let the relevant productivity be equal to zero. The occupational choice of an agent can then be expressed as:

$$s(z_l, z_h, z_e, w_l, w_h) = \arg\max_{x \in \mathcal{S}} v_x(z_l, z_h, z_e, w_l, w_h). \tag{9}$$

The production problem for a non-entrepreneur firm is the same as equation (3), except that z_e is replaced by z_f. I will denote the net output of a non-entrepreneur firm by $y(z_e, w_l, w_h)$ and its profit by

$$\pi_f(z_f, w_l, w_h) = \Gamma(w_l, w_h) z_f^{\frac{1}{1-\alpha-\eta}}.$$

There are 3 markets that need to clear: the markets for low skill labor, high skill labor and the market for the final good. The market clearing conditions are:

$$\int \mathbb{1}\{s=l\}z_l \, dG = \int \mathbb{1}\{s=e\}\ell_l(z_e, w_l, w_h) \, dG + \int \ell_l(z_f, w_l, w_h) \, dG_f, \tag{10}$$

$$\int \mathbb{1}\{s=h\}z_h \, dG = \int \mathbb{1}\{s=e\}\ell_h(z_e, w_l, w_h) \, dG + \int \ell_h(z_f, w_l, w_h) \, dG_f, \tag{11}$$

$$\int \mathbb{1}\{s=e\}(y(z_e, w_l, w_h) - \delta) \, dG + m \int y(z_f, w_l, w_h) - \delta \, dG_f$$

$$= \int \sum_{x \in \{l,h,e\}} \mathbb{1}\{s=x\}v_s(z_l, z_h, z_e, w_l, w_h) \, dG + m \int \pi(z_f, w_l, w_h) \, dG_f, \tag{12}$$

where G denotes the joint distribution over z_l, z_h and z_e, $\int \cdot dG$ is the triple integral over these variables with respect to this distribution, and $\int \cdot dG_f$ is the integral over z_f with respect to $G_f(z_f)$. The definition of the equilibrium is as follows.

Equilibrium *An equilibrium is a set of prices $\{w_l, w_h\}$, a function for occupational choices $s(z_l, z_h, z_e, w_l, w_h)$, and production input decisions for entrepreneurs and non-entrepreneur firms $\{\ell_l(z_e, w_l, w_h), \ell_h(z_e, w_l, w_h), k_o(z_e, w_l, w_h), k_i(z_e, w_l, w_h)\}$ with $z = z_e$ for entrepreneurs and $z = z_f$ for non-entrepreneurs, such that:*

- *occupational choices satisfy (9);*
- *the production input decisions satisfy (4), (5), (6) and (7) for entrepreneurs and analogous conditions for non-entrepreneur firms; and*
- *the markets for low skill labor, high skill labor and the final good clear in accordance with equations (10), (11) and (12).*

3.4   Occupational sorting in equilibrium

Figure 6 presents a stylized picture of the occupational choices of agents in equilibrium. First consider low types whose occupational choices are presented in panel (a). Some agents have an entrepreneurial idea and others do not. Those who do not are on the horizontal axis and have a choice between working as an employee or being out of the labor force. The agent who is indifferent between these choices has a productivity that satisfies $w_l z_l = b$, so the threshold productivity for working is $\underline{z}_l = b/w_l$. Next consider an agent who has an entrepreneurial idea and whose low skill productivity is below $\underline{z}_l$. This agent will choose to to be out of the labor force if the entrepreneurial idea is sufficiently bad and otherwise will be an entrepreneur. The threshold for this choice is at the entrepreneur productivity that satisfies $v(z_e, w_l, w_h) = b$. If the agent has an entrepreneurial idea and a low skill productivity above $\underline{z}_l$ then the agent will choose to be an entrepreneur if

$v(z_e, w_l, w_h) > z_l w_l$. Thus the threshold for being an entrepreneur for a low skill type is

$$\underline{z}_e^l(z_l) = \begin{cases} \left(\frac{b+\delta}{\Gamma_e(w_l,w_h)}\right)^{1-\alpha-\eta} & \text{if } z_l < \underline{z}_l, \\ \left(\frac{z_l w_l+\delta}{\Gamma_e(w_l,w_h)}\right)^{1-\alpha-\eta} & \text{otherwise.} \end{cases}$$

The threshold for being an entrepreneur for $z_l \geq \underline{z}_l$ 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.

For high skill types the tradeoffs are the same except that the value of being an employee is $z_h w_h$ instead of $z_l w_l$. Thus the threshold for being an employee instead of out of the labor force if b/w_h and the threshold for being an entrepreneur is

$$\underline{z}_e^h(z_h) = \begin{cases} \left(\frac{b+\delta}{\Gamma_e(w_l,w_h)}\right)^{1-\alpha-\eta} & \text{if } z_h < \underline{z}_h, \\ \left(\frac{z_h w_h+\delta}{\Gamma_e(w_l,w_h)}\right)^{1-\alpha-\eta} & \text{otherwise.} \end{cases}$$

The two panels in Figure 6 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. 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.

It should also be noted that the size of the regions in Figure 6 should not be interpreted as indicating the relative shares of the occupation categories. For example a larger fraction of the low skill type panel is for entrepreneurs than for low skill employees. This does not mean that more low skill types are entrepreneurs than low skill employees because this also depends on the joint distribution of z_l and z_e. Similarly, it is not true that a larger share of low types are entrepreneurs than high types because the entrepreneur region is larger for low types. Low and high types will have different distributions of entrepreneur and employee productivities and this needs to be considered to determine this. I will determine these distributions using the data, which I'll turn to next.

4 Calibration

The objective of the quantitative exercise is to evaluate the contribution of three forces to explaining the changes in entrepreneurship documented in Section 2. The first force is skill biased technical change, which in the model will be generated by an increase in the productivity of IT capital, a. The second force is an increase in the fixed cost of operating a business. Third is the superstar firm hypothesis which I model with an increase in the relative productivity of non-entrepreneur firms. In this section I outline the methodology for this exercise and in the next section I analyze the results. For the methodology I describe the additional assumptions made to
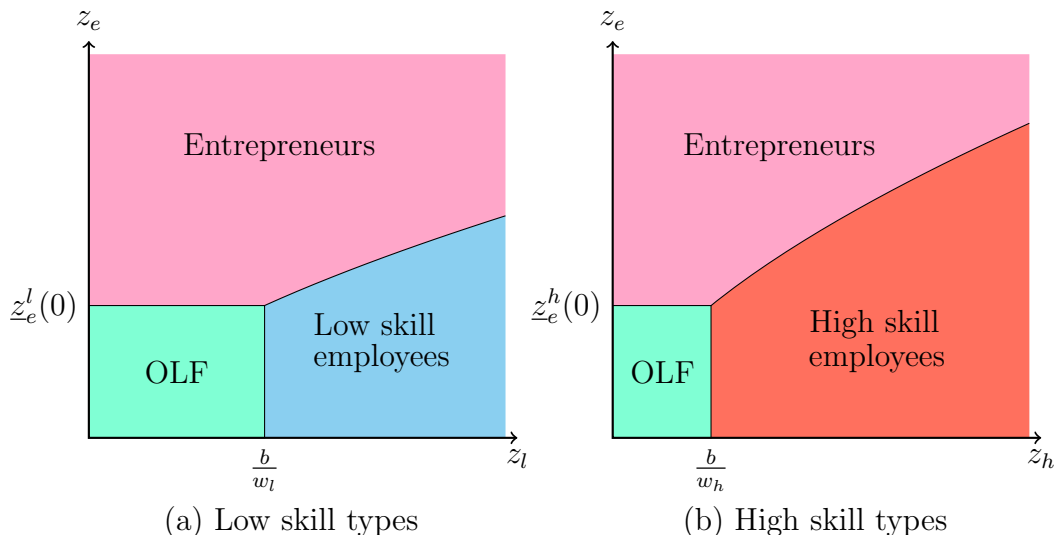
(a) Low skill types   (b) High skill types

Figure 6: **Equilibrium occupational choices**

take the model to the data, outline the calibration strategy and present the calibration.

4.1 Additional structure for taking model to data

To take the model to the data I need to specify how I define 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. I will cover these issues in this order.

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 using their occupations. To do this I use the occupation classification scheme from Acemoglu and Autor (2011). This 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

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

cognitive occupations as high skill occupations and the rest as low skill occupations.

There is a line of research on routine-biased technical change that distinguishes between non-routine manual occupation 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. I have chosen to abstract 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 a lot across the education distribution. In order to evaluate the ability of the model to explain this fact it needs to incorporate heterogeneity in education. To do this 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). In the model I assume that each agent is endowed with an education level and I make these draws so that the model matches the education shares in the data. Education will matter in the model because I assume that the probability of being a high skill type θ_h, the two employee productivity distributions $G_l(z_l)$ and $G_h(z_h)$, the probability of getting an entrepreneurial idea θ_e, and the distribution that entrepreneurial ideas are drawn from $G_e(z_e)$ are all conditional on education. I will distinguish between these objects for non-college and college agents with N and C superscripts, respectively (e.g. $G_l^N(z_l)$ for non-college and $G_l^C(z_l)$ for college).

Entrepreneurs Next I need to define an entrepreneur in the data. In the model an entrepreneur is a person who owns and manages a business, and has 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 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. 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.[26] This

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[26]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

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.[27] 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 need to be for the whole population to be comparable to the BDS data. I then 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.[28] 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 4) I estimate the share of people who 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. Additional details of the data that I use in the procedure that I have just described are provided in the appendix. Moments of these distributions are used in the calibration and results. The full details of the distributions are presented in the Appendix.

Out of labor force shares and occupation distributions A second challenge with matching up the data and model 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

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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.

[27]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 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.

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

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. 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 take for men and women 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. Additional details of the data used in this procedure are in the Appendix.

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.[29] 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.[30] 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.

Distributional assumptions   There are seven distributions that require functional forms: distributions of low skill productivity, high skill productivity and entrepreneur productivity for low and high skill agents, and a distribution of productivity for non-entrepreneur firms. I assume that all of the employee productivity distributions are log normal. Let the parameters of the low skill distribution for non-college agents be denoted μ_l^N and σ_l^N (these are the mean and standard deviation of the normal distribution underlying the lognormal) and define μ_h^N, σ_h^N, μ_l^C, σ_l^C, μ_h^C and σ_h^C analogously for other three employee productivity distributions. For the entrepreneur and firm productivity distributions I assume that they are all Pareto. This is guided by the fact that the size distribution of establishments is well approximated by a Pareto distribution. The functional form of the probability density function for entrepreneur productivity draws for non-college agents

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[29]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.

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

is

$$g_e^N(z_e) = \frac{1}{\kappa_e^N}[1 + (z_e - \tau_e^N)]^{-\left(\frac{1}{\kappa_e^N}+1\right)},$$

for $z_e > \tau_e^N$ and $g_e^N(z_e) = 0$ otherwise. τ_e^N determines the minimum value that z_e takes and κ_e^N controls the shape. Define τ_e^C, κ_e^C, τ_f and κ_f analogously for the distribution of entrepreneur productivity for the college educated and the productivity distribution of non-entrepreneur firms.

In terms of correlations I assume that all random variables are drawn independently. In particular this means that, conditional on education, each agent has the same probability of getting an entrepreneurial idea (θ_e^N for non-college and θ_e^C for college) and, conditional on getting an idea, their draw of z_e is independent of their level of z_l or z_h. The next draft of the paper will contain analysis of variations to this assumption.

4.2   Quantitative strategy and calibration

In order to describe the calibration of the model it is useful to first outline the quantitative experiment that the model will be used for. The experiment is to take the model fitted to the data for 1988, then change five parameters to simulate changes to the economy from 1988 to 2016 and solve the model with these new parameters for 2016. The analysis will focus on comparing the 1988 economy with the hypothetical 2016 economy and the data for 2016 to evaluate how much of the changes from 1988 to 2016 the model can explain. The five parameters that will change are:

1. the share of agents who are college educated;
2. the productivity of IT capital a;
3. the fixed cost of a business δ;
4. the minimum productivity of non-entrepreneur businesses τ_f; and
5. the value of being out of the labor force b.

The share of agents with a college education changes because there has been a significant change in the education level of the population over the sample period and, since education is related to the skills of agents, this is important for getting the supply of skills right. The change in the productivity of IT capital is what drives skill-biased technical change. The change in the fixed cost captures both the effects of more regulation and technological effects on this cost. The change in τ_f is simulating the change in the relative productivity of non-entrepreneur firms. When I adjust this parameter I will rescale all entrepreneur and non-entrepreneur productivities so that the aggregate supply of firm productivities is unchanged.[31] I adjust the value of being out of the labor force since the out of labor force share has changed significantly over the sample period and this parameter needs to change to match this feature of the data. I will discuss this in more detail with the results.

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[31] That is, I multiply all z_e and z_f by a constant so that the aggregate supply of z_f and z_e is unchanged. This aggregate supply is $\int z_e\, dG + \int z_f\, dG_f$.

To implement this exercise there are 34 parameters to calibrate: the shares of the population without a college education in 1988 and 2016, denoted ω_{1988} and ω_{2016} respectively; the six parameters of the production function, η, ϕ, γ, λ, ρ, α; the fixed costs of an entrepreneur business in 1988 and 2016, δ_{1988} and δ_{2016}; the mass of non-entrepreneur firms m; the productivity of ICT capital in 1988 and 2016, a_{1988} and a_{2016}; the out of labor force values for 1988 and 2016, b_{1988} and b_{2016}; the probabilities of being a high skill type and of getting an entrepreneurial idea for non-college and college agents, θ_h^N, θ_h^C, θ_e^N and θ_e^C; the eight parameters of the low and high skill probability distributions for the two education levels; the four parameters of the entrepreneur productivity distributions for the two education levels; and the two parameters of the non-entrepreneur productivity distribution for 1988, $\tau_{f,1988}$ and κ_f, and the value of the minimum of this distribution for 2016, $\tau_{f,2016}$.

Some of these parameters can be normalized, some can be calibrated directly with the data and the remainder need to be calibrated with the model. I will discuss the parameters in these three groups.

Normalized parameters   Four parameters of the model can be normalized. I normalize the productivity of IT capital for 1988 to 1, the mean of low and high skill productivity for non-college agents to 1 and the fixed cost of entrepreneur businesses in 1988 to 0.

Externally calibrated parameters   Five parameters can be calibrated externally. The shares of the population that are non-college educated in 1988 and 2016 can be computed with the CPS and are 77.90% and 65.13%, respectively. I choose a value for the returns to scale of the production technology from the macro-entrepreneurship literature. Estimates for this parameter are in the range of 0.8 to 0.9 (e.g. Cagetti and De Nardi, 2006; Terajima, 2006) and I take a value near the middle of this range, 0.84.

The mass of non-entrepreneur firms, m, is also the ratio of the mass of non-entrepreneur firms to agents (since the population is one). This ratio can be expressed as

$$\frac{\text{Share of employment at non-entrepreneur firms}}{\text{Average employment at non-entrepreneur firms}} \times \frac{\text{Total employment}}{\text{Population}}.$$

I have already described how I compute the occupation distribution for the data. This provides the total employment to population ratio, which is 0.761. For the share of employment at non-entrepreneur firms I use one minus the share at entrepreneur firms. I approximate the share at entrepreneur firms with Asker et al.'s (2014) estimate of the share of employment accounted for by private firms, which is about 70%. For estimating the average employment at non-entrepreneur firms I use the average size of establishments at firms with at least 500 employees in the BDS in 1988, which is 62. I focus on firms with at least 500 employees since, as the earlier discussion of the data in Table 1 indicated, non-entrepreneur firms are mostly large firms. I use the number of

employees at establishments of these firms because the production technology is being calibrated for a business that is run by a single person and an establishment is probably a better measure of what one person can manage than a whole large firm. The model therefore thinks of large firms as a collection of production technologies. These numbers imply that the ratio of non-entrepreneur firms to population is 3.68×10^{-3}. This is the estimate of m.

To calibrate the productivity of IT capital in 2016 I use Eden and Gaggl's (2016) estimate of the evolution of the price of this type of capital relative to GDP for 1988 to 2013.[32] They estimate that the price of IT capital has decreased by about two-thirds over this period, which corresponds to an increase in the productivity of IT capital in the model by a factor of 3. The trend for the IT capital price is nearly flat by the end of their sample so I set $a_{2016} = 3$.

Internally calibrated parameters   This leaves 25 parameters to be calibrated using the model and data. All of these parameters are calibrated using data for 1988 unless specified otherwise. These parameters are calibrated jointly.

In addition to the data that has already been discussed I will also use data on the wages of employees for this part of the calibration. These moments come from the CPS dataset described in Section 2. I use moments of the income distributions of low and high skill agents with non-college education, and with college education. One limitation of this data is that it only includes wage and salary income and not other forms of compensation. This matters not only because it affects the measure of the growth of income over time, but also because it affects the change in the relative income of different groups. I adjust the income distributions estimated from the CPS for this using data from the Bureau of Labor Statistics' Employer Costs of Employee Compensation dataset. The details of how I compute wages from the CPS and how I compute the adjustment factors are provided in the appendix.

There are five remaining parameters of the production function to calibrate. η, ϕ and λ are calibrated using the share of income going to employees (from the BEA),[33] the ratio of the median low skill income to the median high skill income and the ICT share of capital (from the BEA detailed fixed assets tables). The two elasticity of substitution parameters γ and ρ are calibrated so that the model matches the growth of the average real wages of high skill and low skill employees. Since the CPS income data is topcoded, and to omit outliers, to compute the average high skill wage I compute the average within the 5th to 95th percentile, and do the same for the average low skill wage. In the model I compute these average wages in exactly the same way.

For the employee productivity distributions the standard deviations of the low and high skill

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[32]Note that using the price of IT capital relative to non-durable consumption instead would make little difference. The BEA's GDP price deflator increases by 81.2% from 1988 Q1 to 2016 Q1 while the Personal Consumption Index for Non-Durables increased 70.8%. Using the later would imply that a has increased by a factor of 2.83 instead of 3.

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

productivity distributions of non-college agents, σ_l^N and σ_h^N, are calibrated to target the to 90-10 ratios of non-college low skill employee wages and non-college high skill employee wages, respectively.[34] For these standard deviations for college educated agents, σ_l^N and σ_h^N, I use the same 90-10 ratios for these groups of agents. I calibrate the mean low skill productivity for college educated agents to target the ratio of their median wage to the median wage of non-college low skill employees. I take the same approach for the mean high skill productivity of the college educated using their median wage and that of high skill non-college agents. To determine the share of agents of each education level who are high skill types I target the shares who are high skill types in the data.

For entrepreneur productivities there are six parameters to calibrate: the probabilities that a person with each education level gets an entrepreneurial idea, θ_e^N and θ_e^C, and the four parameters of the productivity distributions. For each education level the three parameters are calibrated to target the share who are entrepreneurs, the share of entrepreneurs with businesses with 1–9 employees and the share with businesses with 10–99 employees.

There is a slight mismatch between the size distribution of entrepreneur businesses in the model and data. This arises because in the data self-employed people are asked to report the number of employees at their firm, which may have multiple owners who work at the firm as their main job. The data in Table 1 suggest that this is not common for entrepreneurs at firms with less than 100 employees, but is prevalent for firms above this threshold. In contrast in the model the size of an entrepreneur's business is the number of people that they alone employ in their production activities. To deal with this mismatch I use the share of entrepreneurs with firms with 1–9 and 10–100 employees as calibration targets (because nearly all of these appear to be run by one entrepreneur) and minimize the sum of the squared differences between the model and data for these moments.

The productivity distribution for non-entrepreneur firms has three parameters to calibrate. The minimum values for 1988 and 2016 and the shape parameter. The minimum values are calibrated so that the model matches the share of the employment at non-entrepreneur firms in 1988 and 2016. As already discussed I estimate this to be 30% for 1988. For 2016 I estimate the decline in the share of total employment at entrepreneur firms using the decline in the share of the labor force who are entrepreneurs (because the data indicates that the size distribution of entrepreneur firms has been constant, see Figure 4). Given the estimate of the occupation distribution described above, the share of the labor force who are entrepreneurs has declined by 13.5%. This implies that the 2016 employment share of entrepreneur firms is 39.45%. I calibrate the shape parameter κ_f to target the share of establishments with at least 100 employees in the BDS data.

This leaves three remaining parameters. The fixed cost of an entrepreneur firm in 2016 is

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[34]I use 90-10 ratios instead of variances because the income data in the CPS is topcoded.

calibrated to target the share of the population who are entrepreneurs in 2016. The out of labor force values for 1988 and 2016 are chosen to target the aggregate out of labor force shares for these years.

4.3 Calibrated model

The parameters, their values and the calibration procedure are summarized in Table 3. The calibration targets in the data and the corresponding values for the model are presented in Table 4. The model fits the data quite well and should be close to matching the data exactly with further refinement in the next draft. Before moving onto results I will comment on a few features of the calibration.

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 (56.4% compared to 12.1%) and high skill workers earn more (43% more at the median compared to low skill). They also earn more conditional on skill: the median high skill college educated worker earns 22% more than the median high skill non-college worker, and for low skill workers this education premium is 33%. The model captures this with different means of the productivity distributions for the two education levels (see Table 3). College agents also have larger businesses than non-college agents, with 70.3% of their non-college entrepreneurs having 1–9 employees compared to 59.2% of college entrepreneurs. They therefore earn more from this type of employment as well.

The elasticity of substitution parameters have been calibrated so that the model matches the changes in average low skill and high skill income from 1988 to 2016. These moments increase by 8% and 37%, respectively, in the data and the model matches these changes (see Table 4). The estimated elasticity of substitutions are 2.86 ($\frac{1}{1-\rho}$) between low skill labor and IT capital and 0.4 ($\frac{1}{1-\gamma}$) between high skill labor and the combined IT capital and low skill labor input. Thus the model has capital-skill complementarity as in Krusell et al. (2000).[35]

5 Results

In this section I evaluate the effects of the five changes to the economy from 1988 to 2016 that were outlined at the start of Section 4.2. The emphasis will primarily be on the share of agents who are entrepreneurs (the entrepreneur share). There are two main results: that the main force driving the decrease in entrepreneurship is the increase in fixed costs and the model fully accounts for the larger decline in entrepreneurship for college educated people compared to the non-college educated, with this difference being caused by skill-biased technical change.

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[35]Note that my parameter estimates are not directly comparable to those in Krusell et al. (2000) since our production functions and definitions of capital and labor types are slightly different. The same is true for the parameter estimates in vom Lehn (2015) and Eden and Gaggl (2016).

Parameter	Value	Calibration target/procedure
Normalized parameters		
a_{1988}	1	
μ_l^N	1	
μ_h^N	1	
δ_{1988}	0	
Externally calibrated parameters		
ω_{1988}	0.7790	1988 non-college share of population, CPS
ω_{2016}	0.6513	2016 non-college share of population, CPS
$\alpha + \eta$	0.84	From literature
m	3.68×10^{-3}	Number of non-entrep. establishments/labor force
a_{2016}	3	IT capital prices from Eden and Gaggl (2016)
Internally calibrated parameters		
η	0.252	Employee share of income
ϕ	0.484	Ratio of low to high skill median incomes
λ	0.227	ICT share of capital
γ	-1.5	Change in average high skill income
ρ	0.65	Change in average low skill income
σ_l^N, σ_l^C	0.57, 0.85	90-10 ratio for low skill wages by education
σ_h^N, σ_h^C	0.97	90-10 ratio for high skill wages for non-college
μ_l^C, μ_h^C	1.20, 2.35	Median college to non-college income for low and high skill
θ_h^N, θ_h^C	0.121, 0.564	High skill shares of by education
θ_e^N, θ_e^C	0.052, 0.094	Entrepreneur shares of by education
τ_e^N, τ_e^C	2.65, 2.65	Share of entreps. with 1–9 employees by education
κ_e^N, κ_e^C	0.170, 0.176	Share of entreps. w/t 10–99 employees by education
$\tau_{f,1988}, \tau_{f,2016}$	3.99, 4.32	Non-entrepreneur share of employment
κ_f	0.104	Share of firms with 100+ employees
b_{1988}, b_{2016}	0.14, 0.175	Out of labor force share
δ_{2016}	0.4	2016 entrepreneur share of population

Table 3: **Parameter values**

Moment	Model	Data
Technology		
Employee share of income	56.1%	52%
IT share of capital	10.5%	10%
Occupation distribution 1988		
Out of labor force share	19.1%	19.4%
High skill share, non-college	11.2%	12.1%
High skill share, college	51.3%	56.4%
Entrepreneur share, non-college	4.3%	4.5%
Entrepreneur share, college	6.9%	7.9%
Income distribution 1988		
Medians of high skill to low skill	1.47	1.43
College:non-college low skill medians	1.32	1.33
College:non-college high skill medians	1.28	1.22
90-10 ratio for low skill, non-college	4.2	3.6
90-10 ratio for high skill, non-college	3.6	3.5
90-10 ratio for low skill, college	5.1	4.2
90-10 ratio for high skill, college	3.6	3.6
Business size distribution 1988		
Share of non-college entrep. businesses with:		
1–9 employees	69.7%	70.3%
10–99 employees	29.5%	20.3%
Share of college entrep. businesses with:		
1–9 employees	64.1%	59.2%
10–99 employees	34.5%	25.9%
Share of businesses with:		
100+ employees	1.3%	2.3%
Non-entrepreneur employment share	26.3%	30%
Occupation distribution 2016		
Out of labor force share	24.6%	24.9%
Entrepreneur share	4.1%	4.1%
Income distribution 2016		
2016:1988 average low skill income	1.08	1.08
2016:1988 average high skill income	1.39	1.37
Business size distribution 2016		
Non-entrepreneur employment share	37.7%	39.5%

Table 4: **Calibration moments**

Parameter	1988	Baseline	SBTC	Prod	FC	All\$\backslash b$	All
Non-college population share, ω	0.78	0.65	0.65	0.65	0.65	0.65	0.65
IT capital productivity, a	1	1	3	1	1	3	3
Minimum non-ent'neur productivity, τ_f	3.99	3.99	3.99	4.32	3.99	4.32	4.32
Fixed cost, δ	0	0	0	0	0.4	0.4	0.4
Out of labor force value, b	0.14	0.14	0.14	0.14	0.14	0.14	0.175

Table 5: **Parameter values for experiments.** This table contains the parameter values for the five parameters that I am varying in the experiments.

To understand these results I am going to use six experiments. I will outline these now so that the path for the results, and the figures and tables, are clear. For each experiment and the 1988 economy the parameter values are presented in Table 5.[36] In the first experiment the only adjustment to the 1988 economy is to change the education distribution to the 2016 distribution. This provides a benchmark for what the economy would have looked like absent other parameter changes. For reasons that I will explain shortly this change to the economy increases the entrepreneur share. Since this works against the decline in entrepreneurship that the model aims to explain I will take this version of the economy as the baseline for the analysis and evaluate the ability of the other forces to explain the changes from this economy to the 2016 data. I will call this the *Baseline* economy in tables and figures. In the next three experiments I simulate skill-biased technical change, the increase in the relative productivity of non-entrepreneurs and the increase in fixed costs (one at a time) from the Baseline economy. These experiments are labeled *SBTC*, *Prod* and *FC*, respectively. In the fifth experiment (labeled *All\$\backslash b$*) I evaluate the effects on the Baseline economy of changing all three of these forces jointly. Finally I also change the out of labor force value to evaluate the effect of this change to the economy (labeled *All*). The values for the parameters that are being varied in these experiments are presented in Table 5.

Before discussing the results it is useful to review what changes in the data are targeted and which moments are free. Under the calibration strategy five moments for 2016 are used as calibration targets: the shares of the population who are out of the labor force and entrepreneurs, the average real low and high skill incomes, and the share of employment at non-entrepreneur businesses.[37] All other moments that I will discuss are endogenous outcomes of the model. While the model is designed to match the decrease in the entrepreneur share the contribution of each force to this change is endogenous so the model will speak to their relative importance. Also of particular interest are the changes in the entrepreneur shares for non-college and college agents and the size distribution of entrepreneur businesses. These moments are endogenous.

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[36]Additional details for the results presented in this section are provided in a Table in Appendix D.

[37]I also use the education distribution of the population and the productivity of IT capital in 2016, but these are measured externally to the model and don't constrain any of the moments that I discuss in the results.

5.1 Changes in education

Take the 2016 economy and increase the share of people with a college education to the 2016 level (from 22.1% to 34.87%). The effects of this on key moments of the economy are presented in Table 6. The results show that this change causes an increase in the aggregate entrepreneur share by 0.6 percentage points, and that the entrepreneur share also increases for both education levels. This means that once the change in education is factored in the decline in entrepreneurship to 2016 is larger than it appears in the raw data.

The driving force for these changes is that the increase in the share of the population with a college education increases the supply of high skill labor. This occurs because people with a college education are more likely to be high skilled and, conditional on being high skilled, have a higher productivity (see the calibration moments in Table 4). This change in the supply of skills affects wages. Table 6 shows that the low skill wage w_l increases by 13% while high skill wage w_h decreases by 28%. These two price changes have opposite effects on the profits of entrepreneurs, but it is the decrease in the cost of high skill workers that dominates, making entrepreneurship more profitable. The increase in the profits of entrepreneurs and the increase in the low skill wage result in more low skill agents entering the labor force and the shares of low skill agents who are employees and entrepreneurs increasing. For high skill agents their incentive to be entrepreneurs is stronger because its profitability has increased while the wage for high skill employees has decreased. Also note that the non-entrepreneur share of the economy is fairly stable when this change occurs so these changes are not resulting from a reallocation of production towards the entrepreneur sector. Rather, more people are choosing to be entrepreneurs and on average they have smaller firms.

From here on I will focus on this hypothetical economy in which all parameters are at their 1988 level except for the education share and assess how much of the change from this economy to the 2016 data each of the other forces in the model can explain.

5.2 Skill-biased technical change

The effects of skill-biased technical change on entrepreneurship are shown by the bars labeled SBTC in Figure 7. Recall that skill-biased technical change is modeled as an increase in the productivity of IT capital, which the calibration found to be substitutable with low skill labor and complementary to high skill labor. This causes the entrepreneur share for non-college agents to increase (the SBTC bar is positive), the entrepreneur share for college agents to decrease (the SBTC bar is negative), and the aggregate entrepreneur share decreases a little. In terms of explanatory power for the data, skill-biased technical change causes the difference between the entrepreneur shares for college and non-college agents to decrease from 3.14 percentage points to 2.65 percentage points, which is 25% of the decrease from the Baseline economy to the 2016 data. For the aggregate entrepreneur share this force generates 4% of the decrease.

	1988	Baseline
Entrepreneur shares (%)		
Non-college	4.3	4.5
College	6.9	7.6
Aggregate	4.9	5.5
Low skill wage, w_l	1	1.13
High skill wage, w_h	1	0.72
Non-entrepreneur share (%)	26.3	25.8
Out of labor force share (%)	18.3	13.7

Table 6: **Effect of changes in the education distribution.** The 1988 column presented moments for the model calibrated to the data for 1988. The Baseline column presents moments when the non-college share of the population, ω, changes to its 2016 value. The two wages are normalized to 1 for 1988 and the wages for the Baseline case are relative to 1988. The non-entrepreneur share is the share of employees who work for non-entrepreneur businesses.

The mechanism for these effects is as follows. Since under the calibration high skill labor is complementary to IT capital while low skill labor is substitutable, this change causes demand for high skill labor to increase and demand for low skill labor to decrease. The top two panels of Figure 8 show the effects on wages. The low skill wage decreases by 22% and the high skill wage increases by 105%. To determine the effects of these changes on entrepreneurship choices you need to consider the effects on the value of being an entrepreneur and on the value of being an employee. For entrepreneurs, the increase in productivity and the decrease in the low skill wage make them more profitable, but this is offset by the large increase in the high skill wage. For low skill agents the value of the alternative—working as an employee—goes down, while for high skill agents it goes up. Overall these forces work against entrepreneurship for high skill agents, push low skill agents into entrepreneurship and generate a small decrease in the aggregate entrepreneurship rate.

These results show that the main effect of skill-biased technical change is to shift entrepreneurship towards less educated people. On its own this force accounts for 25% of this shift, but as we'll see in the later results its power is amplified when it interacts with the other forces in the model.

5.3 Increase in relative productivity of non-entrepreneurs

The effects of increasing the relative productivity of non-entrepreneur firms on the share of agents who are entrepreneurs are presented in Figure 7 with the bars labeled Prod. We see that this change causes the entrepreneur shares for both education groups and in the aggregate to decrease, but the changes are small relative to the 2016 data (see the bars labeled 2016). The decrease in the aggregate entrepreneurship rate is from 5.53% to 5.31% which is 15% of the change that has occurred from the Baseline economy to the 2016 data. The mechanism for these changes is that the increase in the relative productivity of non-entrepreneur firms causes production to shift
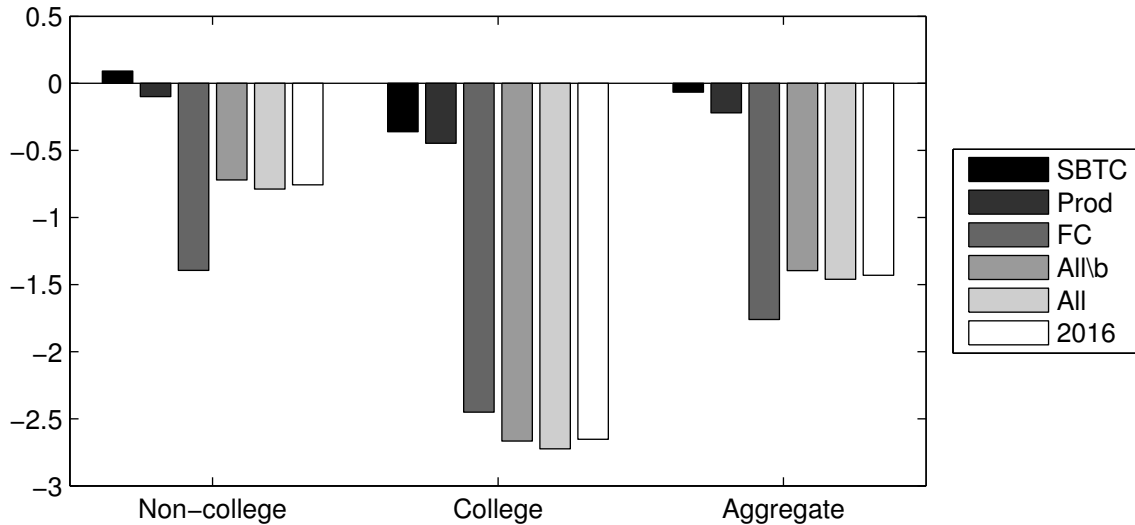
Figure 7: **Change in entrepreneur share from baseline economy** This figure presents the change in the entrepreneur shares for non-college agents, college agents, and the aggregate population from the Baseline economy (1988 economy with the 2016 education distribution) to other sets of parameters and the 2016 data. The relevant parameter values are described in Table 5. The units are percentage points (-1 is a 1 percentage point decrease).

towards them (see panel (c) in Figure 8). The increase in the non-entrepreneur share is about 10 percentage points, which is most of what is observed in the data. I will discuss exactly why the model and data tell us that the increase in the relative productivity of non-entrepreneur firms explain only a small fraction of the decline in entrepreneurship in a moment, once I discuss the effects of increasing the fixed cost.

5.4 Increase in fixed cost

For the effects of the increase in the fixed cost on the entrepreneur share focus on the bars labeled FC in Figure 7. They show that the increase in the fixed cost has a large effect on the aggregate entrepreneurship rate decreasing it by 1.7 percentage points to 3.8%, a little below the 2016 value. The mechanism for this effect is straightforward. An increase in the fixed cost directly decreases the profits of entrepreneurs, causing some of them to leave entrepreneurship. There are small decreases in wages as a result of this—see panels (a) and (b) of Figure 8—because the supply of labor increases and demand decreases. This dampens the decline, but these effects are second order.

Why does the model find the fixed cost to be more powerful for explaining the decrease in the entrepreneur share than the increase in the relative productivity of non-entrepreneur firms? The reason stems from the fact that the model is constrained to match the increase in the share of the economy accounted for by non-entrepreneur firms as well as the decline in the share of people who are entrepreneurs. Both forces could generate the decrease in the entrepreneurship that we have
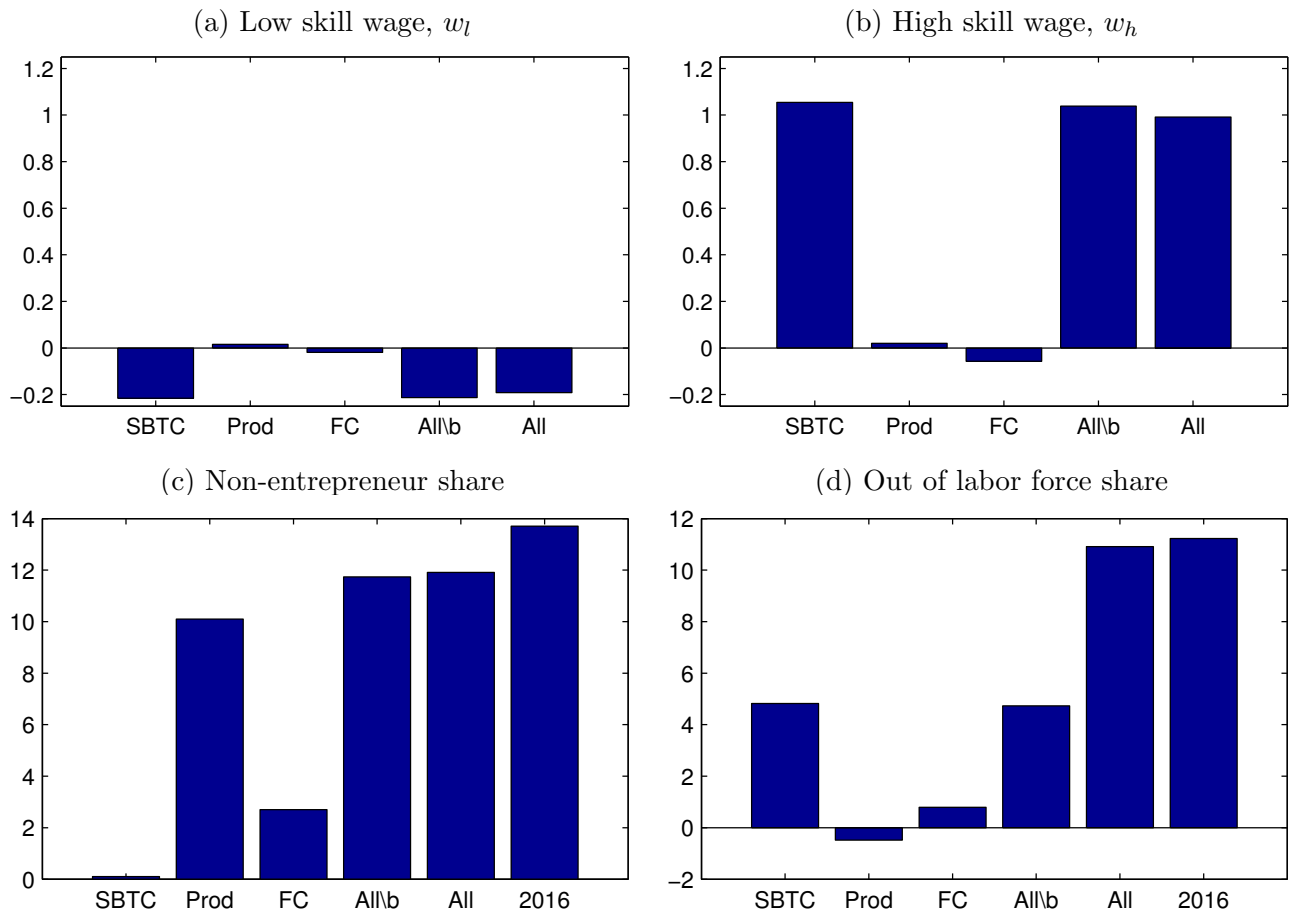
Figure 8: **Changes in low and high skill wages, the non-entrepreneur share of employment and the out of labor force share from the baseline economy.** This figure presents the changes in four moments of the model from the Baseline economy (1988 economy with the 2016 education distribution) to five other simulated economies and the 2016 data. The parameters for the simulated economies are described in Table 5. The non-entrepreneur share is the share of employees at non-entrepreneur firms. The units for the top two panels are the growth from the Baseline economy (0.1 is a 10% change). The units for the bottom two panels is the percentage point change (10 is an increase of 10 percentage points).

seen, but would have quite different implications for the non-entrepreneur share of the economy. Relative to the change in this share, the increase in fixed costs generates a much more rapid decline in entrepreneurship. It generates a decline in the share of people who are entrepreneurs of 1.7 percentage points for an increase in the non-entrepreneur share of the economy of 2.7 percentage points (see Figures 7 and 8(c)). In contrast the increase in the relative productivity of non-entrepreneur firms results in the share of people who are entrepreneurs decreasing by 0.22 percentage points for a 10 percentage point increase in the non-entrepreneur share of the economy. The model and data tells us that to generate the decline in entrepreneurship that we have seen given the size of the shift towards non-entrepreneur firms, most of it must have been driven by the fixed cost.

The reason why these forces affect the entrepreneurship rate at a different pace relative to the

shift towards non-entrepreneur firms is because they affect the extensive and intensive margins of entrepreneurship production differently. An increase in the fixed cost affects production decisions primarily on the extensive margin rather than the intensive margin. As the fixed cost increases the entrepreneurs who are making the least profit relative to their best outside option will drop out. But, conditional on choosing to be an entrepreneur agents will make the same production decisions given prices. In contrast when the productivity of entrepreneurs shrinks relative to the productivity of non-entrepreneurs those entrepreneurs who choose to continue operating will produce less. So in that case the reallocation happens on the intensive and extensive margins so for a given increase in the non-entrepreneur share of the economy the decrease in entrepreneurship is smaller.

A second point to note is that the increase in the fixed cost does not generate heterogeneous changes in the entrepreneurship rates for college and non-college educated agents. While the decrease is larger in levels for college educated agents (Figure 7 shows this), for both groups the decrease in the entrepreneurship rate is about 30%.

5.5   Joint effects

Now let's turn to considering the effects of the changes to the economy jointly. Start with the Baseline economy and consider simultaneous changes to the the productivity of IT capital, the relative productivity of non-entrepreneur firms and the fixed cost. Note that I am not changing the out of labor force value yet. The effects of these changes on the entrepreneur share are shown in Figure 7 with the bars labeled All\b.

The first thing to note is that the decrease in the aggregate entrepreneur share is virtually the same as for the data (compare with the 2016 bar in Figure 7). This was a calibration target, but since I am not changing the out of labor force value in the current experiment this means that that parameter does not play a role is explaining the change in the entrepreneur share. Comparing the bars for the SBTC, Prof, FC and All\b experiments it is clear that it is the increase in the fixed cost that accounts for nearly all of the decline.

Next consider the entrepreneur shares for each education level and recall that these are endogenous moments, they are not targeted. Figure 7 shows that the model generates changes in these shares that are the same as in the data. For non-college agents the increase in the fixed cost on its own would generate a decrease in the entrepreneur share that is too large. But this force is offset by skill-biased technical change attracting low skilled people into entrepreneurship. For college educated agents the increase in the fixed cost on its own generates most, but not all of the decrease in the entrepreneur share, and skill-biased technical change and the increase in the productivity of non-entrepreneur firms do the rest. Note that it is skill-biased technical change that is key to explaining why the decline in entrepreneurship is stronger for higher education people. It dampens the decline for non-college agents while amplifying the decline for college agents.

The results discussed earlier showed that on its own it can account for 25% of the change in the difference between the entrepreneurship rates of these groups, but when interacted with the other forces the model explains all of the change.

5.6   Increase in out of labor force value

I have left the effect of the change in the value of being out of the labor force until last since this force is not important for generating changes in entrepreneurship. The effects of this change to the economy are shown by comparing the results for the All\b and All experiments. The difference between them is the effect of increasing the out of labor force value. The results in Figures 7 and 8 show that this change to the economy does not affect the entrepreneur share, wages or the share of the economy accounted for non-entrepreneur firms in any significant way. The main effect is to increase the out of labor force share (panel (d) of Figure 8). What is happening is that the increase in the out of labor force value is attracting the agents with the lowest values to leave the labor force. These are the least productive low skill employees. Since they have low productivities, when they stop working the aggregate supply of low skill labor does not decrease much, so wages hardly change and the decisions of other agents are not affected.

5.7   Entrepreneur business size distribution

An additional check of the model is what it predicts for the size distribution of entrepreneur businesses. The results in Section 2 showed that the size distribution of entrepreneur businesses has been quite stable over time in the data. Figure 9 presents the size distributions of entrepreneur businesses for the experiments that I have discussed. Comparing the bars labeled 1988 with those labeled All shows the change to the size distribution resulting from all of the changes to the economy I am simulating. They show that the size distributions for these two economies are very similar. The second economy has slightly fewer small (1–10 employees) and large businesses (50+ employees) and slightly more businesses in the middle of the distribution, but the differences are small.

Interestingly this is despite the fact that some of the individual changes to the economy have a large impact on the size distribution. In particular the increase in the fixed cost of entrepreneur businesses (shown with the bars labeled FC) causes a significant shift in the size distribution towards larger firms. This is because the increase in fixed costs decreases the profits of all entrepreneurs by the same amount, pushing those with the smallest businesses to leave entrepreneurship. If one considered this change to the economy on its own they might conclude that it is not a plausible explanation for the decrease in entrepreneurship because of the stable size distribution in the data. However, the results show that when this change in considered in conjunction with the others it can be consistent with the stable size distribution. The main offsetting factors are the increase in the relative productivity of non-entrepreneur firms (the bars labeled Prod) and
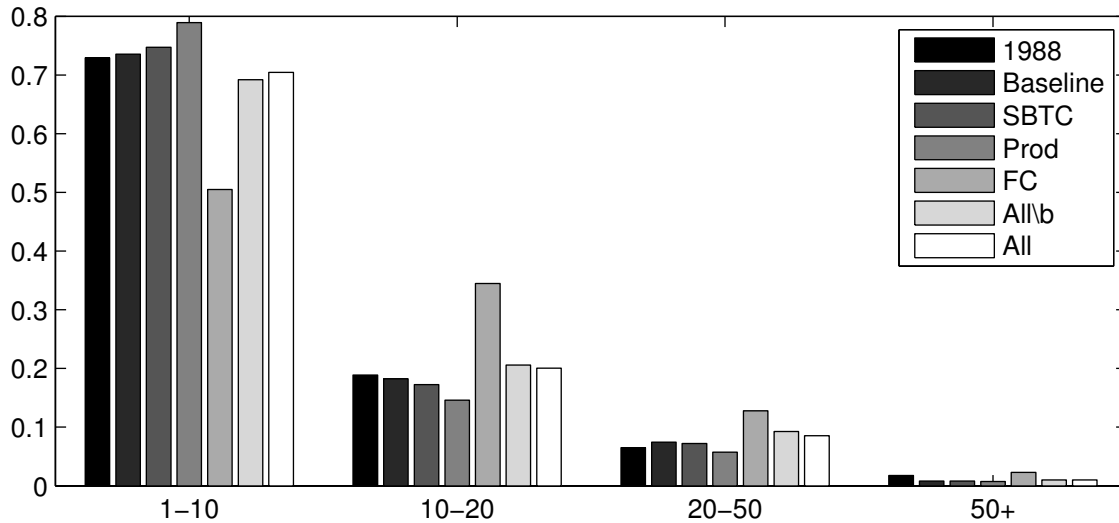
Figure 9: **Size distribution of entrepreneur businesses.** This figure presents the size distribution of entrepreneur businesses for seven sets of parameters of the model. These are the seven sets of parameters are presented in Table 5. The units are the share of entrepreneurs with businesses in each size category (0.7 is 70%).

skill-biased technical change (the bars labeled SBTC). As discussed above increases in the relative productivity of non-entrepreneur firms causes entrepreneur firms to shrink while skill-biased technical change results in a shift in entrepreneurship towards people with lower productivity businesses, which are smaller. When these forces are combined with the change in the fixed cost the resulting firm size distribution is quite stable.

5.8 Implications

The final question I consider is what the implications of these findings are for the economy. Of the three changes that are generating changes in entrepreneurship two of them are causing changes to the economy that are efficient. Skill-biased technical change and the increase in the relative productivity of non-entrepreneur firms cause changes in the occupation decisions of agents, but since there are no externalities to these decisions they are efficient.

For the increase in the fixed cost the interpretation depends on what exactly these fixed costs capture. Under my methodology I am inferring the change in fixed costs from other moments of the data. The advantage of this approach is that it avoids directly measuring changes in costs due to regulations, which is a difficult problem due to the large number of regulations in the economy in many different jurisdictions. However, it also means that I don't have direct evidence of what has caused the change in fixed costs. There is evidence that regulations that have affected them over time (see, for example, Kleiner, 2015)) but some of the increase could be due to other causes, such as a change in production technologies. It is beyond the scope of this paper to resolve this question. To the extent that the increase in fixed costs is due to regulations it has costs for the economy. By assuming that all of the increase in fixed costs is due to regulations we can estimate

an upper bound on the losses for the economy. To do this I compare aggregate consumption in two economies: one in which the model matches the 2016 data and a second in which all parameters are at their 2016 values except for the fixed cost, which takes its 1988 value. The result is that the increase in the fixed cost causes a decline in aggregate consumption of 3.4%. Most of this (82%) is due to the direct effect of more output being used for these costs and the remainder is due to efficiency losses because of the reallocation of production activities.

6   Conclusion

This paper has studied why the entrepreneurship in the US has declined over the last three decades. I have shown that the decline has been larger for more educated people, that the size distribution of entrepreneur businesses has been quite stable and that the decline has been virtually uniform across age groups. Based on this evidence I have argued that three forces appear relevant for understanding how entrepreneurship has changed: skill-biased technical change, an increase in fixed costs of entrepreneurs due to more regulation or technological reasons, and the superstar firm hypothesis which posits that technology changes have advantaged the largest firms.

Using a model of occupational choice calibrated to detailed data on occupations, income distributions and business size distributions I have evaluated these explanations. I find that the key driver of the decline in entrepreneurship is an increase in fixed costs. This conclusion stems from two results. First, skill-biased technical change creates a reallocation of entrepreneurship towards less educated people, but only a small decline in the aggregate rate. Second, for a given shift in economic activity towards non-entrepreneur firms an increase in fixed 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 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.

The changes to the economy caused by skill-biased technical change and the rise of superstar firms are efficient in the model. To the extent that the increase in the fixed cost is a result of regulations it is costly. I estimate that an upper bound on these loses is 3.4% of aggregate consumption, with about 80% of this due the direct costs and the remainder due to resulting production inefficiency. Uncovering the exact cause of the increase in fixed costs is a topic for future research. While there is existing evidence that regulations have generated an increase in the fixed costs of entrepreneurs, this paper does not decompose the increase in fixed costs by source. As well as changes in regulations there are other possible explanations, such as changes in production technologies. Identifying the cause of the increase in fixed costs is important for evaluating its consequences and determining policy responses.

The effects of skill-biased technical change in the model show that this force is altering the allocation of talent in the economy, shifting it away from entrepreneurship. In the environment in this paper this change is efficient. However, in different settings this may not be the case. For example if there are externalities from entrepreneurship, such as in a model of growth in which agents learn from the innovations of others, then a shift towards less productive entrepreneurs may not be optimal. Unpacking the effects of the change in the composition of entrepreneurs is an interesting path for future research.

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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.[38] 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 Section 2 I show 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 10(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.
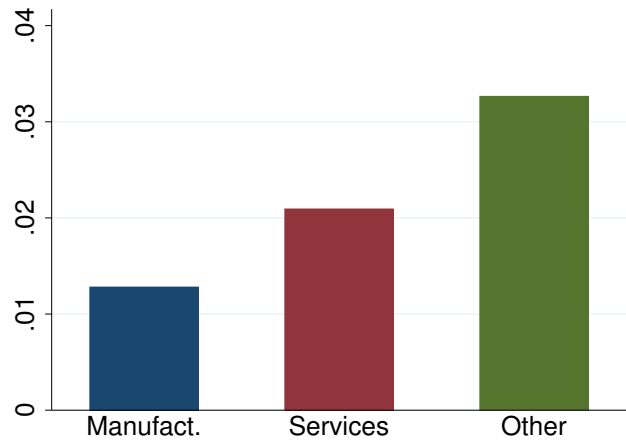
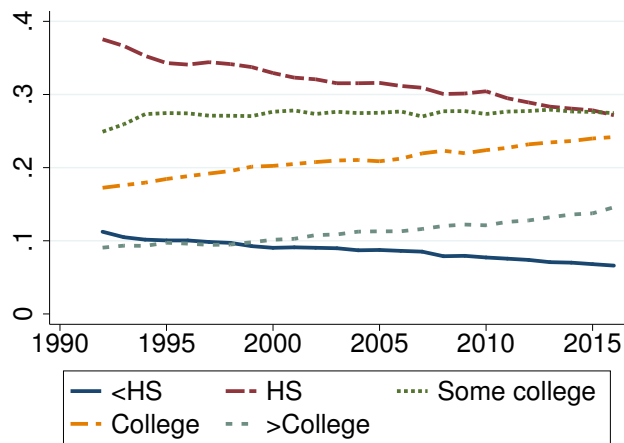Panels (c) and (d) show the illustrate the effects of changes in the education distribution. Over

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[38]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.
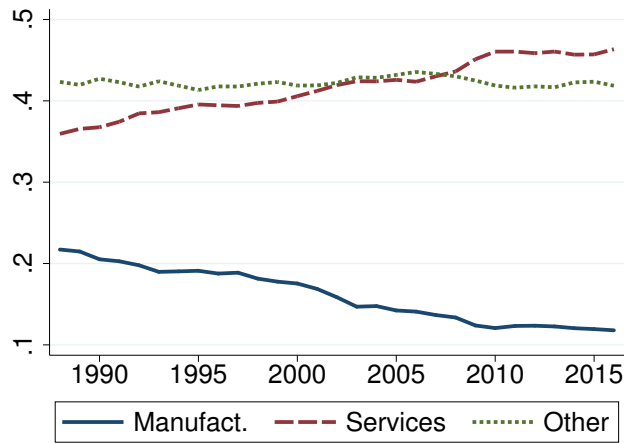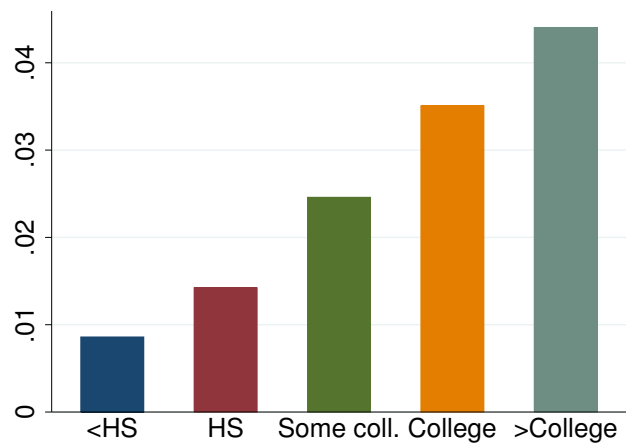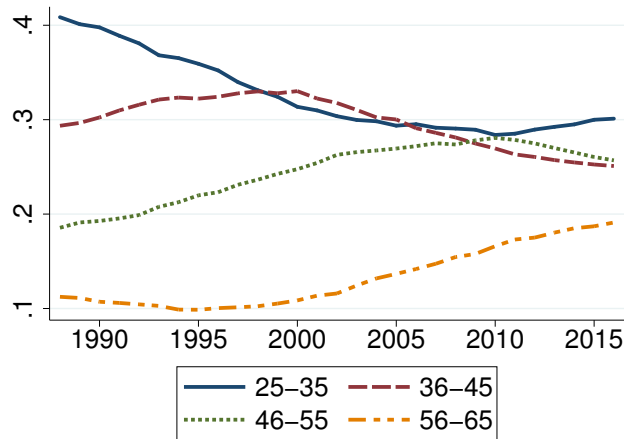
(a) Sectoral distribution
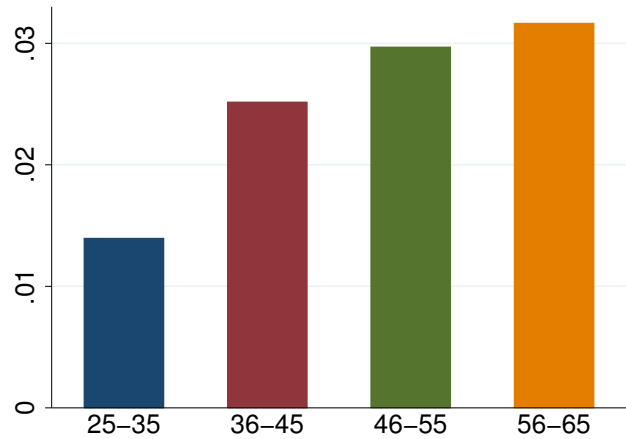
(b) Entrepreneurship rates by sector, 1992

(c) Education distribution

(d) Entrepreneurship rates by education, 1992

(e) Age distribution

(f) Entrepreneurship rates by age, 1992

Figure 10: **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.
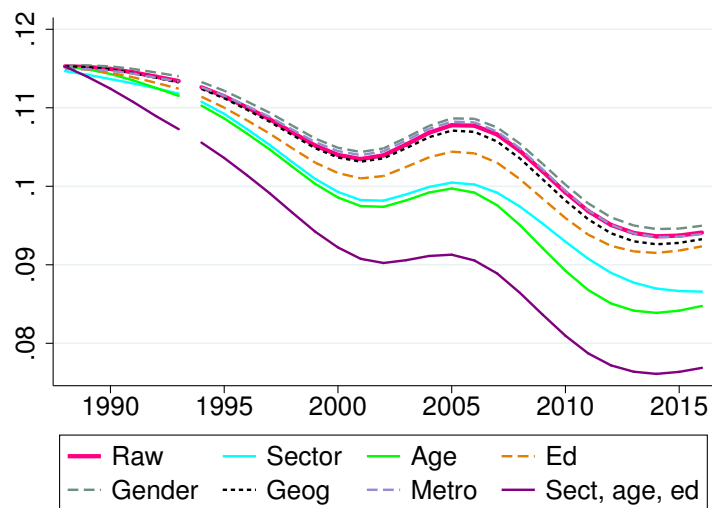
49

Figure 11: **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 (1). 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.

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 10(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 11 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 2 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 optimal input choices for firms and the value function for entrepreneurs are given by equations
(4), (5), (6), (7) and (8), respectively. The Γ terms for these expressions are:

$$\Gamma_{k_o}(w_l, w_h) = (\eta^{1-\alpha} D_3^\alpha)^{\frac{1}{1-\eta-\alpha}} \left(\phi + (1-\phi) D_1^{\frac{\gamma}{1-\gamma}} D_2^{\frac{\gamma(1-\rho)}{\rho(1-\gamma)}} \right)^{\frac{\alpha(1-\alpha)}{\gamma(1-\eta-\alpha)}},$$

$$\Gamma_{\ell_h}(w_l, w_h) = D_3^{\frac{1}{1-\alpha}} \Gamma_{k_o}^{\frac{\eta}{1-\alpha}},$$

$$\Gamma_{\ell_l}(w_l, w_h) = \left(D_1 D_2^{\frac{\gamma-\rho}{\rho}} \right)^{\frac{1}{1-\gamma}} \Gamma_{\ell_h},$$

$$\Gamma_{k_i}(w_l, w_h) = \left[\left(\frac{\lambda}{1-\lambda} \right) w_l a^\rho \right]^{\frac{1}{1-\rho}} \Gamma_{\ell_l},$$

$$\Gamma_w(w_l, w_h) = \Gamma_{k_o}^\eta \left[\phi \Gamma_{\ell_h}^\gamma + (1-\phi) \left(\lambda (a\Gamma_{k_i})^\rho + (1-\lambda)\Gamma_{\ell_l}^\rho \right)^{\frac{\gamma}{\rho}} \right]^{\frac{\alpha}{\gamma}}$$
$$- \Gamma_{k_o} - \Gamma_{k_i} - \Gamma_{\ell_h} w_h - \Gamma_{\ell_l} w_l,$$

where

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

$$D_2 = \lambda \left[\left(\frac{\lambda}{1-\lambda} \right) w_l a \right]^{\frac{\rho}{1-\rho}} + 1 - \lambda,$$

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

C   Additional details for the quantitative exercise

C.1   Estimating the entrepreneur share in the data

To take the model to the data I need an estimate of the share of people who are self-employed
with employees. I have outlined the procedure that I use for this in Section 4.1 of the main text.
Here I provide some additional detail on the data used in this procedure.

The data on the number of firms with 1–9 employees comes from the Business Dynamics
Statistics from the Census Bureau. 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.

As I mentioned in the main text, when I use the BDS data to estimate the share of people who
are self-employed with less than 10 employees who have at least one employee I use a different
CPS sample to what I use in the rest of the paper. Rather than restricting the sample to people
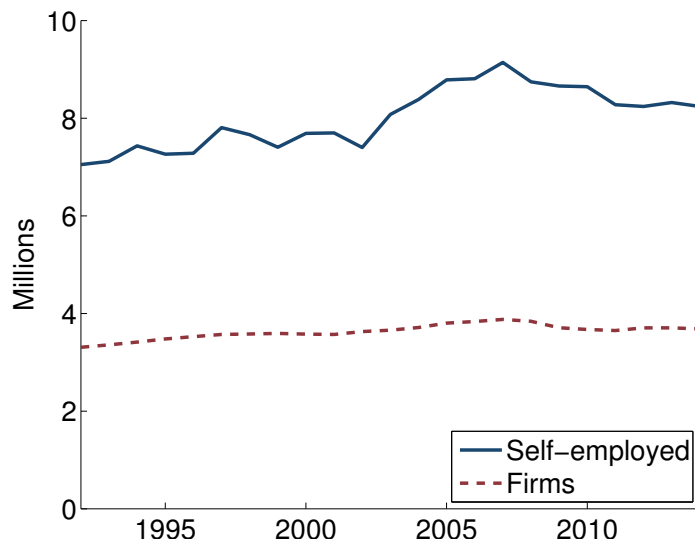
Figure 12: **Numbers of self-employed people with <10 employees and firms with 1–9 employees.** The *self-employed* series is the number of people aged 16+ in the US who are self-employed, are not in agriculture, and whose businesses have <10 employees. The *firms* series is the number of non-agriculture firms in the US with 1–9 employees.

aged 25–65 I use the full sample, which includes everyone aged at least 16. The reason for doing this is to estimate how many self-employed people there are in the US population so that the sample is comparable to the BDS sample.

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 12. 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.

C.2 Estimating the out of labor force share in the data

In the main text I describe how I make adjustments to the data in order to get an estimate of the out of labor force share that is consistent with the model. The aim of these adjustments is to remove the effect of increasing female labor force participation prior to the late 1990s. Some additional details on the data used in this procedure are as follows. Panels (a) and (b) of Figure 13 presents the out of labor force shares for women with non-college and college education levels. For both groups the out of labor force share starts increasing in the late 1990s. I take 1999 and 1997 as the turning points for non-college and college women, respectively. Panels (c) and (d) present the out of labor force shares for men and women with each education level for 1988 to 2016. These are overlaid with the linear trends for 1999–2016 for non-college agents and 1997–2016 for college agents, which are extrapolated back to 1988.

C.3 Occupation distribution from data

As described in the main text I make a number of adjustments to the data in order to estimate occupation distributions that are comparable to those from the model. The occupation distributions that result from this procedure are presented in Table 7.

(a) Non-college women, 1962–2016   (b) College women, 1962–2016

(c) Non-college men and women, 1988–2016   (d) College men and women, 1988–2016
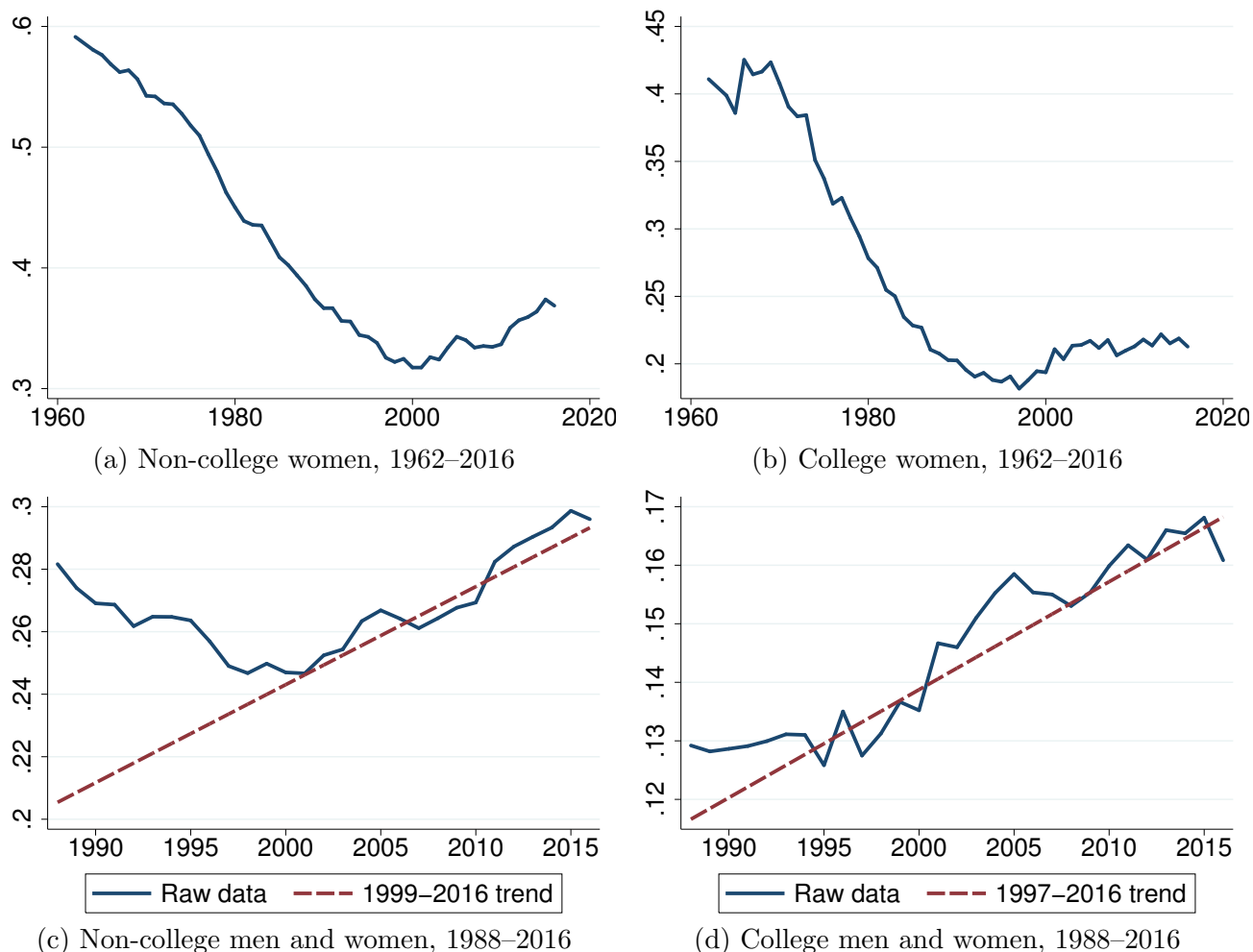
Figure 13: **Out of labor force share by education level** Panels (a) and (b) present the out of labor force share for women with the two education levels for 1962–2016. Panels (c) and (d) present the out of labor force shares for men and women for the two education levels for 1988–2016. These panels also show linear trends for 1999–2016 and 1997–2016, respectively, extrapolated back to 1988.

C.4 Computing wage distributions and adjusting for other compensation

For each skill group and each education-skill group I compute the distribution of real wages using data from the CPS. The income data in the March CPS is income earned in the previous calendar year. To estimate the wage distribution 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. To compute each person's average hourly wage I take their income earned from their main job and divide it by the number of weeks he or she worked multiplied by the usual hours worked per week. To put 2016 wages in 1998 dollars I use the Personal Consumption Expenditures Index from the BEA. This index is equal to 61.103 in March 1988 and 110.044 in March 2016.

I adjust the growth in wages from 1988 to 2016 for each skill group to account for growth in non-wage compensation. To do this I use data from the BLS' Employer Costs of Employee

	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 7: **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.

Compensation (ECEC) survey. 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. Particularly relevant for the purposes of this paper is that it separates wage and salary costs (which I'm calling wages for brevity) from other forms of compensation. The data is annual up to 2001 and uses payroll data that includes March 12th each year. From 2002 onwards the data is quarterly and I use the observation for the first quarter of each year.

My approach to adjusting the growth in the average wage for each skill level from 1988 to 2016 from the CPS data to account for growth in non-wage compensation is as follows. For each skill level I use the ECEC data to compute the gross growth rates of the average wage from 1988 to 2016 and average compensation for the same period. I then take the ratio of the gross growth rate of average compensation to the gross growth rate of the average wages from the ECEC and multiple it by the gross growth rate of the average wage from the BLS to get my estimate of the gross growth rate of compensation for my BLS sample. This procedure assumes that growth of compensation relative to wages is the same for my BLS sample as for the ECEC sample. The gross growth rates of average wages and average compensation for low and high skill wokers from 1988 to 2016 in the ECEC data are presented in Table 8. Based on these estimates I scale up the gross growth rate of low skill the average low skill wage in the CPS by a factor of 1.01 to account for faster compensation growth and for the aver high skill wage the scaling factor is 1.07.

It remains to specify exactly how I compute the growth in average wages and compensation for each skill level using the ECEC data. This data is by occupation so I start by allocating each occupation to a skill level using the division described in Section 4.1 of the paper.[39] 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 I compute the average wage and average total compensation for each skill for 1988, 2003, 2004 and 2016. This requires aggregating the data across occupations. To do this I weight each occupation by the share of my CPS sample in that occupation. In doing this I use the same occupations 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.[40] Finally I compute the gross growth rate in the average wage and average

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[39]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 2016.

[40]One mismatch between my CPS sample and the ECEC data arises because the ECEC data for 2004–16 groups construction and extraction occupations with farming, fishing and forestry, which I exclude from my sample. To

	Low skill	High skill
Wage growth	2.00	2.41
Compensation growth	2.03	2.59

Table 8: **Gross wage and compensation growth by skill, 1988–2016.** 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 1988 to 2016. 2.00 means that relevant variable grew by 100%. The data is from the Employer Cost of Employee Compensation dataset from the BLS.

total compensation for each skill level from 1988 to 2003 and from 2004 to 2016 and multiple the growth rates for the two periods to get a gross growth from from 1988 to 2016.

D   Additional results

Table 9 provides additional details for the results presented in the paper.

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deal with this I assume that the relative growth rates of compensation and wages are the same for these two types of occupations.

	1988	Baseline	SBTC	Prod.	FC	All\$\backslash b$	All	2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parameters								
ω	0.78	0.65	0.65	0.65	0.65	0.65	0.65	–
a	1	1	3	1	1	3	3	–
τ_f	3.99	3.99	3.99	4.32	3.99	4.32	4.32	–
δ	0	0	0	0	0.4	0.4	0.4	–
b	0.14	0.14	0.14	0.14	0.14	0.14	0.175	–
Entrepreneur shares (%)								
Non-college	4.3	4.46	4.55	4.36	3.1	3.7	3.7	3.7
College	6.9	7.6	7.2	7.1	5.1	4.9	4.8	4.9
Aggregate	4.9	5.53	5.47	5.31	3.8	4.1	4.1	4.1
Other moments								
Av. low skill income	1	1.13	0.96	1.14	1.11	0.96	1.07	1.08
Av. high skill income	1	0.72	1.44	0.73	0.69	1.42	1.39	1.37
Non-entrepreneur share (%)	26.3	25.8	25.9	35.9	28.5	37.5	37.7	39.5
Out of labor force share (%)	18.3	13.7	18.5	13.2	14.5	18.4	24.6	24.9

Table 9: **Effect of changes to the economy** Column (1) is for the model calibrated to the data for 1988. Column (2) is the 1988 calibration with the non-college share of the population, ω, changed to its 2016 value. Columns (3), (4) and (5) take the parameters from column (2) and adjust the IT capital productivity, the minimum productivity of non-entrepreneur firms and the fixed cost of entrepreneur firms, respectively, to their 2016 values. Column (6) changes all the parameters that have different values for 2016 except for the out of labor force value b (these are ω, a, τ_f and δ). Column (7) is the same as column (6) except that the out of labor force value is changed as well. Column (8) contains the data for 2016. The two average incomes in the third and fourth last rows are normalized to 1 for 1988 and the other columns provide the average incomes relative to 1988. The non-entrepreneur share is the share of employees who work for non-entrepreneur businesses.