What's Driving the Decline in Entrepreneurship?*

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Abstract

Why has there been a steady decline in entrepreneurship in the US in recent decades? 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 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.

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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

[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).

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 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 produc-

[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

tivity 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 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.

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).

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 con-

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

struction 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.

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

[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).

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 working in the agriculture or government sectors.[9] This provides cross-sectional sam-

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

[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.

ples 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

[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.

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.

this size category have one firm each, which the data supports,[13] there are 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

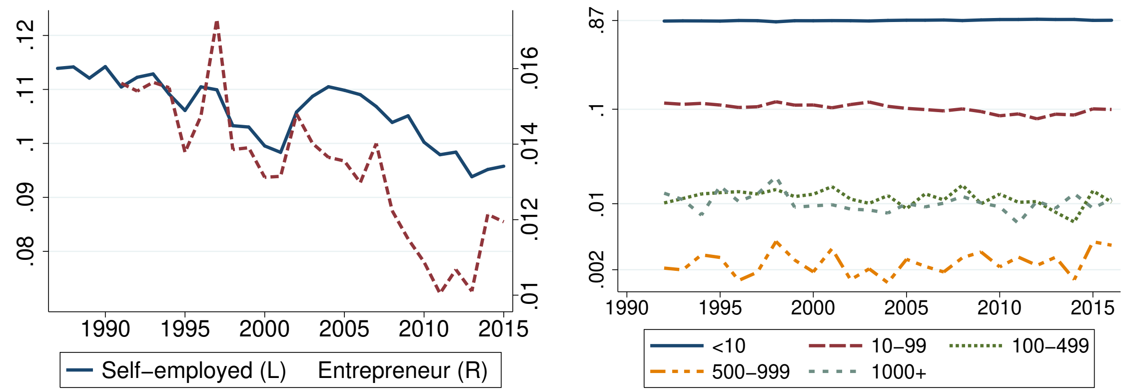
I define the aggregate entrepreneur share to be the share of the labor force who are entrepreneurs.[16] I use the labor force as the numerator rather than the population to abstract from the effect of changes in labor force participation over time. I define the self-employed share analogously. These two shares are presented in

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

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.

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-

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

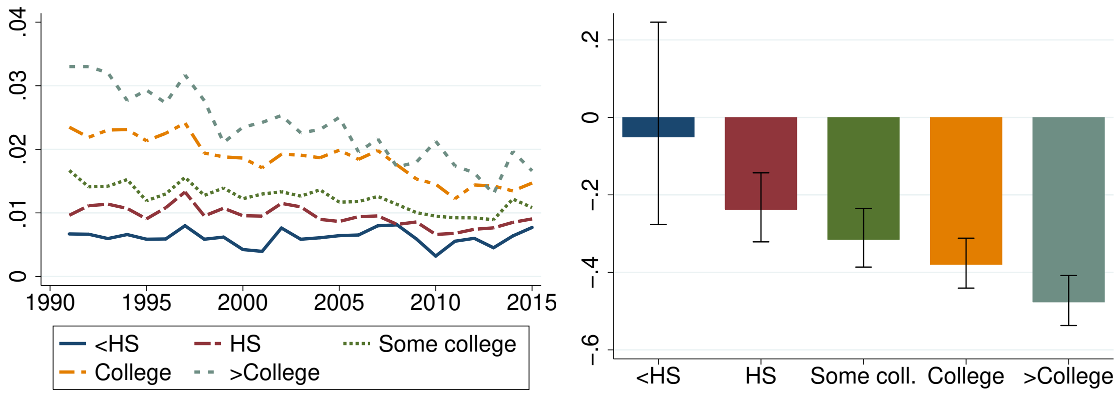
employed with businesses with 500–999 employees at the end of the sample, but this is only in the last three years and so does not establish a long run upward trend.

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 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 busi-



(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.

nesses 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 Șahin, 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.

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 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 $\lim_{c \to 0} u'(c) = \infty$.

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

[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.

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.

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

[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).

things, provides information services that were previously provided by workers such as travel agents and call center employees. Google needs few low-skill employees to provide these services but needs a lot of computer scientists.

The functional form for the production technology is

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

where $\eta, \phi, \lambda, \alpha \in (0, 1)$; $\alpha + \eta < 1$; and $\tau, \gamma < 1$. The nested CES structure follows other papers that study the effects of technical change quantitatively (Krusell et al., 2000; vom Lehn, 2015; Eden and Gaggl, 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 $\epsilon \in \{0, 1\}$ be an indicator for whether an agent was an entrepreneur in the previous period. The value function of an agent at the start of a period is denoted $V(\mathbf{z}, \epsilon)$.[23] The value functions for being out of the labor force, a low-skill employee, a high-skill employee, and an entrepreneur are, respectively:

$$V_{\text{olf}}(\mathbf{z}, \epsilon) = u(b + \pi_f) + \beta(1-\delta)\mathbb{E}[V(\mathbf{z}', 0)|\mathbf{z}], \tag{2}$$

$$V_{\text{l}}(\mathbf{z}, \epsilon) \quad = u(z_l w_l + \pi_f) + \beta(1-\delta)\mathbb{E}[V(\mathbf{z}', 0)|\mathbf{z}], \tag{3}$$

$$V_{\text{h}}(\mathbf{z}, \epsilon) \quad = u(z_h w_h + \pi_f) + \beta(1-\delta)\mathbb{E}[V(\mathbf{z}', 0)|\mathbf{z}], \tag{4}$$

[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.

$$V_{\mathrm{e}}(\mathbf{z},\epsilon) \quad = u(\pi(z_e,\epsilon)+\pi_f)+\beta(1-\delta)\mathbb{E}[V(\mathbf{z}',1)|\mathbf{z}]. \tag{5}$$

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

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

$\mathbb{1}_a(A)$ is the indicator function for whether variable a 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

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

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

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

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

The production problem for the representative non-entrepreneur firm is

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

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

Agents in the model are distributed over the states $(\mathbf{z},\epsilon) \in \mathbb{R}^3_+ \times \{0,1\} \equiv \mathbb{Z}$. 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 conditions are:

$$\int_{\mathbb{Z}} \mathbb{1}_\sigma(s) z_s \, dQ = \int_{\mathbb{Z}} \mathbb{1}_\sigma(e)\ell_s(z_e)\, dQ + \ell_s(z_f), \text{for } s \in \{l,h\}, \tag{8}$$
$$\int_{\mathbb{Z}} \mathbb{1}_\sigma(e)\Big(\pi_e(z_e,\epsilon) + w_l\ell_l(z_e) + w_h\ell_h(z_e) + r_ok_o(z_e) + r_ik_i(z_e) + \mathbb{1}_\epsilon(0)\psi_e + \psi\Big)\, dQ$$

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

$$+ \pi_f(z_f) + r_o k_o(z_f) + r_i k_i(z_f) = \int_{\mathbb{Z}} \mathbb{1}_{o}(e) y(z_e)\, dQ + y(z_f). \quad (9)$$

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 $o(z_l, z_h, z_e, \epsilon)$, production input decisions for entrepreneurs and non-entrepreneur firms $\{\ell_l(z), \ell_h(z), k_o(z), k_i(z)\}$ with $z = z_e$ for entrepreneurs and $z = z_f$ for non-entrepreneurs, and a distribution 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

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

has 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

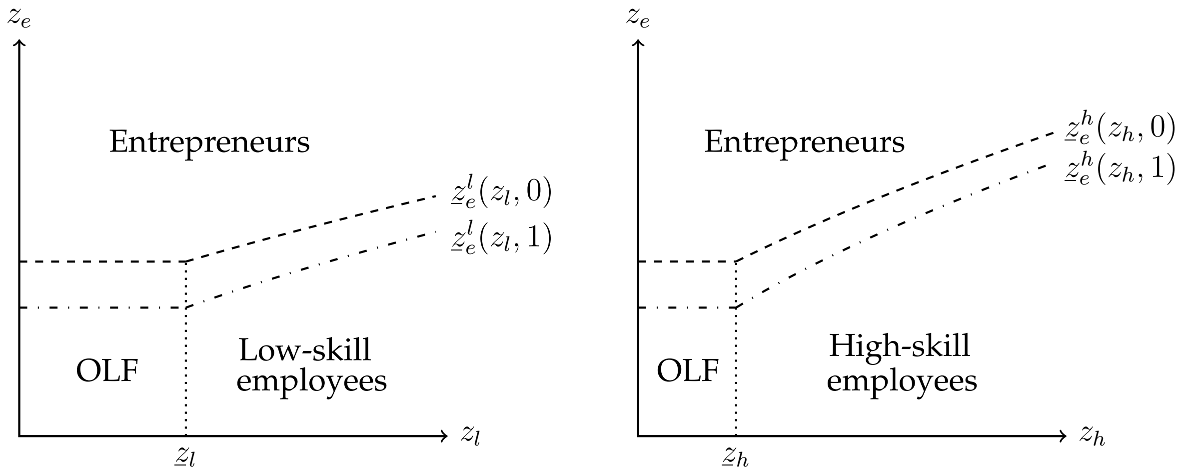
Consider a version of the model which has a single period. Agents are either low or high-skill, and each is endowed with a vector of productivities $\mathbf{z}$. Agents choose their occupation and the payoffs are given by equations (2)–(5) with $\beta = 0$. To maintain the effect of the entry cost on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

Figure 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

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

the value of being out of the labor force is constant, there is a threshold ($\underline{z}_l = b/w_l$) above which agents choose to work and otherwise they do not. Moving vertically up the figure, there are two thresholds that separate agents who are entrepreneurs from those who are out of the labor force or working as employees. These thresholds are a function of the employee productivity of an agent, z_l, and whether she is endowed with a business, ϵ. The higher of these, $\underline{z}_e^l(z_l, 0)$, is the threshold for agents who are not endowed with a business ($\epsilon = 0$). In general, agents with higher entrepreneurial productivity are more likely to be entrepreneurs. For low values of z_l the threshold is flat because the outside option to entrepreneurship is being out of the labor force, and this has the same value for everyone. For $z_l > \underline{z}_l$ this threshold is increasing in the level of z_l because agents with higher z_l earn more as employees and therefore need to make higher profits as entrepreneurs in order to choose that profession. The threshold is concave because the return to being an employee is linear in z_l while the return to being an entrepreneur is convex in z_e. The second threshold, $\underline{z}_e^l(z_l, 1)$, is for agents who are endowed with a business ($\epsilon = 1$). These agents choose to be entrepreneurs for lower values of z_e because they do not need to pay the entry cost. In the dynamic model, $\underline{z}_e^l(z_l, 0)$ corresponds to the threshold for entering entrepreneurship, while $\underline{z}_e^l(z_l, 1)$ corresponds to the exit threshold.

For high-skill types the tradeoffs are the same except that the value of being an employee is $z_h w_h$ instead of $z_l w_l$. The two panels in Figure 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:

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

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 $s \in \{l,h\}$, $\epsilon \in \{0,1\}$ and $z_s > 0$,

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

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

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

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

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

Parts (a) and (b) of this proposition tell us about the effects of 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, $\underline{z}_e^s(z_s,\epsilon)$ for $\epsilon \in \{0,1\}$, will increase for both skill types, and the increases will be larger for high-skill types. This will decrease the share of agents of each skill type who are entrepreneurs. Whether the decrease is larger for high-skill types will depend on the shape of the distributions of low and high-skill agents in the productivity space. If the mass of agents distributed near the entrepreneurship threshold is similar for the two skill types, then the 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 $\epsilon = 1$. For the purposes of this section I will call this the "entry rate." A key factor affecting this is the size of the wedge between the productivity thresholds for running a business for people with and without an endowed business. As this wedge decreases, the entry rate will tend to increase.[29] For an agent with skill type s and $z_s > \underline{z}_s$, this wedge is

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

[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.

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.

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 $s \in \{l, h\}$, $\epsilon \in \{0, 1\}$ and $z_s > 0$,

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

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

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

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 $o(\mathbf{z}, \epsilon|\mathcal{P})$. 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:

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

where $\mathbb{R}_+$ denotes the set of strictly positive real numbers. The following proposi-

[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.

tion 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*

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

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

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

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

[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.

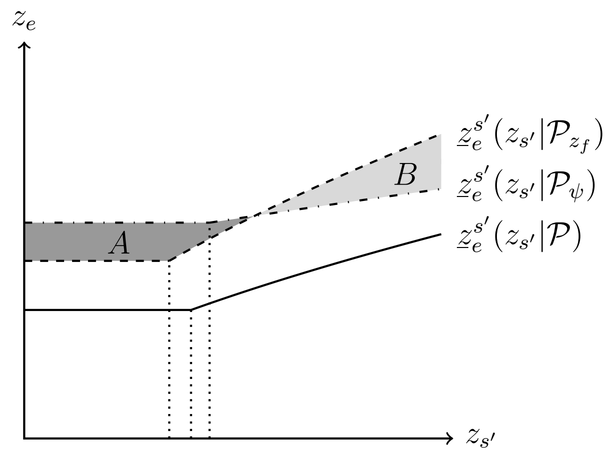


Figure 4: **Occupational choice when non-entrepreneur productivity or fixed costs increase.** This is a stylized representation of the entrepreneur threshold for agents of type s' for the sets of parameter values $\mathcal{P}$, $\mathcal{P}_{z_f}$ and $\mathcal{P}_{\psi}$, introduced in Proposition 13,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

slope of $\underline{z}_e^{s'}(z_{s'}, \epsilon)$ to the right of the kink point:

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

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.

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 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 $\xi \in \{N, C\}$,

[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.

[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.

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 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 $\nu \neq 1$.

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

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 value of 0.95 in accordance with the estimate of Storesletten et al. (2004). The returns to scale of

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

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

[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.

	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.

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 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.

[40] Additional details for these moments are provided in the Appendix.
[41] See Appendix for details of the occupation distribution calculations in the data.

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 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,

[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.

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.

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 pro-

[44] See Appendix for more details on this comparison.

ductivity 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 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

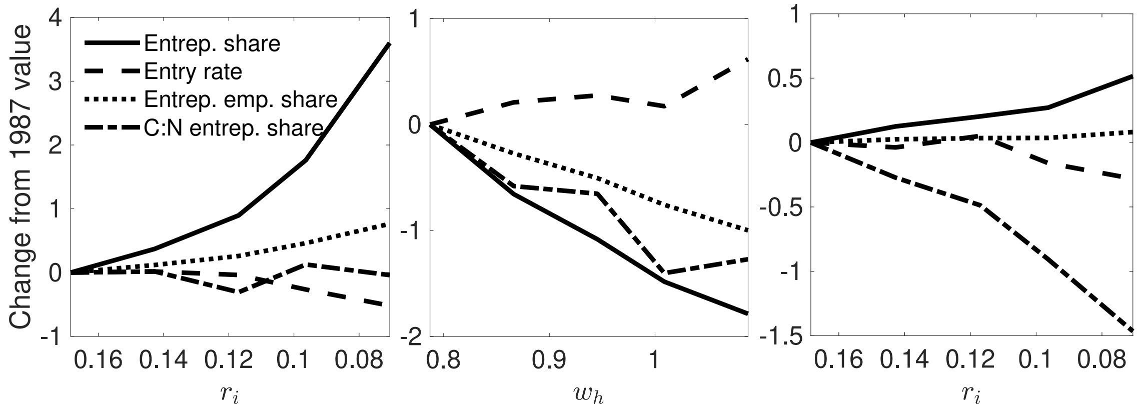
[45]These shares are 65% and 15%, respectively (Table 2).

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 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

[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.



(w_h and w_l fixed) (w_l fixed) (General equilibrium)

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.

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. 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

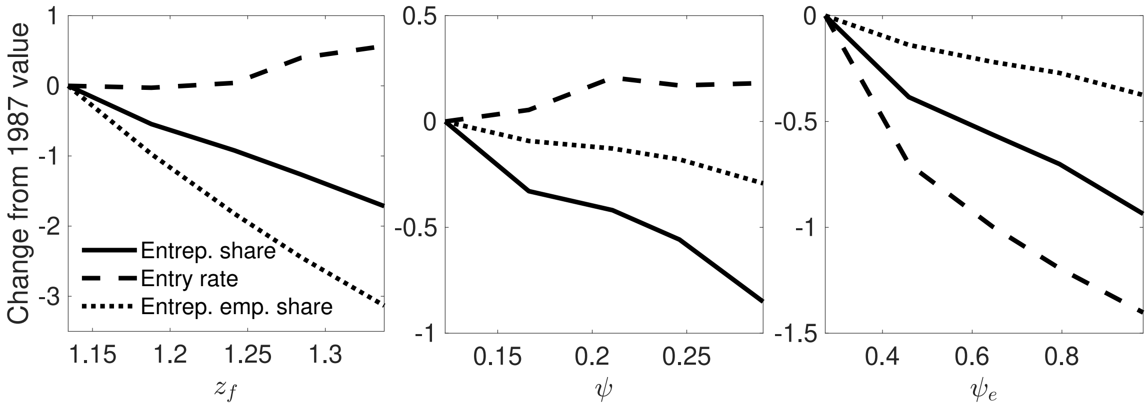


Figure 6: **Comparative statics for non-entrepreneur productivity, fixed costs and entry costs.** This figure has the same setup as Figure 5. Here it is z_f, ψ and ψ_e changing. In all cases wages adjust so that the model is in equilibrium.

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 increases

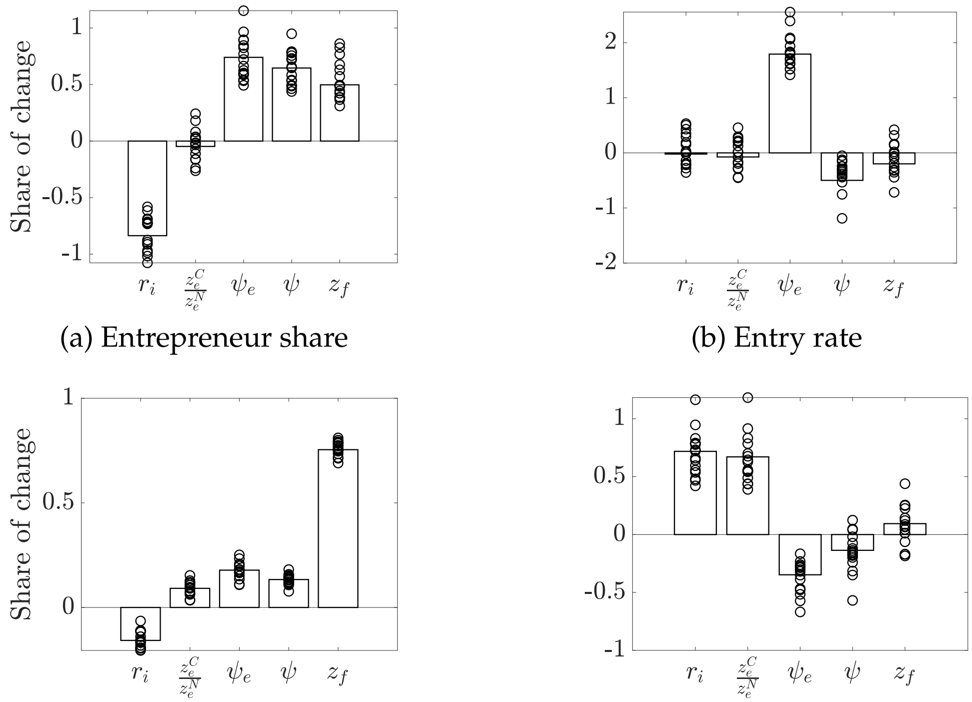
	Secondary parameters	2015 data
Entrepreneur share	0.93	0.71
Entry rate	0.92	0.72
Entrepreneur emp. share	1.06	0.80
College:non-college entrep. share	1.34	0.85
OLF share	1.56	1.66

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.

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

[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.

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 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]

[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 in-

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.

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

creases 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.

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 *rel-*

[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.

ative 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 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

[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.

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

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:

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

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 vari-

[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.

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

	(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.

able 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 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

[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.

is useful for disentangling the effects of rising fixed costs, entry costs, and the 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, 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, 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, 257–98.

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

Atkeson, Andrew and Patrick Kehoe (2005), "Modeling and measuring organization capital." *Journal of Political Economy*, 113, 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, 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, 1279–1333.

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

Barkai, Simcha and Stavros Panageas (2021), "Value without employment." Working paper.

Bloom, Nicholas, Charles Jones, John Van Reenen, and Michael Webb (2020), "Are ideas getting harder to find?" *American Economic Review*, 110, 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, 221–272.

Cagetti, Marco and Mariacristina De Nardi (2006), "Entrepreneurship, frictions, and wealth." *Journal of Political Economy*, 114, 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, 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, 3–24.

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, 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, 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.

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

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

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

Karahan, Fatih, Benjamin Pugsley, and Aysegul Sahin (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, 4–6.

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, 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.

Luttmer, Erzo (2011), "On the mechanics of firm growth." *Review of Economic Stud-*

ies, 78, 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.

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

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

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