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Lisboa, 2022 • www.bportugal.pt

Working Papers | Lisboa 2022 • Banco de Portugal Rua do Comércio 148 | 1100-150 Lisboa • www.bportugal.pt •
Edition Banco de Portugal • ISBN (online) 978-989-678-844-5 • ISSN (online) 2182-0422

What's Driving the Decline in Entrepreneurship?

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December 2022

Abstract
Why has there been a steady decline in entrepreneurship in the US in recent decades? To answer this question, I develop a general equilibrium occupation choice model and combine it with data on these choices. Skill-biased technical change can account for much of the decline in the relative entrepreneurship rate of more educated people, but cannot explain the decline in the aggregate level of entrepreneurship. The major factors in the decline in the share of people who are entrepreneurs, the firm entry rate, and the size of the entrepreneur sector are rising entry costs and outsized productivity gains by large non-entrepreneur firms.

JEL: E23, E24, J24, J31

Keywords: Entrepreneurship, firm entry, technical change, occupation choice, productivity.

Acknowledgements: Thanks to Tom Sargent, Laura Veldkamp and Mike Waugh for their guidance. Thanks to Andrew Atkeson, Anmol Bhandari, Jarda Borovička, Gian Luca Clementi, Chris Edmond, Raquel Fernandez, Loukas Karabarbounis, Pete Klenow, Jacob Madsen, Ellen McGratten, Virgiliu Midrigan, Simon Mongey, Michael Peters, Venky Venkateswaran, Gianluca Violante and numerous seminar and conference participants for their comments and suggestions. The views expressed in this article are the author's and do not necessarily represent those of Banco de Portugal or the Eurosystem. I acknowledge support from FCT—Portuguese Foundation of Science and Technology for the project UID/GES/00407/2020. This research was also funded in part by the Ewing Marion Kauffman Foundation. The contents of this publication are solely the responsibility of Nicholas Kozeniauskas.

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1. Introduction

The US is famous for providing an environment that fosters entrepreneurship and for its high degree of competition that ensures that the best firms flourish. Research supports the idea that entrepreneurship plays an important role in the economy by identifying its relevance for growth, job creation, income and wealth inequality, and economic mobility.[1] Entrepreneurship also receives considerable policy attention, for example through the Small Business Administration, and discussion in the media. In light of this, research documenting that measures of entrepreneurship in the US have declined in recent decades (e.g. Davis *et al.* 2006; Decker *et al.* 2014a,b; Pugsley and Șahin 2019) have generated considerable concern.[2]

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

To answer this question I develop a general equilibrium occupational choice model to capture peoples' decisions about whether to run a business, and study corresponding choices in the data. The occupational choice perspective provides new empirical facts about the decline in entrepreneurship, which allow me to evaluate a range of potential explanations. Simultaneously evaluating several explanations has an additional advantage. Some of the explanations are difficult to measure directly in the data. A common approach is to fit a model to match the change in a particular moment of the data, and then assess the performance of the explanation with respect to changes in other moments. This risks overfitting the model to the targeted moment, and thereby overestimating the quantitative power of the explanation in question. Considering a range of explanations and a range of moments simultaneously, reduces this issue.

Empirically, I consider three dimensions of entrepreneurship: the share of the labor force who own and operate a business (the *entrepreneur share*), the size of entrepreneurial businesses, and the entry rate of new firms in the economy. While the decline in the entry rate is a widely documented fact (see, for example, Decker *et al.* 2014a,b; Pugsley and Șahin 2019), the other facts come from looking at

1. For growth of the economy see, for example, Luttmer (2011); Acemoglu *et al.* (2018); Akcigit and Kerr (2018). For job creation see Haltiwanger *et al.* (2013); Adelino *et al.* (2017). For inequality and economic mobility see, for example, Quadrini (2000) and Cagetti and De Nardi (2006).

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

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

occupational choice data. I show that the entrepreneur share has declined by 16–24%, depending on the definition used, between 1987 and 2015. Additionally, the businesses of entrepreneurs have not grown in size to offset this decline, implying that economic activity has shifted towards non-entrepreneurial firms over time, such as large publicly-listed firms. A further striking feature of the data is that the decline in the entrepreneur share has been much larger for more educated people.

To interpret these changes in the data, I use a dynamic, general equilibrium, occupation choice model. Agents have a productivity for doing either low- or high-skill work, and an entrepreneurial productivity. All productivities are stochastic, which drives changes in occupational choices over time. I include two skill types to speak to the heterogeneity in changes in entrepreneurship with respect to education. Each period agents choose whether to be out of the labor force, work as an employee (*dependent employment*), or run a firm as an entrepreneur. There is an entry cost for starting a business, a fixed costs of operating each period, and production requires hiring labor and capital. There is also a non-entrepreneurial sector.

Within this framework I consider several changes to the economy that have the potential to explain the data. A natural consideration for the larger decline in entrepreneurship for the more educated is skill-biased technical change (SBTC). This force has pushed up the wages of high-skill people making dependent employment relatively attractive. The model captures SBTC in a standard way (e.g. Krusell *et al.* 2000; Autor *et al.* 2003), with two types of capital and changes in their prices shifting labor demand. Other types of technical changes are also promising. The 'superstar firms' idea (Autor *et al.* 2017) is that technological developments have disproportionately advantaged larger firms, which I model as increasing productivity in the non-entrepreneur sector.[4] Another line of thinking links productivity increases with larger fixed or entry costs (see Aghion *et al.* 2019; Hsieh and Rossi-Hansberg 2019; De Ridder 2019; Weiss 2020). There are other potential causes of rises in these costs, including increases in regulations covering areas such as occupation licensing, environmental protection, occupational health and safety, and food safety.[5]

SBTC is most promising as an explanation for the empirical changes in entrepreneurship because it increases the high-skill wage. In isolation, this makes dependent employment more attractive for the high-skilled and decreases the profits of all entrepreneurs. This pushes down the entrepreneur share for everyone, and

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

5. See Decker *et al.* (2014a), Davis and Haltiwanger (2014) and Davis (2017) for discussions of increasing regulation as an explanation for changes in business dynamism. Kleiner (2015) shows that the prevalence of occupational licenses has increased over time. Some other possibilities for rising fixed and entry costs include increases in the cost of finding a new idea (Bloom *et al.* 2020) or increasing market entry costs, such as the cost of establishing a customer base (Bornstein 2021).

more so for the high-skilled. However, these effects of SBTC do not occur in isolation. It is important to consider their origin, and the other associated changes in the economy. Specifically, the decrease in the price of IT capital increases profits, since this is a production input, making entrepreneurship more attractive. It also decreases the low skill wage, since that type of labor is relatively substitutable for IT capital, further increasing profits. The overall effect on the aggregate entrepreneur share is therefore a quantitative question. To answer this, the model is estimated using a rich array of empirical moments, with careful attention to matching changes in wages over time. The result is that while SBTC explains much of the decline in the *relative* entrepreneur share of more educated people, it cannot explain the decline in the aggregate entrepreneur share.

Regarding increases in fixed costs, entry costs and the productivity of non-entrepreneur firms, there are two key distinctions between their effects on entrepreneurship. The first is about how they affect the extensive margin of entrepreneurship (whether people are entrepreneurs or not) versus the intensive margin (how big their firms are). All of these changes to the economy cause fewer people to be entrepreneurs. However, an increase in the productivity of non-entrepreneur firms causes entrepreneur firms to shrink more than an increase in fixed or entry costs that generates the same decline in the entrepreneur share. The reason is that these changes to the economy have very different effects on wages. An increase in fixed or entry costs causes labor demand to fall, because fewer people choose to be entrepreneurs, so wages fall. In contrast, when non-entrepreneur productivity increases, the demand for labor from this sector increases, pushing up wages. The increase in wages attracts more high-productivity agents out of entrepreneurship. Since these are the entrepreneurs with relatively large businesses, it causes a larger decline in the employment of the entrepreneur sector.

The second key distinction arises from the effects of fixed and entry costs on the entry rate. An important determinant of this rate is the size of the wedge between the thresholds for entering and exiting entrepreneurship. A small wedge means that small shocks can cause new entrepreneurs to exit, and vice versa, so there is a lot of churn of entrepreneurs. When the wedge is larger, there is less churn. Increasing fixed and entry costs have different effects on this wedge. Rising entry costs increase the size of the wedge because they only affect the entry threshold. Larger fixed costs move both thresholds. More importantly, when fixed costs are larger, entrepreneurs need to be larger to operate. For larger firms, entry costs are less important relative to their profits, and therefore less relevant for their entry and exit decisions. This decreases the wedge between the thresholds and pushes the entry and exit rates up.

By showing that increases in fixed costs, entry costs, and the relative values of average entrepreneur and non-entrepreneur productivity have independent effects on three moments of entrepreneurship, the theory provides an identification strategy for these parameters.[6] Using this, these parameters are estimated for 1987 and 2015. I start the quantitative analysis by evaluating each explanation individually. All of these changes to the economy have some explanatory power for the data, but none of them is a home run on its own. When the changes to the economy are assessed jointly, the results decompose the contribution of each change to the economy on each moment of entrepreneurship. The relevance of each factor depends on the moment being considered. Increasing entry costs are the dominant factor in generating the decline in the firm entry rate, increasing productivity of non-entrepreneur firms accounts for most of the shift in employment to the non-entrepreneur sector, and all three factors contribute significantly to the decline in the entrepreneur share. A robustness exercise considers how allowing for changes in labor force growth to affect entrepreneurship, as argued by Karahan *et al.* (2021), Hopenhayn *et al.* (2021) and Peters and Walsh (2021), affects the results. By construction this decreases the magnitude of the changes in the data that need to be accounted for, but the messages about the relative roles of the mechanisms hold.

The results count against the decline in entrepreneurship being the result of a simple technological improvement, in the form of SBTC or increasing productivity of large non-entrepreneur firms. There are several possible causes for the increases in fixed and entry costs, and distinguishing between them may be important for understanding their economic implications. As a step towards this, the final section of the paper assesses two possibilities that have been considered in the literature: that they are linked to improvements in technology, and that they are the due to increasing regulation. I find that cross-sectional correlations between changes in entrepreneurship and measures of these theories are consistent with both theories, indicating that further investigation into them is a valuable direction for future research.

Contribution to the literature. The main contribution of the paper is to further our understanding of what has caused the decrease in entrepreneurship. There are other papers that have also tackled this question. Two contemporaneous papers, Salgado (2019) and Jiang and Sohail (2022), also consider the relevance of SBTC for the decline in entrepreneurship. Aghion *et al.* (2019) and De Ridder (2019) develop theories for a number of macroeconomic trends, including declining entry, based on improvements in IT technology allowing firms to operate with higher fixed costs and lower variable costs. Barkai and Panageas (2021) propose a theory with similar features. Hsieh and Rossi-Hansberg (2019) and Weiss (2020) argue that this type of technical change is relevant for other macroeconomic trends as well. Gutierrez *et al.* (2019) argue that increasing entry costs can rationalize increasing markups, low inflation, and push the entry rate down. The present paper adds to this body of work by studying these factors in a unified framework.

6. Independence is in the linear algebra sense of the term.

Karahan *et al.* (2021), Hopenhayn *et al.* (2021) and Peters and Walsh (2021) evaluate the effect of a decreasing labor force growth rate on the firm entry rate. A robustness exercise considers the impact of this explanation on the results. There are also demographic theories based on the aging of the population (Kopecky 2017; Engbom 2017),[7] research into the relevance of changes in market power (De Loecker *et al.* 2021), and analysis of the effect of increasing inertia in customer bases (Bornstein 2021). Akcigit and Ates (2019, 2021) study the effect of a range of changes to the economy in an innovation model. Methodologically, De Loecker *et al.* (2021) and Akcigit and Ates (2019) are closest to this paper. They also use a range of data moments to disentangle competing explanations.

On the empirical side, evidence of declining entrepreneurship has been documented in a number of recent papers (see Davis *et al.* 2006; Decker *et al.* 2014a,b; Pugsley and Şahin 2019; Hyatt and Spletzer 2013). This research primarily focuses on measuring entrepreneurship with the firm entry rate and uses firm microdata to study the phenomenon. By using occupational choice data I provide new facts that are useful for evaluating competing theories.[8] 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; Lee and Shin 2016) by showing that these changes to the economy effect entrepreneurial decisions as well as the types of jobs and wages for employees. The model builds on previous macro models of entrepreneurship (e.g. Quadrini 2000; Cagetti and De Nardi 2006; Buera and Shin 2013).

From here, Section 2 provides empirical facts and Section 3 the model. Section 4 uses a simplified version of the model to study explanations for the decline in entrepreneurship theoretically. Section 5 calibrates the model, quantitative results are presented in Section 6, and Section 7 provides additional empirical evidence for interpreting the results. Section 8 concludes.

2. Empirics

2.1. Data description

The data is the Current Population Survey (CPS) from the Bureau of Labor Statistics (BLS). 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 civilian non-institutionalized population of people aged 25–65 who are not

7. The empirical evidence underlying these is controversial as the aging of the population implies an increase in the entrepreneur share and the entry rate over time, based on estimates of these rates, conditional on age, from the Current Population Survey and Azoulay *et al.* (2020).

8. Two contemporaneous papers share some of these facts: Salgado (2019) and Jiang and Sohail (2022).

working in the agriculture or government sectors.[9] This provides cross-sectional samples taken in March each year that, once weighted, are representative of this population. The surveys ask respondents about their employment experience in the previous year, so the data covers the years 1987–2015. The sample size ranges from 63,019 to 105,283 individuals with an average of 87,292. I restrict attention to ages 25–65 to reduce the effect of changes in education and retirement decisions over time. I exclude the agriculture sector since there has been a significant decline in self-employment in this sector over time and want to eliminate concern that any of the results are driven by this.

For the empirical analysis I define an entrepreneur to be a person who is self-employed and has at least 10 employees in their business. The paper focuses on classifying people according to their main job in the calendar year prior to when each survey was conducted, since the March supplement provides information on income and firm size for these jobs.[10] The CPS classifies peoples' main jobs into five categories depending on who the work was for: the government; a private for profit company; a non-profit organization, including tax exempt and charitable organizations; self-employment; or for a family business.[11] In defining an entrepreneur I place a size threshold on their business to focus attention on the most economically significant businesses and avoid concern that any of the results are driven by very small businesses. I choose a threshold of 10 employees since this is the smallest threshold (other than zero) that is available for most of the sample period (1991–2015). All results hold without this size threshold.[12]

To give a sense of what component of the economy self-employed people account for, Table 1 presents information on the size distribution of the businesses of the self-employed and the size distribution of all firms in the economy for an example year, 1997. 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. Self-employed people account for a little less than half of the smallest businesses (<10 employees). Assuming that the self-employed in this size category have one firm each, which the data supports,[13] there are

9. The data has been accessed from the Integrated Public Use Microdata Series (Flood *et al.* 2015), commonly known as IPUMS. Data prior to 1988 is omitted because the pre-1988 survey does not allow for a consistent measure of self-employment over time. See the Appendix for a discussion of this.

10. A person's main job is their longest job in the previous year. Over the sample period, employed people earned an average of 96.4% of their self-employment and dependent employment income in the previous calendar year from their longest job—see the Appendix for more details on this.

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

12. For those not presented in the main text, see the Appendix.

13. In 1992 there was 1.07 owners per business for businesses with less that 10 employees in the US. Assuming that most of these owners work in their business as their main job, which seems

Firm size (employees)	*Self-employed (000's)*	*Firms (000's)*
<10	8,205.5	18,750.8
10–99	1,040.3	1,035.1
100–499	135.0	75.3
500–999	26.2	8.0
1000+	133.3	9.5

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 (CPS and BLS). The Firms column is the number of firms in each size category (Business Dynamics Statistics and Non-employer Statistics). Agriculture and public administration sectors are excluded where relevant.

approximately 8.2 million business in this size category associated with a self-employed person, and 10.5 million without. The latter can arise because of people owning businesses which they don't run as their main occupation. For medium sized businesses (10–99 employees), self-employed people account for most of them. In this size category there is an average of 1.35 owners per firm so the self-employed account for 770 thousand out of the 1.04 million firms.[14] For large businesses (100+ employees) there are many more self-employed people than firms: 133,300 compared to 9,500. While I don't have an estimate of the number of owners per firm in this category these numbers indicate that there are many self-employed people running large businesses.[15]

2.2. Aggregate entrepreneur share

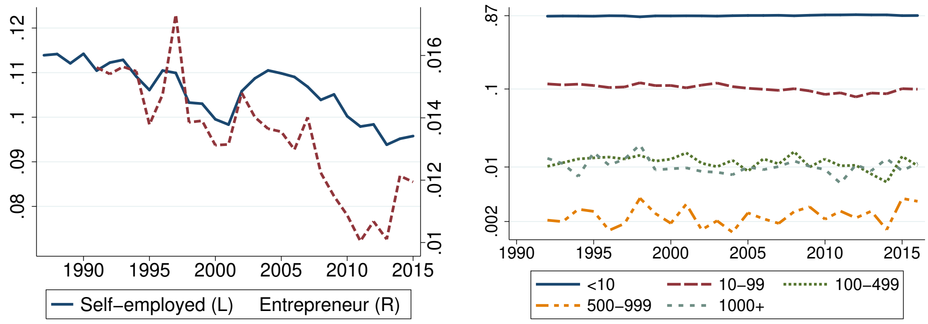
I define the aggregate entrepreneur share to be the share of the labor force who are entrepreneurs.[16] I use the labor force as the numerator rather than the population to abstract from the effect of changes in labor force participation over time. I define the self-employed share analogously. These two shares are presented in Figure 1(a). The entrepreneur share (right hand axis) has declined from 1.56% to 1.19%, a 24% decrease, while the self-employed share (left hand axis) has declined from 11.4% to 9.6%, a decrease of 16%. Both rates have cyclical fluctuations but downward trends.

reasonable for small businesses, this supports that there is approximately one self-employed person per business in this size category. The data source for this is discussed in the Appendix.

14. See the Appendix for a discussion of this owners per firm estimate.

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

16. See the Appendix for the details of the labor force definition.



(a) Entrepreneur and self-employed shares (b) Size distribution of businesses

Figure 1: **Entrepreneur share and size distribution of businesses.** The self-employed and entrepreneur shares are the shares of the labor force who are self-employed and entrepreneurs, respectively. Their values are presented on the left and right axes of panel (a), respectively. The scales are such that the relative values of the two axes are constant. Panel (b) presents the distribution of the number of employees of businesses of the self-employed (log scale).

There are a number of factors that could explain this fact, which would not imply that there has been a general decline in entrepreneurship. The aggregate decline could be the result of composition effects, it could be driven the a small number of sectors, it could be due to a decreasing share of entrepreneurs being captured by the definition over time because of changes in time allocation between occupations or ownership structure. In the Appendix I show that the fact is robust to these considerations. I also provide evidence from an alternative dataset, the Survey of Income and Program Participation, for a slightly different time period (1983–95) as further evidence.

2.3. Entrepreneur firm size

The second fact is that the size distribution of entrepreneur firms has been stable over time. Figure 1(b) presents the share of self-employed people with firms in different size categories for 1991–2015.[17] It shows that the shares in each category have been approximately flat over time. There is an uptick in the share of the self-employed with businesses with 500–999 employees at the end of the sample, but this is only in the last three years and so does not establish a long run upward trend.

This fact has two important implications. First, it means that the decline in entrepreneurship has not been concentrated among 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

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

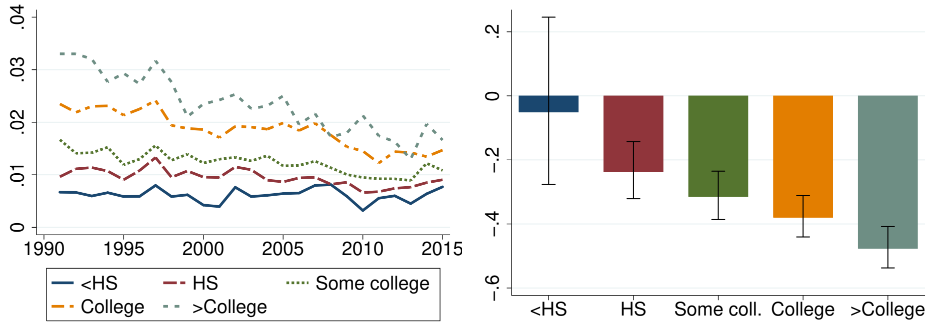
decreased indicates that over time there has been a shift in economic activity towards firms that aren't run by a self-employed people. I will call these *non-entrepreneur* firms.

2.4. Changes in entrepreneurship by education

The third fact is about how the decrease in the entrepreneur share 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). Figure 2(a) shows that the entrepreneur share is higher for more educated people throughout the period of analysis and has been decreasing more rapidly. To compare the changes in entrepreneur shares across these groups, panel (b) presents the percentage change in the entrepreneur share from 1991–94 to 2012–15 for each group. I pool data across years at the end points to smooth out year to year volatility. It shows a clear pattern of larger decreases in the entrepreneur share for higher education levels. At less than a high school education the decrease is 5.1% while for more than a college education the decrease is 47.7%.

The larger decline in entrepreneurship for more educated people is robust to a number of considerations, which are explored in detail in the Appendix. The fact holds when the self-employed share is used instead of the entrepreneur share, so it applies for people with smaller business as well as larger ones. The professional services, and finance, insurance and real estate sectors, account for a relatively high share of employment for higher education groups, so it could be that these sectors are driving the result. This would be the case, for example, if the fact was due to lots of lawyers, doctors and accountants switching from running their own businesses to working for someone else. However, the fact holds when these sectors are dropped from the sample, and the magnitudes of the declines conditional on education remain very similar.

To summarize, the share of the labor force who are entrepreneurs has declined and, since entrepreneurial firms have not increased in size, that labor has shifted towards the non-entrepreneurial sector. In addition to these two margins of entrepreneurship declining, it is well known that the rate at which new businesses are being formed has also declined (see, for example, Decker *et al.* 2014b; Pugsley and Şahin 2019). The decline has been skill-biased, with a larger fall in the entrepreneur share for more educated people. These four moments of the data will form the basis for evaluating potential explanations.



(a) Entrepreneur share, 1991–2015 (b) Percentage change, 1991/94–2012/15

Figure 2: **Entrepreneur share by education and percentage change.** Panel (a) is the share of the labor force for each education level who are entrepreneurs. Panel (b) is the relative change in the entrepreneur share from 1991–94 (pooled date) to 2012–15 for each education group (i.e. -0.1 is a decline of 10%). The whiskers are 95% confidence intervals estimated by Poisson regression.

3. Model

3.1. Environment

Time is discrete and infinite, and there is a unit mass of agents. When an agent is born it has a type, high or low-skill, which is fixed for life. With probability θ_h an agent is a high type, and otherwise she is a low type. An agent that is a high type draws a productivity z_h for doing high-skill work at birth, and if she is low type then she draws a productivity for low-skill work z_l. Each agent also receives an entrepreneurial productivity z_e at birth. To simplify notation going forward, let $\mathbf{z} = [z_l, z_h, z_e]$ be the productivity vector of an agent, with $z_l = 0$ for high types and $z_h = 0$ for low types. At birth this productivity vector is drawn from a distribution $G(\mathbf{z})$. It then evolves stochastically over time according to a Markov chain, $G(\mathbf{z}'|\mathbf{z})$. The distribution for initial draws, $G(\mathbf{z})$, is the stationary distribution of the Markov chain. Agents discount the future at rate β and each agent dies at the end of each period with probability δ. An agent that dies is replaced by a new agent at the start of the next period.[18]

For the quantitative exercise later in the paper, θ_h and the productivity distributions will be allowed to depend on an agent's education level so that the model can be mapped to the data. Education will be taken as given. For now, education is suppressed, as it is not essential for the theory.

Each period agents must choose whether to work and what kind of work to do: their *occupational choice*. If an agent chooses not to work she receives b units

18. The setup of the model is related to existing macroeconomic models of entrepreneurship, such as Quadrini (2000) and Cagetti and De Nardi (2006).

of consumption, which can be thought of as the output of home production, consumption-equivalent units of leisure, or a combination of both. If an agent has low-skill productivity $z_l > 0$ then she can work as a low-skill employee. She will provide z_l efficiency units of low-skill labor and earn income $z_l w_l$, where w_l is the low-skill wage per efficiency unit. If an agent has high-skill productivity $z_h > 0$, then she can work as a high-skill worker and earn $z_h w_h$, with these variables interpreted analogously to z_l and w_l. Finally agents can choose to be entrepreneurs. If an agent was not an entrepreneur last period then she needs to pay an entry cost ψ_e. Then each period of entrepreneurship the agent pays a fixed operating cost, ψ, and can run a production technology $f(z_e, k_o, k_i, \ell_l, \ell_h)$. It is assumed that being an entrepreneur is a full-time occupation so that an entrepreneur can't also be an employee.[19] As an entrepreneur the agent hires inputs to produce and keeps the profits from the operation. There are four inputs. The two types of capital, k_o and k_i, can be rented at rates r_o and r_i, respectively. The two labor inputs are high and low-skill labor measured in efficiency units, ℓ_l and ℓ_h, which have prices w_l and w_h.

The objective of each agent is to maximize the present discounted value of utility. The utility function is $u(c)$, satisfying $u'(c) > 0$, $u''(c) < 0$ and $\lim_{c \to 0} u'(c) = \infty$. Agents consume what they earn each period.[20]

There is also a non-entrepreneurial sector, modeled by a representative non-entrepreneur firm. It has productivity z_f and produces using the same production function as entrepreneurs, $f(z_f, k_o, k_i, \ell_l, \ell_h)$.[21] This firm should be thought of as representing large firms in the economy, such as public firms, that don't have an owner who runs them. In contrast to entrepreneurial firms, the productivities of non-entrepreneurial firms are assumed to be intrinsic to the firm, embodied in the ideas and institutional structures that have been developed over time rather than being attached to an owner-manager.[22] The representative non-entrepreneur firm is owned equally by all agents and is operated to maximize the present discounted value of profits.

19. The data supports this approach. For every year in the CPS from 1987 to 2015, the average share of annual income from a person's main job is over 95% for both the self-employed and the dependent employed. See Appendix for more details.

20. Saving is abstracted from since its not central to the mechanisms being studied.

21. It would be equivalent to have a continuum of non-entrepreneur firms with a distribution of productivities, as they would aggregate to a representative firm. I abstract from fixed and entry costs for this sector, since it is composed of large firms for whom these costs would be insignificant.

22. An alternative approach would be to allow non-entrepreneur firms to have managers whose entrepreneurial productivities affect the productivities of these firms. However, the number of non-entrepreneur firms in the economy is small, so, if you were to count such people as entrepreneurs, it would not be quantitatively important for moments of entrepreneurship. For example, in the quantitative exercise the non-entrepreneur sector is estimated to account for 50% of employment in the economy in 1987. In that year in the data, this share of the economy was accounted for by the largest 0.7% of firms (Business Dynamics Statistics).

3.2. Production technology

The production technology is chosen to embody SBTC. The motivation for this is that this type of technical change has caused the wages of higher skill people to increase in absolute terms, and relative to those of lower skill workers (e.g. Krusell *et al.* 2000). All else being equal, this creates a incentive for high-skill people to be employees instead of entrepreneurs, in a way that would be consistent with the data. We also 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 2018).

The specific production function builds on existing research on technical change. The core idea is that improvements in capital technology have allowed capital to substitute for lower skill labor, and increased demand for higher skill workers (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, among other things, provides information services that were previously provided by workers such as travel agents and call center employees. Google needs few low-skill employees to provide these services but needs a lot of computer scientists.

The functional form for the production technology is

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

where $\eta, \varphi, \lambda, \alpha \in (0,1)$; $\alpha + \eta < 1$; and $\tau, \gamma < 1$. The nested CES structure follows other papers that study the effects of technical change quantitatively (Krusell *et al.* 2000; vom Lehn 2015; Eden and Gaggl 2018). The main difference here is the use of a decreasing returns to scale technology since this paper studies production at the firm, rather than the aggregate, level and needs a distribution of firms. The productivity of the firm z is z_e for an entrepreneur and z_f for the non-entrepreneur sector. There are two types of labor, low-skill ℓ_l and high-skill ℓ_h, both measured in efficiency units. k_i and k_o are two types of capital. k_i is the type of capital that drives technical change. Its degree of substitutability/complementarity with low and high-skill labor are determined by τ and γ, respectively. There are no restrictions on whether, and the degree to which, these inputs are substitutes or complements, allowing the data to determine this when the model is calibrated. When I take the model to the data I will measure k_i with information and communication technology, as others have (e.g. Eden and Gaggl 2018; Cortes *et al.* 2017), so I will call this IT capital. The fourth production input is k_o, which is all other capital. This is combined with the other inputs in Cobb-Douglas form. It is 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 $\varepsilon \in \{0,1\}$ be an indicator for whether an agent was an entrepreneur in the previous period. The value function of an agent at the start of a period is denoted

$V(\mathbf{z},\varepsilon)$.[23] The value functions for being out of the labor force, a low-skill employee, a high-skill employee, and an entrepreneur are, respectively:

$$V_{\mathsf{olf}}(\mathbf{z},\varepsilon) = u(b+\pi_f) + \beta(1-\delta)\mathbb{E}[V(\mathbf{z}',0)|\mathbf{z}], \tag{2}$$
$$V_{\mathsf{l}}(\mathbf{z},\varepsilon) \quad = u(z_l w_l + \pi_f) + \beta(1-\delta)\mathbb{E}[V(\mathbf{z}',0)|\mathbf{z}], \tag{3}$$
$$V_{\mathsf{h}}(\mathbf{z},\varepsilon) \quad = u(z_h w_h + \pi_f) + \beta(1-\delta)\mathbb{E}[V(\mathbf{z}',0)|\mathbf{z}], \tag{4}$$
$$V_{\mathsf{e}}(\mathbf{z},\varepsilon) \quad = u(\pi(z_e,\varepsilon) + \pi_f) + \beta(1-\delta)\mathbb{E}[V(\mathbf{z}',1)|\mathbf{z}]. \tag{5}$$

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

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

$\mathbb{1}_a(A)$ is the indicator function for whether variable a has value A, when A is a real number, and whether $a \in A$, when A is a set. The optimal choice for input x and the resulting profit function are

$$x(z_e) = \Gamma_x z_e^{\frac{1}{1-\alpha-\eta}}, \tag{6}$$
$$\pi_e(z_e,\varepsilon) = \Gamma_\pi z_e^{\frac{1}{1-\alpha-\eta}} - \mathbb{1}_\varepsilon(0)\psi_e - \psi,$$

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

Denote the set of possible occupations $\mathcal{O} \equiv \{\mathsf{olf}, l, h, e\}$ where the notation corresponds to the subscripts on the relevant value functions. The value function and occupation choice function satisfy:

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

The production problem for the representative non-entrepreneur firm is

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

which yields the same functions for input choices and output as for entrepreneur firms, $x(z_f)$ and $y(z_f)$, and the profit is $\pi_f = \Gamma_\pi z_f^{\frac{1}{1-\alpha-\eta}}$.

Agents in the model are distributed over the states $(\mathbf{z},\varepsilon) \in \mathbb{R}^3_+ \times \{0,1\} \equiv \mathbb{Z}$. There will be a stationary distribution of agents over these states, $Q : \Sigma_{\mathbb{Z}} \to [0,1]$, where $\Sigma_{\mathbb{Z}}$ is the relevant σ-algebra on the state space.[24] The market clearing

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

24. See the Appendix for the mathematical details of the stationary distribution.

conditions are:

$$\int_{\mathbb{Z}} \mathbb{1}_{o}(s) z_s \, dQ = \int_{\mathbb{Z}} \mathbb{1}_{o}(e) \ell_s(z_e) \, dQ + \ell_s(z_f), \text{for } s \in \{l, h\}, \tag{8}$$

$$\int_{\mathbb{Z}} \mathbb{1}_{o}(e) \Big(\pi_e(z_e, \varepsilon) + w_l \ell_l(z_e) + w_h \ell_h(z_e) + r_o k_o(z_e) + r_i k_i(z_e) + \mathbb{1}_{\varepsilon}(0) \psi_e + \psi \Big) \, dQ$$
$$+ \pi_f(z_f) + r_o k_o(z_f) + r_i k_i(z_f) = \int_{\mathbb{Z}} \mathbb{1}_{o}(e) y(z_e) \, dQ + y(z_f). \tag{9}$$

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

Equilibrium. A stationary equilibrium is a pair of wages $\{w_l, w_h\}$*, a function for occupational choices* $o(z_l, z_h, z_e, \varepsilon)$*, production input decisions for entrepreneurs and non-entrepreneur firms* $\{\ell_l(z), \ell_h(z), k_o(z), k_i(z)\}$ *with* $z = z_e$ *for entrepreneurs and* $z = z_f$ *for non-entrepreneurs, and a distribution* Q *of agents over idiosyncratic states, such that: the production input decisions of entrepreneurs and non-entrepreneur firms satisfy* (6)*; occupational choices satisfy* (7)*; the distribution of agents* Q *is stationary; and the markets for low-skill labor, high-skill labor and the final good clear in accordance with* (8) *and* (9).

4. Sources of declining entrepreneurship

The analysis of declining entrepreneurship focuses on a set of theories that are guided by the empirical facts presented in Section 2, and theories that have been proposed in the literature. The first is SBTC, as previewed in the previous section. This force has pushed up the wages of higher skill people, in a way that could decrease their entrepreneur share, and thereby the aggregate entrepreneur share as well.

The second idea that is explored is that there have been other changes in technology that have advantaged the largest firms in the economy and resulted in production becoming increasingly concentrated among them.[25] This type of force has the potential to decrease both the entrepreneur share, and the size of the entrepreneur sector, consistent with the data. 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. In the model I treat this as an increases in the productivity of the non-entrepreneur sector. Ideas for why technological change would have advantaged these firms 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.

There is a third class of explanations that relate to increasing fixed and entry costs in the model. One explanation in this class is that the level of regulation has

25. See Davis and Haltiwanger (2014) for discussion of this idea.

increased and, because regulations have a large fixed cost of compliance, they have burdened smaller businesses more.[26] Regulations that are commonly discussed as having this effect include increases in occupational licensing, weaker enforcement of anti-trust laws and zoning restrictions.[27] Another idea that focuses on rising fixed or entry costs is that changes in technology have increased the fixed cost component of production, generating an advantage for larger firms (Aghion *et al.* 2019; Hsieh and Rossi-Hansberg 2019; De Ridder 2019). Examples of this include firms like Amazon and Walmart that have sophisticated logistic systems that would be expensive to replicate, but allow them to deliver products with low variable cost. Another example from the services sector is restaurant chains centralizing the development of menus and the training of chefs (see Hsieh and Rossi-Hansberg 2019).[28]

4.1. Occupational sorting in a simplified model

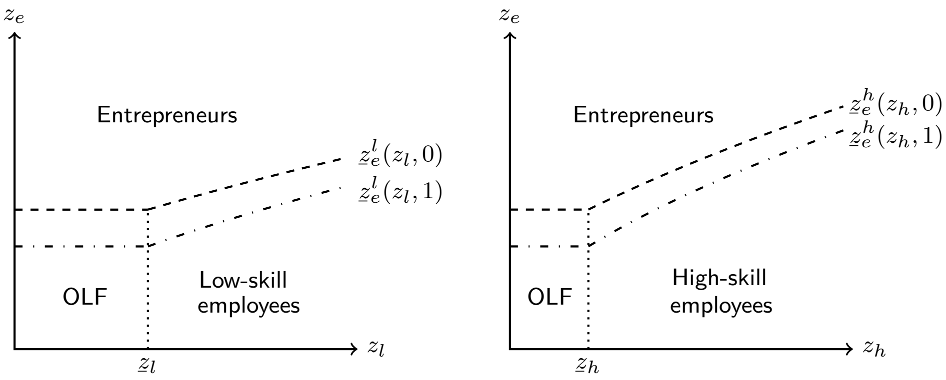
Consider a version of the model which has a single period. Agents are either low or high-skill, and each is endowed with a vector of productivities $\mathbf{z}$. Agents choose their occupation and the payoffs are given by equations (2)–(5) with $\beta = 0$. To maintain the effect of the entry cost on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

Figure 3 presents the occupational choice policies of agents in this version of the model. First consider low types whose occupational choices are presented in panel (a). The productivity of an agent when working as an employee is on the horizontal axis and their productivity as an entrepreneur is on the vertical axis. For low levels of z_e agents will either work as an employee or chose to be out of the labor force. Since the value of being a low-skill employee is increasing in z_l and the value of being out of the labor force is constant, there is a threshold ($\underline{z}_l = b/w_l$) above which agents choose to work and otherwise they do not. Moving vertically up the figure, there are two thresholds that separate agents who are entrepreneurs from those who are out of the labor force or working as employees. These thresholds are a function of the employee productivity of an agent, z_l, and whether she is endowed

26. See Decker *et al.* (2014a), Davis and Haltiwanger (2014) and Davis (2017) for discussions of this explanation.

27. 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.

28. There are, of course, other possible causes of rising fixed and entry costs including increases in the cost of finding a new idea (Bloom *et al.* 2020) or increasing market entry costs, such as the cost of establishing a customer base (Bornstein 2021).



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

Figure 3: **Equilibrium occupational choices.** $\underline{z}_e^s(z_s, \varepsilon)$ is the threshold value of z_e above which agents of skill type $s \in \{l, h\}$, worker productivity z_s, and business endowment state ε, choose to be an entrepreneur. $\underline{z}_s$ is the minimum employee productivity level for which an agent of skill type s could choose to be an employee.

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

For high-skill types the tradeoffs are the same except that the value of being an employee is $z_h w_h$ instead of $z_l w_l$. The two panels in Figure 3 are drawn to depict a case in which z_l and z_h have the same range and $w_h > w_l$. This illustrates two points. The first is that since high-skill agents earn more for a given productivity they will choose to be out of the labor force for a smaller range of productivities. That is, $\underline{z}_h = b/w_h < \underline{z}_l$. Second, for a given employee productivity, the z_e threshold for being an entrepreneur is higher for high-skill types because they earn more as employees: $\underline{z}_e^h(x, 1) > \underline{z}_e^l(x, 1)$ and $\underline{z}_e^h(x, 0) > \underline{z}_e^l(x, 0)$ for all $x > \underline{z}_h$. The functional form for the entrepreneurship boundaries for an agent with skill type $s \in \{l, h\}$ is:

$$\underline{z}_e^s(z_s, \varepsilon) = \begin{cases} \left(\dfrac{b + \psi + \mathbb{1}_\varepsilon(0)\psi_e}{\Gamma_\pi} \right)^{1-\alpha-\eta} & \text{for } z_s \in (0, \underline{z}_s], \\ \left(\dfrac{z_s w_s + \psi + \mathbb{1}_\varepsilon(0)\psi_e}{\Gamma_\pi} \right)^{1-\alpha-\eta} & \text{for } z_s > \underline{z}_s. \end{cases} \tag{10}$$

It should also be noted that the size of the regions in Figure 3 should not be interpreted as indicating the relative shares of the occupation categories. This depends on the thresholds depicted as well as the distribution of agents over the productivity space.

4.2. Skill-biased technical change

The force driving SBTC in the model is a decrease in the rental rate of IT capital, r_i. As is well understood from the technical change literature (e.g. Krusell *et al.* 2000) this will affect the equilibrium wages of high and low-skill workers, with the changes depending on the values of the two elasticity of substitution parameters for the production function. For the period of time being studied, the main change in wages was an increase in the high-skill wage. So this analysis focuses on the effect of decreasing r_i and increasing w_h on occupational choices.

The following proposition characterizes the effects of these changes on agents' decisions about whether to be entrepreneurs. Derivatives that are conditional on $\mathbf{w}$ hold the wages fixed. Otherwise they express equilibrium relationships. All proofs are in the Appendix.

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

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

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

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

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

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

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

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

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

In the static model, the analog of the entry rate is the share of entrepreneurs who were not endowed with a business, i.e. those with $\varepsilon = 1$. For the purposes of this section I will call this the "entry rate." A key factor affecting this is the size of the wedge between the productivity thresholds for running a business for people with and without an endowed business. As this wedge decreases, the entry rate will tend to increase.[29] For an agent with skill type s and $z_s > \underline{z}_s$, this wedge is

$$\underline{z}_e^s(z_s, 0) - \underline{z}_e^s(z_s, 1) = \left(\frac{1}{\Gamma_\pi}\right)^{1-\alpha-\eta} \Big([z_s w_s + \psi + \psi_e]^{1-\alpha-\eta} - [z_s w_s + \psi]^{1-\alpha-\eta}\Big). \tag{11}$$

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

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

The overall message is that while there are good theoretical reasons for SBTC to decrease the relative entrepreneur share of high-skill agents, there are competing forces determining the changes in other moments of entrepreneurship that need to be determined quantitatively. Sections 5 and 6 will do this.

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

4.3. Non-entrepreneur productivity, fixed costs and entry costs

The next proposition characterizes the effects of the expansion of non-entrepreneur firms, and increases in fixed and entry costs on the entrepreneur thresholds.

Proposition 2 *Increases in non-entrepreneur productivity, fixed costs and entry costs have the following effects on the entrepreneur thresholds.*

(a) If $\partial w_s/\partial z_f > 0$, then for all $s \in \{l, h\}$, then for all $s \in \{l, h\}$, $\varepsilon \in \{0, 1\}$ and $z_s > 0$,

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

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

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

and

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

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

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

and, if $\partial w_s/\partial \psi_e < 0$ for all $s \in \{l, h\}$,

$$\frac{\partial \underline{z}_e^s(z_s, 1)}{\partial \psi_e} < 0.$$

By characterizing how the non-entrepreneur thresholds change, this proposition provides guidance on how the changes to the economy being studied affect the share of agents who are entrepreneurs and the entry rate. Start by considering the effects of increasing non-entrepreneur productivity, which the proposition assumes causes wages to increase. This restriction is weak in the sense that an increase in z_f causes demand for both types of labor to increase, so, under reasonable parameter values such as those in the quantitative exercise, this will be satisfied. The increase in wages makes entrepreneurship less profitable and increases the returns to being a worker, so entrepreneur thresholds increase and fewer agents choose to be entrepreneurs.

The increase in non-entrepreneur productivity doesn't have a clear qualitative effect on the entry rate of entrepreneurs. This can be seen with equation (11). On one hand, the increase in wages that this change generates decreases the profits of entrepreneurs (captured by the Γ_π term in the equation). This increases the wedge between the two entrepreneur thresholds. On the other hand, the increase in wages pushes up the outside option, so that the marginal entrepreneur is more profitable and the entry cost matters less to them.

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

An increase in the entry cost has some qualitatively different effects (part c of the proposition). For entrepreneurs who need to start a business the effect is the same as for an increase in fixed costs: the threshold for becoming an entrepreneur increases. Holding wages fixed, there is no effect on the occupational choice of agents endowed with a business. Under reasonable parameters, wages will decrease in equilibrium since, with fewer people choosing to be entrepreneurs, demand for both types of labor falls. The decrease in wages makes it more profitable to be an entrepreneur, pushing the entrepreneur threshold down for agents endowed with a business. These forces increase the wedge between the entrepreneur thresholds for agents who are endowed with a business and those who aren't, which can decrease the entry rate. The differing effects on the occupational choices of agents endowed with businesses is the key distinction between the effects of increasing fixed and entry costs.

In accordance with part (b) of the proposition, and the first half of (c), this discussion of the effects of increasing fixed and entry costs has mostly put general equilibrium effects though wages to the side. Increases in these costs put downward pressure on wages by decreasing the number of entrepreneurs, and therefore decreasing demand for labor. These wage effects complicate the analysis of the effect on entrepreneur thresholds by changing the value of the outside option to entrepreneurship. When wages are lower, agents need to make a lower return on entrepreneurship to choose this occupation. This works against upward pressure that rising fixed and entry costs have on the entrepreneur thresholds. The quantitative analysis will show that for the estimated parameters values these general equilibrium effects are not strong enough to overturn the forces emphasized here.

Putting these results together, while increasing non-entrepreneur productivity, fixed costs and entry costs can all generate a decrease in the entrepreneur share, rising entry costs are the most likely to push the entry rate down. Increasing non-entrepreneur productivity has an ambiguous effect on this moment, while higher fixed costs push it up.

4.4. Parameter identification

The quantitative exercise will require measures of fixed costs, entry costs and non-entrepreneur productivity for 1987 and 2015. Due to difficulties measuring these directly, they will be inferred from other moments of the data. I now show that these parameters have independent effects on three moments—the entrepreneur share, the entry rate and the share of employment at entrepreneur firms—so that these moments can be used to identify them.[30]

While increases in all parameters in question push the entrepreneur share down, as explained above, they have quite different effects on the other moments and this is what provides the identification. For distinguishing between fixed costs and entry costs, the key moment is the entry rate. The previous analysis shows that while higher fixed costs tend to increase the entry rate, higher entry costs tends to decrease it. So with values of the entrepreneur share and the entry rate, both of these costs can be estimated.

For measuring non-entrepreneur productivity, it is the share of employment at entrepreneur firms that is key. To see how this is useful, another result is necessary. Let $\mathcal{P}$ denote a set of values for the parameters of the model and let $x(\mathcal{P})$ denote the value of parameter x in $\mathcal{P}$. Allow functions to be conditional on parameters so that, for example, the occupation choice function for parameter set $\mathcal{P}$ is $o(\mathbf{z}, \varepsilon|\mathcal{P})$. Now consider the employment by entrepreneurs of workers of skill type $s \in \{l, h\}$ and restrict attention to entrepreneurs who have skill type $s' \in \{l, h\}$ themselves (recall that an agent with skill type l, for example, has $z_l > 0$ and $z_h = 0$). Let the employment of skill type s by such entrepreneurs under parameters $\mathcal{P}$ be defined as:

$$L_s^{s'}(\mathcal{P}) \equiv \int_{\mathbb{Z}} \mathbb{1}_{z_{s'}}(\mathbb{R}_+) \mathbb{1}_{o}(e|\mathcal{P}) \ell_s(z_e|\mathcal{P}) \, dQ(\mathbf{z}, \varepsilon|\mathcal{P}),$$

where $\mathbb{R}_+$ denotes the set of strictly positive real numbers. The following proposition provides a result regarding the relative effects of changes in non-entrepreneur productivity and fixed costs on $L_s^{s'}$, for a given change in the entrepreneur share for agents of type s'.

Proposition 3 *Let $\mathcal{P}$, $\mathcal{P}_{z_f}$ and $\mathcal{P}_\psi$ be sets of parameter values and take an $s' \in \{l, h\}$. Assume that $\partial w_s/\partial z_f > 0$ and $\partial w_s/\partial \psi < 0$ for all $s \in \{l, h\}$. For $\mathcal{P}_{z_f}$, $x(\mathcal{P}_{z_f}) = x(\mathcal{P})$ for all parameters x except z_f, and $z_f(\mathcal{P}_{z_f}) > z_f(\mathcal{P})$. For $\mathcal{P}_\psi$, $x(\mathcal{P}_\psi) = x(\mathcal{P})$ for all parameters x except ψ, and define $\psi(\mathcal{P}_\psi)$ to satisfy*

$$\int_{\mathbb{Z}} \mathbb{1}_{z_{s'}}(\mathbb{R}_+) \mathbb{1}_{o}(e|\mathcal{P}_\psi) \, dQ(\mathbf{z}, \varepsilon|\mathcal{P}_\psi) = \int_{\mathbb{Z}} \mathbb{1}_{z_{s'}}(\mathbb{R}_+) \mathbb{1}_{o}(e|\mathcal{P}_{z_f}) \, dQ(\mathbf{z}, \varepsilon|\mathcal{P}_{z_f}). \tag{12}$$

If ψ_e is sufficiently small, then, for all $s \in \{l, h\}$,

$$\frac{L_s^{s'}(\mathcal{P}_\psi)}{\ell_s(z_f|\mathcal{P}_\psi)} > \frac{L_s^{s'}(\mathcal{P}_{z_f})}{\ell_s(z_f|\mathcal{P}_{z_f})}. \tag{13}$$

30. The effects need to be independent in the linear algebra sense of this term. If the values of the three moments are plotted in $\mathbb{R}^3$, then the effects of the three parameter changes need to generate vectors that are linearly independent in this space.

This proposition starts by taking increases in non-entrepreneur productivity and fixed costs, relative to a benchmark set of parameters $\mathcal{P}$, such that they generate the same entrepreneur share for agents of skill type s'. The result is that this increase in fixed costs generates a higher level of employment of both low and high-skill labor in the entrepreneurial sector, relative to the non-entrepreneurial sector, than the increase in non-entrepreneur productivity. The reason for this is that the two changes to the economy cause very different types of agents to switch from choosing entrepreneurship to being workers or out of the labor force.

This is illustrated in Figure 4, which plots the entrepreneur thresholds for type s' agents for the special case of $\psi_e = 0$. There are thresholds for an initial set of parameter values $\mathcal{P}$, and for increases in non-entrepreneur productivity and fixed costs, $\mathcal{P}_{z_f}$ and $\mathcal{P}_{\psi}$. For each set of parameters there is only one threshold, since with $\psi_e = 0$ the problems of agents with and without an endowment of a business are the same. Under both $\mathcal{P}_{z_f}$ and $\mathcal{P}_{\psi}$ the entrepreneur share is the same,[31] but $\mathcal{P}_{\psi}$ is associated with more higher-productivity entrepreneurs (area B) and fewer lower-productivity ones (area A). This higher productivity is associated with firms that employ more workers, as Proposition 3 provides.

There are three reasons for the different effects of increasing non-entrepreneur productivity and fixed costs. These can be seen by looking at the equation for the slope of $\underline{z}_e^{s'}(z_{s'}, \varepsilon)$ to the right of the kink point:

$$\frac{\partial \underline{z}_e^{s'}(z_{s'}, \varepsilon)}{\partial z_{s'}} = (1-\alpha-\eta)\left(\frac{1}{\Gamma_{\pi}^{1-\alpha-\eta}}\right)\frac{w_s}{(z_{s'}w_{s'} + \psi + \mathbb{1}_{\varepsilon}(0)\psi_e)^{\alpha+\eta}}.$$

The first reason is that an increase in ψ decreases the slope of the threshold because it cuts into the profits of lower-productivity entrepreneurs more, in relative terms, than for higher-productivity entrepreneurs. The second difference between increases in non-entrepreneur productivity and fixed costs is how they affect operating profits, which is captured by Γ_{π}. An increase in fixed costs causes these to increase, due to lower wages, while higher non-entrepreneur productivity increases wages and decreases profits. These effects scale with entrepreneur productivity, so that they shift the entrepreneur threshold more for high-productivity agents than low-productivity ones. For increasing fixed costs, this effect flattens the entrepreneur threshold, while higher entrepreneur productivity makes it steeper. The third effect operates through changes in employee income, which is one of the outside options for entrepreneurs. This effect is captured by $w_{s'}$ in the above equation. A change in $w_{s'}$ has a larger effect on the entrepreneur threshold for high-productivity agents because its effect is scaled by employee productivity, $z_{s'}$. When increasing fixed costs lower wages, this flattens the entrepreneur threshold, while increasing wages as a result of increasing non-entrepreneur productivity makes the threshold steeper.

31. The figure is drawn with a uniform distribution over $(z_{s'}, z_e)$ in mind, so that the masses of agents in areas A and B are equal.

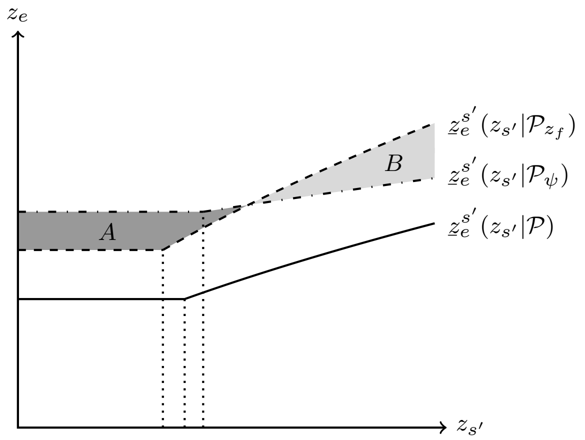


Figure 4: **Occupational choice when non-entrepreneur productivity or fixed costs increase.** This is a stylized representation of the entrepreneur threshold for agents of type s' for the sets of parameter values $\mathcal{P}$, $\mathcal{P}_{z_f}$ and $\mathcal{P}_{\psi}$, introduced in Proposition 13, when $\psi_e = 0$.

Turning back to parameter identification, if Proposition 3 holds for both skill types simultaneously then, in the aggregate, an increase in fixed costs will result in a larger entrepreneur share of employment than an increase in non-entrepreneur productivity, for a given change in the entrepreneur share.[32] This distinction between the effects of these parameters is what will allow them to be separately identified. The quantitative analysis will verify this strategy for the full model, and also show that the same distinction exists between increasing entry costs and increasing non-entrepreneur productivity. For entry costs, the same intuition applies as for fixed costs.[33]

5. Calibration

5.1. Details for taking model to data

Skills. I define people doing high skill work to be those working in non-routine cognitive occupations, as defined by Acemoglu and Autor (2011), and define low skill work to be all other occupations. I abstract from the differences within this second category of occupations since the key force under my theory is the increase in

32. For the aggregate, the additional consideration is that increasing fixed costs and non-entrepreneur productivity are likely to cause different changes in the entrepreneur shares, conditional on skill type. This reallocation of entrepreneurship between skill groups can work against the result. The quantitative analysis will confirm that, to the extent that this happens, the effect is not strong enough to undo this feature of the economy.

33. Potential changes in the shares of entrepreneurs with and without a business endowment make the result less general for this case, so it will be verified quantitatively.

demand for high-skill employees as technology changes, rather than the differential effects among low-skill workers who are all worse off relative to the high-skilled.[34]

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

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

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

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

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

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

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

with $\varepsilon_{e,j,t} \sim N(0,1)$ being independent of $\varepsilon_{s,j,t}$.[35] The correlation between worker and entrepreneur productivity comes through the term $\mu_{e,j,t}$, which is a function of agent j's contemporaneous worker productivity:

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

where $\mathbb{E}^\xi[\tilde{z}_s]$ and $\mathbb{V}^\xi[\tilde{z}_s]$ are the unconditional expected value and variance, respectively, of $\tilde{z}_s$ for agents with education level ξ. This specification allows mean entrepreneur productivity to differ across education levels through the $\bar{\mu}_e^\xi$ term, and the strength and direction of the correlation between worker and entrepreneur productivity is controlled by χ^ξ, which is also dependent on education. The final

34. See Acemoglu and Autor (2011), Autor and Dorn (2013), Goos *et al.* (2014), Jaimovich and Siu (2020), vom Lehn (2015), Cortes *et al.* (2017), and Lee and Shin (2016) for research emphasizing the distinction between these lower skill occupations. More details on the occupation classification are in the Appendix.

35. The innovations $\varepsilon_{s,j,t}$ and $\varepsilon_{e,j,t}$ are also independent across agents and over time.

term is the deviation of an agent's worker productivity from its mean value, in units of the relevant standard deviation. This specification standardizes the effect of worker productivity on entrepreneur productivity for low and high-skill agents so that the effect of changes in low or high-skill productivity on entrepreneurial productivity is not affected by the scale or dispersion of these variables.

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

5.2. Quantitative strategy and calibration

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

1. the share of agents who have not completed college, ω;
2. the out of labor force value, b;
3. the level of entrepreneur productivity, ζ, and the relative level of entrepreneur productivity of college and non-college agents through $\bar{\mu}_e^C$;
4. capital rental rates, r_o and r_i;
5. non-entrepreneur productivity, z_f;
6. entry and fixed costs, ψ_e and ψ.

Four of these parameters change for consistency with the data. The education distribution has changed significantly over time, which matters for the skill distribution. As is well known, the out of labor force share has been increasing, which the model can match with an increasing value of this activity. The level of entrepreneur productivity increases because of productivity growth, and the non-IT capital rental rate, r_o, increases as measured in the data. Four of the remaining parameters are adjusted to simulate the forces that this paper is focused on: r_i is the capital rental rate that drives SBTC. The change in z_f is simulating increasing productivity of non-entrepreneur firms, and fixed and entry costs can change. I additionally allow the relative productivity of college and non-college entrepreneurs to adjust to account for changes in their relative entrepreneur rates, above and beyond what the other parameters generate. This should be thought of as capturing all forces outside of SBTC that have affected the relative profitability of college and non-college entrepreneurs. Parameter values are determined as follows.

1987 parameters. The share of the population without a college education can be computed with the CPS and is 77.90% in 1987.[36] The death rate is set to a value of 0.025 to achieve an expected working life of 40 years. Given this value, β is chosen so that the effective annual discount rate is 4%. The CRRA parameter is set to 2.0. The value for the parameter controlling the persistence of employee productivity is assumed to be equal for low and high skill agents, and is given a

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

value of 0.95 in accordance with the estimate of Storesletten *et al.* (2004). The returns to scale of the production function are given by $\alpha + \eta$. Atkeson and Kehoe (2005) provide an extensive discussion of returns to scale and settle on a value of 0.85, which is used here as well. The rental rates for IT capital are 16.9% in 1987 and 7.1% in 2015, and for non-IT capital they are 8.2% and 12.1%, respectively (Eden and Gaggl 2018). For productivities, the average productivity of low-skill workers, high-skill workers and entrepreneurs can be normalized for one of the education levels. I make this normalization for non-college agents, setting μ_l^N and μ_h^N so that average low and high-skill productivities for this group are equal to 1. $\bar{\mu}_e^N$ is normalized to zero. ζ can also be normalized for 1987 and is set to one.

All but one of the remaining 1987 parameters are calibrated internally. While the parameters are determined jointly by simulated method of moments, the approximate mapping between the moments and parameters is as follows. The consumption level for agents who are out of the labor force is set to target the out of labor force share.[37] The production function parameters η, φ and λ affect the demand for the various production inputs. To determine their values I use moments related to the division of income among inputs: the share of income going to employees, the ratio of the average high-skill income to average low-skill income, and and the IT share of capital.[38] The productivity level of the non-entrepreneur sector z_f, the fixed cost ψ, and the entry cost ψ_e are pinned down using the identification strategy outlined in Section 4. Regarding the moments used for this, the share of employment at entrepreneur firms is estimated using data from the CPS and Business Dynamics Statistics (BDS), and the share of agents who are entrepreneurs comes from the CPS.[39] To estimate the entry rate into entrepreneurship, the entry rate of firms in the BDS is used since, as discussed earlier, self-employed people account for a large share of firms.[40]

Parameters relating to skill shares and productivities remain. The share of agents who are high-skill conditional on education, θ_h^ξ for $\xi \in \{N, C\}$, is chosen

37. In computing the out of labor force share in the data, I correct for the trend decline in this share for women up until the late 1990s. See the Appendix for details. Since the model is solved on a discrete grid for z_e, z_l and z_h, a small amount of noise is added to the out of labor force value, b, to smooth out occupational choice functions. Specifically, for each agent in each period, b is drawn from normal distribution with mean equal to the calibrated value of b and standard deviation of 0.01. This helps with solving and calibrating the model and has virtually no effect on the aggregate moments of interest.

38. The first moment is from the BEA data on value-added by industry. The second moment is from the CPS. Since there is no variation in hours worked in the model, moments of the empirical income distributions are computed using average hourly income for each person. Full details of income calculations are in the Appendix. The third moment is from the BEA detailed fixed assets tables.

39. In the model an entrepreneur is a person who spends their time managing a firm with employees, so in the data I define an entrepreneur as a self-employed person (which means that they spend the majority of their working hours in self-employment) with at least one employee. See the Appendix for details on how this entrepreneur share is estimated.

40. Additional details for these moments are provided in the Appendix.

	1987	2015	Parameters with the same values for 1987 & 2015					
b	0.303	0.423	θ_h^N	0.151	σ_l^N	0.173	η	0.235
z_f	1.134	1.338	θ_h^C	0.650	σ_l^C	0.211	φ	0.140
ψ	0.122	0.290	μ_l^C	0.008	σ_h^N	0.181	λ	0.203
ψ_e	0.272	0.981	μ_h^C	0.009	σ_h^C	0.176	τ	0.610
$\bar{\mu}_e^C$	0.159	0.128	χ^N	-0.083	σ_e^N	0.036	ρ_e	0.986
ζ	1.0	1.136	χ^C	0.058	σ_e^C	0.035		

Table 2. **Values for internally calibrated parameters.** All parameters are internally calibrated except for the 1987 value of ζ, which is normalized to 1.0. Where necessary, values are rounded to three decimal places.

to target the share of people in the relevant education group who work in high-skilled occupations.[41] The parameters that determine the level of low and high-skill productivity for college educated agents, μ_l^C and μ_h^C, are chosen to target the ratio of average income for college and non-college people in each of these skill groups. The level of entrepreneur productivity for college agents, $\bar{\mu}_e^C$, determines the share of college agents who are entrepreneurs. χ^ξ affects the correlation between worker and entrepreneur productivity for agents with education level ξ. A higher correlation increases the productivity of entrepreneurs, so this parameter is chosen to target the ratio of average entrepreneur to average high-skill employee income for this education level. There are six standard deviation parameters: for each education level there is one for each skill level and one for entrepreneurship. These determine the coefficient of variation of income for people in the corresponding occupation-education group. The persistence of entrepreneur productivity shocks affects the persistence of entrepreneur income. From the data I use the fraction of continuing entrepreneurs who remain in the same decile of the entrepreneur income distribution from one year to the next (37.5%), from DeBacker *et al.* (2018).

2015 parameters. The share of agents without a college education, ω, and the capital rental rates, r_o and r_i, are taken directly from the data, using the same sources as for 1987. The consumption level of agents who are out of the labor force, the level of non-entrepreneur productivity, and the fixed and entry costs are all calibrated internally using the 2015 values of the same moments as are used for 1987. The level of entrepreneur productivity for college-educated agents $\bar{\mu}_e^C$ is chosen to target the relative entrepreneur shares of college and non-college agents in 2015.

The remaining parameters are the two elasticity of substitution parameters (τ and γ), which take the same value for both years, and the level of entrepreneur productivity ζ for 2015. These parameters are key for determining how the wages of low and high-skill workers change from 1987 to 2015. Getting these changes right is crucial for the analysis since wages are fundamental for the tradeoff between being a worker and an entrepreneur. To calibrate these parameters, I fix one of the elasticity

41. See Appendix for details of the occupation distribution calculations in the data.

of substitution parameters, γ, with guidance from the literature and use the other two parameters to target the changes in average real income of low-skill workers and high-skill workers from 1987 to 2015. Since the CPS omits non-wage income, I adjust the growth rates from that source using data on non-wage compensation from the Bureau of Labor Statistics' Employer Costs of Employee Compensation dataset. Using similar production functions to in the present model, Krusell *et al.* (2000) and vom Lehn (2015) have estimated the elasticity of substitution between high-skill workers, defined on the basis of education or occupation, and capital equipment, generating estimates of 0.67 and 0.13 respectively.[42] γ is set to achieve an elasticity of substitution in the middle of this range (0.4).

5.3. Calibrated model

The values of internally calibrated parameters are presented in Table 2, and the calibration moments for the model and the data are in Table 3. Overall the model fits the data well given its high dimensionality. The estimated elasticity of substitution between low-skill labor and IT capital ($\frac{1}{1-\tau}$) is 2.56.[43] To put the estimates of entry and fixed costs for 1987 in perspective, they imply that it costs 25% of the median annual operating profit (sales less labor and capital costs) of entrepreneur firms to enter, and 11% to cover fixed costs. Fixed costs are estimated to have increased by a factor of 1.9 from 1987 to 2015, and entry costs by a factor of 3.1. There is empirical support for these types of costs increasing over time (De Ridder 2019; De Loecker *et al.* 2020), and the estimated growth of fixed costs is slightly smaller than De Ridder (2019)'s estimates from French and US data.[44] The productivity of college educated entrepreneurs, relative to non-college educated ones, is estimated to decrease slightly between 1987 and 2015. In 1987 the average productivity of college agents is 16.8% higher than that of non-college agents, and in 2015 this difference decreases to 13.3%. The feature of the data driving this is that the relative entrepreneur share of college-educated agents declines by more than the changes in wages and capital prices can explain. One interpretation of this is that non-college entrepreneurs compete more with non-entrepreneurial firms, and therefore are more affected by their technological improvements. Poschke (2018) argues that this kind of polarization of the firm size distribution has occurred.

In the Appendix I compare untargeted moments of the occupation and income distributions in the model and data. In particular, the income distributions for 2015

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

43. There is no direct benchmark for this in the literature that I am aware of. See the Appendix for a discussion of the closest comparisons.

44. See Appendix for more details on this comparison.

Moment	Model	Data
Income moments, 1987		
Entrepreneur:high-skill averages, non-college	1.32	1.36
Entrepreneur:high-skill averages, college	1.89	1.82
High-skill:low-skill averages	1.49	1.45
College:non-college low-skill averages	1.42	1.40
College:non-college high-skill averages	1.31	1.29
CV, low-skill non-college	0.51	0.51
CV, low-skill college	0.69	0.67
CV, high-skill non-college	0.58	0.60
CV, high-skill college	0.60	0.61
CV, entrepreneurs non-college	0.91	0.96
CV, entrepreneurs college	0.91	0.94
Entrepreneur income persistence	38.6%	37.5%
Occupation distribution, 1987		
Out of labor force share	14.8%	15.1%
High-skill share, non-college	13.1%	13.1%
High-skill share, college	59.0%	60.0%
Entrepreneur share	5.3%	5.1%
Entrepreneur share, college	7.1%	7.2%
Other moments, 1987		
Employee share of income	54.6%	52.5%
IT share of capital	10.2%	10.1%
Entrepreneur share of employment	49.6%	50.0%
Entry rate of entrepreneurs	11.4%	11.7%
2015 moments		
1987–2015 growth of average low-skill income	18.1%	16.6%
1987–2015 growth of average high-skill income	43.5%	44.3%
2015:1987 out of labor force share	1.66	1.66
2015:1987 entrepreneur share	0.70	0.71
2015:1987 entrepreneur share of employment	0.78	0.79
2015:1987 entry rate of entrepreneurs	0.72	0.72
2015:1987 college to non-college entrepreneur shares	0.85	0.85

Table 3. **Calibration moments.** Colons denote ratios. E.g. 'High-skill:low-skill averages' for income is the ratio of high-skill to low-skill average income. CV is the coefficient of variation. Entrepreneur income persistence is the share of continuing entrepreneurs in the same decile of the entrepreneur income distribution in consecutive years. Income growth rates are for real income.

are almost entirely untargeted, and the model fits these quite well. This indicates that the model is doing a good job of capturing the tradeoffs that agents face when making their occupational choice.

6. Quantitative results

This section assesses the explanations for declining entrepreneurship in two steps. I quantify the theory from Section 4 to assess the explanations individually, and independently of the estimated magnitudes of parameter changes. I then use the 2015 parameter estimates to study them jointly, and evaluate their relative importance.

6.1. Individual forces

Skill-biased technical change. Figure 5 analyzes the effects of SBTC in partial and general equilibrium. The starting point for these exercises is the 1987 calibration of the model. In the left panel the effects of changing r_i, holding wages fixed, are presented. In the middle panel w_h changes holding w_l fixed, and in the right panel, r_i changes with wages adjusting so that the model is in equilibrium. In the panels with r_i changing, the horizontal axis is flipped so that, as you go to the right, r_i decreases, as it has in the data. In all panels the changes in four moments are presented: the entrepreneur share, the entry rate, the share of employment at entrepreneur firms, and the ratio of the entrepreneur shares of college and non-college agents. While the theory was framed to compare low and high skill agents rather than education groups, the results carry over since a much higher share of college educated than non-college educated people are high skill.[45] All of the moments being considered decrease in the data, so a downward sloping line means that the relevant moment is moving in the same direction as in the data. The magnitude of the vertical axis is normalized so that a value of -1 means that the percentage change in the moment in the model is equal to the percentage change in that moment in the data from 1987 to 2015.

The results in the middle panel, for the change in the high skill wage, confirm the predictions of the theory. This change causes the entrepreneur share to decrease, and the decrease is proportionally larger for college educated agents. The decrease in the entrepreneur share also drives down the employment share of entrepreneurs. Quantitatively, this mechanism can generate much of the declines in these three moments seen in the data.[46] The issue, as identified by the theory, is that that decrease in the price of IT capital that drives the change in the high skill wage, has offsetting effects on the entrepreneur share and the employment share of entrepreneurs. Quantitatively the opposing effects are similar in magnitude, so that neither of these moments change much as a result of SBTC. As for the entry rate, the theory showed that the changes in the IT capital price and high skill wage have several effects on this moment, some increasing it and others decreasing it. On balance, this moment increases, but the change in modest relative to the change in the relative entrepreneur shares of college and non-college agents. The overall message is that SBTC is a relevant for understanding changes in relative

45. These shares are 65% and 15%, respectively (Table 2).

46. To help with using the results from the graph for w_h to understand the magnitudes in the right panel, w_h changes from 0.79 to 1.09 as r_i changes from 0.1685 to 0.0706 in that graph.

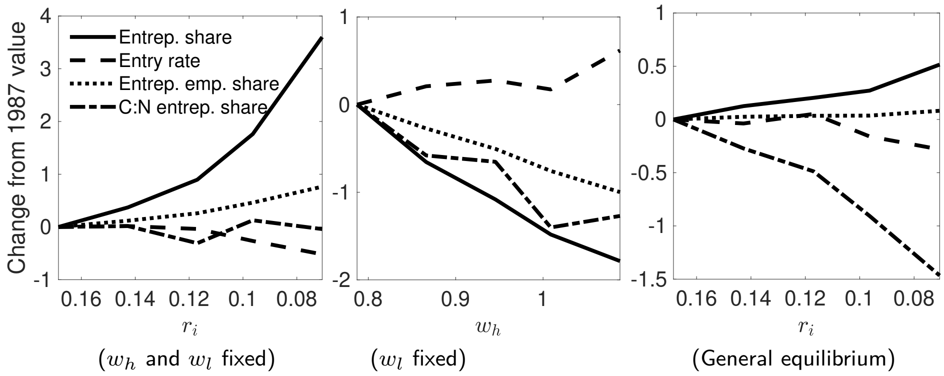


Figure 5: **Comparative statics for skill-biased technical change.** Parameter values are set to their 1987 values. In the left panel r_i is changed holding wages fixed; in the middle only w_h changes; and on the right, r_i changes and wages adjust so that the model is in equilibrium. The vertical axis is normalized so that a magnitude of one means that the percentage change in a moment is the same as in the data from 1987 to 2015. 'Entrep. emp. share' is the share of employment at entrepreneur firms. 'C:N entrep. share' is the ratio of the college to non-college entrepreneur shares.

entrepreneur shares across the education distribution, but does not appear relevant for understanding the change in the aggregate moments of entrepreneurship.

Non-entrepreneur productivity. The left panel of Figure 6 presents the effects of decreasing z_f on moments of entrepreneurship. The setup for the figure is the same as for Figure 5. The theory told us that increasing non-entrepreneur productivity would decrease the entrepreneur share and that the effect on the entry rate was ambiguous because of opposing effects from increasing wages. Figure 6 shows that these opposing effects on the entry rate essentially cancel each other out. For the entrepreneur share we see the predicted negative effect. For the share of employment at entrepreneur firms, the theory indicated that increasing non-entrepreneur productivity would have a larger effects on this, relative to the effect on the entrepreneur share, than increasing fixed or entry costs. The figure confirms this (compare the three panels), with increasing non-entrepreneur productivity having about twice as large an effect on the share of employment at entrepreneur firms as on the entrepreneur share, while for increasing fixed and entry costs the effect is about half as large. Comparing to the data, when increasing non-entrepreneur productivity generates all of the reallocation of employment away from entrepreneurs, the decline in the entrepreneur share is about 60% as large as in the data. This implies that increasing non-entrepreneur productivity causes entrepreneur firms to shrink too much, rather than decreasing the number of them, in order to fully explain the data.

Fixed and entry costs. For the effects of increasing fixed and entry costs, see the middle and right panels of Figure 6. The theory indicated that in partial equilibrium rising fixed costs should decrease the entrepreneur share and increase the entry rate—the quantitative results confirm that these effects hold in general equilibrium.

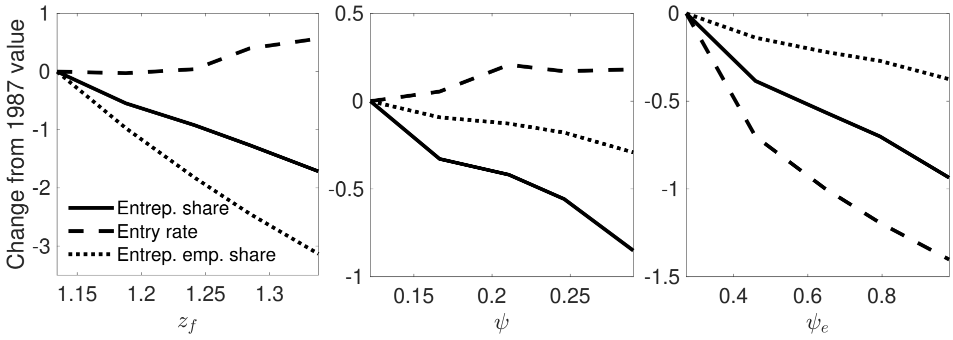


Figure 6: **Comparative statics for non-entrepreneur productivity, fixed costs and entry costs.** This figure has the same setup as Figure 5. Here it is z_f, ψ and ψ_e changing. In all cases wages adjust so that the model is in equilibrium.

The effect on the share of employment at entrepreneur firms was qualitatively ambiguous, but quantitatively we see that this moment declines. This is because increasing fixed costs have a strong negative effect on the entrepreneur share, which pushes down the employment share of entrepreneurs, and this is only partially offset by entrepreneurs having more employees, conditional on operating.

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

A final note on Figure 6 is that it confirms the identification strategy for fixed costs, entry costs and non-entrepreneur productivity that was described in the theory. It is clear that their relative effects on the three moments of the data are different, so that these moments can be used to identify them.

6.2. Joint effects

To assess the full array of changes in the model from 1987 to 2015, the parameter changes are divided into two groups. The first group consists of changes in parameters that are necessary for consistency with the data, but are not the main focus for understanding changes in entrepreneurship. I'll call these parameter changes the *secondary parameter changes*. The education level changes, consistent with the increase in the attainment of college education in the data; productivity

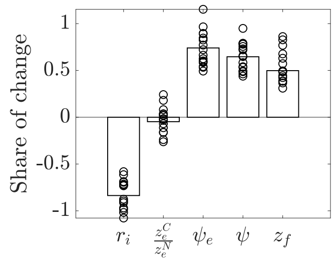
	Secondary parameters	2015 data
Entrepreneur share	0.93	0.71
Entry rate	0.92	0.72
Entrepreneur emp. share	1.06	0.80
College:non-college entrep. share	1.34	0.85
OLF share	1.56	1.66

Table 4. **Effects of changes in secondary parameters.** The *Secondary parameters* column provides the effect of the secondary parameter changes on the listed moments, expressed relative to their 1987 values in the model. The *2015 data* column is the 2015 values of the moments in the data, relative to the 1987 values.

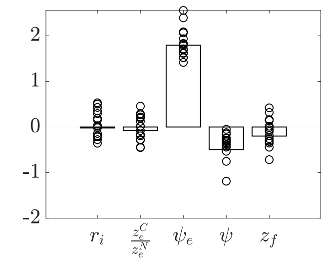
increases to allow the economy to match general wage growth;[47] the value of being out of the labor force changes to fit the evolution of the share of people in this state; and the rental rate of non-IT capital changes, per the data. The remaining parameter changes—fixed costs, entry costs, non-entrepreneur productivity, the rental rate of IT capital, and the relative productivity of college and non-college entrepreneurs—are the main focus and I'll call these the *primary parameter changes*. The approach for studying the joint effects of these changes is to start by performing the secondary parameter changes. I'll then take that economy as the *baseline*, and assess the contribution of each of the primary parameter changes in moving the economy to 2015.

The effects of the secondary parameter changes on selected moments are presented in Table 4. Each value is expressed relative to its 1987 value, and the same is done for the 2015 values from the data, so that we can assess how far the secondary parameters go towards explaining these. The effects of the individual parameter changes are discussed in detail in the Appendix. Here I highlight the main points. The secondary parameter changes have mostly modest effects on moments of entrepreneurship. The entrepreneur share decreases by seven percent because a higher out of labor force value and higher costs of non-IT capital make entrepreneurship less attractive. These effects are smaller for college entrepreneurs, which is why their relative entrepreneur share increases. The entry rate also falls. Increasing education increases the supply of high skill workers and drives down their wage. This increases the gap between the values of entrepreneurship and high skill work, resulting in less churn between these occupations. The share of employment at entrepreneur firms increases, going against the trend in the data. This is because education is increasing, and more educated entrepreneurs have larger firms on average. Finally, the secondary parameter changes account for almost all of the increase in the out of labor force share, with the increase in the out of labor force value accounting for most of this. This tells us that the changes to the

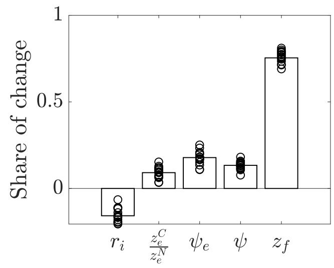
47. To simulate a general increase in productivity I increase ζ so that the average level of entrepreneur productivity equals its 2015 value ($\zeta = 1.122$), and increase non-entrepreneur productivity z_f and the out of labor force value b by the same factor. I also scale fixed costs ψ and entry costs ψ_e by the same factor so that their relevance is not diminished.



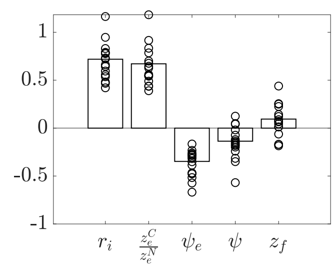
(a) Entrepreneur share



(b) Entry rate



(c) Entrepreneur employment share



(d) College:non-college entrepreneur share

Figure 7: **Effects of changes in primary parameters.** Each panel decomposes the change in a moment from its value in the baseline scenario to its 2015 value. r_i, ψ_e, ψ and z_f indicate the effects of the changes in these parameters. z_e^C/z_e^N indicates the effect of the change in the relative productivity of college and non-college entrepreneurs. The vertical scale is the share of the change in the relevant moment accounted for by each parameter change (0.5 equated to 50%). Circles are values for particular orderings of the parameter changes, and the bars are averages of these.

economy generating this trend are not closely related to those driving changes in entrepreneurship.

Now turn to the effects of the primary parameter changes on moments of entrepreneurship. These changes adjust the following things from their baseline to 2015 values: the IT capital rental rate, the fixed cost, the entry cost, non-entrepreneur productivity, and the relative entrepreneur productivity of the two education groups.[48] The focus will be on how moments of entrepreneurship change from their values in the baseline scenario to 2015, and the quantitative relevance of each of the parameter changes for this. There are 120 ways to order the parameter changes, generating 16 unique values for the effect of each change.[49] While the main messages do not depend on the exact ordering, I will present results for all orderings and focus the discussion on average effects.

48. To change the relative entrepreneur productivity of college and non-college agents without changing average entrepreneur productivity, $\bar{\mu}_e^C$ decreases from its 1987 to 2015 value, and ζ increases from its baseline value of 1.122 to its 2015 value of 1.136.

49. Some orderings generate the same estimates for some parameters. E.g. The orderings $(r_i, z_e^C/z_e^N, \psi_e, \psi, z_f)$ and $(r_i, z_e^C/z_e^N, \psi, \psi_e, z_f)$ yield identical estimates for the effects of r_i, z_e^C/z_e^N and z_f.

Figure 7 presents the results. The scale of the vertical axis in all panels is the share of the change in the relevant moment from the baseline outlined above, to 2015, accounted for by each change. The bars represent the average effect of each change across the 16 estimates, and the circles are the individual values. Consistent with the prior analysis, the main role of SBTC is to shift entrepreneurship towards lower education agents. From Figure 7(d), this force accounts for about half of this change after offsetting effects from fixed and entry costs are allowed for, with the other half accounted for by the decrease in the relative productivity of college-educated entrepreneurs. Its other significant effect on entrepreneurship is to increase the entrepreneur share, which goes against the trend in the data (Figure 7a).

The increasing entry cost is primarily important for generating the decrease in the entry rate (Figure 7b), as was clear from the analysis of the primary parameters in isolation. It is also the most quantitatively important factor in accounting for the decline in the entrepreneur share (Figure 7a). For this moment though, the increases in the fixed cost and non-entrepreneur productivity are also quantitatively relevant. Their effects are 90% and 74% as large, respectively, as the effect of the entry cost. For the decline in the entrepreneur share of employment, most (76%) of this is due to increasing non-entrepreneur productivity. The earlier analysis supports this as an increase in this productivity has a larger effect on the size of entrepreneurial firms than rising fixed or entry costs.

To summarize, the results provide three main messages. First, for understanding the declines in the entry rate into entrepreneurship and the share of people who are entrepreneurs, increasing entry costs are the main factor. Increasing fixed costs and non-entrepreneur productivity play a secondary role in explaining the decline in the second moment. Second, increasing non-entrepreneur productivity accounts for most of the shift in employment out of the entrepreneur sector. Third, SBTC accounts for approximately half of the shift in entrepreneurship towards less educated people, but this force is not relevant for understanding the decline in the aggregate level of entrepreneurship.

Additional analysis. One question that the results raise is whether the role of rising fixed and entry costs is consistent with a stable entrepreneur size distribution in the data. The size distribution of entrepreneur firms in the model is very similar in 1987 and 2015. While rising fixed and entry costs have the expected effect of causing firms to be larger, this is mostly offset by SBTC. This force decreases the size of firms because: (i) it increases the share of people who are entrepreneurs, which lowers the average productivity of entrepreneurs; (ii) it causes labor to be substituted for capital; and (iii) it shifts entrepreneurship towards less educated people, who have smaller firms on average. Additional discussion and quantification of this is in the Appendix.

Another consideration is that, while the analysis has considered a range of factors that could explain the changes in entrepreneurship, there are possibilities outside the framework. One that has been considered in the literature is changes in the growth rate of the labor force (see Karahan *et al.* 2021; Hopenhayn *et al.*

2021).[50] To assess the effects of this theory on the results, I take estimates of the shares of changes in various moments that it accounts for, and then recalibrate the model to target the changes that remain. Ordinarily, an issue with this approach would be that this factor could interact with the changes occurring in the present model, such that they cannot be studied independently in this way. However, under the theory, changes in the labor force growth rate generate changes in the entry rate of firms, while having little or no impact on prices.[51] This absence of price effects means that this change in the economy should not interact with the changes studied in this paper. I consider three alternative calibrations of the model to implement this approach, based on the results of Karahan *et al.* (2021) and Hopenhayn *et al.* (2021). The main result is that while factoring in this explanation changes the magnitude of the changes in entrepreneurship that the mechanisms in this paper account for (which is by design), it generally does not significantly affect their *relative* importance. Even if a declining labor force growth rate accounts for some of the decline in the entrepreneur share and the entry rate, for example, it is still the case that rising entry costs is the more important factor for explaining the remainder of the decline in the entry rate. Full details of the alternative calibrations and the quantitative results are in the Appendix.

7. Interpreting cost changes

The quantitative results show that increases in both fixed and entry costs have contributed to the declines in the entrepreneur share and the entry rate, with increasing entry costs being particularly important. As discussed earlier, two potential explanations for the increase in these costs are that the level of regulation in the economy has increased or that changes in production technologies have caused the fixed and entry components of firms' costs to rise. This section presents cross-sectional correlations to assess the plausibility of these explanations.[52]

7.1. Data and methodology

The strategy is to assess the relationship across industries between changes in entrepreneurship and measure of changes in regulations and technologies that could have driven fixed and entry costs up. The period of analysis is 1987–2015. To

50. In a more recent contribution, Peters and Walsh (2021) also study this theory. For the purpose of the exercises undertaken here, I focus on Karahan *et al.* (2021) and Hopenhayn *et al.* (2021) since they use models that are closer to this paper's.

51. In Hopenhayn *et al.* (2021) the impact is precisely zero, while in Karahan *et al.* (2021) it is small.

52. While causal evidence of the effect of changes in IT technology and regulations would be valuable, tackling the identification challenge associated with such evidence is beyond the scope of this paper.

measure entrepreneurship I use the share of the labor force in an industry who are self-employed from the CPS. Unlike in Section 2, I do not restrict attention to self-employed people with at least 10 employees because at the industry level this would leave too few observations to construct reliable entrepreneur shares.

To quantify changes in regulations at the industry level I use two measures. The first is the measure of the number of Federal regulations at the industry level from the RegData dataset, constructed from the Code of Federal Regulations by McLaughlin and Sherouse (2018).[53] For the second measure I construct a proxy for the level of industry regulations by computing the share of employees in regulation-related occupations using the CPS. These are occupations in which people are likely to be performing tasks related to regulatory compliance, such as legal, human resources, accounting and auditing occupations. The full list of occupations that I classify as regulation-related is in the Appendix.

For changes in technology that could drive the increase in fixed and entry costs I focus on a particular theory for why these costs have increased. This theory is that improvements in IT technology have allowed firms to adopt technologies with higher upfront costs and lower marginal costs (see Aghion *et al.* 2019; Hsieh and Rossi-Hansberg 2019; De Ridder 2019). Under this theory measures of IT technology adoption should be positively related to the rise in fixed and entry costs. I use four such measure at the industry level. There are two measure of IT capital intensity: the ratio of the IT capital stock to value added, and the real capital stock per employee.[54] The third and fourth measures are based on the occupation composition of each industry. I identify occupations in the CPS data that are IT-related and compute the share of employees in each industry in these occupations.[55] The idea is that if an industry is adopting more IT technology over time then it should also have more employees in these occupations. The fourth measure is the share of employees in non-routine cognitive occupations.[56] There is a long literature (e.g. Krusell *et al.* 2000; Autor *et al.* 2003; Acemoglu and Autor 2011; Autor and Dorn 2013) arguing that these occupations are complementary to IT capital such that we should see more employees in these occupations when more IT capital is in use.

To assess the relationship between changes in entrepreneurship, and changes in regulations and technology related to fixed and entry costs across industries, I use the following regression:

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

53. See the Appendix for a discussion of how this measure is constructed.

54. The IT capital stock is taken from BEA detailed fixed assets tables. Value added is also from the BEA and employment is from the CPS.

55. See the Appendix for a list of these occupations.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔIT employment share	-7.022						-4.919
	(2.353)						(2.506)
ΔNR cognitive emp. share		-1.194					
		(1.037)					
$\Delta\log$(IT capital per employee)			-0.109				
			(0.069)				
Δ(IT capital/Value-added)				-0.072			
				(0.388)			
$\Delta\log$(Regulations)					-0.254		-0.230
					(0.144)		(0.144)
ΔRegulatory employment share						-2.587	
						(1.616)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	139	144	144	144	102	140	98
R^2	0.083	0.027	0.035	0.018	0.063	0.037	0.119
Adjusted R^2	0.048	-0.008	0.001	-0.018	0.014	0.002	0.061

Table 5. **Relationship between changes in the self-employment share, and changes in IT technology and regulations.** The regression is specified in equation (14). The unit of observation is industry-time. Observations are for three time periods: 1988–89 to 1999/2000, 1999/2000 to 2005/06, and 2005/06 to 2014/15, with variables averaged over the two years at the start and end of each. IT capital per employee is measured in real terms. 'Regulations' is the number of Federal regulations for an industry, from RegData. The controls are the shares of people in an industry who are college educated, male, and living in a metropolitan area, and their average age.

where $\Delta \log e_{jt}$ is the change in the log of the entrepreneur share from an earlier period (specified shortly) to period t for industry j,[57] $\boldsymbol{\Delta x}_{jt}$ is vector of changes in IT and regulation measures (in most regressions it will just have one element), and $\boldsymbol{\Delta y}_{jt}$ is a vector of changes in control variables: changes in the average age of people working in each industry, the share who are males, the share who have a college degree, and the share who live in a metropolitan area. I divide the sample into three sub-periods to increase the number of observations, and average each variable over two years at the start and end points to smooth them. The sub-periods are 1988-89 to 1999/2000, 1999/2000 to 2005/06, and 2005/06 to 2014/15. With the exception of the final endpoint, each sub-period starts and ends just before a business cycle peak to reduce the risk of higher frequency fluctuations contaminating the results. Of course the data does not contain another peak after 2007, so the last years of the dataset are used for the final endpoint.

7.2. Results

The results are presented in Table 5. In columns (1)–(6) I take one measure of technological change, or changes in regulation, at a time, and regress it on the change in the entrepreneur share. The control variables are included in all

57. After harmonization across datasets, there are 48 industries. The Appendix discusses this and the sample size further.

regressions, with their coefficients suppressed in the table. The main result is that the coefficients on all variables are negative, consistent with both the increasing use of IT technology and increasing regulation driving up fixed and entry costs, and pushing entrepreneurship down. As expected with a small number of observations, the statistical power of the results is generally low, so the evidence should only be taken as suggestive.[58] To give a sense of magnitudes, one percentage point increases in the IT employment share and the regulatory employment share in an industry are associated with 7.0% and 2.6% declines in the self-employed share, respectively. When I include measures of both changes in IT technology adoption and changes in regulations (focusing on the measures that had the highest statistical significance in the individual regressions), both variables have negative coefficients with similar significance levels to in the individual regressions.[59] Overall the data provides support for both of the proposed theories for the rise in fixed and entry costs: that they are a result of increasing regulation and changes in IT technology.

8. Conclusion

This paper has studied why entrepreneurship in the US has declined over the last three decades. While it is well known that the rate at which new firms are created has declined, occupational choice data shows additional features of the decline in entrepreneurship. The entrepreneur share has declined, and this has not been offset by the businesses of entrepreneurs growing larger, implying that an increasing share of economic activity is accounted for by non-entrepreneur firms. The decline in the entrepreneur share has also been larger for more educated people. This array of facts provides a rich set of moments for evaluating theories for the decline in entrepreneurship.

The analysis has used the structure of a dynamic, general equilibrium, occupation choice model for interpreting the data. While SBTC can account for much of the larger decline in the entrepreneur share for more educated people, it does not explain other dimensions of the decline. One effect of SBTC that is useful for accounting for the data is the increase in the high-skilled wage—on its own this could generate the decline in many dimensions of entrepreneurship. However, once the other aspects of SBTC are considered, namely the decreases in the price of IT capital and the decrease in the low-skill wage, the aggregate entrepreneur share and the size of the entrepreneurial sector change little. The main effect is decreasing the *relative* entrepreneur share of more educated people.

Having measures of the decline in entrepreneurship along several dimensions is useful for disentangling the effects of rising fixed costs, entry costs, and the

58. In columns (1)–(6) two coefficients are significant at the traditional levels: the coefficients on ΔIT employment share and Δlog(Regulations) are significant at 1% and 10%, respectively.

59. The p-values are 5% and 11% for the IT employment share and log of regulations, respectively.

productivity of large non-entrepreneur firms. These factors have distinctly different effects on the dimensions of entrepreneurship measured in the data, providing a rich test for each of them, and allowing for changes in them to be identified. The quantitative analysis has shown that, while they have all played a role in accounting for the decline in the entrepreneur share, the contributions to the decline in the other dimensions of entrepreneurship are starkly different. Rising entry costs are the main factor behind the declining entry rate, while increasing productivity of large non-entrepreneur firms account for most of the decline in the size of the entrepreneur sector.

The final section of the paper has provided some initial evidence for interpreting the increases in fixed and entry costs. The cause is important because it matters for the consequences. Cross-industry correlations provide supporting evidence for increases in these costs being due to more regulations and the increasing use of IT technology, but there is scope for further research into this. There are other possible causes of these increases—for example, ideas getting harder to find, increasing costs of attracting customers, or increasing barriers to entry due to strategic behavior by incumbents—and an important challenge for future research is to provide causal evidence for the drivers of these cost increases, and quantify the contribution of the various hypotheses. An additional interesting avenue to be explored is whether the drivers of increased fixed and entry costs are different. To the extent that the declining entry rate is the moment of interest, it is entry costs that should be the focus. The results from this paper provide a foundation for distinguishing between these cost and fixed costs, since they have distinct effects on the entry rate. Finding factors that are related to the decline in the entry rate, but not the decline in the entrepreneur share, is a way to identify drivers of the increase in entry, as opposed to fixed costs.

References

(2014). "American dynamism dimmed." *The Economist*, 05/10/14.

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr (2018). "Innovation, reallocation, and growth." *American Economic Review*, 108(11), 3450–91.

Acemoglu, Daron and David Autor (2011). "Skills, tasks and technologies: Implications for employment and earnings." *Handbook of Labor Economics*, 4, 1043–1171.

Adelino, Manuel, Song Ma, and David Robinson (2017). "Firm age, investment opportunities, and job creation." *Journal of Finance*, 72(3), 999–1038.

Aghion, Philippe, Antonin Bergeaud, Timo Boppart, Peter Klenow, and Huiyu Li (2019). "A theory of falling growth and rising rents." Working paper.

Akcigit, Ufuk and Sina Ates (2019). "What happened to US business dynamism?" Working paper.

Akcigit, Ufuk and Sina Ates (2021). "Ten facts on declining business dynamism and lessons from endogenous growth theory." *American Economic Journal: Macroeconomics*, 13(1), 257–98.

Akcigit, Ufuk and William Kerr (2018). "Growth through heterogeneous innovations." *Journal of Political Economy*, 126(4), 1374–1443.

Atkeson, Andrew and Patrick Kehoe (2005). "Modeling and measuring organization capital." *Journal of Political Economy*, 113(5), 1026–1053.

Autor, David and David Dorn (2013). "The growth of low-skill service jobs and the polarization of the US labor market." *American Economic Review*, 103(5), 1553–1597.

Autor, David, David Dorn, Lawrence Katz, Christina Patterson, and John Van Reenen (2017). "The fall of the labor share and the rise of superstar firms." Working paper.

Autor, David, Frank Levy, and Richard Murnane (2003). "The skill content of recent technological change: an empirical exploration." *Quarterly Journal of Economics*, 118(4), 1279–1333.

Azoulay, Pierre, Benjamin Jones, J. Daniel Kim, and Javier Miranda (2020). "Age and high-growth entrepreneurship." *American Economic Review: Insights*, 2(1), 65–82.

Barkai, Simcha and Stavros Panageas (2021). "Value Without Employment." Working paper.

Bhandari, Anmol and Ellen McGrattan (2021). "Sweat equity in US private business." *Quarterly Journal of Economics*, 136(2), 727–781.

Bloom, Nicholas, Charles Jones, John Van Reenen, and Michael Webb (2020). "Are ideas getting harder to find?" *American Economic Review*, 110(4), 1104–44.

Bornstein, Gideon (2021). "Entry and profits in an aging economy: the role of consumer inertia." Working paper.

Buera, Francisco and Yongseok Shin (2013). "Financial frictions and the persistence of history: A quantitative exploration." *Journal of Political Economy*, 121(2),

221–272.
Cagetti, Marco and Mariacristina De Nardi (2006). "Entrepreneurship, frictions, and wealth." *Journal of Political Economy*, 114(5), 835–870.
Casselman, Ben (2014). "The slow death of American entrepreneurship." *Five Thirty Eight*, 05/15/14. Accessed online 08/14/15.
Cortes, Guido Matias, Nir Jaimovich, and Henry Siu (2017). "Disappearing routine jobs: Who, how, and why?" *Journal of Monetary Economics*, 91, 69–87.
Davis, Steven (2017). "Regulatory complexity and policy uncertainty: headwinds of our own making." Working paper.
Davis, Steven and John Haltiwanger (2014). "Labor market fluidity and economic performance." Working paper.
Davis, Steven, John Haltiwanger, Ron Jarmin, and Javier Miranda (2006). "Volatility and dispersion in business growth rates: publicly traded versus privately held firms." *NBER Macroeconomics Annual 2006*, 21, 107–180.
De Loecker, Jan, Jan Eeckhout, and Simon Mongey (2021). "Quantifying market power and business dynamism in the macroeconomy." Working paper.
De Loecker, Jan, Jan Eeckhout, and Gabriel Unger (2020). "The Rise of Market Power and the Macroeconomic Implications." *Quarterly Journal of Economics*, 135(2), 561–644.
De Ridder, Maarten (2019). "Market power and innovation in the intangible economy." Working paper.
DeBacker, Jason, Vasia Panousi, and Shanthi Ramnath (2018). "A risky venture: Income dynamics within the non-corporate private business sector." Working paper.
Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda (2014a). "The role of entrepreneurship in US job creation and economic dynamism." *Journal of Economic Perspectives*, 28(3), 3–24.
Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda (2014b). "The secular decline in business dynamism in the US." Working paper.
Eden, Maya and Paul Gaggl (2018). "On the welfare implications of automation." *Review of Economic Dynamics*, 29, 15–43.
Engbom, Niklas (2017). "Firm and Worker Dynamics in an Aging Labor Market." Working paper.
Flood, Sarah, Miriam King, Steven Ruggles, and J. Robert Warren (2015). *Integrated Public Use Microdata Series, Current Population Survey: Version 4.0*. [Machine-readable database], Minneapolis: University of Minnesota.
Goos, Maarten, Alan Manning, and Anna Salomons (2014). "Explaining job polarization: routine-biased technological change and offshoring." *American Economic Review*, 104(8), 2509–2526.
Gutierrez, German, Callum Jones, and Thomas Philippon (2019). "Entry costs and the macroeconomy." Working paper.
Haltiwanger, John, Ron Jarmin, and Javier Miranda (2013). "Who creates jobs? Small versus large versus young." *Review of Economics and Statistics*, 95(2), 347–361.

Harrison, J D (2015). "The decline of American entrepreneurship—in five charts." *Washington Post*, 02/12/15. Accessed online 08/14/15.

Hopenhayn, Hugo, Julian Neira, and Rish Singhania (2021). "From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share." Working paper.

Hsieh, Chang-Tai and Enrico Moretti (2017). "Housing constraints and spatial misallocation." Working paper.

Hsieh, Chang-Tai and Esteban Rossi-Hansberg (2019). "The industrial revolution in services." Working paper.

Hurst, Erik, Geng Li, and Benjamin Pugsley (2014). "Are household surveys like tax forms? Evidence from income underreporting of the self-employed." *Review of Economics and Statistics*, 96(1), 19–33.

Hyatt, Henry and James Spletzer (2013). "The recent decline in employment dynamics." *IZA Journal of Labor Economics*, 2(1).

Jaimovich, Nir and Henry Siu (2020). "Job Polarization and Jobless Recoveries." *The Review of Economics and Statistics*, 102(1), 129–147.

Jiang, Helu and Faisal Sohail (2022). "Skill-biased entrepreneurial decline." *Review of Economic Dynamics*, Forthcoming.

Karahan, Fatih, Benjamin Pugsley, and Ayşegül Şahin (2021). "Demographic origins of the startup deficit." Working paper.

Kleiner, Morris (2015). "Border battles: The influence of occupational licensing on interstate migration." *Employment Research*, 22(4), 4–6.

Kopecky, Joseph (2017). "An aging dynamo: demographic change and the decline of entrepreneurial activity in the United States." Working paper.

Krusell, Per, Lee Ohanian, José-Víctor Ríos-Rull, and Giovanni Violante (2000). "Capital-skill complementarity and inequality: A macroeconomic analysis." *Econometrica*, 68(5), 1029–1053.

Lee, Sang Yoon Tim and Yongseok Shin (2016). "Horizontal and vertical polarization: task-specific technological change in a multi-sector economy." Working paper.

Levine, Ross and Yona Rubinstein (2017). "Smart and illicit: who becomes an entrepreneur and do they earn more?" *Quarterly Journal of Economics*, 132(2), 963–1018.

Luttmer, Erzo (2011). "On the mechanics of firm growth." *Review of Economic Studies*, 78(3), 1042–1068.

McLaughlin, Patrick A. and Oliver Sherouse (2018). *RegData US 3.1 Annual (dataset)*. https://quantgov.org/regdata-us/, QuantGov, Mercatus Center at George Mason University, Arlington, VA.

Peters, Michael and Conor Walsh (2021). "Population growth and firm dynamics." Working paper.

Polivka, Anne and Stephen Miller (1998). "The CPS after the redesign: Refocusing the economic lens." In *Labor Statistics Measurement Issues*, edited by John Haltiwanger, Marilyn Manser, and Robert Topel, pp. 249–289. University of Chicago Press.

Poschke, Markus (2018). "The firm size distribution across countries and skill-biased change in entrepreneurial technology." *American Economic Journal: Macroeconomics*, 10(3), 1–41.

Pugsley, Benjamin Wild and Ayşegül Şahin (2019). "Grown-up business cycles." *Review of Financial Studies*, 32(3), 1102–1147.

Quadrini, Vincenzo (2000). "Entrepreneurship, saving, and social mobility." *Review of Economic Dynamics*, 3(1), 1–40.

Salgado, Sergio (2019). "Technical change and entrepreneurship." Working paper.

Storesletten, Kjetil, Chris Telmer, and Amir Yaron (2004). "Cyclical dynamics in idiosyncratic labor market risk." *Journal of Political Economy*, 112(3), 695–717.

vom Lehn, Christian (2015). "Labor market polarization, the decline of routine work and technological change: a quantitative analysis." Working paper.

Weiss, Josh (2020). "Intangible investment and market concentration." Working paper.

Weissmann, Jordon (2012). "The 30-year decline of American entrepreneurship." *The Atlantic*. Accessed online 08/14/15.

Yellen, Janet (2014). "Perspectives on Inequality and Opportunity from the Survey of Consumer Finances." Speech at the Conference on Economic Opportunity and Inequality, Federal Reserve Bank of Boston, Boston, MA, 17 October 2014.

Appendix A: Empirics (Section 2)

A.1. Discussion of sample and variable definitions

The sample period of 1987–2015 has been chosen to ensure that self-employment can be measured consistently over time. The CPS does have data prior to 1987 on self-employment, but for this period the BLS only reported people as self-employed if their business was not incorporated. From 1987 onward people with incorporated businesses have been counted as self-employed as well. The exclusion of people with incorporated businesses from self-employment prior to 1987 is likely to downwardly bias the trend in self-employment since people have been increasingly likely to incorporate their businesses over time. Since the share of people who are self-employed is a critical moment for the analysis, I exclude the pre-1987 data.[60] 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 moments that I consider, this redesign had no systematic impact, so no adjustments are made for this.

The entrepreneur and self-employed shares are calculated with respect to the labor force throughout the analysis. The labor force is defined to include all people who worked for profit, pay, or as an unpaid family worker for at least 8 weeks during the relevant year. A week is counted even if a person only worked for a few hours, or was on paid time off (for vacation or illness). The weeks requirement is intended to omit people with very low labor force participation, while maintaining a broad sample. 2.3% of the sample are excluded from the labor force due to this criteria.

A.2. Source of owners per firm estimate

The estimates of the number of owners per business in various size categories 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 with less than 100 employees owned by self-employed people.

60. In their analysis of entrepreneurs Levine and Rubinstein (2017) distinguish between people with incorporated and unincorporated businesses arguing that incorporation is a signal of 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.

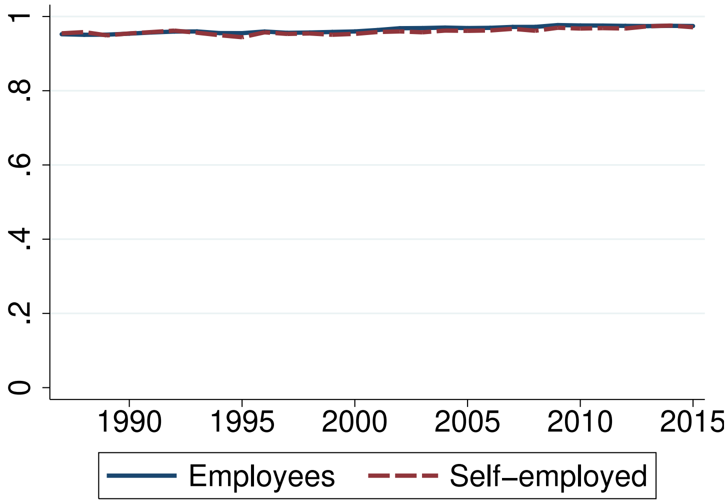


Figure A.1: **Average share of income from longest job for employees and the self-employed.** Each line is the average value of income from the longest job as a share of total income from self-employment and dependent employment. For each person the share is winsorized to be in $[0, 1]$.

A.3. Income share of main job

The March supplement of the CPS asks respondents for information about their "longest" job in the previous calendar year. The data shows that on average, a person's longest job accounts for nearly all of their income from employment. To see this in detail, Figure A.1 plots a person's income from their longest job as a share of their total income from self-employment and dependent employment.[61] This share is plotted separately for those whose longest jobs were self-employment and dependent employment. The figure shows that throughout the period of analysis the share of income from the main job was above 95% for both groups.

This feature of the data also supports the way that occupational choice is modeled. In the model agents who are working have to choose between being being an entrepreneur and an employee. They can't split their time between the two. While this is a simplification of reality, the data shows that it is a reasonable approximation.

61. Due to negative income from self-employment, it is possible for this share to fall outside $[0, 1]$. For the purposes of these calculations I bound the shares by 0 and 1. This affects a small number of observations, for example, 0.56% for 1991 and 0.01% for 2015.

A.4. Composition effects on the entrepreneur share

In this section I will show that the decline in entrepreneurship is not driven by changes in the composition of the population over time. To evaluate whether changes in composition are driving the result I compute the entrepreneur share holding the composition of the economy fixed along several dimensions. Specifically, the entrepreneur share 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 over time with respect to partition $\mathcal{G}$ the entrepreneur share in year t is

$$e_{\mathcal{G},t} \equiv \sum_{g \in \mathcal{G}} \omega_{g,1991} e_{g,t}. \tag{A.1}$$

This equation keeps the share of each subset of the economy fixed while allowing the entrepreneur share 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;[62] for age $\mathcal{G}$ has four categories: 25–35, 36–45, 46–55 and 56–65; for education $\mathcal{G}$ is composed of five categories for the highest level of education a person has completed: less than high school, high school, some college education but less than a bachelor's degree, a bachelor's degree and more education than a bachelor's degree; for gender $\mathcal{G}$ is male and female; for geographic distribution $\mathcal{G}$ is the nine Census divisions; and to control for the metropolitan and non-metropolitan shares of the labor force $\mathcal{G}$ has these two categories.

The results for $e_{\mathcal{G},t}$ for each of these composition controls are presented in Figure A.2. They show that the decrease in the entrepreneur share is either virtually unchanged or larger when each of these composition controls is imposed. This implies that changes in composition are not causing the decrease in the entrepreneur share and, in fact, the decrease in the entrepreneur share would be larger without changes in composition. Due to sample size limitations I can not 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

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

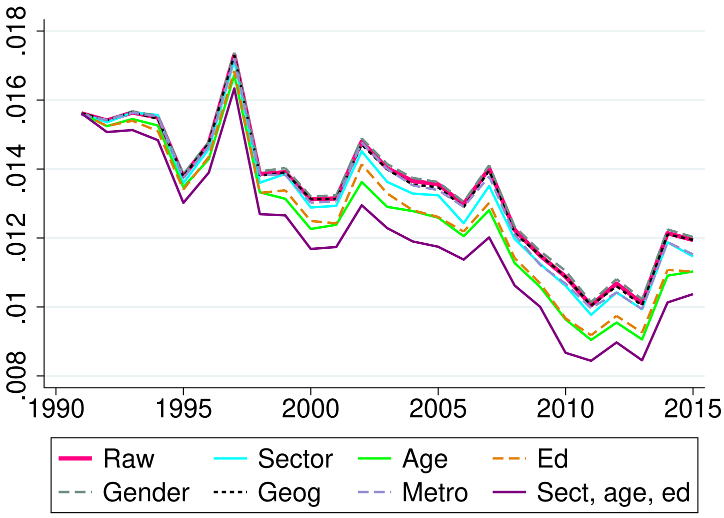


Figure A.2: **Entrepreneur share with composition controls.** The *Raw* line is the entrepreneur share without any composition control. For the remaining lines the composition of the labor force along various dimensions is held fixed at its 1991 distribution, per equation (A.1). The subsets of the labor 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 (see text for details), four age groups (25–35, 36–45, 46–55 and 56–65) and two education groups (less than college and at least college).

sizes are large enough for this exercise I use three sectors (mining, manufacturing, construction, and utilities; wholesale and retail trade; and finance, insurance, real estate, and services), two education groups (less than college and at least college) and all four age categories. $\mathcal{G}$ is the set of all possible intersection of these sets.[63] The resulting $e_{\mathcal{G},t}$ series is presented in Figure A.2 and labeled *Sect, age, ed*. The decrease in the entrepreneur share is larger again under these joint controls, emphasizing that composition changes not are causing this decline, they are working against it.

This exercise has been replicated for the self-employed share, instead of the entrepreneur share, with the results in Figure A.3. The main message is the same.

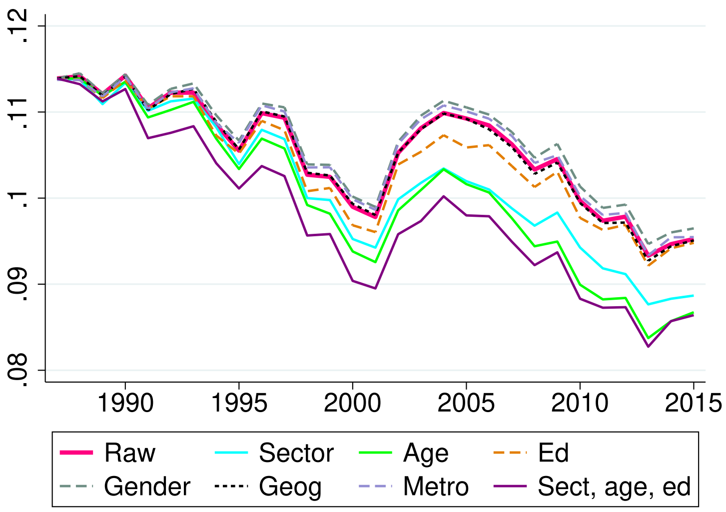


Figure A.3: **Self-employed share with composition controls.** This figure has exactly the same setup as Figure A.2. The difference is that the results are for the self-employment rate instead of the entrepreneurship rate. See notes of Figure A.2 for details.

A.5. Additional details on composition changes

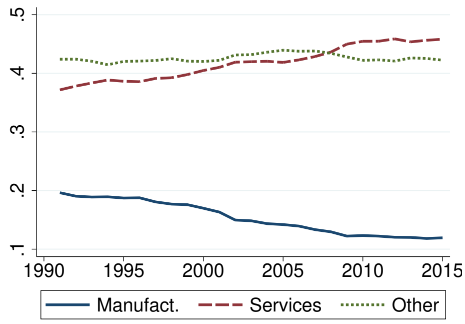
In the previous section I showed that changes in the composition of the economy have generally worked against the decrease in the entrepreneur share. In this section I provide additional details for the composition changes that have had the largest effect on the entrepreneur share: changes in the sectoral,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

Figure A.4(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 entrepreneur share since, as panel (b) shows, the share of people in the services sector who are entrepreneurs is larger than the share in manufacturing.[64]

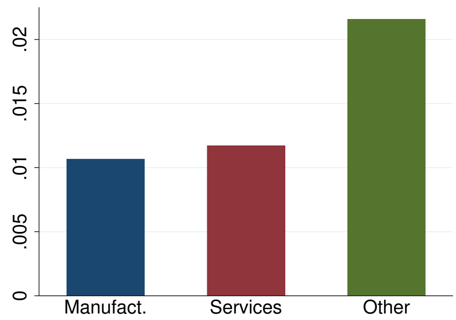
Panels (c) and (d) illustrate the effects of changes in the education distribution. Over time the share of people with a college or more than a college education has increased, while the shares in all lower education categories have decreased. Since more educated people have higher entrepreneur shares—see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

63. An example of an element of $\mathcal{G}$ for this case is all people in the sample aged 25–35 with less than a college education working in mining, manufacturing, construction or utilities.

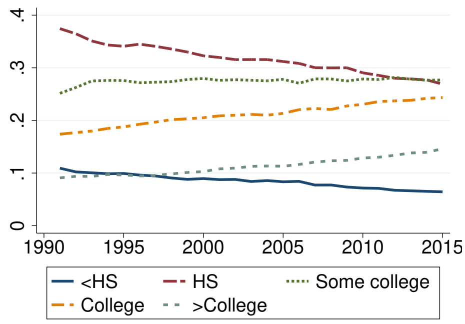
64. The entrepreneur shares are shown for 1991 as an illustration. The ranking of entrepreneur shares across sectors, and also across education and age, are stable over time.



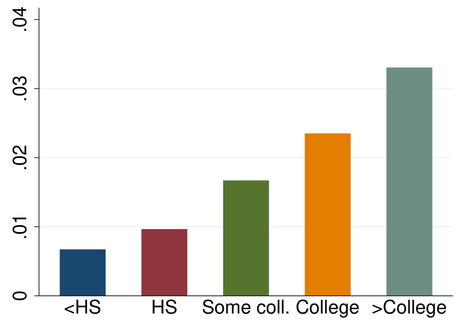
(a) Sectoral distribution



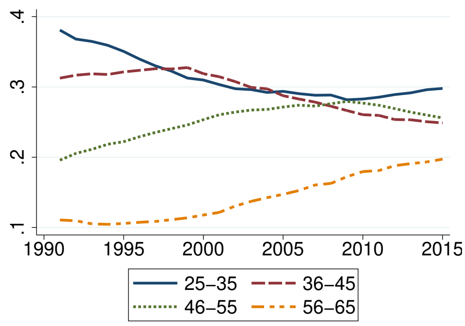
(b) Entrepreneur shares by sector, 1991



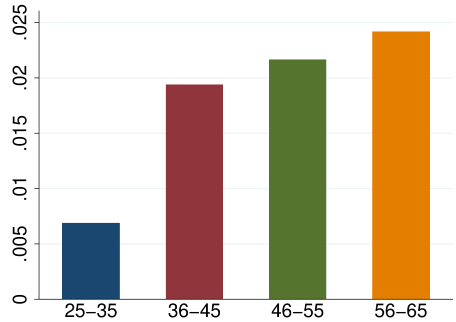
(c) Education distribution



(d) Entrepreneur shares by education, 1991



(e) Age distribution



(f) Entrepreneur shares by age, 1991

Figure A.4: **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 education and age distributions are the share of the labor force in each education and age group, respectively. The entrepreneur shares are the share of the labor force who are entrepreneurs within each group.

The effects of the changes in the age distribution are demonstrated by Figures A.4(e) and (f). While the change in the share of the labor force in each age category has not been monotone in age, in general there has been an aging of the population. This has pushed the entrepreneur share upwards since the entrepreneur share is

Sector	1991	Entrepreneur share			% of total
	share	'91–'94	'12–'15	% change	change
Mining, Construction and TCU	15.8	1.7	1.4	-17.2	10.2
Manufacturing	19.6	1.0	0.7	-28.8	12.6
Wholesale and retail trade	19.3	2.5	1.5	-39.0	40.9
FIRE	7.2	2.1	1.2	-43.0	14.5
Professional services	26.3	1.1	0.7	-33.5	20.5
Other services	10.9	1.5	1.5	-3.4	1.3

Table A.1. **Entrepreneur share by sector.** The columns contain: (1) share of the labor force in each sector in 1991; (2)–(3) the average share of the labor force in each sector who are entrepreneurs for 1991–94 and 2012–15, respectively; (4) percentage change in these rates from 1991–94 to 2012–15; (5) each sector's share of the total change in the entrepreneur share when the sector distribution is held fixed at 1991.TCU stands for the transportation, communication, and public utilities sector.

increasing in age. Note that the entrepreneur share 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.

A.6. Decline in entrepreneurship by sector

To establish that the decline in the entrepreneur share is not driven by one sector Table A.1 presents details of the change in the entrepreneur share 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. I also add the wholesale trade sector to the retail sector, since the former is relatively small and the entrepreneur shares have very similar trends in the two sectors. To smooth out year-to-year volatility in the data I take averages of the entrepreneur share in the first four and last four years of the sample. The table shows that there was a large decline in the entrepreneur share in all sectors except other services, for which the decline was more modest. The last column of the table presents the share of the decrease in the aggregate entrepreneur share that each sector accounts for when the sectoral composition of the economy is held fixed. For sector g this is

$$\frac{\omega_{g,1991}(\bar{e}_{g,2015} - \bar{e}_{g,1994})}{\bar{e}_{\mathcal{G},2015} - \bar{e}_{\mathcal{G},1994}}$$

where the partition $\mathcal{G}$ is the set of sectors being used and $\bar{x}_t \equiv (x_t + x_{t-1} + x_{t-2} + x_{t-3})/4$ for any variable x_t. The results show that all sectors contribute to the decline, with the largest contributions coming from wholesale and retail trade, and professional services, with other services only making a small contribution.

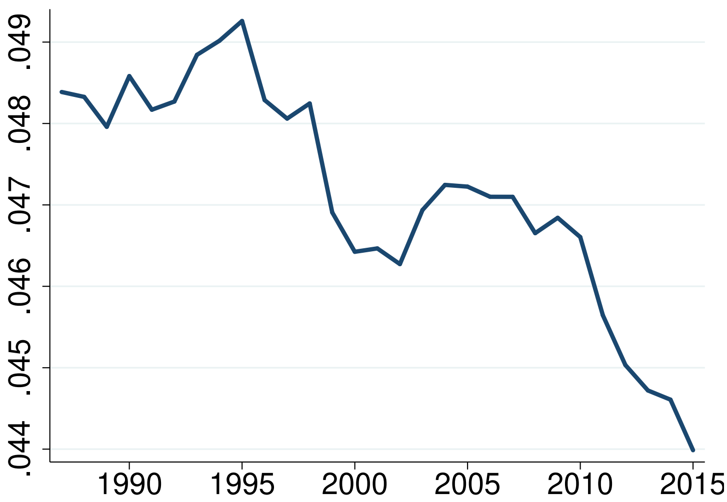


Figure A.5: **Ratio of employer firms to the labor force.** The number of employer firms is from the BDS. The labor force is estimated, using the CPS, as the number of people in the civilian non-institutional population aged 16 and over who worked in the private non-farm sector in the relevant calendar year.

A.7. Broader definitions of an entrepreneur

The questions in the CPS dictate how an entrepreneur can be defined. There are a number of types of people who one might want to include, that are omitted by this definition. This section discusses a number of these and explains why the data suggests that these omissions are unlikely to reverse the trend decline in the entrepreneur share.

The first relevant class of people are those who own and manage a business, but are not classified as self-employed. This could be because they do not work the majority of their hours in the business or because the ownership or legal structure of the business is such that they consider themselves to be an employee rather than self-employed. If the share of people in this category has increased over time, then it could explain some of the decline in the entrepreneur share. One way to assess this is to use an alternative dataset on businesses that doesn't rely on employment status of the manager of the firm for its classification. One such dataset is the BDS from the Census Bureau. Using this, we can compute the ratio of employer firms in the economy, relative to the number of working people in the economy.[65] This ratio is presented in Figure A.5 and shows a decline over time.

65. Specifically I use the number of non-agricultural firms from the BDS and estimate the number of employees and self-employed in the non-farm private sector using the CPS.

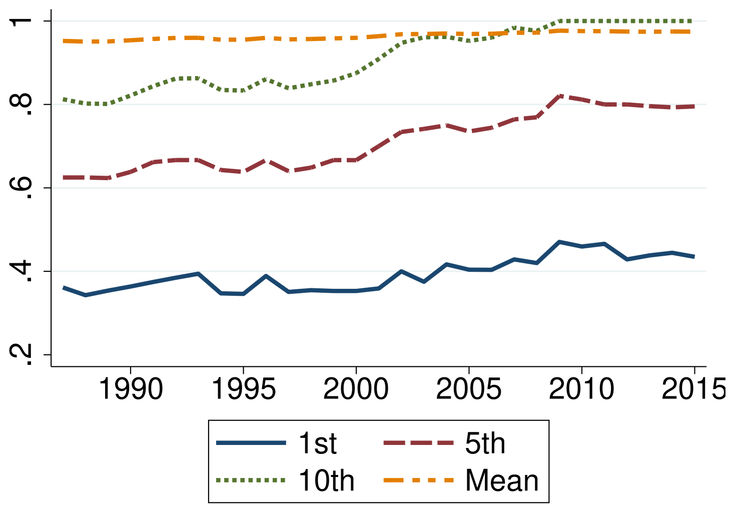


Figure A.6: **Share of income from main job for people working as employees.** This figure presents the 1^{st}, 5^{th} and 10^{th} percentiles, and the mean, of the distribution of the share of income that employees earn from their main job.

A second class of people missed by the definition is people who were self-employed in the previous year, but self-employment was not their main job. One way of looking at this is to use Figure A.5 again, since the measure of entrepreneurship in that figure does not depend on whether someone manages a firm that they own as their primary job. Another approach is to look at whether there is evidence that people have earned an increasing share of their income from secondary occupations over time. This would be consistent with an increasing share of people running businesses as a supplementary source of income. With the CPS we can measure a person's income from their main job in a year, as a share of all of their income from working as an employee and from self-employment.[66] In Figure A.6 I plot the mean, and several percentiles from the left tail, of the distribution of this share for people who work as employees in their main job. The data show that on average secondary income sources make up a very small share of income ($< 5\%$ in all years), and this share has actually decreased over time, rather than increasing. Looking at the mean only could hide a decrease in the share of income from the main job for people in the left tail of the distribution for this variable. However, the figure clearly shows that that left tail has increased in value as well.

A third note on measurement issues is that the definition of an entrepreneur is likely to omit some people whose businesses have merged with others, or been acquired. If merger and acquisition activity has increased over time then this could

66. For income from self-employment I include farm and non-farm income.

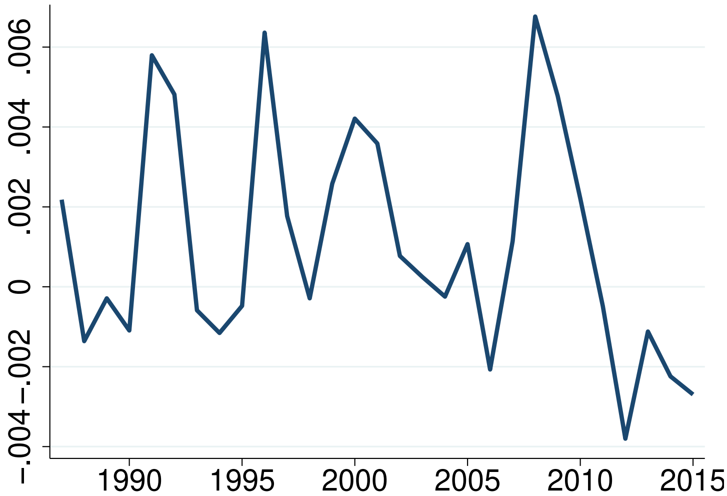


Figure A.7: **Net merger and acquisition rate.** This is the implied net merger and acquisition rate from the BDS, computed using equation (A.2). It is a net rate because it measures M&A less firm splits. A negative value implies that there were more firms splitting than merging or being acquired.

be contributing to the decline in entrepreneurship. The relevance of this can be assessed using the BDS data. This dataset provides information, *inter alia*, on the number of firms each year, the number of new firms, and the number of firm exits. A firm exit occurs when all establishments of a firm close down, so that mergers and acquisitions (M&A) that keep at least one establishment operating are not included. The number of firms in the dataset can also change due to firms splitting into multiple firms. The net M&A rate (the rate of M&A less splits) can be computed as:

$$\text{M\&A rate}(t) = \frac{\text{firms}(t) - \text{deaths}(t) + \text{entrants}(t+1) - \text{firms}(t+1)}{\text{firms}(t)}, \qquad \text{(A.2)}$$

where firms(t), entrants(t) and deaths(t) are the total number of firms, the number of entrants and the number of firms that die in year t, respectively. This measure of M&A is plotted in Figure A.7 and shows that there is not an upward trend over time.

A.8. Evidence of declining entrepreneurship from the Survey of Income and Program Participation

To provide additional evidence of the decline in the entrepreneur share, including showing that it holds for a different period that excludes the Great Recession, I have computed the change in the entrepreneur share from 1983 to 1995 using the Survey of Income and Program Participation (SIPP) from the Census Bureau.

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. For my analysis I use the interviews conducted in October 1983–January 1984 and October 1995–January 1996. 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. Note that 1983 is the year after a recession trough while 1995 is four years after a recession trough, so the cyclicality of the entrepreneur share should work against any decline over this period.

For the analysis of the entrepreneur share 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 the owner and co-owners in the same household. For the first sample I find that the entrepreneur share (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%.

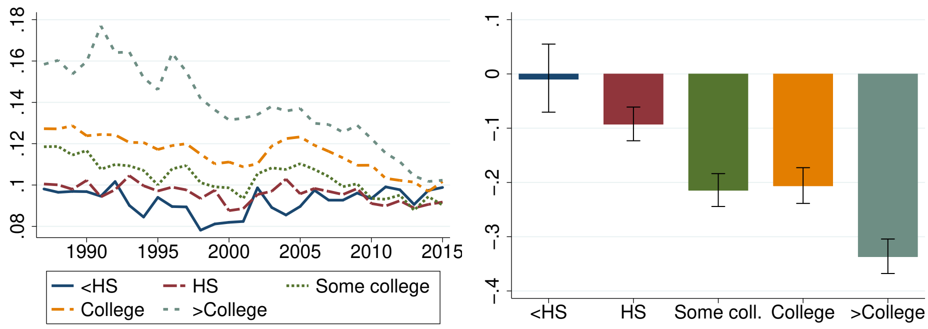
A.9. Robustness exercises for the change in entrepreneurship by education

This section contains two robustness exercises for the result that the decline in entrepreneurship has been larger for higher education groups.

Figure 2 in the main text shows how the entrepreneur share has changed over time for each education group. This analysis is reproduced for the self-employed share in Figure A.8 to show that the results hold for this broader measure of entrepreneurship as well. This analysis goes back to 1987, rather than starting in 1991, since it does not require firm size information.

A second potential concern is that the larger decline in entrepreneurship for more educated people could be driven by changes in the structure of specific industries. Specifically, there are a number of professional services industries such as legal services, accounting, financial consulting and medical services, that seem to have shifted over time from small practices to larger companies containing many professionals. To assess whether this change is driving the result, I redo the analysis for the change in the entrepreneur share by education group, excluding the professional services and FIRE sectors. This changes the sample significantly. For example, the total sample for the analysis shrinks by 38%, and for people with more than a college education the decline is 75%.[67] Despite this, the point

67. The full sample decrease from 521 to 324 thousand, and for people with more than a college education it is from 62 to 16 thousand.



(a) Self-employmed share, 1987–2015 (b) Self-employment, 1987/90–2012/15

Figure A.8: **Self-employed share by education and percentage change.** Panel (a) is the share of the labor force for each education level who are self-employed. Panel (b) is the the relative change in the self-employed share from 1987–90 (pooled data) to 2012–15 for each education group (i.e. -0.1 is a decline of 10%). The whiskers are 95% confidence intervals estimated by Poisson regression. The education categories are people who did not finish high school (<HS), finished high school (HS), have some college education less than a bachelor's degree (some college), completed a bachelor's degree (college), and have more education than a bachelor's degree (>College).

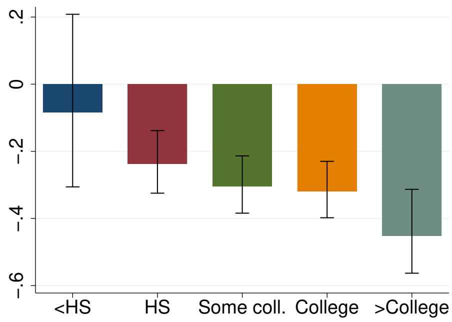


Figure A.9: **1991–2015 percentage change in entrepreneur share by education, omitting professional services and FIRE.** This figure presents the relative change in the entrepreneur share from 1991–94 (pooled date) to 2012–15 for each education group with the professional services and FIRE sectors omitted (i.e. -0.1 is a decline of 10%). The whiskers are 95% confidence intervals estimated by Poisson regression. The education categories are the same as in Figure A.8.

estimates in Figure A.9 are very similar to the main results. Confidence intervals are, of course, wider due to the smaller sample size.

Appendix B: Model and proofs

B.1. Optimal input choices and profit function for entrepreneurs

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

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

where

$$\begin{aligned}
D_1 &= \Big(\frac{1-\varphi}{\varphi}\Big)\Big(\frac{w_h}{w_l}\Big)(1-\lambda), \\
D_2 &= \lambda\Big[\Big(\frac{\lambda}{1-\lambda}\Big)\Big(\frac{w_l}{r_i}\Big)\Big]^{\frac{\tau}{1-\tau}} + 1 - \lambda, \\
D_3 &= \frac{\alpha\varphi}{w_h}\Big(\varphi + (1-\varphi) D_1^{\frac{\gamma}{1-\gamma}} D_2^{\frac{\gamma(1-\tau)}{\tau(1-\gamma)}}\Big)^{\frac{\alpha-\gamma}{\gamma}}.
\end{aligned}$$

B.2. Stationary distribution

The state space is the Cartesian product $\mathbb{R}^3_+ \times \{0,1\}$, denoted by $\mathbb{Z}$. Let the σ-algebra $\Sigma_{\mathbb{Z}}$ be defined as $B_{\mathbb{R}^3_+} \otimes P(\{0,1\})$, where $B_{\mathbb{R}^3_+}$ is the Borel σ-algebra of $\mathbb{R}^3_+$ and $P(\{0,1\})$ is the power set of $\{0,1\}$. Let the typical subset of $\Sigma_{\mathbb{Z}}$ be denoted by $\mathcal{Z} \times \mathcal{E}$. With this notation, the transition function for the distribution of agents, $q : \mathbb{Z} \times \Sigma_{\mathbb{Z}} \to [0,1]$, can be expressed as:

$$q((\mathbf{z},\varepsilon), \mathcal{Z}\times\mathcal{E}) = (1-\delta)\big[\big(1-\mathbb{1}_{\not{o}}(e)\big)\mathbb{1}_{\mathcal{E}}(0) + \mathbb{1}_{\not{o}}(e)\mathbb{1}_{\mathcal{E}}(1)\big] \int_{\mathcal{Z}} g(\mathbf{z}'|\mathbf{z})d\mathbf{z}' + \delta \mathbb{1}_{\mathcal{E}}(0) \int_{\mathcal{Z}} g(\mathbf{z}')d\mathbf{z}',$$

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

$$Q(\mathcal{Z} \times \mathcal{E}) = \int_{\mathbb{Z}} q((\mathbf{z}, \varepsilon), \mathcal{Z} \times \mathcal{E}) dQ(\mathbf{z}, \varepsilon). \tag{B.1}$$

B.3. Proofs of propositions

Proposition 1.

(a) First consider the derivative with respect to r_i, holding wages fixed. $\underline{z}_e^s(z_s, \varepsilon)$ is a piecewise function with two parts. When wages are held fixed, r_i only enters both parts through Γ_π. $\underline{z}_e^s(z_s, \varepsilon)$ is strictly increasing in r_i if Γ_π is strictly decreasing in it. $\partial \Gamma_\pi / \partial r_i < 0$ can be proved by contradiction. Take any entrepreneur with productivity $z_e > 0$ and any rental rate of IT capital, $r_{i,1} > 0$. Let the entrepreneur's profit maximizing input choice be $(k_{o,1}^*, k_{i,1}^*, \ell_{l,1}^*, \ell_{h,1}^*)$ and its profit (before fixed and entry costs) be π_1^*. Now consider any $r_{i,2} > r_{i,1}$. Denote the optimal input choices and the resulting profit in the same way as for $r_{i,1}$, but with subscript 2 this time. Suppose that $\pi_2^* > \pi_1^*$. Then if, for $r_i = r_{i,1}$, the firm chose inputs $(k_{o,2}^*, k_{i,2}^*, \ell_{l,2}^*, \ell_{h,2}^*)$ instead of $(k_{o,1}^*, k_{i,1}^*, \ell_{l,1}^*, \ell_{h,1}^*)$ it would achieve a profit strictly great than π_2^*, and therefore strictly greater than π_1^*. This contradicts $(k_{o,1}^*, k_{i,1}^*, \ell_{l,1}^*, \ell_{h,1}^*)$ being the optimal input choice for $r_i = r_{i,1}$.

The proof for the derivative with respect to w_h (holding w_l fixed) follows the same logic. By the same argument just outlined, $\partial \Gamma_\pi / \partial w_h < 0$, which causes $\underline{z}_e^s(z_s, \varepsilon)$ to increase in w_h. For $s = h$, w_h also enters in the numerator of the expression for $\underline{z}_e^s(z_s, \varepsilon)$ for $z_h > \underline{z}_h$. This also causes $\underline{z}_e^h(z_h, \varepsilon)$ to increase in w_h.

(b) This part of the proposition restricts attention to $z_s > \underline{z}_h$, so the relevant expression for the entrepreneur thresholds is:

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

From part (a) it is established that $\partial \underline{z}_e^s(z_s, \varepsilon)/\partial r_i|_{\mathbf{w}} > 0$. This derivative is larger for $s = h$ because the wage w_s is in the numerator and $w_h > w_l$. The derivative of $\underline{z}_e^s(z_s, \varepsilon)$ with respect to w_h is also positive from part (a). It is larger for $s = h$ because (i) $w_h > w_l$, which increases the value of the numerator, and (ii) w_s increases in the numerator for the case of $s = h$, while it does not for $s = l$.

(c) This part of the proposition follows from equation (11) and the proof of part (a) of this proposition. From equation (11), $\underline{z}_e^s(z_s, 0) - \underline{z}_e^s(z_s, 1) > 0$ since $\psi_e > 0$. The proof of part (a) established that $\partial \Gamma_\pi / \partial r_i|_{\mathbf{w}} < 0$. The inequality in this part of the proposition follows from this.

Proposition 2.

(a) Since $\partial w_s/\partial z_f > 0$ and $\partial \Gamma_\pi/\partial w_s < 0$ for all $s \in \{l, h\}$,[68] it follows that $\partial \underline{z}_e^s(z_s, \varepsilon)/\partial z_f > 0$ for $z_s \in (0, \underline{z}_s]$. For $z_s > \underline{z}_s$, the decrease in Γ_π also causes $\underline{z}_e^s(z_s, \varepsilon)$ to increase. The increases in w_l and w_h cause this function to increase further through the w_s term in the numerator.

(b) The first inequality comes from taking the derivative of the function specified in equation (10) with respect to ψ.

For the second inequality, it follows from equation (11) that, for $z_s > \underline{z}_s$,

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

This derivative is strictly negative since $z_s w_s + \psi + \psi_e > z_s w_s + \psi > 0$.

For $z_s \in (0, \underline{z}_s]$, the analysis is identical, with $z_s w_s$ replaced by b in the previous equation.

(c) The first inequality comes from taking the derivative of the function specified in equation (10), with ε set equal to zero, with respect to ψ_e.

For the second inequality, since $\partial w_l/\partial \psi_e < 0$ and $\partial w_h/\partial \psi_e < 0$, $\partial \Gamma_\pi/\partial \psi_e > 0$. Using equation (10), it follows that $\partial \underline{z}_e^s(z_s, 1)/\partial \psi_e < 0$.

Proposition 3. Using equation (6) for $\ell_s(z)$, inequality (13) can be expressed as

$$\frac{\int_{\mathbb{Z}} \mathbb{1}_{z_{s'}}(\mathbb{R}_+)\mathbb{1}_{\sigma}(e|\mathcal{P}_\psi) z_e^{\frac{1}{1-\alpha-\eta}}\, dQ(\mathbf{z}, \varepsilon|\mathcal{P}_\psi)}{z_f(\mathcal{P}_\psi)^{\frac{1}{1-\alpha-\eta}}} > \frac{\int_{\mathbb{Z}} \mathbb{1}_{z_{s'}}(\mathbb{R}_+)\mathbb{1}_{\sigma}(e|\mathcal{P}_{z_f}) z_e^{\frac{1}{1-\alpha-\eta}}\, dQ(\mathbf{z}, \varepsilon|\mathcal{P}_{z_f})}{z_f(\mathcal{P}_{z_f})^{\frac{1}{1-\alpha-\eta}}}.$$

Since $z_f(\mathcal{P}_{z_f}) > z_f(\mathcal{P}_\psi)$, a sufficient condition for this is that

$$\int_{\mathbb{Z}} \mathbb{1}_{z_{s'}}(\mathbb{R}_+)\mathbb{1}_{\sigma}(e|\mathcal{P}_\psi) z_e^{\frac{1}{1-\alpha-\eta}}\, dQ(\mathbf{z}, \varepsilon|\mathcal{P}_\psi) > \int_{\mathbb{Z}} \mathbb{1}_{z_{s'}}(\mathbb{R}_+)\mathbb{1}_{\sigma}(e|\mathcal{P}_{z_f}) z_e^{\frac{1}{1-\alpha-\eta}}\, dQ(\mathbf{z}, \varepsilon|\mathcal{P}_{z_f}). \tag{B.2}$$

To condense notation, let

$$\tilde{Z}_e^{s'}(\mathcal{P}) \equiv \int_{\mathbb{Z}} \mathbb{1}_{z_{s'}}(\mathbb{R}_+)\mathbb{1}_{\sigma}(e|\mathcal{P}) z_e^{\frac{1}{1-\alpha-\eta}}\, dQ(\mathbf{z}, \varepsilon|\mathcal{P}),$$

so that (B.2) can be expressed as $\tilde{Z}_e^{s'}(\mathcal{P}_\psi) - \tilde{Z}_e^{s'}(\mathcal{P}_{z_f}) > 0$.

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68. $\partial \Gamma_\pi/\partial w_s < 0$ can be proved in the same way that $\partial \Gamma_\pi/\partial r_i < 0$ is proved for Proposition 1(a).

Since $\partial w_s/\partial z_f > 0$ and $\partial w_s/\partial \psi > 0$ for all $s \in \{l, h\}$, $\partial \Gamma_\pi/\partial z_f < 0$ and $\partial \Gamma_\pi/\partial \psi > 0$. It follows that, for $z_{s'} > \underline{z}_{s'}(\mathcal{P}_{z_f})$,[69]

$$\frac{\partial \underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_{z_f})}{\partial z_{s'}} > \frac{\partial \underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_{\psi})}{\partial z_{s'}}.$$

Since the share of agents of skill type s' who are entrepreneurs must be equal under $\mathcal{P}_{z_f}$ and $\mathcal{P}_\psi$ (equation 12), the previous inequality implies that there are thresholds $z_{s'}^*(\varepsilon)$, for $\varepsilon \in \{0, 1\}$, such that

$$\begin{aligned}
\underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_\psi) &> \underline{z}_e^{s'}(z_s, \varepsilon | \mathcal{P}_{z_f}) \text{ for } z_{s'} < z_{s'}^*(\varepsilon), \\
\underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_\psi) &= \underline{z}_e^{s'}(z_s, \varepsilon | \mathcal{P}_{z_f}) \text{ for } z_{s'} = z_{s'}^*(\varepsilon), \\
\underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_\psi) &< \underline{z}_e^{s'}(z_s, \varepsilon | \mathcal{P}_{z_f}) \text{ for } z_{s'} > z_{s'}^*(\varepsilon).
\end{aligned}$$

Using this mapping of the entrepreneur thresholds for the two sets of parameter values, $\tilde{Z}_e^{s'}(\mathcal{P}_\psi) - \tilde{Z}_e^{s'}(\mathcal{P}_{z_f})$ can be expressed as

$$\begin{aligned}
\tilde{Z}_e^{s'}(\mathcal{P}_\psi) - \tilde{Z}_e^{s'}(\mathcal{P}_{z_f}) = \sum_{\varepsilon \in \{0,1\}} \int_{z_{s'}^*(\varepsilon)}^{\infty} \int_{\underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_\psi)}^{\underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_{z_f})} \mathbb{1}_{z_{s'}}(\mathbb{R}_+) z_e^{\frac{1}{1-\alpha-\eta}} Q(\mathbf{z}, \varepsilon) dz_e dz_{s'} \\
- \int_0^{z_{s'}^*(\varepsilon)} \int_{\underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_{z_f})}^{\underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_\psi)} \mathbb{1}_{z_{s'}}(\mathbb{R}_+) z_e^{\frac{1}{1-\alpha-\eta}} Q(\mathbf{z}, \varepsilon) dz_e dz_{s'}, \quad \text{(B.3)}
\end{aligned}$$

where $Q(\mathbf{z})$ is the marginal distribution of $\mathbf{z}$. Taking the limit as $\psi_e \to 0$,

$$\begin{aligned}
\lim_{\psi_e \to 0} \tilde{Z}_e^{s'}(\mathcal{P}_\psi) - \tilde{Z}_e^{s'}(\mathcal{P}_{z_f}) = \int_{z_{s'}^*(0)}^{\infty} \int_{\underline{z}_e^{s'}(z_{s'}, 0 | \mathcal{P}_\psi)}^{\underline{z}_e^{s'}(z_{s'}, 0 | \mathcal{P}_{z_f})} \mathbb{1}_{z_{s'}}(\mathbb{R}_+) z_e^{\frac{1}{1-\alpha-\eta}} g(\mathbf{z}) dz_e dz_{s'} \\
- \int_0^{z_{s'}^*(0)} \int_{\underline{z}_e^{s'}(z_{s'}, 0 | \mathcal{P}_{z_f})}^{\underline{z}_e^{s'}(z_{s'}, 0 | \mathcal{P}_\psi)} \mathbb{1}_{z_{s'}}(\mathbb{R}_+) z_e^{\frac{1}{1-\alpha-\eta}} g(\mathbf{z}) dz_e dz_{s'}. \quad \text{(B.4)}
\end{aligned}$$

Observe that every value of z_e in the range $(\underline{z}_e^{s'}(z_{s'}, 0 | \mathcal{P}_\psi), \underline{z}_e^{s'}(z_{s'}, 0 | \mathcal{P}_{z_f}))$ for $z_{s'} > z_{s'}^*(0)$ is greater than every value of z_e in the range $(\underline{z}_e^{s'}(z_{s'}, 0 | \mathcal{P}_{z_f}), \underline{z}_e^{s'}(z_{s'}, 0 | \mathcal{P}_\psi))$ for $z_{s'} < z_{s'}^*(0)$. Since equation (12) ensures that the weights placed on these two sets of values of z_e are equal, therefore $\lim_{\psi_e \to 0} \tilde{Z}_e^{s'}(\mathcal{P}_\psi) - \tilde{Z}_e^{s'}(\mathcal{P}_{z_f}) > 0$.

69. The one exception to this is at $z_{s'} = \underline{z}_{s'}(\mathcal{P}_\psi)$ because $\underline{z}_e^{s'}(z_{s'}, \varepsilon | \mathcal{P}_\psi)$ is not differentiable at this point; but that is not material for the proof.

Appendix C: Model-data mapping and calibration moments

C.1. Additional details for mapping model to data

Data. The main dataset that is used for the calibration is the CPS March supplement, which was introduced in Section 2. The sample is the same as the main sample for the analysis in that section: people aged 25–65 not working in the agriculture or government sectors. The main moments that are used are from the occupation distribution and the income distribution. Full details of how these moments are computed are below. Wherever other datasets are used, this is specified.

Skills. The occupation classification scheme from Acemoglu and Autor (2011) divides occupations into four categories according what types of tasks each occupation is most intensive in: non-routine cognitive, routine cognitive, routine manual or non-routine manual tasks.[70] For a detailed discussion of these categories see Autor *et al.* (2003) and Acemoglu and Autor (2011). Briefly, routine tasks are repetitive tasks that could be summarized by a set of instructions that a machine could follow. They are cognitive if they require mostly mental effort (e.g. book-keeping) while they are manual if they require mostly physical effort (e.g. production line assembly). Non-routine tasks are difficult to get a machine to do with a set of instructions. Cognitive non-routine tasks include research, marketing activities and managerial tasks. Manual non-routine tasks include many low-skill service jobs. In terms of relative wages, non-routine manual occupations earn the lowest wages, followed by routine occupations and then non-routine cognitive occupations. I therefore use non-routine cognitive occupations as high-skill occupations and the rest as low-skill occupations.

There is a line of research on routine-biased technical change that distinguishes between non-routine manual occupations and routine occupations (e.g. Acemoglu and Autor 2011; Autor and Dorn 2013; Goos *et al.* 2014; Jaimovich and Siu 2020; vom Lehn 2015; Cortes *et al.* 2017; 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. The present paper abstracts from the difference between non-routine manual and routine occupations by grouping them together since the key force under my theory is the increase in demand for high-skill employees as technology changes, rather than the differential effects among 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.

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

Figure C.1: **Numbers of self-employed people with <10 employees and firms with 1–9 employees (millions).** The *self-employed* series is the number of people aged 16+ in the US who are self-employed and whose businesses have <10 employees. The *firms* series is the number of firms in the US with 1–9 employees. Agriculture and public-administration sectors are excluded

C.2. Entrepreneur share

In the model an entrepreneur is a person who owns and manages a business with employees. In the data I define these people to be the self-employed with employees. This creates a challenge for the data. The size information provided in the CPS does not separate self-employed people with businesses with no employees from those that have a small number of employees. For 1991–2015 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 1991–2014 there are two steps. First, data from the BDS provides information on the number of firms in various size categories on an annual basis up to 2014, including establishments with 1–9 employees.[71] 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.[72]

71. 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.

72. Some supporting evidence for this that for firms in the next size category up, 10–99 employees, the average ratio of the number of self-employed people, estimated from the CPS, to the number of firms in the BDS is 0.96.

This gives me an estimate of the number of self-employed people with businesses with 1–9 employees each year. I exclude the agriculture sector from the data, just as I did in the empirical analysis in Section 2.

Second, using the CPS data I estimate the number of people in the population who are self-employed with non-agricultural businesses in a range of size categories.[73] 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. 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 C.1. Both series grow steadily over time and the ratio of the number of firms to self-employed people is fairly stable, starting at 0.42 and ending at 0.40. I use the estimate of the number of self-employed people with 1–9 employees from the BDS data to divide the number of self-employed people with <10 employees in the CPS data into those with 0 employees and those with 1–9 employees. This provides the information necessary to compute the share of self-employed people with <10 employees who have at least one employee. Finally I assume that this share also holds for the restricted sample that I am studying (ages 25–65) and for both of the education levels I use.[74] This allows me to then compute the number of entrepreneurs in the data for each education level, and thereby the entrepreneur shares.

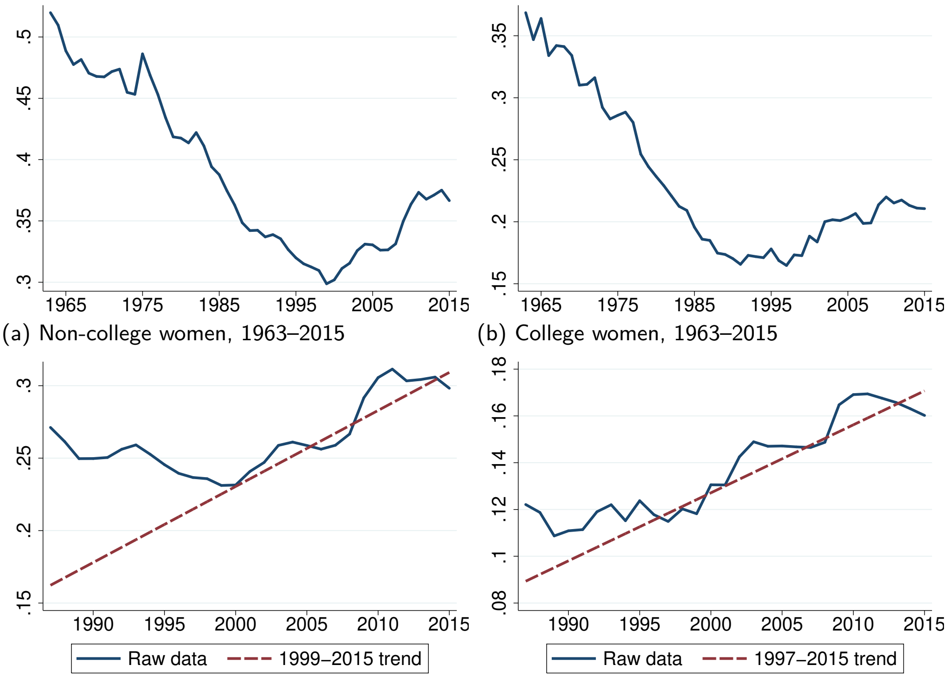
For 1987–90 the size categories for small firms in the BDS and CPS don't match up. Since the size distribution of self-employed businesses is quite stable over time (see Figure 1(b)) I estimate the share of people who are self-employed with at least one employee for each education level by taking the share who are self-employed each year and multiplying it by the average share of the self-employed who have employees for 1991–1993 for the relevant education level. For 2015 BDS data on the number of firms with 1–9 employees is not yet available. I assume that the share of the self-employed with less than 10 employees who have at least one employee equals to the average of this moment for 2012–14.

C.3. Out of labor force share

A second challenge with matching up the occupation distributions in the model and data arises because of changes in female labor force participation over time. As is well known, there was a strong and steady increase in the female labor force

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

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



(a) Non-college women, 1963–2015

(b) College women, 1963–2015

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

(d) College men and women, 1987–2015

Figure C.2: **Out of labor force share by education level** Panels (a) and (b) present the out of labor force share for women with the two education levels for 1963–2015. Panels (c) and (d) present the out of labor force shares for men and women for the two education levels for 1987–2015. These panels also show linear trends for 1999–2015 and 1997–2015, respectively, extrapolated back to 1987.

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 1987 and I do not model gender this creates a disjunction between the model and the data. I deal with this by making adjustments to the data so that the two are comparable. The approach is as follows. I start with the out of labor force shares for women in my sample with non-college and college educations. For each education level there is a strong downward trend from when the CPS starts in the early 1960s until the late 1990s when both out of labor force shares start to rise. For non-college women the turning point is 1999, while for college educated women it is 1997 (see panels a and b of Figure C.2). I assume that after these turning points the force generating the long run increase in female labor participation has ended. I therefore interpret the data after the turning points as representing the effect of other forces operating in the economy. To estimate what the data would have looked like prior to the turning points without the trend increase in female labor force participation I take the series for men and women combined for each education level, estimate the trend in the out of labor force share from the turning point (1999 for non-college

	Non-college		College	
	1987	2015	1987	2015
Out of labor force	16.8	29.8	9.2	16.0
Low-skill	65.6	53.2	23.5	21.2
High-skill	13.1	13.8	60.0	58.4
Entrepreneur	4.5	3.2	7.3	4.4

Table C.1. **Occupation distributions from data.** These are the occupation distributions for college and non-college agents for 1987 and 2015 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.

and 1997 for college) to 2015, and then extrapolate the trend back to 1987. For both education groups the out of labor force share is approximately linear after the turning points, so I use a linear trend. See panels (c) and (d) of Figure C.2.

C.4. Occupation distribution

To complete the occupational distribution for each education level I also need estimates of the shares of low and high-skill employees. The low and high-skill employee shares can be measured directly from the CPS data. Since I don't have unemployed people in the model I treat them as employees and use the occupation of their last job to determine their skill type.[75] 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.[76] To compute the aggregate occupation distribution I sum the two distributions conditional on education, weighting them by the shares of people with and without a college education. The final empirical occupation distributions that are used in the paper are presented in Table C.1.

C.5. 1987 income moments

The calibration moments require computing the mean and coefficient of variation of income for low-skill people, high-skill people and entrepreneurs, within each education group. These moments are computed using the March CPS, which

75. 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.

76. 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 equals one minus the out of labor force share.

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

There are three additional issues with the income data that are addressed. First is top coding. While there is income top coding in the CPS data, replacement values are available to maintain the top of the income distribution while protecting the anonymity of respondents. The replacement values for the 1988 March CPS have been taken from the CPS IPUMS website[77]. Second, there is evidence that self-employed people underreport their income in the Panel Study of Income Dynamics, another income survey in the US. Hurst *et al.* (2014) estimate an underreporting rate of 25%. To adjust for this I scale up the income of entrepreneurs by a factor of $1/0.75$.

The third issue arises because the CPS does not provide information on the exact number of employees of each self-employed person. Thus it is necessary to estimate moments for the group of people who are defined as entrepreneurs in the model—self-employed people with at least one employee. I use the CPS data for 1991 for this purpose since, as described in Section 2 of the paper, it has more detailed information on the size of small firms than the data for 1987. I combine the 1991 estimates with information for 1987 to get estimates for that year, as I describe in detail below. For the coefficient of variation I use the data for 1991 to compute this moment of entrepreneur income for the two education groups for all self-employed people, and self-employed people with at least 10 employees. These moments are very similar, so the exact employment threshold doesn't appear to affect this moment very much. Therefore to estimate the 1987 coefficient of variation for entrepreneur income, I just use the value of this moment for all self-employed.

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

77. https://cps.ipums.org/cps/income_cell_means.html, accessed 4 May 2020

- Compute average income of the self-employed, for each of the two education groups, conditional on three employment levels: any number of employees, < 10 employees and ≥ 10 employees.
- Take the estimate of the share of people who are self-employed with 0–10 employees who have at least one employee from the work done to estimate the share of people who are entrepreneurs (see discussion above). This value is 42.03% for 1991.
- Construct a lower bound for the average income of self-employed people with at least one employee, conditional on education, using a weighted average of the average income of the self-employed with < 10 employees and the average income of the self-employed with at least 10 employees:

$$\frac{(0.4203 \times shr^{\xi}_{<10})inc^{\xi}_{<10} + shr^{\xi}_{\geq 10}inc^{\xi}_{\geq 10}}{(0.4203 \times shr^{\xi}_{<10}) + shr^{\xi}_{\geq 10}}$$

  where shr^{ξ}_{x} is the share of the self-employed with education level $\xi \in \{N, C\}$ in size category x and inc^{ξ}_{x} is the average income of self-employed in this education-size category.
- Construct an upper bound for the average income of self-employed people with at least one employee, conditional on education, in a similar way:

$$\frac{(0.4203 \times shr^{\xi}_{<10})inc^{\xi}_{\text{10–24}} + shr^{\xi}_{\geq 10}inc^{\xi}_{\geq 10}}{(0.4203 \times shr^{\xi}_{<10}) + shr^{\xi}_{\geq 10}}.$$

  The difference for the upper bound is that the average income of the self-employed with 10–24 employees is being used to put an upper bound on the income of the self-employed with 1–10 employees.
- The last step is to use these lower and upper bounds for 1991 to estimate such bounds for 1987. To do this I compute the ratio of 1987 to 1991 average self-employed income, and scale the lower and upper bounds by this factor, all conditional on education.

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

The moments of entrepreneur income abstract from the asset value of entrepreneurs' businesses due to data limitations. To the extent that these businesses are a savings vehicle for entrepreneurs, this should not significantly affect results since I am also abstracting from savings for other agents.[78] The more important omission is the sale value of intangible capital accumulated by businesses. For recent work on measuring this, see Bhandari and McGrattan (2021).

78. This assumes that the return on savings invested in private businesses and elsewhere are similar.

C.6. 1987–2015 income growth

Two of the key moments for the calibration are the growth of average real income for low and high-skill agents from 1987 to 2015. A limitation of using the CPS data on its own for these estimates is that it does not include non-wage compensation, the growth of which has differed across skill levels over time. To adjust for this, data from the BLS' Employer Costs of Employee Compensation (ECEC) survey is used. This dataset provides information going back to 1986 on compensation costs for employers by employee occupation and breaks the cost of compensation down into different components.[79] Particularly relevant for the purposes of this paper is that it separates wage and salary costs (which I'll call wages for brevity) from other forms of compensation. The data is annual up to 2001 and uses payroll data that includes March 12th each year. From 2002 onward the data is quarterly and I use the observation for the first quarter of each year to match up with the timing of the annual data.

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

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

The one detail that has been omitted so far is how to compute the growth in average wages and total compensation for each skill level in step two. The ECEC data is by occupation so start by allocating each occupation to a skill level using the division described in Section C.1.[80] There is a change in the occupation classification system that the data uses from 2003 to 2004 so there is discontinuity

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

80. 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

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

Table C.2. **Gross wage and compensation growth by skill, 1987–2015.** This table presents the gross growth rate of average wage and salary income and average total compensation for low-skill employees and high-skill employees for 1987 to 2015. 2.00 means that the relevant variable grew by 100%. The data is from the Employer Cost of Employee Compensation dataset from the BLS.

in the data between these years. Next compute the average wage and average total compensation for each skill for 1987, 2003, 2004 and 2015. This requires aggregating the data across occupations. To do this weight each occupation by the share of the CPS sample in that occupation in the relevant year. In doing this use the same occupation classification system from the CPS as the ECEC data uses. Note that some service occupations are not covered by the ECEC so I place zero weight on these occupations and scale up the other weights proportionally so that the total weights equal one.[81] Compute the ratios of the 2003 to 1987, and the 2015 to 2004, values of the average wage for each skill level, and do the same for average total compensation. Finally multiply each 2003 to 1987 ratio by the corresponding 2015 to 2004 ratio to get estimates of the 2015 to 1987 ratios.

C.7. Entrepreneur employment share

The share of employment in the entrepreneur sector is estimated using data from the BDS and CPS. For 1987 the idea is to create a mapping from self-employed people in the CPS to establishments in the BDS, since the BDS provides richer information on size. Since the BDS covers the universe of private sector employer firms in the US, I use the full CPS sample for these calculations so that the coverage of the two datasets matches up, rather than restricting the sample based on age. From the CPS the public and agricultural sectors are omitted, as is the case for all of the analysis, and the agriculture sector is omitted from the BDS as well. The BDS does not include the public sector. For the mapping between the CPS and BDS I assume that each self-employed person in the CPS accounts for one establishment in the BDS at a firm in the same size class as the self-employed person's firm. Some support for this assumption is that for 1992 the number of owners per firm at firms with 10–99 employees was similar to the number of establishments per firm, at 1.35

growth rates from 2007 to 2015. The occupational crosswalk used for the mapping between CPS and ECEC occupations is available on request.

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

and 1.23 respectively.[82] From a theoretical perspective the idea is that there is one person responsible for each establishment, who is also an owner. This would be the case, for example, under a partnership or franchise structure where each member of the partnership or franchise operates a location for the business. To give a sense of the implication of this for large firms, it implies that in 1992 self-employed people operated 17.2% of establishments of firms with at least 1000 employees.

This mapping provides an estimate of the share of establishments in each firm size class in the BDS that are run by self-employed people. To translate the establishment share into an estimate of the employment share of the self-employed I assume that within firm size classes in the BDS, each establishment is equal to the average size.[83] Since the size classes of firms used in the CPS change over time, they do not line up exactly with the BDS size classes in every year. However, they do line up for 1991, which is close to the start of the period of analysis. For this year the estimated share of employment at firms of the self-employed is 49.5%. Based on this, in the calibration for 1987 I use a share of employment at entrepreneur firms of 50%.

To provide some context for this estimate, using the Longitudinal Business Database from the Census Bureau and Computstat, Davis *et al.* (2006) estimate that privately held firms accounted for 75% of private sector employment in 1990. This value should be higher than the estimate just outlined since not every privately held firm will have a self-employed person operating it. For example, there may be large privately owned firms who are managed on a day-to-day basis by employed managers and executives, and therefore won't have a self-employed person under the CPS definition. Given this, an estimate of 50% seems reasonable.

For 2015 the estimate is based on the fact that the size distribution of firms of the self-employed was stable over the period of analysis (see Figure 1(b)). This implies that the percentage change in the share of employment at entrepreneur firms (firms of self-employed people with employees) equaled the percentage change in ratio of the share of people who are entrepreneurs to the share of people who are employees. After making adjustments for female labor force participation (discussed above), I estimate that this share declined by 21.1%. This implies a entrepreneur share of employment of 39.5% in 2015. As further validation of the methodology that I adopted for computing this employment share for 1987, I have repeated the calculations for 2015 and get a share of 39.0%. The fact that the two approaches to estimating the employment share of entrepreneurs in 2015 provide very similar answers supports the use of these estimates.

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

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

C.8. Entry rate

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

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

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

where entry(t) is the entry rate in year t, entrants(t) is the number of entrants in the BDS in year t, and firms(t) is the total number of firms in the BDS in that year.[84]

Appendix D: Parameter values and model fit

D.1. Additional discussion of parameter values and calibration moments

Values for internally calibrated parameters and the calibration moments are presented in Tables 2 and 3 of the main text. Table D.1 summarizes the values of externally calibrated parameters. The moments presented in Table 3 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

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

Parameter	*Value*		*Remark*
	1987	2015	
ω	0.779	0.651	Non-college share of agents from CPS
β	0.985		
ν	2.0		
δ	0.025		Expected working life of 40 years
ρ_l, ρ_h	0.95		Storesletten *et al.* (2004)
γ	-1.5		Guided by Krusell *et al.* (2000) and vom Lehn (2015)
$\alpha + \eta$	0.85		Atkeson and Kehoe (2005)
r_o	0.082	0.121	Eden and Gaggl (2018)
r_i	0.169	0.071	Eden and Gaggl (2018)
μ_l^N	-0.008		Normalized so that $E[z_l^N] = 1$
μ_h^N	-0.008		Normalized so that $E[z_h^N] = 1$
$\bar{\mu}_e^N$	0.0		Normalization

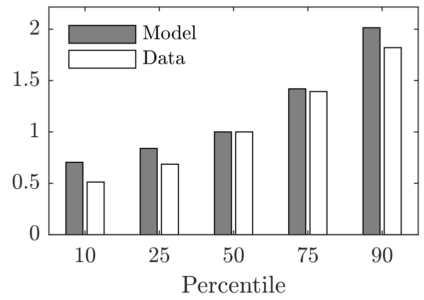
Table D.1. **Parameter values: externally calibrated and normalized parameters.** 2015 values are the same as 1987 values unless stated otherwise. Where necessary, parameter values are rounded to three decimal places.

non-college educated people (60% compared to 13%) and high-skill workers earn more (45% more on average compared to low-skill). The college educated also earn more conditional on skill: the average high-skill college educated worker earns 29% more than the average high-skill non-college worker, and for low-skill workers this education premium is 40%. The model captures this with different means of the productivity distributions for the two education levels.

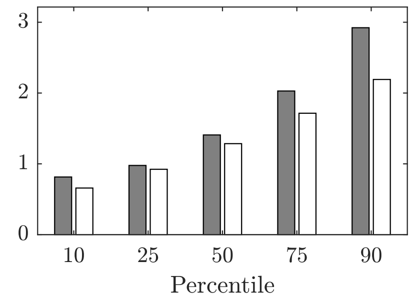
The parameters controlling the correlation between worker and entrepreneur productivities are estimated to be small, positive for college-educated agents and negative for non-college agents. The implied correlations between z_s, $s \in \{l, h\}$, and z_e for non-college and college agents are -0.31 and 0.23, respectively.[85] Recall that these parameters are primarily determined by the relative level of entrepreneur income and worker income. The negative correlation between worker and entrepreneur productivity for non-college educated agents is driven by the income premium for entrepreneurs in this education group being relatively low. From the perspective of the model, this implies that it is relatively low-productivity people in this education group who choose to be entrepreneurs. In terms of the quantitative importance of worker productivity in determining entrepreneur productivity, its role is modest. For the four education-skill groups, variation in worker productivity only accounts for 5.0–13.4% of the variance of entrepreneur productivity.[86]

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

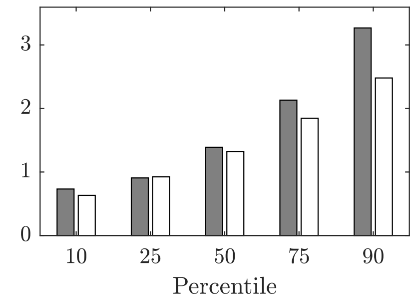
86. These shares are computed by comparing the counterfactual variance in z_e if χ_n or $\chi_c = 0$ with the variance in the full model.



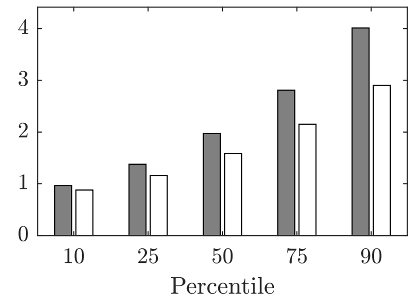
(a) Non-college, low-skill, 1987



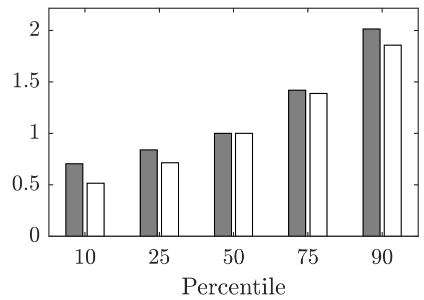
(b) Non-college, high-skill, 1987



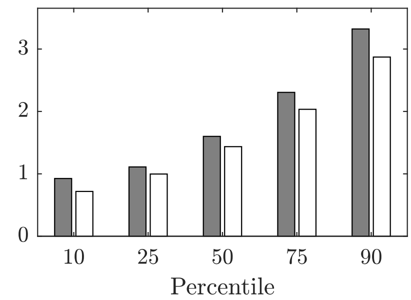
(c) College, low-skill, 1987



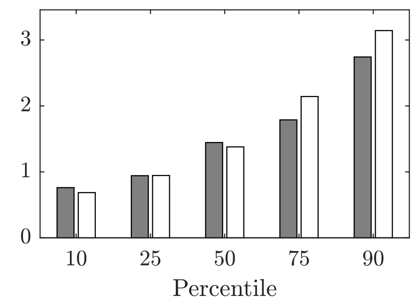
(d) College, high-skill, 1987



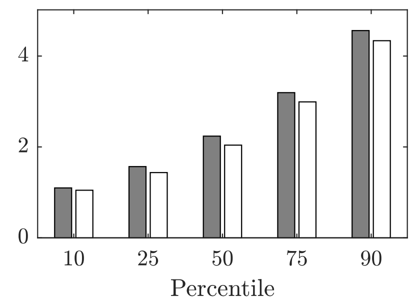
(e) Non-college, low-skill, 2015



(f) Non-college, high-skill, 2015



(g) College, low-skill, 2015



(h) College, high-skill, 2015

Figure D.1: **Income distributions for model and data.** Each percentile is plotted relative to the 50^{th} percentile of the non-college, low-skill distribution for the same year. For example, a value of 2.0 for the 75^{th} percentile for non-college, high-skill people in 2015 means that this percentiles is twice as large as the 50^{th} percentile for non-college, low-skill people in 2015. High-skill income in 2015 is scaled up to account for greater growth in non-wage compensation compared to that of low-skill workers—see the discussion of wage growth calculations in Section C.6 for the details.

Moment	Model	Data
Non-college		
High-skill:low-skill averages	1.60	1.47
Entrepreneur:high-skill averages	1.49	1.40
College		
High-skill:low-skill averages	1.50	1.43
Entrepreneur:high-skill averages	1.90	1.87
College to non-college ratios		
Low-skill average income	1.39	1.54
High-skill average income	1.31	1.51
Entrepreneur average income	1.67	2.01

Table D.2. **2015 income moments.** This table presents values for relative average incomes for various groups of workers for 2015. The moments in the non-college and college sections provide relative average incomes for low-skill employees, high-skill employees and entrepreneurs within education groups. The college to non-college ratios provide the relative average incomes of low-skill employees, high-skill employees and entrepreneurs between the two education groups. The high to low-skill income ratios are scaled up from the raw data to account for greater growth in non-wage income for high-skill agents between 1987 and 2015—see the discussion of wage growth calculations in Section C.6 for the details.

The estimated elasticity of substitution between low-skill labor and IT capital ($\frac{1}{1-\tau}$) is 2.56. As a point of comparison, Krusell *et al.* (2000) estimate the elasticity of substitution between capital equipment and low education labor to be 1.67. Since the capital and labor inputs in this paper are defined more specifically to capture their substitutability, a higher elasticity of substitution makes sense. vom Lehn (2015) estimates the elasticity of substitution between routine labor and capital equipment at 1.39. While the labor input in this paper and vom Lehn (2015) are slightly different, the higher value that I estimate suggests that IT capital is more substitutable for lower skill labor inputs than capital equipment in general.

The main text notes that fixed costs are estimated to have increased by a factor of 1.9 from 1987 to 2015, and entry costs by a factor of 3.1. De Ridder (2019) provides some analysis to put these numbers in context. That paper analyses the trend in fixed costs using a range of methodologies, and documents consistent increases. Under that paper's baseline approach, the ratio of fixed costs to total costs increased by 64% for US public firms from 1979 to 2015, and by 47% for the universe of French firms from 1994 to 2016. In broad terms the model is consistent with these patterns, generating a slightly more modest growth rate of 25% for this ratio for entrepreneur firms from 1987 to 2015.[87]

87. The analog of De Ridder (2019)'s fixed costs to total costs ratio in the model is fixed costs to variable costs plus fixed costs. Scaling fixed costs in this way decreases the growth rate because firms, and their costs, have grown larger over time. I am comparing growth rates rather than levels of costs, since the latter are not comparable. Fixed costs are defined more narrowly in the model than in the empirical estimates.

D.2. Untargeted moments

Most moments of the occupation distributions for 1987 and 2015 are calibration targets, but there are a few free moments to check. The shares of college and non-college agents who are high-skill employees are targeted in 1987, but free for 2015. These moments don't change much over time in the data, and the model is consistent with this. In 2015 the values for the model are 13.2% and 60.9% for non-college and college agents, respectively, while the corresponding data values are 13.8% and 58.4% (values for 1987 are in Table 3). The out of labor force shares conditional on education are untargeted in both years. This moment closely matches the data in both years for non-college agents: 17.2% and 16.8% for 1987 for the model and data, respectively, and 31.8% and 29.8% for 2015. For college agents the out of labor force share is a few percentage points lower than in the data, but exhibits a similar proportional increase over time. It goes from 6.2% to 11.1% in the model, compared to 9.2% to 16.0% in the data.

Figure D.1 and Table D.2 present a range of moments of income distributions for 1987 and 2015, for the model and the data, to further assess the fit of the model.[88] Figure D.1 provides income distributions for all education-skill pairs, for both 1987 and 2015. For each year all percentiles of the distributions are plotted relative to the median low-skill, non-college income for the relevant year. In this way the figure provides information on relative income between groups, as well as dispersion within groups. These relative incomes are obviously important for the occupation decisions of agents in the model. Panels (a)–(d) provide the results for 1987. In the calibration two moments of each distribution are targeted, so there are many more moments than targets presented. Overall the model fits the data reasonably. As indicated by the moments in Table 3, high-skill income is a little higher in the model than the data, and this is also true for the income of college agents. The model has more dispersion in the right tail of the distributions than the data.

Panels (e)–(h) of Figure D.1 present the income distributions for 2015. The only moments related to these distributions that were targeted in the calibration were the growth of average low and high-skill income, so the moments in these panels are almost entirely untargeted. Given this, the model does a very good job of fitting the data. Relative income between groups are close to the data and the dispersion of income within groups is also similar. Table D.2 provides additional moments for relative average incomes across groups for 2015, including for entrepreneurs. The model and data are reasonably close, with the main differences being that the premium for high-skill agents conditional on education is a little larger in the model, while the college premium is somewhat smaller. Overall the model replicates the

88. Note that in Figure D.1 income distributions for entrepreneurs are not included since the relevant distributions from the data are not available. This is because the data does not distinguish between self-employed people without employees, and those with 1–9 employees, so the left tails of the entrepreneur income distributions in the model can't be easily mapped to the data.

	Prod. growth	Education	OLF value	r_o	2015
Entrepreneur share	1.05	1.10	1.02	0.93	0.71
Entry rate	0.99	0.93	0.93	0.92	0.72
Entrepreneur emp. share	1.01	1.08	1.07	1.06	0.80
College:non-college entrep. share	0.97	1.05	1.18	1.34	0.85
OLF share	0.87	0.69	1.28	1.56	1.66
w_l	1.14	1.33	1.36	1.21	–
w_h	1.24	0.94	0.93	0.79	–
Av. low-skill income	1.13	1.31	1.43	1.30	1.166
Av. high-skill income	1.22	1.00	1.04	0.93	1.443

Table E.1. **Effects of changes in productivity, education and the out of labor force value, and SBTC.** All moments are presented relative to their 1987 values. For the *Productivity growth* column ζ is changed to its 2015 value and z_f, ψ, ψ_e and b are scaled by the the same percentage amount. For the next three columns, several parameters are changed to their 2015 values additively. For *Education* ω is changed to its 2015 value, for *OLF value* b is also changed to its 2015 value, and finally r_i and r_o are changed to their 2015 values as well in the *SBTC* column. The 2015 column provides moment values for 2015 relative to 1987 from the data.

relative incomes of the various types of agents in the model well, suggesting that it is doing a good job of capturing the tradeoffs that agents face when making their occupation choice decisions.

Appendix E: Quantitative results

E.1. Effects of secondary parameter changes

The effects of the secondary parameter changes on key moments are presented in Table 4 of the main text. Table E.1 decomposes these effects into the contribution of each type of parameter change and also adds wages, and average low and high skill income to the set of moments. There are four types of parameter changes in the decomposition, which are done in sequence, in a *cumulative* way. The first column shows just the effects of productivity growth, the second column shows the effects of productivity growth *and* the change in education, etc. For comparison, the final column of the table shows values for 2015 from the data. All values are presented relative to their 1987 values (i.e. 1.20 means a 20% increase), as in Table 4.

The parameter changes in the education, out of labor force value and r_o columns are straightforward. They involve changing the share of agents with a non-college education (ω), the out of labor force value (b) and the non-IT capital rental rate from their 1987 to 2015 values (refer back to Table 2 for these). The parameter changes in the productivity growth column are slightly more involved. The objective in this column is to account for the effects of general productivity growth in the economy. To this end, the main parameter that changes is ζ, which changes the productivity level of all entrepreneurs by the same factor. Specifically, ζ is increased so that average entrepreneur productivity equals its 2015 value.[89] To simulate a general rise in productivity, rather than just for entrepreneurs, I increase z_f and the out of labor force value by the same factor. I also scale fixed costs and entry costs by the same factor so that their relevance is not diminished.

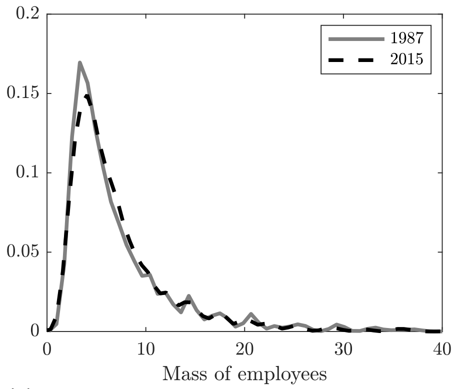
The main text explains that increasing education accounts for most of the decline in the entry rate resulting from the secondary parameter changes, and most of the increase in the entrepreneur employment share. The results in Table E.1 confirm this, with the increase in education being the only parameter change that affects these moments by more than one percent.

The secondary parameter changes push the entrepreneur share down slightly, and the ratio of college to non-college entrepreneur shares up substantially. As mentioned in the main text, the main forces driving these changes are the increasing out of labor force value and the increasing cost of non-IT capital. To explain the mechanisms in more detail, the increasing out of labor force value has a direct effect on these moments in the following way. It attracts people out of entrepreneurship into not working, pushing the entrepreneur share down. This effect is stronger for less educated entrepreneurs because more or them have low enough profits for this this change to be relevant.[90] As for the increase in the rental rate of non-IT capital, it also pushes profits down, causing the entrepreneur share to fall. In equilibrium, fewer entrepreneurs means less demand for labor, so wages fall. This offsets the decline in the entrepreneur share, but only partially. This offsetting effect is larger for high-skill agents, because their wage declines by a larger percentage. This is why the increase in r_o increases the relative entrepreneur share of the college educated.

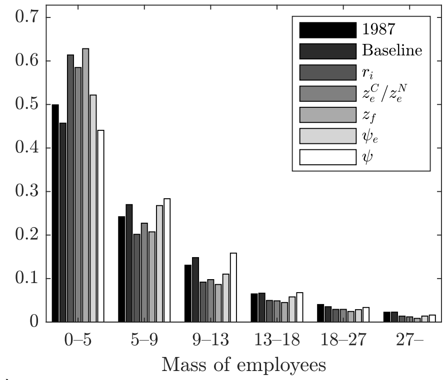
The out of labor force share increases significantly with the secondary parameter changes, almost fully accounting for the change in the data from 1987 to 2015. Productivity growth and increasing education work against this trend by pushing up the wages of low-skill people, and increasing the share of high-skill agents (who earn more on average). The increases in the out of labor force value and the non-IT capital rental rate have sufficiently strong effects to offset these, and account for most of the increase in the out of labor force share in the data. The connection between this moment and the out of labor force value is straightforward, and this change accounts for 61% of the increase in the out of labor force share that is needed to match the 2015 data, once the countervailing effects of productivity growth and increasing education are accounted for. The increasing cost of non-IT

89. There are two parameters changing from 1987 to 2015 affecting entrepreneur productivity: ζ and $\bar{\mu}_e^C$. For the secondary parameter changes being discussed here, it is ζ that increases so that average entrepreneur productivity changes from its 1987 to 2015 value. This requires ζ changing from its 1987 value of 1.0 to 1.122. The primary parameter changes, discussed in the main text, include a change in the relative entrepreneur productivity of college and non-college educated agents. This is achieved by changing $\bar{\mu}_e^C$ from its 1987 to 2015 value, and increasing ζ (to its 2015 value) to offset the effect of this on average entrepreneur productivity.

90. The increase in the out of labor force value also pushes up the low-skill wage, strengthening these effects. However the direct effect, with wages held fixed, is quantitatively more relevant.



(a) Size distributions, 1987 and 2015



(b) Decomposition of 1987–2015 changes

Figure E.1: **Entrepreneur firm size distributions.** Panel (a) presents the size distribution of entrepreneur firms in the model for 1987 and 2015. Panel (b) presents discretized size distributions for entrepreneur firms. The darkest bars are for the model in 1987. The second set of bars are for the baseline economy, after the secondary parameter changes. The remain bars capture the distribution after each of the primary parameter changes, in a cumulative way, such that the last set of bars represent the 2015 economy.

capital is also quantitatively important, accounting for 29%. This effect primarily operates through the negative impact on wages.

As a final comment on the results for the secondary parameter changes, the last two rows show that these changes work against the increase in the relative income of high-skill employees. The gaps to the 2015 data are almost fully accounted for by SBTC (the declining cost of IT capital). This comes from the negative effect that this has on low-skill wages due to the substitutability between this type of capital and low-skill labor, and the positive effect on high-skill wages due to complementarity.

E.2. Firm size distribution

The main text discusses that, despite fixed and entry costs increasing over time, the model has a firm size distribution that is quite stable. Increases in fixed and entry costs make entrepreneur firms larger through two channels. They increase the productivity threshold for becoming an entrepreneur and, because wages decrease, they increase the size of entrepreneur firms conditional on productivity. At first glance this seems at odds with the stable entrepreneur size distribution documented in Figure 1(b). However, this ignores the fact that there are other changes to the economy occurring at the same time. These other changes may not matter much for the entry rate, for example, but can still influence the size distribution. Figure E.1 presents information on how the size distribution changes in the model. Panel (a) shows the size distributions for 1987 and 2015, and they are very similar. Panel (b) discretizes the distribution and shows how various parameter changes from 1987 to 2015 change it. The darkest bars show the 1987 size distribution and the other bars show the effects of various parameter changes in a cumulative way. The increase in fixed and entry costs clearly shift the distribution to the right, as expected. However, SBTC (bars labeled r_i) offsets most of this effect.

SBTC affects entrepreneur firm size through several channels. The following expression for average firm size is useful for understanding these:

$$\bar{n} = \sum_{(\xi,s)\in\{N,C\}\times\{l,h\}} \omega_e(\xi,s)\int \omega_e(z_e|\xi,s)n(z_e)\,dz_e,$$

where $\bar{n}$ is average employment at entrepreneur firms, $\omega_e(\xi,s)$ is the share of entrepreneurs with education level ξ and skill level s, $\omega_e(z_e|\xi,s)$ is the p.d.f. for z_e for agents with education level ξ and skill level s who choose to be entrepreneurs, and $n(z_e)$ is the mass of employees at a firm with productivity z_e. SBTC changes all three variables in a way that decreases average firm size. It increases the share of people who are entrepreneurs within education-skill groups, so people with lower entrepreneur productivity choose to operate firms and this increases the share of small firms. $\omega_e(z_e|\xi,s)$ captures this effect. SBTC also causes the employment level of firms, conditional on productivity to decrease. The essence of this is that low-skill labor is substituted for IT capital and the increase in high-skill labor doesn't fully offset this. The third change is that SBTC shifts entrepreneurship towards people with low skills and education instead of high ones, and the former have smaller firms on average.

E.3. Effects of changes in labor force growth rate on results

Karahan *et al.* (2021) and Hopenhayn *et al.* (2021) have argued that a decline in the labor force growth rate has affected some of the moments of entrepreneurship studied in this paper. My approach to accounting for this theory is to take estimates of the share of changes in various moments that it accounts for, and then recalibrate the model to target the changes that remain. The rationale for this approach is explained in the main text.

The main quantitative exercise performed in the paper uses seven moments of the data from 1987 to 2015 to discipline parameters changes in the model. The labor force growth theory would definitely affect two of these moments—the entrepreneur share and the entry rate—and may affect a third—the entrepreneur share of employment. Karahan *et al.* (2021) and Hopenhayn *et al.* (2021) have results for the effect of their theory on the entry rate, so this is easy to quantify. They do not have direct results about the entrepreneur share, however their results for average firm size can be mapped to this moment (see the end of this section for an explanation of this mapping). Their models do not distinguish between entrepreneur and non-entrepreneur firms, so several cases are considered for the effect of labor force growth on the share of employment in the entrepreneur sector.

In total I consider three scenarios for the share of the changes in these moments accounted for by the labor force growth theory. For scenario one, based on the results from Karahan *et al.* (2021), I assume that this theory accounts for 45% of

Parameter	*Main calibration*	*Alternative calibrations* 1	2	3
b	0.423	0.430	0.432	0.438
z_f	1.338	1.312	1.346	1.318
ψ	0.290	0.329	0.187	0.144
ψ_e	0.981	0.755	0.594	0.411
$\bar{\mu}_e^C$	0.128	0.119	0.128	0.138
ζ	1.136	1.157	1.127	1.136

Table E.2. **2015 parameter values for alternative calibrations.** Where necessary, parameter values are rounded to three decimal places. Parameters not listed maintain their values from Table 2.

the change in the entry rate and 75% of the change in average firm size.[91] For the share of employment at entrepreneur firms, since the shift in economic activity to non-entrepreneur firms may be related to the increasing size of firms, as a baseline I assume that the theory accounts for the same share of the change in this moment as the average size of firms. As an alternative I also consider the case in which this theory does not generate any change in this moment (scenario two). For the last scenario, I allow the theory to generate a greater increase in average firm size than has occurred in the data. Hopenhayn *et al.* (2021) find that the theory generates approximately twice the increase in average firm size as in the data from 1987 to 2014. I consider a scenario between the Karahan *et al.* (2021) and Hopenhayn *et al.* (2021) estimates, in which decreasing labor force growth generates 150% of the increase in average firm size that has occurred from 1987 to 2015 in the data.

The new parameter values for these scenarios and the updated calibration moments are presented in Tables E.2 and E.3. The value of the growth of average low-skill income from 1987 to 2015 is also included. This is the one other moment from the main calibration exercise whose value changes in these exercises. It changes a little, but it remains quite close to its value in the data. For each scenario the main quantitative results from Figure 7 are recomputed. They are presented in Figure E.2. The results now inform us about the relative contribution of the forces in the model in accounting for the changes in the data that are not explained by the change in the labor force growth rate.

91. For the entry rate, Karahan *et al.* (2021) estimate that the labor force growth theory accounts for 1/3 to 60% of the decline in the data from 1979 to 2007, and these estimates decrease if you weaken their free entry assumption. I take approximately the mid-point of the estimated range, assuming that this theory accounts for 45% of the decline in the entry rate. An implicit assumption is that their results for 1979–2007 also hold for 1987–2015. For average firm size, Karahan *et al.* (2021) do not have results for this for the full dynamic exercise. However, from their comparative statics exercise, a decline in the labor force growth rate equal to the data generates a decline in the entry rate that's about 60% as large as in the data (similar to the result from the dynamic model) and a decline in average firm size that is close to the data. Since I discount the 60% estimate for the entry rate to 45%, I discount the average firm size result proportionally, to 75%.

	1		2		3	
Targeted moments	*Model*	*Target*	*Model*	*Target*	*Model*	*Target*
1987–2015 growth of av. high-skill income	44.2%	44.3%	45.4%	44.3%	44.8%	44.3%
2015:1987 out of labor force share	1.66	1.66	1.65	1.66	1.66	1.66
2015:1987 entrepreneur share	0.83	0.83	0.84	0.83	1.00	1.01
2015:1987 entrep. share of employment	1.06	1.05	1.22	1.21	1.06	1.05
2015:1987 entry rate of entrepreneurs	0.84	0.84	0.85	0.84	0.84	0.84
2015:1987 college to non-college entrep. share	0.85	0.85	0.84	0.85	0.85	0.85
Untargeted moments	*Model*	*Data*	*Model*	*Data*	*Model*	*Data*
1987–2015 growth of av. low-skill income	19.1%	16.6%	19.7%	16.6%	20.7%	16.6%

Table E.3. **Calibration moments for alternative calibrations.** Colons denote ratios. For example, '2015:1987 entrepreneur share' is the ratio of the 2015 to 1987 entrepreneur shares. Income growth rates are for real income. Full details of how the data moments are computed are in Section C.

For scenarios one and two, the main results hold. A combination of increasing fixed costs, entry costs and increasing non-entrepreneur productivity generate the decline in the entrepreneur share; the decline in the entry rate is primarily due to increasing entry costs; the most important factor for explaining the decline in the entrepreneur share of employment is the increase in non-entrepreneur productivity; and the decline in the relative entrepreneur share of the college educated is due, in roughly equal measures, to SBTC and declining relative entrepreneur productivity of the college-educated. Taking scenario one as an example, the updated calibration targets require the model to generate smaller decreases in the entrepreneur share, the employment share of entrepreneurs, and the entry rate, and the relative sizes of some of these changes are different to what they were. This changes the size of the estimated increases in fixed costs, entry costs and non-entrepreneur productivity, but the general message that they have increased remains. Furthermore, the roles that they play in explaining the changes in the moments of entrepreneurship being studied remain broadly the same.

For scenario three, there is one qualitative difference. In this case the decrease in the labor force growth rate is assumed to increase average firm size more than has occurred in the data. This corresponds to a decrease in the entrepreneur share that is slightly larger than in the data. Consequently, the changes to the economy from 1987 to 2015 that are studied in the model need to increase this moment slightly, instead of decreasing it (Table E.3). The model achieves this with more modest increases in fixed and entry costs (13% and 20% as large as under the main estimates, respectively). The slight increase in the entrepreneur share is achieved by SBTC pushing this share up, and increases in entry costs and non-entrepreneur productivity partially offsetting this effect (top left panel of Figure E.2(c)). The remainder of the results from the main calibration are preserved. Increasing entry costs is still the primary factor explaining the decline in the entry rate, increasing non-entrepreneur productivity accounts for most of the shift in employment to this sector, and SBTC and declining relative entrepreneur productivity of the college educated still drive the decline in their relative entrepreneur share.

Overall, allowing for changes in the labor force growth rate to account for some of the changes in entrepreneurship in the data reduces the quantitative importance of the factors studied in this paper. However, for the changes in the data not accounted for by that theory, the insights from the analysis about the relative importance of the factors studied in this paper generally hold. The main exception is that if the decrease in labor force growth generates a much larger increase in average firm size than has occurred in the data, then the factors studied in this paper are not needed to generate the decline in the entrepreneur share. However, they are still relevant for changes in the other moments of entrepreneurship.

Average firm size to entrepreneur share mapping. As mentioned in the previous section, the papers on the labor force growth theory present results for changes in the average size of firms over time, which I map to changes in the the entrepreneur share. For this purpose, I approximate the average firm size in the model with

$$\frac{1 - \text{out of labor force share}}{\text{entrepreneur share}}.$$

This is slightly different to the measure of average firm size in the firm data and in the labor force growth papers for three reasons, but the impact should be minor. The first is that this measure omits non-entrepreneur firms from the firm count in the denominator. This only has a small effect, since, as discussed in Section C.8 of this appendix, close to 100% of firms in the economy have less than 100 employees and nearly all of these are associated with the self-employed. The second difference arises from the fact that some firms have multiple self-employed people associated with them, which will increase the firm count in the denominator and decrease average firm size. Since the vast majority of the self-employed are associated with firms with less than 100 employees, and in this size category there is close to one-self-employed person per firm (see the discussion of Table 1 in the main text), this also should not make a large difference. The third difference is to due to the sample being restricted to people aged 25 to 65. To quantify this difference, the average firm size measure outlined above implies a change in average firm size from 16.7 in 1987 to 20.8 in 2015 in the model. In the CPS the change over the same period is from 20.5 to 23.8.

The procedure for mapping average firm size to the entrepreneur share is as follows. Take an example in which it is assumed that changes in the labor force growth rate account for 50% of the increase in average firm size. For the calibration of 2015 parameters, I therefore target an average firm size of 18.75, instead of 20.8. Using the out of labor force value for 2015 of 25.0%, the equation above implies the target value for the entrepreneur share.

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

Table F.1. **Regulation-related occupations** This table listed the occupations from the 1990 Census Bureau Occupational Classification System that are treated as regulation-related or IT-based in the analysis.

Appendix F: Interpreting cost changes

F.1. RegData

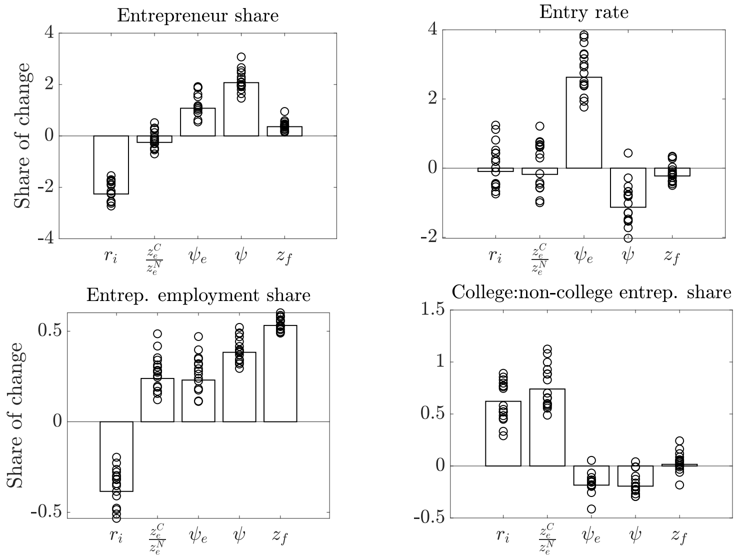
The idea for this dataset is to take the Code of Federal Regulations, which contains all federal level regulations in the U.S., and separate it into its parts. For each part, textual analysis is performed to determine a relevance weight for the part for each industry, and the number of restrictions in the part. For each industry, a measure of regulation for each year is constructed by multiplying the relevance of each part by the number of restrictions in it, and then summing over parts. See McLaughlin and Sherouse (2018) for full details.

F.2. IT and regulation-related occupations

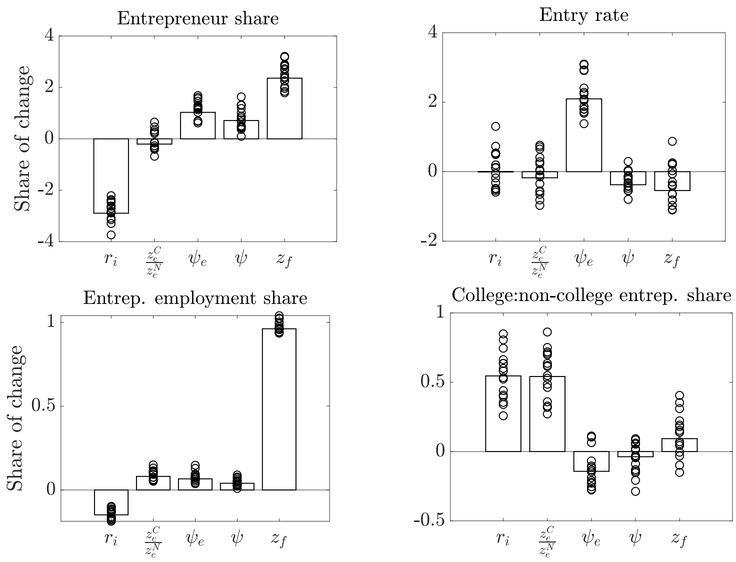
Table F.1 lists the occupations that are treated as regulation-related and IT-related for the purposes of the analysis in Section 7. The occupation codes are from the 1990 Census Bureau Occupational Classification System.

F.3. Industry definitions and sample size

The analysis requires consistent definitions of industries across datasets. The industry definitions from the BEA detailed fixed assets tables are used (a combination and two and three digit ISI codes) and industry codes from other datasets are harmonized with these. This results in a maximum of 144 observations. Some regressions have fewer observations because some industry years have small cell counts that don't allow all variables to be estimated. RegData provides information for fewer industries so any analysis including that data has fewer observations.

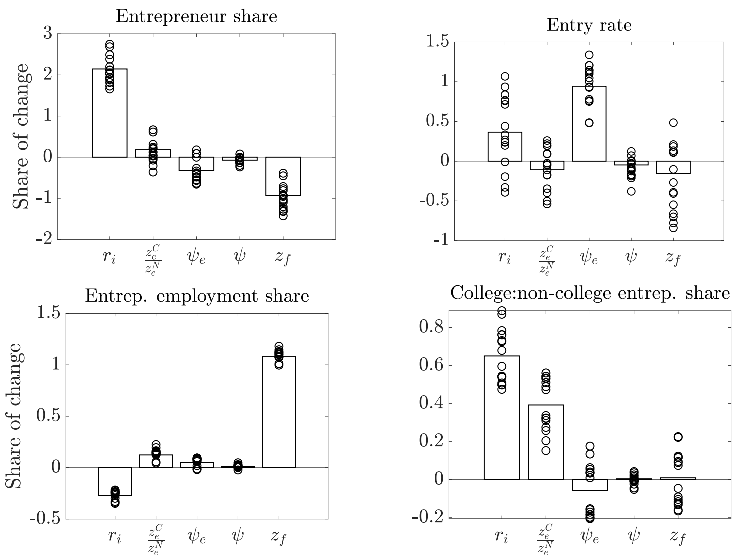


(a) Alternative calibration 1



(b) Alternative calibration 2

Figure E.2: Continued on next page



(c) Alternative calibration 3

Figure E.2: **Effects of changes to the economy on entrepreneurship for alternative calibrations.** This figure replicates Figure 7 for the alternative calibrations. The vertical scale is the share of the change in the relevant moment from its baseline value to its 2015 value in the model under the relevant calibration. The baseline scenario is defined in the same way as in the main text, with the parameter values differing according to the alternative calibrations.

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