Skill-Biased Entrepreneurial Decline*

Helu Jiang[†] Faisal Sohail[‡]

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Abstract

The U.S. is undergoing a long-term decline in entrepreneurship. We show that this slowdown in entrepreneurship has been more pronounced for skilled individuals – those with a college degree. We document new facts on the *skill-biased* nature of declining entrepreneurship and propose that it is a response to the rising worker skill premium observed over the same period. In support of this, we find that workers' earnings grew faster than entrepreneurs', particularly for skilled individuals, discouraging the pursuit of entrepreneurship. To quantify the impact of the skill premium on entrepreneurship, we develop a model of occupational choice with worker heterogeneity. In the model, a rising skill premium – driven by skill-biased technological change – contributes little in lowering entrepreneurship. Instead, around 70% of the observed decline in entrepreneurship is driven by skill-neutral technological change and a rising share of college graduates. A rise in the skill premium interacts with these forces to generate the *skill-biased* decline, and in doing so, shifts the composition of entrepreneurs towards the unskilled, *lowering* average entrepreneurial productivity. Our findings suggest an integral role for the changing income structure of workers in driving the broader decline in business dynamism in the U.S.

Keywords: entrepreneurship, skill premium, occupational choice
JEL Codes: J24, L26, M13

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[†]Shanghai University of Finance and Economics

[‡]Lead Author: University of Melbourne, faisal.sohail@unimelb.edu.au

1 Introduction

The share of entrepreneurs among total employment has declined by around 25% since the early 1980s (see Figure 1a).[1] We document that this decline has been much more pronounced for those with at least a college degree – skilled individuals. Since 1983, the rate of entrepreneurship declined by 43% for skilled and only 16% for unskilled individuals (see Figure 1b). Given the importance of entrepreneurs – particularly skilled entrepreneurs – for job creation and economic growth, understanding the forces behind these trends is important in order to address broader declines in business dynamism observed over the same period.[2] In this paper, we study the role of the changing income structure of workers in explaining the overall and skill-biased trends summarized in Figure 1.

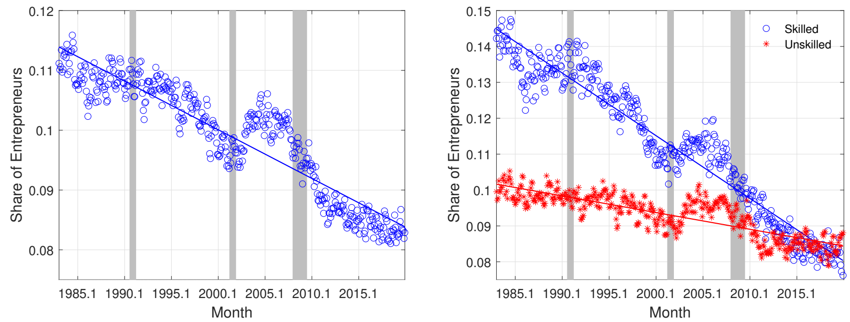
Intuitively, there is a straightforward relationship between workers incomes and entrepreneurship: individuals pursue entrepreneurship by considering its opportunity cost – that is, earnings in employment. So, a relative increase in workers incomes discourages entrepreneurship. We focus on one specific change in the income structure of workers – the rise in worker skill premium – and show that it fully accounts for the *skill-biased* nature of declining entrepreneurship and shifts the composition of entrepreneurs so as to *lower* the average productivity among entrepreneurs.[3]

We begin by documenting new evidence that is consistent with predictions of the intuition above. First, we show that the relatively faster earnings growth of skilled workers since the 1980s (the rising skill premium) has coincided with relatively larger declines in measures of entrepreneurship for skilled individuals. Figure 1b shows this to be the case for one such measure – the share of entrepreneurs. Next, we show that transitions from employment into entrepreneurship also feature a skill-bias – the share of skilled workers entering entrepreneurship has remained relatively stable

[1] We use data from the Current Population Survey (CPS) and define entrepreneurs as the self-employed. Along the lines of Levine and Rubinstein (2016), we think of self-employment as being a necessary step towards entrepreneurship – that is, new product innovation, hiring employees etc. As such, throughout this paper we will refer to self-employment and entrepreneurship interchangeably. In Section 3, we consider alternative definitions for entrepreneurs, including considering only incorporated self-employed to be entrepreneurs. The share of entrepreneurs in the total population exhibits a similar decline as shown in Figure A.1.

[2] Decker et al. (2014) document the role of entrepreneurship in influencing job creation and business dynamism in the U.S. Decker et al. (2013); Hathaway and Litan (2014); Akcigit and Ates (2019) document declines in measures of business dynamism in the U.S. over the last four decades. Doms et al. (2010) document a strong positive association between education and measures of performance in entrepreneurship – including earnings, number of employees and growth. We present similar evidence documenting the performance differences between skilled and unskilled entrepreneurs in Appendix B.

[3] An increase in the worker skill premium – that is, the earnings premium of skilled workers relative to unskilled workers, has been well-documented in Katz and Murphy (1992) and Acemoglu and Autor (2011) among others.



(a) Entrepreneurship Rate

(b) Entrepreneurship Rate, by skill

Figure 1: Share of Entrepreneurs in Total Employment

Notes: Panel (a) plots the share of entrepreneurs in the sample of full-time, non-agricultural employees and entrepreneurs aged between 25 and 64 from the Jan. 1983 to Dec. 2019 CPS basic monthly surveys. Panel (b) plots the same share by skill where skilled individuals are those with at least a college degree and unskilled are those without a college degree. Additional details regarding the data can be found in Appendix B. The shaded bars indicate recessions as determined by the National Bureau of Economic Research (NBER).

over time while the analogous share for unskilled workers has steadily increased. On the other hand, exit out of entrepreneurship into employment has increased steadily in a skill-neutral manner over time.[4] We then conduct a novel decomposition of the decline in the stock of entrepreneurs into flows in and out of entrepreneurship and find that skill-biased changes in entry from employment play a central role in driving the skill-biased decline in entrepreneurship.

While suggestive, the concurrent increase in the workers skill premium and skill-biased declines in measures of entrepreneurship does not establish a causal link between the two phenomena. Indeed, if the skill premium for entrepreneurs kept pace with that of workers, we would predict a skill neutral change in entrepreneurship. We provide novel evidence to argue that this was not the case. By estimating a measure of the entrepreneur skill premium we show that it did not grow as fast as the worker skill premium. We also analyze the evolution of entrepreneurial earnings and find that they have not kept pace with workers earnings, especially for skilled individuals. This suggests that the income structure of workers changed so as to increase the opportunity cost to entrepreneurship, particularly for skilled individuals.

Using geographic differences in the increase in workers' skill premium, we show that U.S. states which experienced larger increases in the skill premium also feature a stronger skill-bias in the decline of entrepreneurship. Similarly, by exploiting variation in the growth of workers earnings

[4]These findings are robust to alternative definitions of entrepreneurship and are evident across industries and demographic characteristics, including age as discussed in Section 3.

across occupations, we document that occupations which experienced the largest increase in workers earnings feature the largest declines in employees transitioning into entrepreneurship (from those occupations). Consistent with evidence of wage polarization – the observation that wage growth has been largest for high and low earnings occupations – we find that decline in entry into entrepreneurship has been largest among high and low earnings occupations. To our knowledge, this is the first paper to document such a pattern of polarization in *entrepreneurship*.

To quantitatively assess the impact of an increasing worker skill premium on skill-biased and aggregate declines in entrepreneurship, we develop a model of occupational choice along the lines of Lucas (1978) that features worker heterogeneity. In the model economy, agents differ in their ability as workers and as entrepreneurs; workers are either skilled or unskilled, while entrepreneurs earn profits given productivity which fluctuates randomly. Agents make an occupational choice each period by comparing the returns to entrepreneurship and wage work. The model features endogenous transitions in and out of entrepreneurship in response to fluctuations in entrepreneurial productivity.

We calibrate the model economy to match key features of the U.S. data in 1983. Then, we introduce changes to this baseline economy that are commonly viewed as influencing the worker skill premium – a rising share of college graduates and technological changes. By comparing the response of a benchmark economy in which the skill premium evolves as in the data to a counterfactual economy in which the skill premium remains stable, we quantify the impact of a rising skill premium on the evolution of entrepreneurship over time.

In the model, we find that, on its own, an increase in the skill premium pushes skilled and unskilled entrepreneurship rates in opposite directions: Raising entrepreneurship among the unskilled while lowering it among the skilled. These changes are such that the rising skill premium contributes little to the aggregate decline in entrepreneurship. Instead, the majority, around 70%, of the aggregate decline in entrepreneurship is due to skill-neutral technological change a rising share of college graduates. A rising skill premium – driven by skill-biased technological change – is crucial for generating the observed *skill-biased* decline in entrepreneurship. Indeed, comparing the benchmark and counterfactual economy reveals that, had the skill premium remained stable, the overall decline in the share of entrepreneurs would have been similar but largely skill-neutral.

In generating the skill-biased decline in entrepreneurship, a rising skill premium *lowers* the average productivity of entrepreneurs as the composition of entrepreneurs shifts away from skilled entrepreneurs – who tend to be more productive – towards unskilled entrepreneurs – who tend to be less productive. Quantitatively, the counterfactual economy with a stable skill premium results in a 12.5% improvement in average entrepreneur productivity compared to only a 10% improvement when the skill premium increases as in the data. This is a significant difference and emphasizes the importance of understanding not only the aggregate decline in entrepreneurship but also the differential declines by skill that we document.

The skill-biased decline in the share of entrepreneurs that results from a rising skill premium is accompanied by skill-biased changes in entry rates and skill-neutral changes in exit rates – changes that are qualitatively consistent with our empirical findings. However, the model economy fails to quantitatively match the observed *trends* in entry and exit rates. We argue that in addition to technological change and a rising supply of college graduates, there has also been a trend increase in the exogenous probability of exit from entrepreneurship to employment. We evaluate the model economy's response to this increase and find that increased exit is critical for quantitatively matching the evolution of flows in and out of entrepreneurship. Increasing exit also contributes modestly to the aggregate decline in entrepreneurship (around 13% of the total) and does so in a *skill-neutral* manner. Notably, a trend increase in exit does not change the impact that a rising worker skill premium has on measures of entrepreneurship – which is the focus of our paper.

Overall, this paper documents new evidence on the skill-biased decline in entrepreneurship and studies the role of the rising worker skill premium in generating it. Our empirical and quantitative findings suggest a significant role for the changing income structure of workers in shaping the evolution of entrepreneurship and, more generally, contributing to the broader decline in business dynamism in the U.S.

Related Literature A growing literature has documented declines in measures of business dynamism in the U.S. (see, for example, Decker et al. (2013), Decker et al. (2014) and Hathaway and Litan (2014)). We contribute to this literature by establishing a decline in the share of entrepreneurs. In contrast to this literature, we use individual-level data rather than firm-level data which allows us to establish a skill-biased decline in entrepreneurship. This skill-bias has important implications as skilled entrepreneurs tend to be relatively more productive – they hire more workers, grow faster and earn higher incomes as documented in Doms et al. (2010) and Levine and Rubinstein (2016).[5]

Explanations for declining dynamism have centered around changing demographics and have been interpreted primarily through theories of firm dynamics which are silent on the characteristics of those that operate firms. Karahan et al. (2018) and Hopenhayn et al. (2018) link the slowing growth rate of the labor force to lower firm entry, while Bornstein (2018) and Engbom (2019) argue for the importance of the population's age composition. In contrast, we focus on the decision of individuals which allows us to study the forces behind both the aggregate and skill-biased declines in the share of individuals that are entrepreneurs.[6] Indeed, we find an important role for both changes in technology and the changing income structure of workers in shaping entrepreneurship. The role of technological changes in contributing to the decline in entrepreneurship highlights the need for policy prescriptions intended to spur entrepreneurship to consider the technological roots of its decline.

Most closely related to this paper is Salgado (2019) and Kozeniauskas (2018). These papers also document a skill-biased decline in entrepreneurship using individual-level data and study the role of technological change and entry costs in influencing it. In addition to using alternative data, our detailed analysis of flows is novel and provides new insights that help us to better understand the drivers of the skill-biased decline in entrepreneurship.[7] Also distinct is our finding that the income structure of workers changed relative to that of entrepreneurs so as to increase the opportunity cost to entrepreneurship, particularly for skilled individuals. This is a critical finding to establish since, as we argued above, if entrepreneurial earnings kept pace with those of workers, theory would predict little role for the rising worker skill premium in driving a skill-biased entrepreneurial decline. Our empirical analysis which exploits variation in workers earnings growth across states and occupations further strengthens the link between a rising worker skill premium and declining

[5]We also document similar performance differences between skilled and unskilled entrepreneurs in Appendix B. This appendix also includes a discussion of the comparability between individual-level data that we use and firm-level data that is often used in many of the studies cited here.

[6]Engbom (2019) also consider the occupational choice of individuals in a model of frictional labor markets and a job ladder.

[7]Kozeniauskas (2018) uses CPS data but does not measure flows in and out of entrepreneurship; entry and exit. Salgado (2019) uses a sample of primarily white heads of households from the Panel Study of Income Dynamics (PSID). In the Appendix, we argue that the PSID sample selection leads to overestimating the decline in measures of entrepreneurship compared to the more complete CPS sample.

entrepreneurship.

We also relate to the literature that documents the earnings structure of workers and entrepreneurs. Changes in worker earnings have been extensively studied; Acemoglu and Autor (2011) provides a review. However, given the difficultly in measurement, entrepreneurial earnings has been relatively unexplored and is an area we contribute to by estimating a skill premium for entrepreneurs and comparing it to that of workers. Michelacci and Schivardi (2016) perform a similar exercise using the Survey of Consumer Finances (SCF). They measure *expected* returns from entrepreneurship and find that the returns to post-graduate education increased relatively faster for entrepreneurs. In contrast, we use the flow of entrepreneurial income, which tracks closely the flow measured in the SCF, and after controlling for observable characteristics, find that the returns to skills (having at least a college degree) have increased faster for workers than for entrepreneurs.[8]

Finally, we relate to the literature studying labor market flows. In particular, we apply the labor market flows framework of Elsby et al. (2015) and Elsby et al. (2019) to conduct a flow-based decomposition of the share of entrepreneurs. To our knowledge, ours is the first paper to conduct such a decomposition of the stock of entrepreneurs and it allows us to provide new evidence behind the determinants of declining entrepreneurship.

An outline of the paper is as follows. Section 2 documents our primary empirical findings. Section 3 presents additional evidence which highlights the robustness of our results by considering i) alternative data sources, ii) alternative definitions of entrepreneurship, iii) demographic characteristics, and iv) industries. Section 4 details the model used for our quantitative analysis and Section 5 details our calibration strategy and the baseline parameters. Section 6 describes the results of our quantitative analysis and Section 7 concludes. Additional details on the data and quantitative analysis are presented in the Appendix.

[8]Accounting for the continuation value of entrepreneurship is important. However, the SCF is not a panel survey so it is not possible to identify failed firms in the sample. This in turn, may lead to overestimating entrepreneurial returns. Further, Michelacci and Schivardi (2016) include older individuals, those above the age of 65, in their sample while we do not. This is an important distinction since older individuals are less likely to view wage employment as part of the opportunity cost to entrepreneurship – a key mechanism of our study.

2 Empirical Findings

This section presents our primary empirical findings. We begin by studying the evolution of measures of entrepreneurship for skilled and unskilled individuals. Then, we conduct a decomposition of the aggregate decline in entrepreneurship to show that the *skill-biased* decline in entrepreneurship is driven almost exclusively by *skill-biased* changes in flows from employment to entrepreneurship. Next, we present evidence on the relative earnings of workers and entrepreneurs and show that workers' earnings have grown faster than those of entrepreneurs – particularly for skilled individuals. Finally, we conduct two empirical exercises which exploit variation in worker earnings across states and occupations to establish a link between changes in earnings and declining entrepreneurship.

Data Description The empirical patterns of the stocks and flows of entrepreneurs are based on the CPS basic monthly surveys from January 1983 to December 2019. We start our analysis in 1983 as that is the first year that allows us to identify both the incorporated and un-incorporated self-employed.[9] Our primary sample is restricted to include respondents aged between 25 and 64 that were either employed by others or self-employed in full-time, non-agricultural occupations. Individuals with at least a college degree are defined as skilled while those without a college degree are unskilled.

We study how three measures of entrepreneurship evolve over time for the skilled and unskilled; i) the entrepreneurship rate, ii) the entry rate and iii) the exit rate. The entrepreneurship rate measures the stock of entrepreneurs and is the share of the self-employed in our sample. Flows, that is entry and exit, in and out of entrepreneurship are measured by tracking CPS respondents over time. We match individuals at an annual frequency and analyze their transitions from employment into entrepreneurship and vice-versa. The entry rate is the share of employees that transition into entrepreneurship over 12 months, while the exit rate is the share of entrepreneurs that become employees over 12 months. Consistent with the literature on labor market flows, we apply an adjustment to flows to correct for margin error as in Elsby et al. (2015). Details of this adjustment as well as the process by which we match respondents and account for redesigns of the CPS are included in Appendix B.

[9] All CPS data are extracted from IPUMS, see Flood et al. (2020) for details.

Our analysis on the earnings of individuals are based on data from the March Annual Social and Economic Supplement to the CPS (CPS ASEC). We employ the same restrictions as in the basic monthly files to estimate the relative earnings of workers and entrepreneurs. The measure of workers earnings is their wage income while for entrepreneurs it is total business income.

Additional data from the American Community Survey (ACS), Survey of Income and Program Participation (SIPP), Survey of Consumer Finances (SCF) and a discussion on the comparability of individual-level CPS data and firm-level employer data from the Business Dynamics Statistics (BDS) are also included in Appendix B.

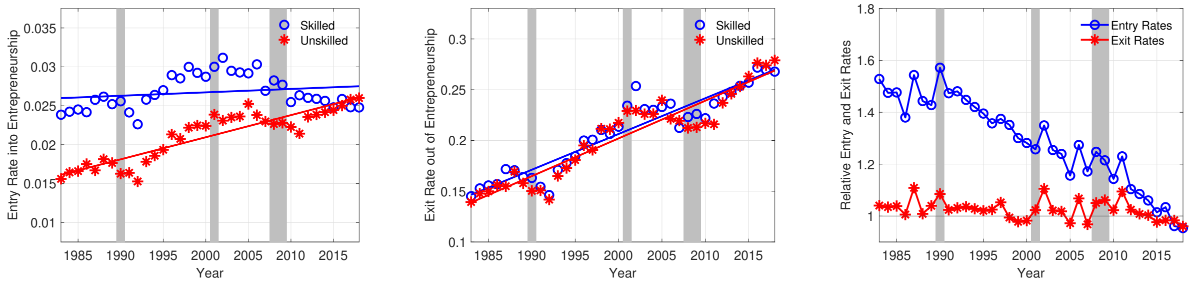
2.1 Skill-Biased Entrepreneurial Decline

Described above, Figure 1b plots entrepreneurship rates by skill and shows i) a steady decline for both skill types, and ii) the decline is more pronounced for skilled individuals. Indeed, the magnitude of an estimated slope is three times larger for skilled individuals.

The entrepreneurship rate, which represents the stock of entrepreneurs, is determined by flows in and out of entrepreneurship. Figure 2 plots these flows between employment and entrepreneurship.[10] Panel (a) plots the entry rate from employment – the share of skilled and unskilled employees that transition into entrepreneurship. As with the entrepreneurship rate, entry rates exhibit a skill bias; transitions into self-employment have remained stable for skilled individuals while they have increased for the unskilled. Entry rates for skilled employees have averaged around 2.5% – they increased by around 0.5 percentage points between 1983 and 2000, and have declined since then to reach roughly the same level as in 1983. The analogous measure for unskilled workers features a strong positive trend over time. Entry rates rise around 1.5% to around 2.6% over our sample period. Together, rising unskilled entry rates and stable skilled entry rates have resulted in the aggregate entry rate (of all workers) to slightly increase over time as shown in Panel (a) of Figure A.2.

Panel (b) of Figure 2 plots the exit rate – the share of entrepreneurs that switch to employment. Given the relatively low share of entrepreneurs, exit rates are an order of magnitude larger than

[10] Figure A.4 plots entry and exit rates that have been adjusted for time-aggregation bias. This adjustment does not alter the trend changes in entry and exit rates for skilled and unskilled individuals. Indeed, as discussed in Shimer (2012), time-aggregation bias largely impacts measures of the *cyclicality* of flows and not the trend, which is what we focus on.



(a) Entry Rate (b) Exit Rate (c) Relative Rates

Figure 2: Entry from and Exit to Employment

Notes: Panel (a) plots the annual transition rate into entrepreneurship from employment – the entry rate. That is, the share of employees that transition into entrepreneurship over a 12 month period. Panel (b) plots the annual transition rate into employment from entrepreneurship – the exit rate. That is, the share of entrepreneurs that transition into employment over a 12 month period. Panel (c) plots the ratio of skilled to unskilled entry and exit rates. Skilled individuals are those with at least a college degree and unskilled are those without a college degree. Data comes from matching respondents in the CPS Monthly Surveys. The sample is restricted to full-time, non-agricultural employees and entrepreneurs aged between 25 and 64. The shaded bars indicate recessions as determined by the NBER. Additional data details can be found in Appendix B.1.

entry rates. In contrast to entry rates, exit rates exhibit a strong upwards trend that is skill-neutral. Indeed, for both skilled and unskilled entrepreneurs, exit rates have roughly doubled, increasing from around 14% to 27% over our sample period.

The skill-bias in entry and skill-neutrality in exit rates is evident in Panel (c) which plots the ratio of skilled and unskilled rates. Skilled entry rates are initially higher than unskilled and converge over time. Skilled and unskilled exit rates have been roughly equal to each other over our entire sample period.

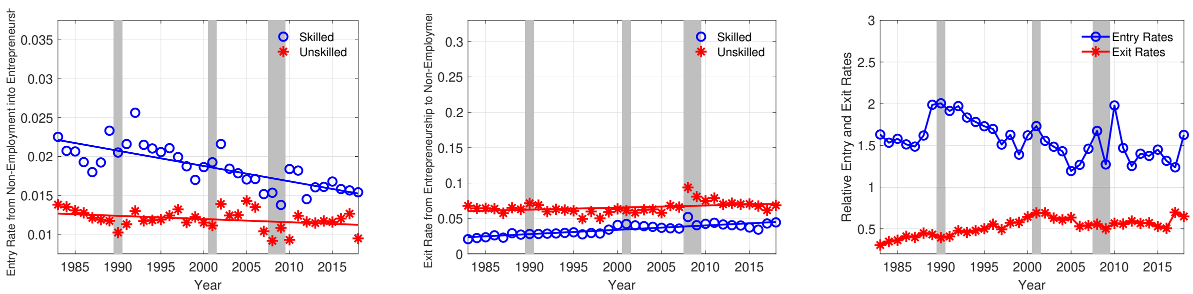
Taken together, Figures 1b and 2 establish a skill-biased decline in entrepreneurship. The skill-neutral increase in exit rates confirms that the *skill-biased* decline in entrepreneurship is driven exclusively by *skill-biased* changes in entry. Indeed, had changes in entry rates also been skill-neutral, changes in the share of entrepreneurship would necessarily be skill-neutral.

2.2 Decomposing the Decline

To evaluate the importance of entry and exit rates in driving both the skill-biased and aggregate declines in entrepreneurship, we perform a flow decomposition of the decline in the share of entrepreneurs. Before doing so, we consider flows between entrepreneurship and *non-employment*, that is those either unemployed or out of the labor force. By incorporating non-employment into our analysis we can decompose the decline in the *population* share of entrepreneurs (shown in Figure

A.1) into flows originating from non-employment and/or employment. Most interestingly, we can quantify the importance of skill-biased changes in entry rates that we have just documented.

Figure 3 plots the evolution of entry and exit rates from non-employment. Focusing first on magnitudes, these flows are significantly smaller than the analogous measures for employment. This lower magnitude combined with the relatively low stock of non-employed in the population suggests that the majority of flows in and out of entrepreneurship will be from workers rather than the non-employed. Indeed, in our matched sample, around 80% of entering entrepreneurs were previously employees and 70% of entrepreneurs exit to employment. In other words, only 20% of inflows into self-employment originate from non-employment and 30% of outflows result in non-employment.[11]



(a) Entry Rate　　(b) Exit Rate　　(c) Relative Rates

Figure 3: Entry and Exit Rates from Non-Employment

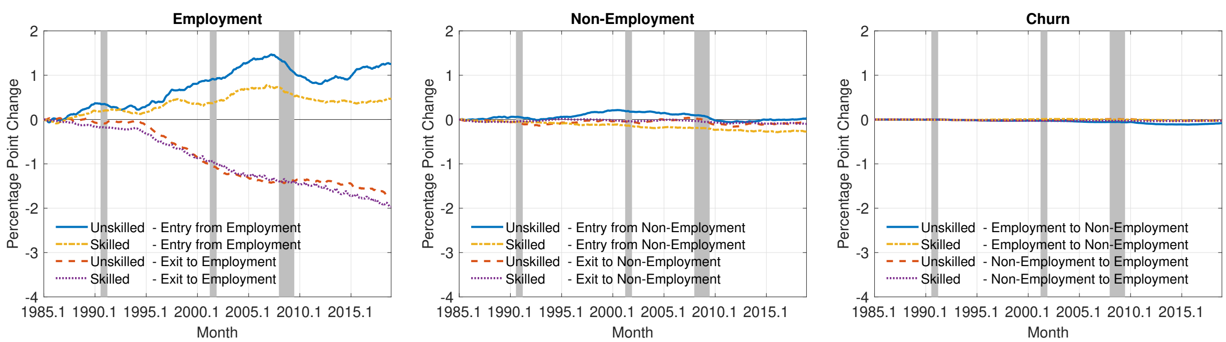
Notes: Panel (a) plots the of share of non-employed that transition into entrepreneurship over a 12 month period. Panel (b) plots the share of entrepreneurs that transition into non-employment 12 month period. Panel (c) plots the ratio of skilled to unskilled entry and exit rates. Data comes from matching respondents in the CPS Monthly Surveys.

Looking next at trends by skill, we find that the entry rate from non-employment declined for skilled and remained stable for unskilled individuals. As with flows from employment, there is a skill-biased decline in entry from non-employment – however from Panel (c) this skill bias is much less pronounced than that of entry from employment. The share of entrepreneurs exiting to non-employment also exhibits a skill-biased trend with rates for skilled individuals increasing from around 2% in 1983 to 5% in 2018 while remaining relatively stable for unskilled individuals at 7%. Combining the trends in entry and exit tells us that net entry from non-employment to entrepreneurship has declined more so for the skilled. Hence, flows from non-employment contribute

[11] The share of non-employed in the population is around 30% with a maximum and minimum of 35% and 26% over our sample period. Figure A.7 reports the shares of entering and exiting entrepreneurs by their source and destination occupations over time and by skill. The relative importance of employment to entrepreneurship transitions is also highlighted in Sohail (2021).

to the skill-biased decline in entrepreneurship among the population. However, given the relatively small size of the pool of non-employed, we expect these flows to play a smaller role in the influencing the share of entrepreneurs.

We confirm this to be the case by conducting a flow decomposition of the decline in the population share of entrepreneurs. To do this, we adapt the non-steady state flow decomposition of Elsby et al. (2019) and decompose the decline in entrepreneurship into inflows and outflows between entrepreneurship, employment, and non-employment. Details of the decomposition exercise are outlined in Appendix C.



(a) Employment (b) Non-Employment (c) Churn

Figure 4: A Flow Decomposition of the Decline in Entrepreneurship

Notes: The figure shows the percentage point change in the population share of entrepreneurs relative to Jan. 1985 due to flows between and within employment and non-employment. Details of the decomposition are in Appendix C, calculated following (C.1). The resulting contributions are weighted by the share of skilled and unskilled in the population following (C.2). Data is from the matched monthly CPS sample and includes both employed and non-employed respondents.

Figure 4 summarizes the results of this decomposition by plotting the percentage point change in the population share of entrepreneurs that is due to flows between i) employment and entrepreneurship in Panel (a), ii) non-employment and entrepreneurship in Panel (b) and iii) employment and non-employment in Panel (c).[12]

By comparing the three panels, it is clear that churn between employment and non-employment play a negligible role in declining entrepreneurship whereas flows to and from employment are the primary contributors shaping the evolution of the entrepreneur share. Flows involving non-employment only account for a small fraction of the overall change. Indeed, if there was no change in flows between non-employment and entrepreneurship, the population share of entrepreneurs

[12]Summing across the three panels in Figure 4 returns the observed percentage point change in the share of entrepreneurs net of changes in skill composition. Figure C.1 plots the component due to skill composition along with the observed aggregate change.

would have declined by 1.55 percentage points rather than the observed 1.62 percentage points over our sample period — a 4% difference.[13]

Decomposing the flow origins of entrepreneurship is not only informative for understanding the relatively small role of churn and non-employment, it also reveals an important role of i) increasing exit to employment and ii) skill-biased declines in entry from employment.

Panel (a) of Figure 4 suggests that the decline in stock of entrepreneurs is driven by exit, with skilled and unskilled entrepreneurs contributing roughly equally over the sample period. This skill-neutrality is consistent with the skill-neutral trend increase in exit rates documented in Figure 2b.

On the other hand, entry from employment acts in the opposite direction, increasing the share of entrepreneurs. Dis-aggregating entry from employment by skill as in Panel (a), highlights the impact of skill-biased changes in entry rates. The solid blue and dashed yellow lines plot, respectively, the contributions of unskilled and skilled entry in changing the population share of entrepreneurs. The gap between these lines captures the impact of the *skill-bias* in entry from employment. At the end of our sample, this gap is 0.79 percentage points which is almost half (47%) of the observed decline in entrepreneurship since 1985.[14]

In other words, the skill-bias in entry from employment may have contributed to up to half of the observed changes in entrepreneurship. For instance, if entry rates had evolved in a skill-neutral manner such that skilled entry rates followed the trend increase of unskilled entry rates, we would have observed a much smaller decline (0.83 percentage points vs 1.62 percentage points) in entrepreneurship. Alternatively, had unskilled entry rates followed the trend decline of skilled entry rates, the decline in entrepreneurship would have been much more pronounced (2.41 percentage points vs 1.62 percentage points).

Of course, considering such counterfactual scenarios in isolation ignores general equilibrium responses and is best suited to a quantitative analysis which we pursue below. Rather, the results

[13] Performing this decomposition separately for the skilled and unskilled populations delivers a similar conclusion. If flows between non-employment and entrepreneurship had remained constant, the decline in unskilled population share of entrepreneurs would have been 0.90 percentage points rather than the observed 0.94 percentage points while the decline in skilled entrepreneurship rates would have been 4.1 percentage points rather than the observed 5.0 percentage points. Flows from non-employment are more important for skilled individuals and they serve to *widen* the skill-biased decline in entrepreneurship — albeit by a small amount.

[14] Just prior to the Great Recession in 2008, this gap is 0.68 percentage points whereas the decline in entrepreneurship was only 0.25 percentage points.

from this flow decomposition emphasize the importance of flows to and from employment and particularly the skill-biased changes in entry from employment in shaping the aggregate decline in entrepreneurship. As such, the analysis that follows refocuses on the decision between employment and entrepreneurship starting with a comparison of earnings in these two occupational states.[15]

2.3 Earnings of Workers and Entrepreneurs

According to standard theories on entrepreneurship, selection into self-employment – as opposed to wage employment – is driven by the relative earnings between employment and entrepreneurship. So, to identify the forces behind the skill-biased decline in entrepreneurship, we explore the extent to which worker earnings have changed relative to entrepreneurial earnings across skill groups.

First, we study the evolution of the skill premium for workers and entrepreneurs. The top panel of Figure 5 shows the already well-documented evolution of worker skill premium. It increased between 1965 and the early '70s before experiencing a decline to 1965 levels by 1980. Since the early '80s, the skill premium has risen, initially growing quickly until slowing in the late '90s. During the same time, the supply of those with a college degree has also risen. This observation has motivated demand-driven explanations for the rise in skill premium – most notably, skill-biased technological change (for example, Card and DiNardo (2002) and Cunha et al. (2011)). In our quantitative analysis, we allow the supply of skills to evolve as observed in the data and introduce exogenous technological change such that we match the worker skill premium.

The bottom panel of Figure 5 reports the analogous skill premium for entrepreneurs, where we use reported business income as our measure of earnings. Firstly, notice that the skill premium for entrepreneurs is higher in levels than that for workers. Secondly, while the skill premium has declined by around 40 percentage points between 1983 and 2017 it has not done so monotonically. It decreased through the 80s until 1990 and again between 2001 and 2010. The two periods during which the premium consistently increased were between 1997 and 2001, and 2010 and 2014. During these periods the annual average growth rate was around 5 percentage points per year. This is in contrast to the (around) 1 percentage point per year increase in the skill premium for workers over

[15] As another justification of abstracting from non-employment, we note that if employment (either for one self or others) is the most salient outside option to non-employment, the same mechanism driving flows from wage work to entrepreneurship will also influence the flows from non-employment to employment.

the same two periods. For the bulk of our sample, workers' skill premium has grown faster than entrepreneurs'. This is a crucial finding to establish since skill-biased changes in workers' earnings alone are not enough to generate a skill-biased decline in entrepreneurship. Indeed, had the skill premium for entrepreneurs kept pace with workers, canonical models would predict skill-neutral changes in entrepreneurship.

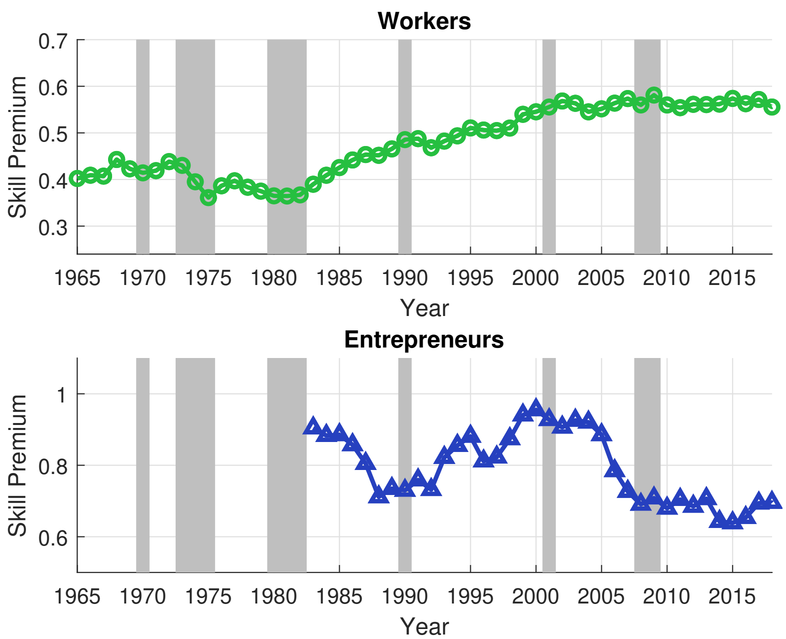


Figure 5: Skill Premium for Workers and Entrepreneurs

Notes: This figure plots the skill premium for workers and entrepreneurs respectively. Sample includes full-time, non-agricultural employees aged between 25 and 64 from the March Supplement of the CPS. The skill premium is the coefficient obtained from an OLS regression of log income on an indicator variable identifying those with at least a college degree (or 16 years of schooling). This regression includes a quartic in years of experience, gender, race and census region dummies. Entrepreneurs skill premium is reported as a two year moving average. Additional details can be found in Appendix B. The shaded bars indicate recessions as determined by the NBER.

Next, we directly compare the relative incomes of workers and entrepreneurs across skill groups. Figure 6 shows the ratio of earnings for entrepreneurs and workers at the first, second, and third quartiles of their respective earnings distribution. In particular, we plot the ratio $\frac{y^e(j)}{y^w(j)}$ by skill group where $y^e(j)$ are hourly earnings at the j^{th} percentile of the entrepreneur earnings distribution and $y^w(j)$ are hourly earnings at the j^{th} percentile of the workers earnings distribution.[16]

Focusing first on level differences across quartiles, we find that the relative earnings of entrepreneurs increase along the earnings distribution for both skill groups. For example, in 2000, unskilled

[16]Hourly earnings are computed as the ratio of annual earnings and the product of weeks worked in the year and usual weekly hours. Figure A.8 in the Appendix plots the relative earnings of workers and entrepreneurs resulting from a regression that controls for observable characteristics.

entrepreneurs in the first quartile of the earnings distribution earned around 50% less than unskilled workers in the first quartile, while unskilled entrepreneurs and workers in the third quartile earned around the same. These findings are consistent with Hamilton (2000) who found that the median worker earns more than the median entrepreneur. Disaggregating by skill groups, as in Figure 6, shows that median entrepreneur-worker earnings gap is mainly driven by the gap among the unskilled.

Focusing next on the evolution of the earnings gap across skill groups, we find that at the beginning of our sample, the relative earnings gap for the skilled is greater than the gap for the unskilled. However, the relative earnings gap for skilled and unskilled groups has converged over time. This convergence is due to both a *decrease* in the relative earnings of skilled entrepreneurs and an *increase* in the relative earnings of unskilled entrepreneurs. For example, in 1985, the median skilled worker earned 20% *less* than the median skilled entrepreneur. In 2015, the median skilled worker earned around 20% *more* than the median entrepreneur. These same measures changed less dramatically for the unskilled: In 1985, the median unskilled worker earned 40% more, and in 2015, 20% more than the median unskilled entrepreneur. A qualitatively similar pattern is also evident in the first and third quartiles of the earnings distributions.

The convergence in relative earnings across skilled groups shows that skilled worker earnings have steadily increased relative to entrepreneur earnings while unskilled worker earnings have decreased moderately compared to unskilled entrepreneurs. This confirms that there have been changes in the opportunity cost to entrepreneurship, and, notably, these changes have differed for skilled and unskilled individuals. Indeed, given our findings, canonical theories will predict a stronger decline in skilled entrepreneurship as observed in the data.

Changes in Earnings Risk Before proceeding, we briefly discuss another critical determinant of occupational choice – the risk in returns to employment and entrepreneurship. This is important as changes in the risk to entrepreneurship relative to risk in employment could explain the decline in entrepreneurship.

A substantial literature has studied the evolution of workers' earnings risk and finds that this risk has remained relatively stable over time. This literature also finds that the inclusion of en-

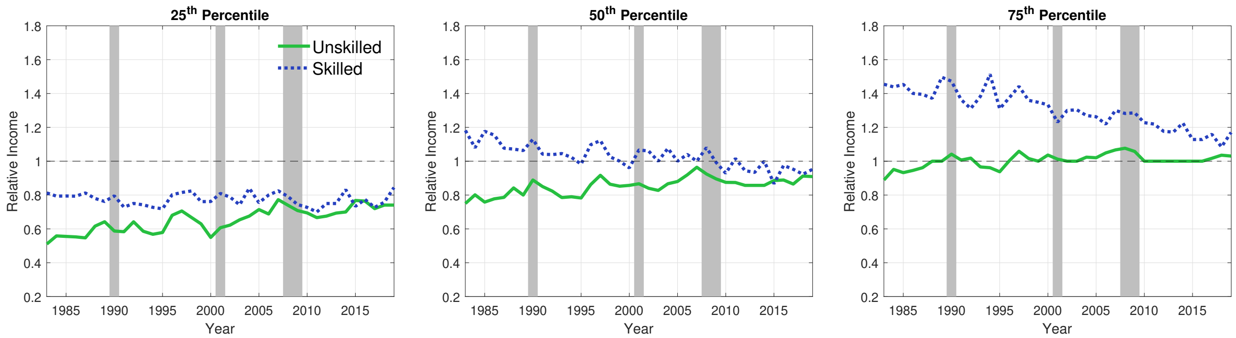


Figure 6: Relative Incomes of Entrepreneurs and Workers

Notes: The figure reports the ratio of entrepreneurial and worker income at a given point in their respective distribution for a given year and skill type. Sample includes full-time, non-agricultural employees aged between 25 and 64 from the March Supplement of the CPS. The shaded bars indicate recessions as determined by the NBER.

trepreneurial earnings, i) raises total earnings risk and ii) does not alter the trend in earnings risk.[17] This suggests that i) entrepreneurial earnings are more volatile than worker earnings and ii) that the relative risk between the two occupations has not changed significantly over time.

We confirm the literature's findings and show that there has been little change in the relative earnings risk of workers and entrepreneurs. In particular, we consider two measures of earnings risk; i) the average growth rate of earnings for continuing entrepreneurs and workers and ii) the standard deviation of earnings growth rates. Figure 7 reports these measures over time using data from the March CPS.[18] Consistent with the literature, growth rates for entrepreneurs are higher and more dispersed. Further, the trend evolution of these measures is similar across occupations – we find no statistically significant difference in the relative trends for workers and entrepreneurs.[19] Overall, Figure 7 suggests that risk in returns to entrepreneurship and employment have not diverged and hence are unlikely to be drivers of skill-biased trends in entrepreneurship.

2.4 Evidence Across States

To provide support for a link between the changing income structure of workers and the skill-biased decline in entrepreneurship, we exploit variation in these two measures across states. In

[17]For example, Guvenen et al. (2014) use administrative data to show a relatively stable level of dispersion in earnings growth rates of workers since the mid-1980s. More recently, Carr et al. (2020) use survey data to confirm the findings from administrative data. Ziliak et al. (2011) discuss the role of including entrepreneurial earnings for total earnings risk.

[18]Our data starts in 1989 as this is the first year it is possible to match respondents from the IPUMS March CPS samples. Figure B.8 in the Appendix show the analogous measures using data from the SIPP.

[19]We also consider earnings risk separately by skill (in Figure A.5) and find that skilled and unskilled individuals track each other quite closely although skilled growth rates are slightly higher than those of unskilled entrepreneurs.

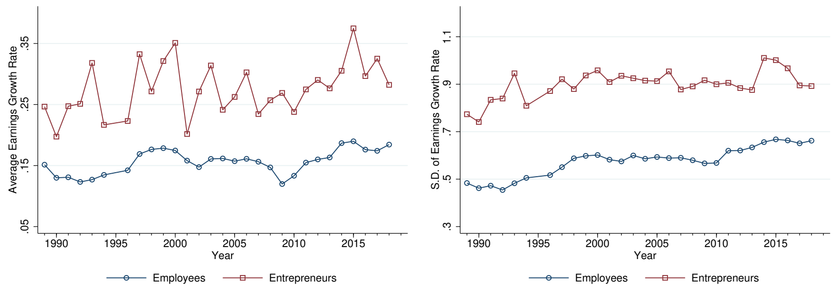
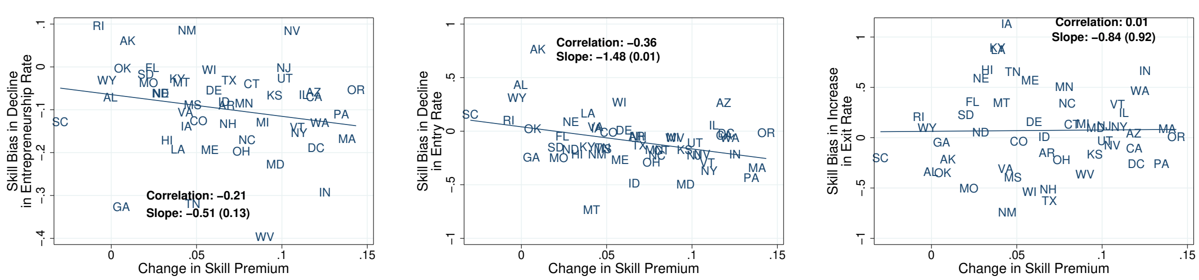


Figure 7: Average and Standard Deviation of Earnings Growth Rates

Notes: The figure reports the average, standard deviation of earnings growth among continuing entrepreneurs and workers in the CPS. Earnings growth is calculated as percentage change in earnings for continuing entrepreneurs. The top and bottom 1% growth rates are excluded when calculating the average and standard deviation of growth rates.

particular, we test whether states that experienced larger increases in the worker skill premium also experienced a more skill-biased declines in entrepreneurship. To account for the smaller sample size at the state level, we pool the sample into two bins covering data from 1983-95 and 1996-2007. Using this pooled data, we find that states which experienced larger increases in the skill premium also experienced a higher degree of skill-biased changes in measures of entrepreneurship. The latter measure is constructed by first computing the growth rates in entrepreneurship, entry and exit rates by skill type for each state. The degree of skill bias in entrepreneurial decline is the difference between growth rates for skilled and unskilled individuals. For example, if the entry rate for skilled and unskilled individuals changed by -5% and +10%, respectively, the degree of skill bias in entry rate decline is -0.15 (-0.05-0.10).



(a) Entrepreneurship Rate (b) Entry Rate (c) Exit Rate

Figure 8: State-Level Variation in Worker skill premium and Skill-Biased Entrepreneurial Decline

Notes: The horizontal axis reports the difference in skill premium between the pooled years 1983-1995 and 1996-2007 as measured in the March CPS sample. For the entrepreneurship and entry rates, values below zero indicate a higher degree of skill-biased decline. For the exit rate, values above zero denote a higher degree of skill-biased increase in the exit rate into entrepreneurship. The reported slope coefficient is obtained from an OLS regression, the associated p-value is reported in the parentheses.

Figure 8 plots this measure of the skill bias in the decline in (a) entrepreneurship, (b) entry, and (c) exit rates against the change in skill premium by state. The first two panels show a significant negative relationship between the change in skill premium and the skill bias in declines of entrepreneurship and entry rates, respectively. Panels (a) and (b) also highlight the broad nature of skill-biased entrepreneurial decline; in most states skilled individuals experienced a steeper decline in entrepreneurship and entry rates relative to unskilled. Panel (c) plots the skill-bias in the increase in exit rate. Unlike the entrepreneurship and entry rates, there is only a weak correlation between the skill-bias in exit rates and the skill premium.

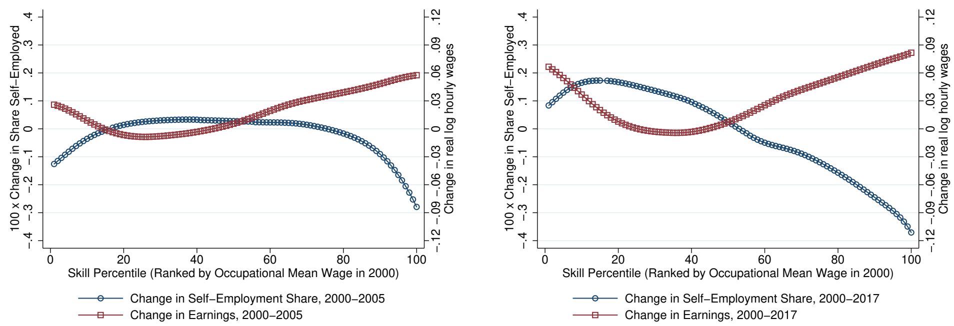
Taken together, Figure 8 tests the intuition from canonical theories and provides suggestive evidence supporting its implications. That is, states that experience larger increases in the skill premium also experience more skill-biased changes in entrepreneurship.

2.5 Polarization in Entrepreneurship

So far, we have focused on the differential wage growth between two broadly defined groups; skilled and unskilled individuals. However, recent work, for example Autor and Dorn (2013), has argued that wage growth has been non-monotonic across the entire skill distribution, with middle skilled workers experienced relatively slower growth in earnings – wage polarization. Dividing skills into two large groups can obscure this heterogeneity. In this section, we consider a finer division of skills and test whether entrepreneurship experienced larger declines among those skill groups whose wages grew faster. That is, we test whether wage polarization has also resulted in entrepreneurial polarization.

We perform two exercises. First, using data from the American Community Survey (ACS), we rank occupations by wages earned. We use this ranking as our measure of worker skills and study the changes in the share of entrepreneurs that report working in these occupations over time. This measures the change in the *share of entrepreneurs* by skill. Second, we investigate possible polarization in entry into entrepreneurship. Using the same occupational ranking as a measure of skills, we consider the sample of the newly self-employed in the CPS, that is those that transitioned from employment into entrepreneurship. We then compute the share of entrants based on the occupation that they were previously employed in and study changes in this share. This measures the change in *entry into self-employment* by skill. Additional details on the data construction and these two measures are included in Appendix B.

Figure 9 shows the change in share of entrepreneurs as well as changes in workers wages between the reference year of 2000 and 2005, and 2017. The figure shows relatively slower income growth for middle skilled entrepreneurs relative to low and high skilled workers. This wage polarization appears also to be reflected in the share of entrepreneurs, with entrepreneurs from the middle of the skill distribution exhibiting a smaller decline than those from either the high or low end of the skill distribution.



(a) Changes between 2000 and 2005

(b) Changes between 2000 and 2017

Figure 9: Smoothed Changes in Entrepreneurs and Real Wages by Skill Percentile

Notes: The horizontal axis reports the skill percentile of occupations ranked by the mean earnings in 2000. The left axis reports 100 times the difference in share of entrepreneurs in an occupation. The right vertical axis reports the change in log real hourly wages in an occupation. Self-employment shares are calculated using ACS weights and are the weeks worked times the usual weekly hours worked in the prior year. Hourly wage data is measured as the ratio of annual earnings, and the product of weeks and usual hours worked. The underlying data is smoothed using locally weighted scatterplot smoothing (`LOWESS`) with bins of size 0.8. Data is from the 2000, 2005 and 2017 ACS. We follow Autor and Dorn (2013) in constructing a consistent sample of occupations over time.

While Figure 9 is suggestive, smoothing the underlying data obscures the heterogeneity across skill percentiles. We perform a more robust test of polarization by testing for a quadratic fit of the data, as in Goos and Manning (2007). More specifically, we estimate the following regression:

$$\Delta y_j = \alpha + \beta j + \gamma j^2 \tag{1}$$

where $j \in \{1, 2 \ldots, 100]$ is the skill percentile and Δy is the change in either i) log hourly real wages or ii) share of entrepreneurs. If changes in the entrepreneur share mirror changes in real wages, we should expect opposite signs on the coefficients β and γ when performing the regression on the changes in share of entrepreneurs and earnings. Table 1 reports these coefficients.

Table 1: Comparing Polarization in Wages and Entrepreneurship

	2000-2005		2000-2017	
	Δ Wages	Δ Self-Employed	Δ Wages	Δ Self-Employed
Percentile	-0.0024	0.0076*	-0.0066	0.0013
	(0.0050)	(0.0042)	(0.0055)	(0.0079)
Percentile Sq.	0.0000	-0.0001**	0.0001	-0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
N	100	100	100	100
R^2	0.0041	0.0469	0.0155	0.0828

Notes: * and ** indicate statistical significance at the 10 and 5 % level respectively.

First, we do not find statistically significant evidence for wage polarization, although the signs of the linear and quadratic coefficients are consistent with polarization. This lack of statistical significance is also found in recent work by Böhm (2018). Our focus is not on establishing the existence of wage polarization but on whether the changes in the income structure of workers are reflected into changes in the overall share of entrepreneurs. As shown in Table 1, the linear and quadratic coefficients on changes in self-employment have the *opposite* sign to those for wage changes and are statistically significant between 2000 and 2005. These results suggest that the share of entrepreneurs in high and low skill occupations declined relative to those with mid-level skills during the same time that wages for high and low skilled workers were rising faster than those for middle skilled workers. This finding is consistent with the canonical theories of occupational choice as well as our findings thus far which have focused on two broad skill groups. However, there are several caveats to this analysis. First, the occupations reported by entrepreneurs may not accurately reflect an individual's skill level. For example, a former financial manager operating a restaurant may report themselves as being in a personal services occupation while their skill level, as inferred from their previous occupation would likely be higher. Second, since the ACS does not include unincorporated self-employed prior to 2000, our analysis is restricted to relatively short time period. To overcome these limitations, we use data from the CPS and consider *entry* into entrepreneurship and measure changes in entry based on the previous occupation (as an employee) of new entrepreneurs.[20]

[20]Notice, that comparing the share of entering entrepreneurs by previous occupation in employment will also capture

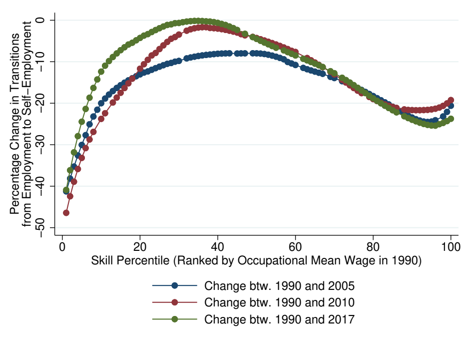


Figure 10: Smoothed Changes in Entry into Self-Employment by Skill Percentile in Employment

Notes: The horizontal axis reports the skill percentile of occupations ranked by the mean earnings in 1990 using ACS data on employees. The vertical axis reports the percentage change in entry into self-employment relative to share of employment for a give occupation. Self-employment shares are calculated using matched CPS while employment shares are calculated using ACS data. Additional details are included in the Appendix B. The underlying data is smoothed using locally weighted scatterplot smoothing (`LOWESS`) with bins of size 0.8. We follow Autor and Dorn (2013) in constructing a consistent sample of occupations over time.

Figure 10 reports the percentage change in transitions into self-employment across skill percentiles for three reference years 2005, 2010 and 2017 relative to the base year of 1990. The figure displays roughly an inverted U-shape for each of the three reference years considered with larger declines in entry for those at the right and left tails of the skills distribution relative to those in the middle. As with changes in overall self-employment, we test for a quadratic fit of the underlying data using specification 1 and report the results in Table 2. While statistically insignificant, the linear and quadratic term coefficients are positive and negative, respectively. This is consistent with the results for changes in the share of entrepreneurship and is suggestive of a polarization in entrepreneurship that is exactly opposite to that observed in wages.

Table 2: Testing for Polarization in Entry into Entrepreneurship

	Δ_{90-05}	Δ_{90-10}	Δ_{90-17}
Percentile	0.9575	1.4199	0.9933
	(0.8591)	(0.8924)	(0.8237)
Percentile Sq.	-0.0100	-0.0144*	-0.0117
	(0.0083)	(0.0085)	(0.0079)
N	93	89	93
R^2	0.0162	0.0332	0.0329

changes in the underlying share of occupations in employment that have occurred over time (i.e. job polarization). Since we are only interested in measuring changes in propensities for entry into entrepreneurship by occupation, we divide the share of newly self-employed by the share of employees in each occupation and report changes in this ratio over time. Details are included in the Appendix B.

The evidence presented in this section suggests that the changes in entrepreneurship are negatively correlated with wage changes of workers, findings that are consistent with the intuition that changes in the income structure have an important role in driving the decline in entrepreneurship.

3 Robustness

In this section, we provide additional evidence which shows that our findings of a skill-biased decline in entrepreneurship are robust. We begin by considering alternative definitions of an entrepreneur and confirm our findings using the sample of incorporated self-employed. As argued in Levine and Rubinstein (2016), the incorporated self-employed are more likely to hire employees and tend to be more productive.[21] We then repeat our analysis using data from the March supplement of the CPS and the SIPP. To study non-casual entrepreneurs, we impose additional restrictions when classifying entrepreneurs using these two data sets. Finally, we confirm that a skill-biased decline in entrepreneurship is evident across demographic characteristics and industries.

3.1 Incorporated Entrepreneurs

Table 3 reports the percentage change in overall, entry and exit rates of self-employment for all self-employed and incorporated self-employed. Considering only the incorporated self-employed is an important restriction as these entrepreneurs are more likely to be employers and earn higher returns as highlighted in, for example, Doms et al. (2010) and Levine and Rubinstein (2016). The table shows that measures of incorporated self-employment feature, over time, skill-biased changes in entrepreneurship and entry rates with skill-neutral changes in exit rates. Unlike the sample which includes both unincorporated and incorporated self-employed, the entry rate into incorporated self-employment for both skilled and unskilled individuals *increases* between 1983 and 2006. However, this increase is flatter for skilled individuals leading once again to the finding of skill-biased decline in entrepreneurship.

[21] Using data from the Contingent Worker Supplement of the CPS, Figure A.6 documents a skill-biased decline in entrepreneurship for both employers and non-employers. We discuss the comparability of CPS data and employer-level data from the Business Dynamics Statistics (BDS) in Appendix B.

Table 3: Percentage Change in Entrepreneurship, Entry and Exit Rates.

Panel A: Entrepreneurship Rate

	All Entrepreneurs		Incorporated	
	Unskilled	Skilled	Unskilled	Skilled
1983-1990	-2.6	-5.7	-1.9	-6.5
1990-2000	-6.9	-20.9	8.0	-13.2
2000-2010	-4.0	-12.8	8.2	-1.5
2010-2019	-3.3	-17.2	5.4	-15.0
1983-2019	-16.8	-56.5	19.7	-36.3

Panel B: Entry Rate

	All Entrepreneurs		Incorporated	
	Unskilled	Skilled	Unskilled	Skilled
1983-1990	7.3	8.3	6.8	3.1
1990-2000	15.7	-9.2	24.8	9.8
2000-2010	-11.1	-22.1	11.4	-11.1
2010-2019	20.1	-1.2	2.3	-13.6
1983-2019	32.0	-24.3	45.3	-11.7

Panel C: Exit Rate

	All Entrepreneurs		Incorporated	
	Unskilled	Skilled	Unskilled	Skilled
1983-1990	5.0	11.1	2.4	11.3
1990-2000	50.4	43.3	52.1	52.4
2000-2010	9.9	13.0	9.6	10.2
2010-2018	20.5	16.6	8.8	13.0
1983-2018	85.8	84.0	72.8	86.9

Notes: The table reports the percentage change (measured as log differences) in the entrepreneurship rate (Panel A), entry rate (Panel B) and exit rate (Panel C) over time separately for all entrepreneurs and incorporated entrepreneurs only. Skilled individuals are those with at least a college degree and unskilled are those without a college degree. The entrepreneurship rate is computed using the CPS Monthly Surveys from Jan. 1983 to Dec. 2019. Entry and exit rates are derived from matching respondents in the CPS over a 12 month period. Data is restricted to full-time, non-agricultural employees and entrepreneurs aged between 25 and 64.

3.2 Additional Restrictions

Next, we compute the entrepreneurship, entry and exit rates from the i) March Annual Social and Economic Supplement of the CPS and ii) the Survey of Income and Program Participation (SIPP). These data sets contain additional information which allow us to study skill-biased entrepreneurial decline while imposing additional conditions relative to the CPS monthly data. First, using the March CPS data, we are able to observe entrepreneurial incomes and compute our stock and flows measures by only including individuals that earn at least \$250 per week (in 2010 dollars) as entrepreneurs. We make this restriction in an attempt to ensure that we only consider entrepreneurs and transitions between employment and entrepreneurship that are not casual. Panel A of Table 4 reports the results from the March CPS sample. Imposing additional restrictions give similar findings as those in the monthly CPS data – there is a skill-biased decline in entrepreneurship and entry rates with a largely skill-neutral increase in exit rates.

Panel B reports measures of entry, exit, and entrepreneurship using the 1996, 2001, 2004, and 2008 panels of the SIPP. Since the SIPP is a monthly panel, we can impose additional restrictions on measuring flows in and out of entrepreneurship. In particular, to measure the entry rate, we compute the share of employees that have switched into entrepreneurship within a year and remain entrepreneurs for at least a quarter. To measure the exit rate, we similarly consider only those entrepreneurs that are observed to be in entrepreneurship for at least a quarter and then measure the share of this group that switches into employment in the following year.[22] The entrepreneurship rate is measured as in the monthly CPS sample. As seen in Panel B of Table 4, imposing these additional restrictions on flows in the SIPP also shows a skill-biased decline in entry rates and a trend increase in exit rates over time which is slightly more biased towards skilled entrepreneurs.

Table 4: Measures of Entrepreneurship in the March CPS and SIPP

Panel A: March CPS

	Entrepreneurship Rate			Entry Rate			Exit Rate		
	Unskilled	Skilled	Ratio	Unskilled	Skilled	Ratio	Unskilled	Skilled	Ratio
1996-2000	0.074	0.103	1.40	0.021	0.029	1.37	0.27	0.24	0.91
2001-2006	0.074	0.098	1.33	0.022	0.030	1.41	0.27	0.27	1.00
2007-2013	0.073	0.090	1.23	0.018	0.022	1.24	0.27	0.29	1.06
2014-2018	0.070	0.076	1.10	0.020	0.022	1.13	0.34	0.32	0.95

Panel B: SIPP

	Entrepreneurship Rate			Entry Rate			Exit Rate		
	Unskilled	Skilled	Ratio	Unskilled	Skilled	Ratio	Unskilled	Skilled	Ratio
1996 Panel	0.086	0.119	1.38	0.0123	0.0156	1.27	0.24	0.20	0.84
2001 Panel	0.087	0.119	1.36	0.0132	0.0160	1.22	0.24	0.19	0.82
2004 Panel	0.088	0.115	1.31	0.0138	0.0148	1.07	0.25	0.22	0.90
2008 Panel	0.082	0.106	1.29	0.0109	0.0135	1.23	0.26	0.23	0.88

Notes: March CPS and SIPP samples includes individuals engaged in full-time, non-agricultural employment aged between 25 and 64. For the March CPS results, only those entrepreneurs with reported weekly earnings above $250 2010USD are included. The March CPS data is pooled for the year bins specified and the SIPP data is for a given wave following 1996. Additional details can be found in the Appendix B

[22]To account for *seam-bias* in the SIPP, we use information from the last reference month in a given wave and the next three reference months of the next wave to measure occupational status. Additional details can be found in Appendix B.

3.3 Demographic Characteristics

We further disaggregate the monthly CPS sample by demographic characteristics. Here, we emphasize that the skill-biased decline in entrepreneurship is evident across different age groups.[23] Analyzing different age groups is important since rates of entrepreneurship differ dramatically with age, see for example Hincapié (2020), and the age composition of the population has shifted since the 1980s. Figure 11 plots the share of entrepreneurs by skill and three age groups. Consistent with existing literature, we find that entrepreneurship rates increase with age. Importantly, the figure shows clear evidence for skill-biased declines in entrepreneurship within age group. The decline has been the most pronounced for the younger age group. Between 1983 and 2018, the share in entrepreneurship fell by 12% (37%) among unskilled (skilled) individuals aged 25 to 35 while the analogous measure for unskilled (skilled) individuals ages 51 to 64 was a 7% (20%) decline.[24]

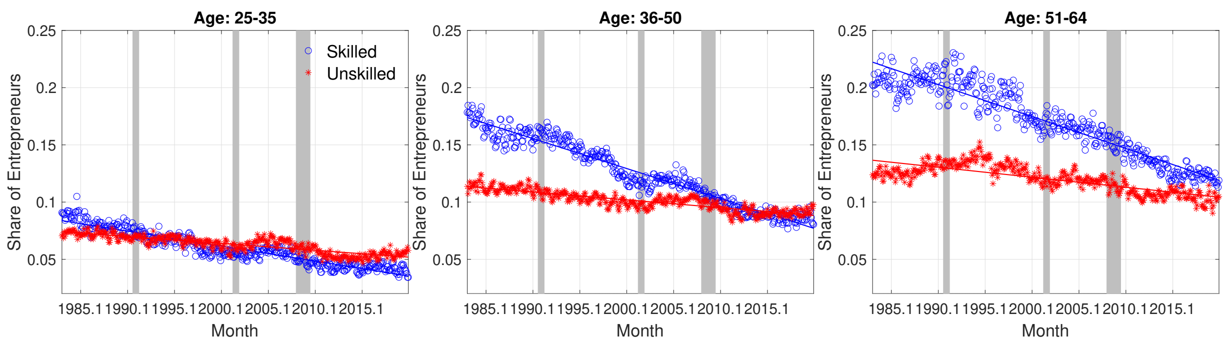


Figure 11: Entrepreneurship Rate by Age Groups

Notes: The vertical axis reports the share of entrepreneurs in the main monthly CPS sample.

3.4 Evidence Across Industries

In addition to changes in the age distribution, the composition of industries has also changed significantly over time. In Table 5, we show that the skill-biased decline in entrepreneurship is a secular phenomenon and evident across industries. The table reports an estimated time trend on measures of entrepreneurship for skilled and unskilled individuals across 2-digit industry groups.

[23] Figure B.1 in the Appendix compares measures of entrepreneurship among white, male heads of households and the rest of the sample.

[24] Figure A.3 in the Appendix reports entry and exit rates by age group.

In particular, we estimate the following OLS regression:

$$y_{ajt} = \alpha_{aj} + \beta_{aj} (t - 1983)$$

where y_{ajt} is a measure of entrepreneurship in year t in industry j for skill type a. Table 5 reports $100 \times \beta_{aj}$ for the entrepreneurship, entry and exit rates. With the exception of transportation, communication and utilities industry, there was a trend decline in the entrepreneurship and entry rate that was more pronounced for skilled individuals. Similarly, the trend increase in exit rate was larger for skilled individuals across most industries.

Table 5: Trends in Measures of Entrepreneurship Across Industries

	Entrepreneurship Rate		Entry Rate		Exit Rate	
	Unskilled	Skilled	Unskilled	Skilled	Unskilled	Skilled
Mining	-0.029	-0.110	0.009	-0.048	0.334	0.840
Construction	-0.097	-0.314	-0.010	-0.003	0.354	0.331
Manufacturing	0.011	-0.054	0.011	-0.020	0.407	0.487
Transportation, Communication and Utilities	0.064	0.048	0.035	0.004	0.411	0.594
Wholesale Trade	-0.209	-0.346	-0.027	-0.090	0.618	0.442
Retail Trade	-0.332	-0.506	-0.016	-0.058	0.614	0.475
Finance, Insurance and Real Estate	-0.009	-0.204	-0.003	-0.048	0.437	0.472
Personal Services	-0.318	-0.386	-0.005	-0.064	0.506	0.402
Professional Services	0.002	-0.227	0.009	-0.016	0.423	0.605

Notes: The table reports the trend coefficient from estimating the following OLS regression specification: $y_{ajt} = \alpha_{aj} + \beta_{aj} (t - 1983)$, where y_{ajt} is one of three measures of entrepreneurship in year t, industry j amongst those of skill type a. The table reports $100 \times \beta_{aj}$. The entrepreneurship rate is measured from the CPS monthly surveys. Entry and exit rates are estimated from the matched CPS sample.

4 Model

In this section, we develop a model of occupational choice along the lines of Lucas (1978) that features worker heterogeneity. We use this model to quantitatively assess the impact of a rising worker skill premium on skill specific and aggregate measures of entrepreneurship.

Setup Time is discrete and the model economy is populated with a unit mass of agents that are heterogeneous in their ability as workers and entrepreneurs. Worker skills (a) can take two values with $a = u$ and $a = s$ representing unskilled and skilled agents, respectively. Entrepreneurial ability (z) has continuous support and follows a skill specific distribution $G_a(z)$ for $a \in \{u, s\}$. The dependence of the entrepreneurial productivity distribution on skill allows for, say, skilled workers to be relatively more productive entrepreneurs on average. The population share of skilled agents is denoted by λ.

Agents choose between earning a wage as an employee or operating a production technology as an entrepreneur. As in Cagetti and De Nardi (2006), workers may be employed either by entrepreneurs or in a "non-entrepreneurial" sector which represents many larger employers that are typically not controlled by a single individual.

After making an occupational choice, production takes place and agents consume their earnings which yields utility following a CRRA utility function $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$. Future utility is discounted with a discount factor β and with probability δ, agents are replaced by offspring that have the same worker ability and (possibly) different entrepreneurial ability z drawn from the distribution $G_a(z)$. Agents are perfectly altruistic and value the utility of their offspring as their own.

Production Function As workers, agents supply one unit of labor to either the entrepreneurial or non-entrepreneurial sector and earn a market-clearing wage. Their wage (w_a) depends only their ability as a worker a. Entrepreneurs produce a homogeneous good by hiring skilled workers (L_s) and unskilled workers (L_u) utilizing the following constant elasticity of substitution (CES) production function,

$$F(L_u, L_s) = \left[\alpha\left(\theta_u L_u\right)^{\sigma} + (1-\alpha)\left(\theta_s L_s\right)^{\sigma}\right]^{\frac{1}{\sigma}}$$

where $\sigma > 0$ governs the elasticity of substitution between labor inputs, and $\alpha \in (0, 1)$. θ_u and θ_s govern the productivity of unskilled and skilled workers, respectively. Relative changes in these parameters will influence the skill premium.

The effective productivity of entrepreneurs depends on i) their innate entrepreneurial ability z, ii) realizations of an idiosyncratic productivity shock κ, and iii) aggregate entrepreneurial sector productivity A that is common to all entrepreneurs. We assume that the idiosyncratic productivity shocks κ evolve according to the following AR1 process,

$$\log \kappa_{t+1} = \rho \log \kappa_t + \nu \epsilon_{t+1}$$

where $\epsilon_{t+1} \sim N(0, 1)$. The conditional distribution of κ_{t+1} is denoted as $\mu(\kappa_{t+1}|\kappa_t)$. We denote the unconditional (stationary) distribution of these shocks as $\bar{\mu}(\kappa_t)$

Then, an entrepreneur of ability (a, z) with a realized shock κ can produce,

$$Az\kappa F\left(L_u, L_s\right)^{\eta}$$

where $\eta \in (0, 1)$ governs the degree of decreasing returns to scale in production. As in Lucas (1978), η captures the limited span of control of entrepreneurs. Notice that employee skill (a) does not directly impact the productivity of a given entrepreneur. That is, given the same innate productivity z and shock κ, both skilled and unskilled entrepreneurs produce the same output.

The productivity shocks κ can be interpreted as capturing idiosyncratic demand shocks faced by entrepreneurs. As we describe below, these shocks generate endogenous transitions between entrepreneurship and employment. For continuing entrepreneurs, these shocks evolve following the conditional distribution $\mu(\kappa_{t+1}|\kappa_t)$ consistent with the AR1 process above. New entrepreneurs, that is entrepreneurs that were workers in the previous period, draw an initial value from the corresponding unconditional distribution $\bar{\mu}(\kappa)$.

Occupational Choice At the beginning of each period t, agents face an occupational choice and decide whether to work for a wage or to pursue entrepreneurship. This decision is the focus of our analysis and involves comparing the value in entrepreneurship $V_t^e\left(a, z, \kappa, o_{t-1}\right)$ to the value in employment $V_t^w\left(a, z, o_{t-1}\right)$ where $o_{t-1} \in \{0, 1\}$ represents the agent's occupation in the previous period. It is equal to 0 if they were workers and 1 if they were entrepreneurs.

Agents that were entrepreneurs in $t-1$ observe their current idiosyncratic productivity shock κ_t and then decide whether to continue in entrepreneurship with effective productivity $(Az\kappa_t)$ or exit and work for a wage w_a. The value at the beginning of period t for incumbent entrepreneurs solves,

$$E_t\left(a, z, \kappa\right) = \max_{o_t^e(a,z,\kappa) \in \{0,1\}} \left\{V_t^e\left(a, z, \kappa, 1\right), V_t^w\left(a, z, 1\right)\right\}$$

where $o_t^e\left(a, z, \kappa\right)$ denotes the occupational choice of incumbent entrepreneurs in period t and is given by,

$$o^e(a,z,\kappa) = \begin{cases} 0 & \text{if } V_t^e(a,z,\kappa,1) < V_t^w(a,z,1) \\ 1 & \text{if } V_t^e(a,z,\kappa,1) \geq V_t^w(a,z,1) \end{cases} \tag{2}$$

Existing entrepreneurs will remain operational if the returns to doing so are greater than the returns to wage employment. In equilibrium, the occupational choice decision is characterized by entrepreneur productivity thresholds as in Lucas (1978). Indeed, equation (2) can be summarized with a function $z_e^\star(a,\kappa)$ which specifies the productivity level at which existing entrepreneurs switch to become workers. This function is implicitly defined by $V_t^e(a, z_e^\star(a,\kappa), \kappa, 1) = V_t^w(a, z_e^\star(a,\kappa), 1)$. An existing entrepreneur with ability (a,z) and idiosyncratic productivity κ will exit if $z < z_e^\star(a,\kappa)$ and will remain as an entrepreneur if $z \geq z_e^\star(a,\kappa)$. Notice, the occupational choice for incumbent entrepreneurs depends not only on their ability a but also κ. As a result, shocks to κ generate endogenous exit from entrepreneurship.

Agents that were workers in the previous period decide whether to continue as workers or to enter as entrepreneurs. Unlike for continuing entrepreneurs, workers do not first observe their (initial) productivity shock κ_t. Instead, they take expectations over it and compare the expected returns from pursuing entrepreneurship to the value of continuing as a worker. The value at the beginning of period t for existing workers is,

$$W_t(a,z) = \max_{o_t^w(a,z)\in\{0,1\}} \left\{ \int_{\kappa'} V_t^e(a,z,\kappa',0)\, d\bar{\mu}(\kappa'), V_t^w(a,z,0) \right\}$$

where $o_t^w(a,z)$ denotes the occupational choice of workers in period t and is given by,

$$o^w(a,z) = \begin{cases} 0 & \text{if } \int_{\kappa'} V_t^e(a,z,\kappa',0)\, d\bar{\mu}(\kappa') < V_t^w(a,z,0) \\ 1 & \text{if } \int_{\kappa'} V_t^e(a,z,\kappa',0)\, d\bar{\mu}(\kappa') \geq V_t^w(a,z,0) \end{cases} \tag{3}$$

Similar to entrepreneurs, in equilibrium, equation (3) can be summarized by a threshold productivity $z_w^*(a)$ implicitly defined by $\int_{\kappa'} V_t^e(a, z_w^*(a), \kappa', 0)\, d\bar{\mu}(\kappa') = V_t^w(a, z_w^*(a), 0)$. Such that, if $z \geq z_w^*(a)$, workers of ability (a,z) will switch to entrepreneurship. So, while the κ shocks generate entrepreneur exit to employment, innate productivity z determines entry from employment into entrepreneurship.

Having described the production function and occupational choice problem of agents, we now characterize the value in entrepreneurship and employment.

Worker's Problem Following their occupational choice, workers earn skill specific wages w_a which they consume before entering the next period to make another occupational choice. So, the value in employment is given by,

$$V_t^w\left(a, z, o_{t-1}\right) = u\left(w_a\right) + \beta\left[\delta W_t\left(a, z\right) + (1-\delta)\int_{z'} W_t\left(a, z'\right) dG_a\left(z'\right)\right]$$

Entrepreneur's Problem Entrepreneurs decide how many workers to hire by maximizing their per-period profits $\pi\left(a, z, \kappa\right)$,

$$\pi\left(a, z, \kappa\right) = \max_{L_s, L_u} Az\kappa F\left(L_u, L_s\right)^{\eta} - w_s L_s - w_u L_u$$

Their optimal labor allocation $\left(L_u\left(z, \kappa\right), L_s\left(z, \kappa\right)\right)$ does not depend on their skill a and satisfies the following first order conditions,

$$\begin{aligned} Az\kappa F\left(L_u\left(z,\kappa\right), L_s\left(z,\kappa\right)\right)^{\eta-1}\left[\alpha\left(\theta_u L_u\left(z,\kappa\right)\right)^{\sigma} + (1-\alpha)\left(\theta_s L_s\left(z,\kappa\right)\right)^{\sigma}\right]^{\frac{1}{\sigma}-1}\eta\left(1-\alpha\right)\theta_s^{\sigma}\left(L_s\left(z,\kappa\right)\right)^{\sigma-1} &= w_s \\ Az\kappa F\left(L_u\left(z,\kappa\right), L_s\left(z,\kappa\right)\right)^{\eta-1}\left[\alpha\left(\theta_u L_u\left(z,\kappa\right)\right)^{\sigma} + (1-\alpha)\left(\theta_s L_s\left(z,\kappa\right)\right)^{\sigma}\right]^{\frac{1}{\sigma}-1}\eta\alpha\theta_u^{\sigma}\left(L_u\left(z,\kappa\right)\right)^{\sigma-1} &= w_u \end{aligned} \tag{4}$$

where w_s and w_u are the wages paid to skilled and unskilled workers respectively.

The value in entrepreneurship includes flow profits and the future utility from either remaining in entrepreneurship or exiting to become a worker. In addition to endogenous exit in response to changes in κ, entrepreneurs also face an exogenous exit shock such that they pursue wage work with probability χ. Such exogenous exit can be considered an extreme form of demand shock that takes an entrepreneur's effective productivity to 0. Alternatively, it can also be interpreted as the probability of receiving a job offer that an entrepreneur cannot refuse. The value in entrepreneurship is,

$$V_t^e(a,z,\kappa,o_{t-1}) = u(c) \quad + \beta\delta\left[(1-\chi)\bar{E}(a,z,\kappa) + \chi V_t^w(a,z,1)\right] \\ + \beta(1-\delta)\int_{z'}\bar{E}(a,z',\kappa)\,dG_a(z')$$

where consumption c depends on the previous occupation,

$$c = \begin{cases} \pi(a,z,\kappa)(1-\tau) & \text{if } o_{t-1}=0 \\ \pi(a,z,\kappa) & \text{if } o_{t-1}=1 \end{cases}$$

and $\bar{E}(a,z,\kappa) = \int_{\kappa_{t+1}} E_{t+1}(a,z,\kappa_{t+1})\,d\mu(\kappa_{t+1}|\kappa)$ is the expected continuation value of the following period. This is computed by taking conditional expectations of $E_{t+1}(a,z,\kappa_{t+1})$ over the AR1 process. Notice, entrepreneurs that are workers in the previous period must pay an entry cost that is proportional to their profits. The size of this entry cost is governed by the parameter $\tau \in [0,1)$ and is only paid upon entry into entrepreneurship from employment.

Non-Entrepreneurial Sector's Problem The non-entrepreneurial sector operates the same technology $F(L_u,L_s)$ without a limited span of control. That is, the non-entrepreneurial sector is effectively constant returns to scale and earns zero profits by solving,

$$\max_{L_u,L_s} BF(L_u,L_s) - w_sL_s - w_uL_u$$

where B is the productivity of the non-entrepreneurial sector and the optimal labor allocation $\left(L_u^{NE},L_s^{NE}\right)$ satisfies,

$$B\left[\alpha\left(\theta_uL_u^{NE}\right)^\sigma + (1-\alpha)\left(\theta_sL_s^{NE}\right)^\sigma\right]^{\frac{1}{\sigma}-1}(1-\alpha)\theta_s^\sigma\left(L_s^{NE}\right)^{\sigma-1} = w_s \\ B\left[\alpha\left(\theta_uL_u^{NE}\right)^\sigma + (1-\alpha)\left(\theta_sL_s^{NE}\right)^\sigma\right]^{\frac{1}{\sigma}-1}\alpha\theta_u^\sigma\left(L_u^{NE}\right)^{\sigma-1} = w_u \tag{5}$$

Stationary Equilibrium

We focus on the stationary equilibrium of the model which consists of wages $\{w_u,w_s\}$, occupational choices of agents$\{o^e(a,z,\kappa),o^w(a,z)\}$, labor demand of entrepreneurs $\{L_u(z,\kappa),\ L_s(z,\kappa)\}$, labor demand by the non-entrepreneurial sector $\left(L_u^{NE}, L_s^{NE}\right)$, and endogenous stationary probability distributions for workers and entrepreneurs $\psi^w(a,z)$ and $\psi^e(a,z,\kappa)$ such that the following conditions are satisfied,

i) Labor markets for both skilled and unskilled workers clear,

$$(1-\lambda)\int \psi^w(u,z)\,dz = L_u^{NE} + (1-\lambda)\int_z\int_\kappa L_u(z,\kappa)\,\psi^e(u,z,\kappa)\,d\kappa dz + \lambda\int_z\int_\kappa L_u(z,\kappa)\,\psi^e(s,z,\kappa)\,d\kappa dz$$
$$\lambda\int_z \psi^w(s,z)\,dz = L_s^{NE} + (1-\lambda)\int_z\int_\kappa L_s(z,\kappa)\,\psi^e(u,z,\kappa)\,d\kappa dz + \lambda\int_z\int_\kappa L_s(z,\kappa)\,\psi^e(s,z,\kappa)\,d\kappa dz$$

where λ if the share of skilled workers.

ii) Agents occupational choices satisfies (2) and (3), and labor demand for all entrepreneurs satisfies (4).

iii) The non-entrepreneurial sector maximizes profits and its labor demand satisfies (5).

iv) The stationary probability distributions of workers $\psi^w(a,z)$ and of entrepreneurs $\psi^e(a,z,\kappa)$ are consistent with the decisions of agents and satisfy the following stationary (steady-state) condition for all (a,z,κ),

$$\begin{aligned}\left[\delta\psi^w(a,z) + (1-\delta)\,g_a(z)\mathcal{L}\right]o^w(a,z)\,\bar{\mu}(\kappa) = {} & \delta\chi\psi^e(a,z,\kappa)\\ & + \left[(1-\delta)\,g_a(z)\int_{z'}\mathcal{E}\left(z',\kappa\right) + \delta(1-\chi)\,\mathcal{E}(z,\kappa)\right](1-o^e(a,z,\kappa))\end{aligned}$$

where $\mathcal{L} = \int_z \psi^w(a,z)\,dz$ is the mass of workers, and $\mathcal{E}(z,\kappa) = \int_{\kappa'}\psi^e(a,z,\kappa')d\mu(\kappa|\kappa')$ is the mass of entrepreneurs with productivity z and a realized demand shock κ. The above condition ensures that the mass of workers transitioning to entrepreneurship (left hand side) is equal to the mass of exiting entrepreneurs (right hand side) for all (a,z,κ).

5 Calibration

In this section, we describe the baseline calibration of the model parameters. We assume that the U.S. is in a stationary equilibrium in 1983 and choose parameters so that the model matches key features of the 1983 U.S. economy.[25] We fix some parameters based directly on evidence or literature and jointly calibrate the remaining parameters by solving the model.

One period in the model corresponds to a year. As such, we pick the discount factor β to match an annual interest rate of 4% in the U.S and set it equal to $\frac{1}{1.04}$. The probability $(1-\delta)$ of being replaced by offspring is set to 0.025 so that agents expect to live 40 years. We choose a standard value for the coefficient of risk aversion and set γ to be 2. The share of skilled agents λ varies over time and is set to the observed share of skilled individuals in the CPS. In 1983, this share is around 0.27. The elasticity of substitution between skilled and unskilled labor $\left(\frac{1}{1-\sigma}\right)$ is set to be 1.41 following Katz and Murphy (1992) and α is normalized to be 0.5. Panel A of Table 6 summarizes these fixed parameters.

Table 6: Baseline Model Calibration and Fit

Panel A: Fixed

Parameter	Description	Value	Basis
β	Discount Factor	0.96	Interest Rate
1-δ	Probability replaced by offspring	0.025	40 yr. expected lifetime
γ	Coefficient of Relative Risk Aversion	2	Normalization
$\frac{1}{1-\sigma}$	Elasticity of Substitution	1.41	Katz and Murphy (1992)
α	Workers Share in Production	0.50	Normalization
λ_{1983}	Share of Skilled Individuals	0.27	CPS Data

Panel B: Calibrated

Parameter	Description	Value	Basis	Model	Data
ξ_u	Unskilled Productivity Distribution Tail	6.79	Share of Unskilled Entrepreneurs	0.10	0.10
ξ_s	Skilled Productivity Distribution Tail	3.93	Share of Skilled Entrepreneurs	0.14	0.14
ρ	Persistence of κ shocks	0.53	Average Entrep. Growth Rate	0.21	0.27
ν	Std. Deviation of κ shocks	0.16	Variance of Entrep. Growth Rates	0.91	0.90
η	Span of Control	0.62	Top 5% Income Share	0.22	0.27
τ	Entry Cost (share of profits)	0.25	Aggregate Entry Rate	0.018	0.018
χ	Exogenous Exit Probability	0.02	Aggregate Exit Rate	0.14	0.14
B/A	Relative Aggregate Productivity	1.19	Employment Share (>500 Employees)	0.45	0.46
θ_s/θ_u	Relative Skill-Biased Productivity	0.31	Worker Skill Premium	0.39	0.39

The remaining parameters are calibrated jointly to match features of the U.S. data in 1983 following the Simulated Method of Moments. That is, we minimize the difference between moments implied by the model and targets observed in the data. Although changes in a single parameter will impact all model implied moments, for each parameter, we choose targets that are most likely to

[25] The share of entrepreneurs implied by the (margin-adjusted) entry and exit rates in an assumed steady state in 1983 is very close the observed share of entrepreneurs. Indeed, in 1983 the implied steady state entrepreneurship rates for skilled and unskilled individuals are 0.1413 and 0.1007 while the data counterparts are 0.1420 and 0.1006.

be determined by that parameter. Panel B of Table 6 reports the calibrated parameter values along with the model's fit to the data.

The entrepreneurial productivity distributions, $G_s(z)$ and $G_u(z)$, are assumed to follow a Pareto distribution over the range $z \geq 1$ with associated tail parameters ξ_s and ξ_u.[26] These tail parameters are chosen to match the 1983 entrepreneurship rates of skilled and unskilled individuals, respectively. Our calibration implies a thicker right tail in entrepreneurial productivity for skilled individuals. This is consistent with the observed thicker right tail of the earnings and employment distribution of skilled entrepreneurs (see Figures B.6 and B.10 in the Appendix). The model implied entrepreneurship rates are a good fit to the data.

The AR1 process governing the κ shocks is discretized following the Rouwenhourst method with 11 grid points as outlined in Kopecky and Suen (2010). Since changes in the shock process are the primary source of earnings growth for continuing entrepreneurs, the persistence ρ and variance ν parameters are calibrated to match the first and second moments of entrepreneurs earnings growth. These moments are plotted in Figure 7 and we take the the average of these measures from 1989 as our targets. The model closely matches the dispersion in growth rates but slightly underestimates the average growth rate of earnings for entrepreneurs.

The parameter η governs the span of control of entrepreneurs and directly influences the earnings of entrepreneurs relative to those of workers. As such, we calibrate η to match the top 5% income share in the U.S. in 1983 as retrieved from the World Inequality Database. The model implied income share is lower than the data target.

Our target for the entry cost τ is the aggregate entry rate from employment to entrepreneurship in 1983.[27] The estimated parameter suggests that new entrepreneurs must pay around 25% of their profits upon entry from employment.

The parameters $\{\xi_u, \xi_s, \rho, \nu, \eta, \tau\}$ are assumed to remain fixed over time. We evaluate this assumption and the sensitivity to changing these parameters in Appendix E. The remaining parameters $\left\{\chi, \frac{\theta_s}{\theta_u}, \frac{B}{A}\right\}$ are re-calibrated as part of our quantitative analysis which is detailed in the next section.

In the baseline model, which matches data from 1983, the probability of exogenous exit χ is set to

[26] We follow Buera and Shin (2013) in discretizing the productivity grid over 25 grid points.

[27] To be consistent with our empirical evidence, we do not include agents who are replaced by their offspring in measuring entry and exit rates.

match the aggregate exit rate in 1983. Our calibration suggests that around 2% of all entrepreneurs face an exogenous exit shock. Below, we argue that this probability has increased over time and re-calibrate it to exactly match the increase in aggregate exit rate over time.

We choose the aggregate productivity parameters A, B to match the relative size of the non-entrepreneurial sector. We define the non-entrepreneurial sector to include those firms that employ over 500 workers.[28] Since we cannot separately identify the aggregate productivity of the entrepreneurial and non-entrepreneurial sectors, we normalize A to be 1 and then choose B to match the employment share of employers with over 500 employees in 1983 as reported in the Business Dynamics Statistics (BDS). In the baseline model around 45% of all workers work in the non-entrepreneurial sector which is close to the data target.

The parameters θ_u and θ_s govern the level of skill-bias in the production technology. With the normalization that θ_u is equal to 1, we estimate θ_s to match the worker skill premium in 1983. The baseline model closely matches the observed skill premium. In our quantitative analysis, we vary θ_s to match changes in the worker skill premium over time. For instance, an increase in θ_s relative to θ_u captures skill-biased technological changes that favor skilled workers and raises the skill premium.

Notice, since the non-entrepreneurial sector features constant returns to scale, an increase in θ_s (relative to θ_u) favors the non-entrepreneurial sector more than the decreasing returns to scale entrepreneurial sector. So, in our quantitative analysis, we also allow the relative productivity of the non-entrepreneurial sector, $\frac{B}{A}$, to vary to match the observed increase in the employment share of the non-entrepreneurial sector.[29] Changes in the relative productivity of sectors represent skill-neutral technological changes as they are not biased towards a particular skill group and do not change the skill premium but instead favor a particular sector. Together, changes in $\frac{B}{A}$ and $\frac{\theta_s}{\theta_u}$ represent those technological changes that i) raise the skill premium by augmenting the productivity of skilled workers and ii) increase the size of the non-entrepreneurial sector. Examples of such changes include the rise of information technology (IT), which not only complements skilled workers but, as argued

[28]Our model implications remain unchanged if we consider alternative size thresholds in defining the non-entrepreneurial sector.

[29]In the data, the employment share of large firms (with more than 500 employees) increases by around six percentage points from 46% to 52% between 1983 and 2018.

by Autor et al. (2020), has disproportionately benefited larger (non-entrepreneurial) firms.[30]

6 Quantitative Analysis

6.1 The Impact of an Increasing Skill Premium

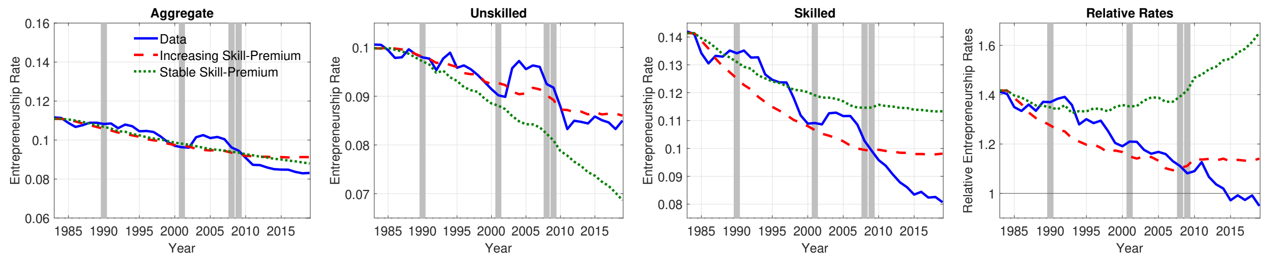
In this section, we quantitatively assess the role of the worker skill premium in influencing the evolution of entrepreneurship since 1983. To do this, we study a "benchmark" economy in which the skill premium increases over time as observed in the data and compare this to a "counterfactual" economy in which the skill premium remains stable. By comparing the two economies, we can quantify the role of a rising skill premium on aggregate and skill specific entrepreneurship.

Since the focus of our quantitative analysis is on quantifying the impact of an increasing skill premium, the changes we introduce to the baseline 1983 economy are those that are commonly viewed as influencing the worker skill premium – the supply of skilled individuals and technological change. In particular, relative to the baseline 1983 calibration, we change the share of skilled individuals, λ, and the parameters governing skill-neutral and skill-biased technology; $\left(\frac{B}{A}\right)$ and $\left(\frac{\theta_s}{\theta_u}\right)$. Since skill-biased technological change influences both the skill premium and the size of the non-entrepreneurial sector, we introduce skill-neutral technological change in order to match the observed size of the non-entrepreneurial sector.

Accordingly, in the benchmark economy we re-calibrate the parameters λ, $\left(\frac{B}{A}\right)$, and $\left(\frac{\theta_s}{\theta_u}\right)$ so that they jointly match the share of college graduates, the size of the non-entrepreneurial sector and the worker skill premium in 2019, respectively. In the counterfactual economy, we impose that the skill premium in 2019 is the same as in 1983 while requiring that the share of college graduates and the size of the non-entrepreneurial sector change as observed between 1983 and 2019. We then construct a time path for parameters between 1983 and 2019 and study the transition dynamics in both benchmark and counterfactual economies in response to these parameter changes assuming agents are myopic, being surprised each period with an updated set of parameters.[31]

[30] Autor et al. (2020) document a rise in large, 'superstar' firms in the US and attribute this to, among other reasons, the decline in the price of IT and intangible capital. Their argument is consistent with Lashkari et al. (2021) who use firm-level data from France and find that larger firms use IT more intensively than smaller firms and hence may benefit more from the declining price of IT. In our framework, changes in $\frac{B}{A}$ can be thought of as summarizing the sector-specific but skill-neutral impacts of the declining costs of IT.

[31] In both the benchmark and counterfactual economy, the time path for the share of college graduates is exactly that



(a) Aggregate (b) Unskilled (c) Skilled (d) Relative Rates

Figure 12: Transition Dynamics of Entrepreneurship Rates

Entrepreneurship Rates Figure 12 shows the entrepreneurship rates resulting from this exercise. It plots the transition dynamics of the entrepreneurship rate in the two model economies along with the data. Focusing first on the benchmark (increasing skill premium) economy (dashed red lines), we find that the model economy accounts for 2.0 percentage points or around 70% of the observed decline in aggregate entrepreneurship. This is striking; technological change and a rising supply of workers can account for a significant share of the decline in entrepreneurship.

The benchmark economy also features a skill-biased decline in entrepreneurship. It closely tracks – particularly prior to 2008 – the evolution of skilled and unskilled entrepreneurship rates. The skill-biased decline is most evident in Panel (d) which plots the ratio of skilled and unskilled entrepreneurship rates (relative rates).

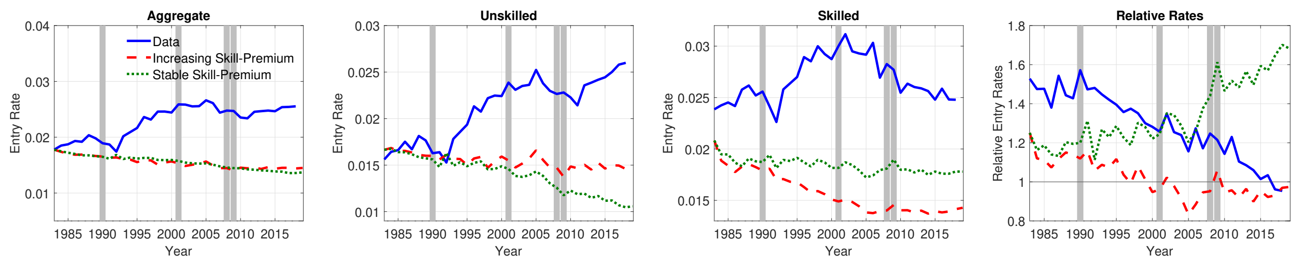
The counterfactual economy – which features a stable skill premium (dotted green lines) – leads to very similar dynamics of the aggregate entrepreneurship rate compared to the benchmark economy. However, it implies a very different evolution for the skill-specific entrepreneurship rates. Indeed, compared to the benchmark, the counterfactual economy features steeper declines in unskilled and flatter declines in skilled entrepreneurship rates, which results in a *skill-neutral* decline in entrepreneurship. This is seen clearly in Panel (d), which shows that relative entrepreneurship rates in the counterfactual economy are either stable or increasing rather than steadily declining as in the data and the benchmark economy.

Comparing the benchmark and counterfactual entrepreneurship rates shows that the rising skill premium is crucial for generating the skill-biased decline in entrepreneurship. At the same time, it

observed in the data. The time path for the parameters governing technological change are a monotonic interpolation between the 1983 and 2019 parameter values. More details regarding the calibration and time path of parameters are discussed in Appendix E. We also show in this appendix that our results are unchanged if we instead assume that agents have perfect foresight regarding the evolution of parameters.

plays a minimal role in shaping aggregate entrepreneurship rates. To understand this, notice that an increase in the skill premium pushes the skilled and unskilled entrepreneurship rates in opposite directions. Relative to the counterfactual economy with a stable skill premium, a rising skill premium *raises* unskilled and *lowers* skilled entrepreneurship rates. These differential movements in skill-specific rates generate a skill bias in entrepreneurship but offset each other so that the aggregate entrepreneurship rate remains almost unchanged.

Next, we study the flows between employment and entrepreneurship in the model. Starting with entry rates, plotted in Figure 13.



(a) Aggregate (b) Unskilled (c) Skilled (d) Relative Rates

Figure 13: Transition Dynamics of Entry Rates

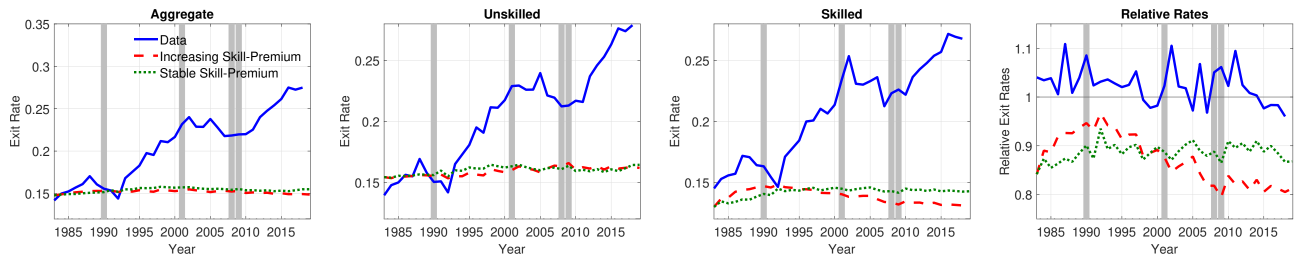
Entry Rates Unlike entrepreneurship rates, the benchmark model does not match the evolution of entry rates over time; there is a trend decline in the benchmark economy entry rates while observed entry rates are increasing. The model economy also over-predicts the initial levels of unskilled and under-predicts the initial level of skilled entry rates.[32]

Having said this, the benchmark economy does feature skill-biased changes in entry rates, with the trend in relative rates closely matching that in the data (see Panel (d)). Indeed, skilled entry rates are initially higher than unskilled entry rates, and they converge over time. In the counterfactual economy, entry rates evolve in a largely skill-neutral – particularly prior to 2008. This suggests that, as with entrepreneurship rates, an increasing skill premium is crucial in generating skill-biased changes in entry rates.

However, the model's inability to match trends in entry suggests that technological change and a rising supply of skilled individuals are not enough to match the data – the model is missing an

[32]The model's fit to the initial year could be improved by introducing additional features to the model, such as skill-specific entry costs.

additional time-varying force(s) that drives the trend in entry rates. We explore this after discussing the model-implied exit rates.



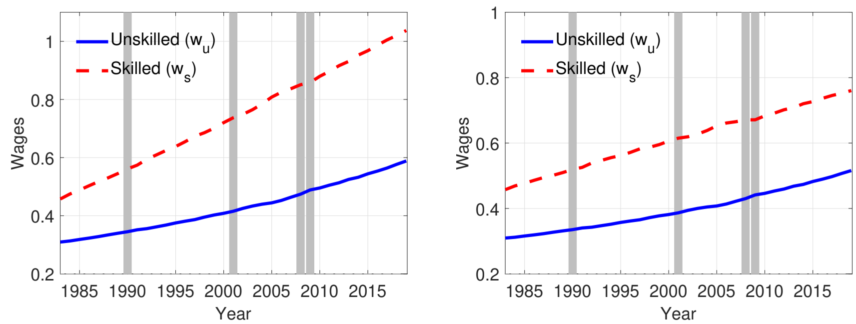
(a) Aggregate (b) Unskilled (c) Skilled (d) Relative Rates

Figure 14: Transition Dynamics of Exit Rates

Exit Rates Figure 14 plots exit rates in the benchmark and counterfactual economies. As with entry rates, neither model proves a good fit for the data – while observed exit rates have trended upwards over time, the benchmark (and counterfactual) models feature only minor increases in the aggregate and skill-specific exit rates. Having said this, as in the data, both the benchmark and counterfactual economies lack a significant time trend in relative exit rates (see Panel (d)). That is, the model economy implies skill-neutral changes in exit rates when the skill premium increase.

Although the model economy does not match observed trends in the levels of entry and exit rates, some key predictions of the benchmark economy are qualitatively consistent with our empirical analysis of flows. In particular, as in the data, the model economy features a skill-biased decline in entrepreneurship which is driven by skill-biased changes in entry rates and skill-neutral changes in exit rates. This qualitative consistency with the data indicates that a rising skill premium is salient for understanding the skill-biased decline in entrepreneurship. As such, understanding the intuition behind the results of the previous three figures can be instructive. So, before discussing factors that might reconcile the observed trends in flows, we briefly discuss this intuition.

Intuition The skill-biased response of the entrepreneurship and entry rates in the benchmark model can be understood by applying the intuition of canonical models of occupational choice. In these models, as in ours, agents compare the returns to entrepreneurship and employment before choosing the occupation which yields the highest returns. As shown in Figure 15, the changes introduced in the model economy lead to an increase in the earnings of both skilled and unskilled workers which discourages entrepreneurship. This, in turn, raises the productivity threshold at which individuals pursue entrepreneurship so that fewer, more productive individuals choose to pursue entrepreneurship.[33] A rise in the worker skill premium necessarily means that earnings of skilled workers have risen faster than earnings of unskilled workers. This leads to a larger shift of the productivity threshold for skilled individuals and hence a larger decline in skilled entrepreneurship.



(a) Benchmark: Increasing skill premium

(b) Counterfactual: Stable skill premium

Figure 15: Transition Dynamics of Wages

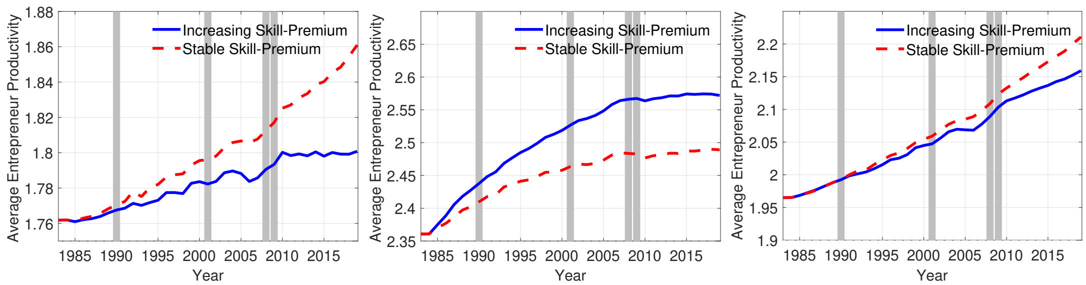
On the other hand, in the counterfactual economy, the skill premium remains stable and earnings for skilled and unskilled workers increase similarly (Panel (b) of Figure 15).[34] This leads to similar shifts in the thresholds for both unskilled and skilled individuals, leading to declines in entrepreneurship and entry rates that are skill-neutral.

This discussion reveals that the worker skill premium has potentially important implications for the average productivity of entrepreneurs. Indeed, increases in the skill premium shift the composition of entrepreneurs away from skilled entrepreneurs – who tend to be more productive – towards unskilled entrepreneurs – who tend to be less productive. The impact of this shift in composition on aggregate productivity can be quantified in our model. Figure 16 reports the average productivity of unskilled, skilled and all entrepreneurs in the benchmark and counterfactual economies. Comparing

[33] Notice, technological change, namely increases in θ_s, also improve the overall productivity of the production technology which serves to encourage entrepreneurship. Importantly, this improvement in the production function benefits entrepreneurs of either skill types in the same manner and, in our model, the increase in worker wages is stronger than the increase in entrepreneurial earnings. We discuss the model implied relative earnings of entrepreneurs and workers in Appendix E. We also show that the benchmark model qualitatively matches the convergence in the skilled and unskilled relative earnings along the lines of the data presented in Section 2. A more detailed discussion of the impact of each of the changes introduced in the benchmark economy is conducted in Section 6.3 below.

[34] The time path of parameters in the counterfactual economy ensures that the skill premium in 2019 is at its 1983 level without imposing that it remain constant along the transition path. Imposing a constant skill premium does not change the implications of our quantitative analysis.

the two economies confirms the intuition above: unskilled (skilled) individuals become more (less) selective in pursuing entrepreneurship when the skill premium is stable. Panel (c) show that this results in *higher* average entrepreneur productivity in the counterfactual economy – average productivity increases by around 12.5% when the skill premium is stable compared to 10% when the skill premium increases. This implies that the skill premium not only drives skill-biased changes in entrepreneurship but, in doing so, also leads to a *reduction* in the quality of entrepreneurs.



(a) Unskilled Entrepreneurs (b) Skilled Entrepreneurs (c) All Entrepreneurs

Figure 16: Transition Dynamics of Average Entrepreneur Productivity

Next, we discuss why exit rates are largely non-responsive in the model economy and the potential forces that might be driving the observed increase. As wages increase in response to technological change, marginal entrepreneurs – those with low draws of κ – endogenously exit (along the transition path). Then, conditional on remaining in entrepreneurship, ever larger increases in wages are required to continue inducing marginal entrepreneurs to exit. In the model economy, the mass of marginal (exiting) entrepreneurs and the mass of all entrepreneurs move proportionally as wages increase – hence the exit rate responds minimally.[35] So, the sustained increases in the share of exiting entrepreneurs suggests that the processes generating exit must be changing over time. Through the lens of our model, this implies changes in either the AR1 process governing κ or increases in the exogenous probability of exit χ.

However, recall that the first and second moments of entrepreneurial earnings growth, as plotted in Figure 7, have remained relatively stable over time (particularly relative to the analogous measures for workers). Changes in the process of idiosyncratic productivity shocks κ would necessarily imply

[35] An alternative specification of the model in which agents experience random shocks to their innate productivity z generates larger changes in exit rates. However, these changes would be skill-biased in nature as the shifts in the (exit) thresholds of productivity would vary by skill. This follows from the same intuition that we discuss above regarding entrepreneurship and entry rates. Since we observe a skill-neutral increase in exit rates, we believe that our specification of an AR1 process for κ is a closer fit to the data.

changes in the distribution of earnings growth rates of entrepreneurs. Since this is not observed in the data, we conclude that there is limited evidence to suggest that the process governing demand shocks has changed over time.

Instead, the data provides stronger empirical support for changes in χ. Appendix D provides additional evidence regarding rising exit rates, and in it we show that the trend increase in exit is observed uniformly across the economy, across different types of entrepreneurs, robust to more restrictive definitions of exit and is likely not driven by survey mis-classification.[36] Most convincingly, we find that the length of time that entrepreneurs *expect* to remain in business has declined over time. Indeed, relative to 1995, entrepreneurs in 2005 expected to spend around 5% less time (around 1 less year on average) in their business. This finding is consistent with an increase in χ over time.[37]

In light of this evidence supporting a change in the exogenous exit rate, we repeat the quantitative exercise above while also varying χ so that it matches the increase in aggregate exit rates over time. We then reassess the model's implications for measures of entrepreneurship in response to a rise in the skill premium.

6.2 The Impact of Increasing Exit Rates

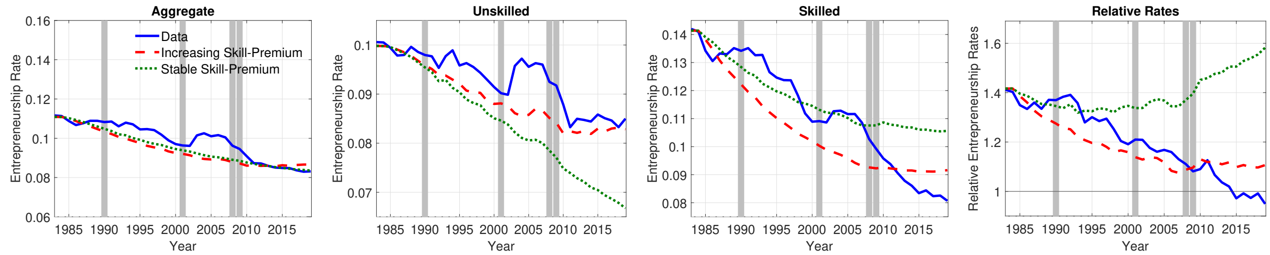
To study the impact of increasing exit rates, we change – as before – the share of skilled individuals, λ and the parameters governing skill-neutral and skill-biased technology; $\left(\frac{B}{A}\right), \left(\frac{\theta_s}{\theta_u}\right)$ we now also change χ so that it exactly matches the aggregate exit rate in 2019. Our calibration implies that χ increases by 15 percentage points from around 2% to 17% between 1983 and 2019.[38]

Entrepreneurship Rates Figure 17 reports the transition dynamics of entrepreneurship rates following these changes. With increasing exit, both the benchmark (dashed red line) and

[36] We also address, in Appendix D, the concern that our model may be missing economic mechanisms present in other models of occupation choice which could match trends in exit either with technological forces alone or other time-varying forces. We argue that the ubiquity and skill-neutrality of exit rates precludes a number of these economic mechanisms as they would predict heterogeneity in exit rates across subgroups of entrepreneurs rather than the uniform increase we document.

[37] Although we abstract from modeling them, several underlying economic factors may underlie the increase in χ that we introduce. Examples include improvements in job search technology such as online job search which may make it easier for entrepreneurs to search for jobs or the increased prevalence of flexible employment arrangements, which may be particularly relevant to those that pursue entrepreneurship for non-pecuniary motives such as flexibility.

[38] Details of the parameter changes with increasing exit are in Appendix E.

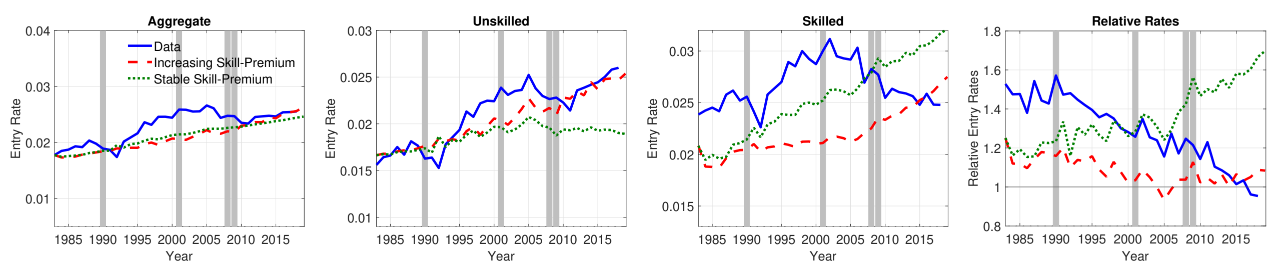


(a) Aggregate (b) Unskilled (c) Skilled (d) Relative Rates

Figure 17: Transition Dynamics of Entrepreneurship Rates, with Increasing Exit

counterfactual (dotted green line) economies exhibit slightly larger declines in the share of entrepreneurs. The aggregate rate declines by 2.4 percentage points (2.7 percentage points) in the benchmark (counterfactual) economy accounting for 83% (93%) of the observed decline. Comparing these results to the model without increasing exit suggests that increasing exit accounts for around 13% of the aggregate decline in entrepreneurship.

Comparing the benchmark and counterfactual economies, we find that the impact of the skill premium remains unchanged when exit rates increase. Indeed, the evolution of relative rates is almost identical to the exercise without increasing exit. These results suggest that increasing exit rates do not influence any of the skill-bias in declining entrepreneurship. Instead, higher exit lower entrepreneurship rates in a skill-neutral manner and, as we will discuss below, primarily impact the trend of flows in and out of entrepreneurship.



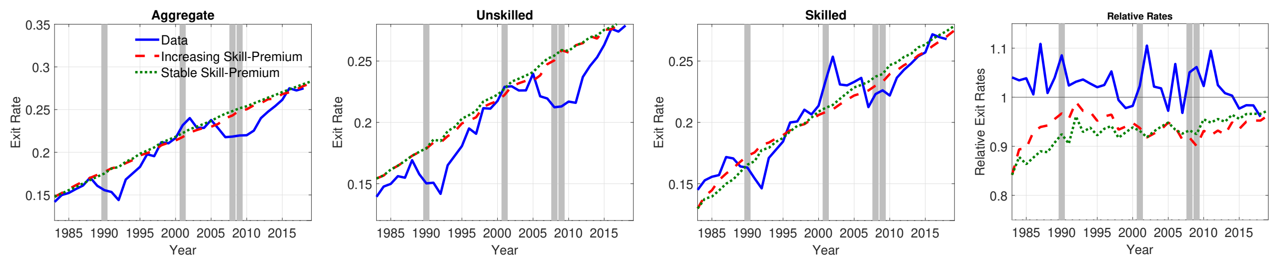
(a) Aggregate (b) Unskilled (c) Skilled (d) Relative Rates

Figure 18: Transition Dynamics of Entry Rates, with Increasing Exit

Entry Rates Panel (a) of Figure 18 shows that both benchmark and counterfactual economies closely track the evolution of aggregate entry rates when we introduce rising exit rates. This is in stark contrast to the previous quantitative exercise which featured declining entry rates and implies that increasing exit rates are critically important in quantitatively matching observed trends in entry.

By design, an increase in probability of exit χ leads more entrepreneurs to exit. In equilibrium, this also results in increasing entry rates along the transition path since those who exit but have high enough productivity z will optimally choose to re-enter entrepreneurship in the following period.

Skill-specific entry rates in the benchmark economy (dashed red lines) are also much closer in matching the data. They feature a trend increase in unskilled entry rates and prior to 2008, a relatively stable level of skilled entry rates. Having said this, the impact of the skill premium, is almost identical to that of the quantitative exercise without increasing exit rates. Indeed, as before, the counterfactual economy (dotted green lines) predicts flatter (steeper) increases in unskilled (skilled) entry rates, completely undoing the skill-bias in entry rates present in the benchmark economy.



(a) Aggregate (b) Unskilled (c) Skilled (d) Relative Rates

Figure 19: Transition Dynamics of Exit Rates, with Increasing Exit

Exit Rates Finally, Figure 19 plots the evolution of exit rates. By design, the model economy exactly matches the initial and final level of aggregate exit rates in both the counterfactual and benchmark economies. Accordingly the trend in aggregate and skill specific exit rates closely track the data. Further, and consistent with the data, both economies generate largely skill-neutral changes in the exit rates – particularly prior to 2008.

As with relative entrepreneurship and relative entry rates, increasing exit makes very little difference to the behaviour of relative exit rates in the benchmark and counterfactual economies. We show in Appendix E that the behaviour of wages and average entrepreneur productivity when exit rates increase is very similar to the case when exit rates are not increasing. This suggests that rising exit plays no role in generating skill-biased declines in entrepreneurship – a rise in the skill premium remains crucial for generating the skill-biased decline in entrepreneurship. Instead, increases in exit rates are critically important in quantitatively matching the observed trends in flows between entrepreneurship and employment. The exit rate also contributes modestly (around 13%) towards declining entrepreneurship.

The relatively small impact of exit rates in driving declines in entrepreneurship may seem at odds with the seemingly larger role of exit implied by our empirical flow decomposition. However, this simply highlights the need to consider general equilibrium responses when interpreting the data. In this case, we find that entry rates also increase in response to rising exit rates. If this equilibrium relationship between entry and exit is ignored, we would overstate the impact of exit rates by looking at the data alone.

6.3 Decomposition

We conclude our quantitative analysis with a simple decomposition exercise which aims to isolate the impact of each one of the time-varying forces we introduce. In this exercise, we start with the baseline (1983) economy and sequentially add time-varying phenomena, one after another, and compare the resulting model stationary equilibrium to the data. This allows us to determine the relative importance of each time-varying force in influencing entrepreneurship.

First, we introduce technological change so that the skill premium increases to match the observed level in 2019, holding the rest of the model economy as in 1983. Second, we increase the supply of skilled workers along with the skill-premium while holding fixed the employment share of the non-entrepreneurial sector and the exogenous exit rate.[39] Third, we increase the relative productivity of the non-entrepreneurial sector so that in addition to the skill premium and share of college graduates, the employment share of the non-entrepreneurial sector also matches the data. Finally, we feed in an increase in exogenous exit rates along with all the previous changes. The parameter values associated with each scenario are reported in Table A.1.

Table 7 reports the results of this exercise with Panel A reporting the measures in the data and

[39]Our results are unchanged if we instead impose that the model-implied aggregate exit rate remains fixed rather than the exogenous exit rate χ remaining fixed. This is due to the fact that exit rates change very little in response to either technological change or a rising supply of college graduates.

Table 7: Decomposing Changes in Entrepreneurship

	Entrepreneurship Rate			Entry Rate			Exit Rate		
	Aggregate	Unskilled	Skilled	Aggregate	Unskilled	Skilled	Aggregate	Unskilled	Skilled
				Panel A: Data					
1983	0.112	0.101	0.142	0.018	0.016	0.024	0.142	0.139	0.145
2019	0.083	0.085	0.081	0.026	0.026	0.025	0.275	0.279	0.268
Observed Δ	0.028	0.016	0.061	-0.008	-0.010	-0.001	-0.133	-0.140	-0.123
				Panel B: Model					
Skill premium $\uparrow$	0.114	0.113	0.116	0.019	0.020	0.018	0.150	0.154	0.140
+ Supply of Skills $\uparrow$	0.105	0.101	0.110	0.017	0.017	0.017	0.145	0.150	0.138
+ Non-Entrepreneurial Sector $\uparrow$	0.091	0.086	0.099	0.015	0.015	0.014	0.145	0.158	0.130
+ Exit Rates $\uparrow$	0.087	0.083	0.093	0.026	0.025	0.028	0.275	0.279	0.270

Panel B reporting model implied measures.

The first row of Panel B shows that an increase in the skill premium, on its own, leads to little change in the share of entrepreneurs – an increase of 0.2 percentage points.[40] The non-responsiveness of the aggregate entrepreneurship rate reflects the opposing movements of skilled and unskilled entrepreneurship rates. Consistent with our previous quantitative analysis, a rising skill premium lowers skilled and raises unskilled entrepreneurship rates. Entry rates mirror this change in entrepreneurship rates, while exit rates remain relatively stable.

To understand the opposing movements of skill-specific entrepreneurship rates, notice that increases in θ_s (relative to θ_u) not only raise the skill premium, but also improve the productivity of the production function $F(L_u, L_s)$. Importantly, this improvement leads to a common (skill-neutral) increase in the returns to entrepreneurship since both skill-types utilize the same production function. In contrast, and by design, wages increase more for skilled than for unskilled workers when θ_s increases. In equilibrium, the increase in the returns to entrepreneurship is greater than the increase in returns to employment for unskilled individuals, while the opposite is true for skilled individuals. As a result, the share of unskilled entrepreneurs increase while skilled decrease such that the aggregate entrepreneurship rate changes little.

The second row of Panel B shows that increasing the share of college graduates while jointly raising the skill premium explains around 24% of the observed decline in aggregate entrepreneurship rates. The model economy continues to exhibit skill-biased declines in entrepreneurship and entry rates with little impact on exit rates. Indeed, introducing a rise in the supply of skills shrinks the skill-

[40] This is similar to the 0.3 percentage points gap between the benchmark and counterfactual economies at the end of the transition path in Figures 12 and 17. Recall that along most of the transition path, the counterfactual and benchmark economies exhibit very similar rates of entrepreneurship.

bias as unskilled entrepreneurship rates decrease significantly while skilled entrepreneurship rates remain relatively stable. To understand this, notice that raising the supply of skilled individuals puts upwards pressure on wages of unskilled workers as the supply of unskilled individuals shrinks. Higher unskilled wages result in lower entrepreneurship rates for the unskilled as they prefer to pursue employment over entrepreneurship. Wages for skilled workers increase more than proportionately in order to generate an increasing skill premium, and as a result, the entrepreneurship rate for skilled individuals remains remains similar to the case where only the skill premium increases. The large decline in unskilled entrepreneurship rates outweighs the composition effect resulting from shifting the population towards skilled individuals (that have higher entrepreneurship rates), so that the aggregate entrepreneurship rate declines.

Raising the relative productivity of the non-entrepreneurial sector to match the size of the non-entrepreneurial sector results in a significant decline in aggregate and skill-specific entrepreneurship rates. With this change, combined with the rise in the skill premium and share of college graduates, the model economy accounts for 71% of the observed decline in aggregate entrepreneurship rates. This suggests that technological change that is skill-neutral (and biased towards the non-entrepreneurial sector) explains around 47% (71-24) of the decline in aggregate entrepreneurship. An increase in $\frac{B}{A}$ raises the non-entrepreneurial sector's demand for workers, which, in turn, raises wages. Higher wages increase the opportunity cost of entrepreneurship through two channels. First, individuals can earn higher wages in employment. Second, profits from entrepreneurship become lower as entrepreneurs must pay higher wages with no compensating improvement in their production function. Together, these channels combine to lower the aggregate entrepreneurship rate. Notice, in response to this change, unskilled entrepreneurship rates decline slightly more than those for the skilled – shrinking the skill-bias in entrepreneurship. As before, entry rates mirror entrepreneurship rates while exit rates remain stable.

Finally, an increase in exit rates results in the model explaining around 86% of the observed decline – decreasing entrepreneurship rates in a skill-neutral manner. Increasing exit rates raise both the entry and exit rates in a skill-neutral manner.

In sum, this decomposition exercise is largely consistent with our earlier analysis of transition dynamics and allows us to summarize our quantitative findings. A rising supply of skills and technological changes that preserve the skill premium, account for the majority of the observed decline in entrepreneurship. On its own, a rising skill premium has little impact on entrepreneurship rates but is the key driving force behind their *skill-biased* decline – shifting the composition of entrepreneurs towards the unskilled. Increasing exit rates contribute modestly to the overall decline and is essential for matching the observed trends in flows in and out of entrepreneurship.

7 Conclusion

This paper documents new evidence on the skill-biased nature of the decline in entrepreneurship in the U.S. over the last several decades. Motivated by this evidence, we study the extent to which the rise in the worker skill premium has influenced the overall and skill-biased declines in entrepreneurship.

Using data from the CPS, we first document that the overall fall in entrepreneurship has been more pronounced for skilled individuals – a finding that we argue is robust. A flow decomposition of the decline in entrepreneurship reveals that this skill-bias is driven entirely by skill-biased changes in the rate at which workers flow from employment to entrepreneurship – entry rates.

We posit that the rise in worker skill premium explains this skill-biased decline in entrepreneurship – a prediction of canonical theories of entrepreneurship that is also supported by our empirical findings. In particular, we present empirical evidence showing that the earnings of workers rose faster than those of entrepreneurs – particularly so for skilled individuals. We also demonstrate a connection between the extent of skill-bias in worker earnings growth and entrepreneurial decline by documenting a positive correlation between the two phenomena in the cross-section of states and occupations.

To assess the impact of the changing worker skill premium on the skill-biased and aggregate entrepreneurial decline, we augment an otherwise standard model of occupational choice by introducing worker skill.

Using a calibrated version of this model, we find that on its own, an increase in the skill premium – driven by skill-biased technological change – does not contribute significantly to lowering the aggregate entrepreneurship rate. Instead, the majority of the decline in entrepreneurship is driven by skill-neutral technological changes and a rising supply of college graduates. The rising skill premium interacts with these forces and fully accounts for the *skill-biased* changes in entrepreneurship and entry rates observed in the data. In addition, we show that a rise in the skill premium lowers average productivity of entrepreneurship by shifting the composition of entrepreneurs towards unskilled individuals.

We also evaluate the impact of increasing exit rates from entrepreneurship and find that this increase is critical for matching observed trends of flows in and out of entrepreneurship while contributing modestly to the overall decline in entrepreneurship in a largely skill-neutral manner. Notably, increasing exit rates do not change the role played by the rising skill premium in shaping entrepreneurship. Although we take changes in the probability of exit from entrepreneurship to be exogenously given, these changes are likely determined by endogenous economic factors. A promising avenue for future research would be to identify these economic factors and separately quantify their impact on entrepreneurship.

Taken together, this paper contributes to the growing literature intended to understand the causes and consequences of declining business dynamism and studies the role of a rising worker skill premium. Our empirical and quantitative findings suggest an integral role for changes in the income structure of workers in shaping the evolution of entrepreneurship and influencing the broader decline of business dynamism in the U.S.

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Online Appendix

Not for Publication

A Additional Figures and Tables

Table A.1: Parameters Values for Decomposition Exercise

	λ	$\frac{\theta_s}{\theta_u}$	$\frac{B}{A}$	χ
Baseline Calibration	0.27	0.31	1.19	0.02
Skill premium ↑	0.27	0.62	1.09	0.02
+ Supply of Skills ↑	0.43	3.40	0.81	0.02
+ Non-Entrepreneurial Sector ↑	0.43	3.40	0.83	0.02
+ Exit Rates ↑	0.43	3.43	0.79	0.17

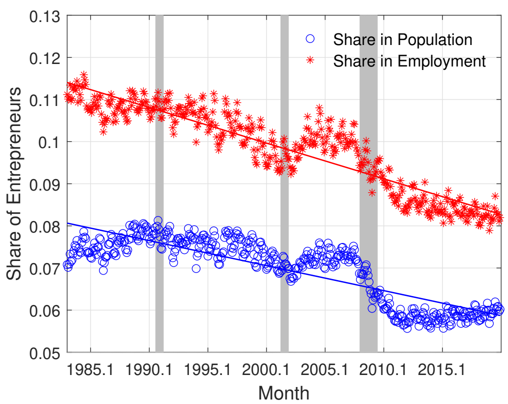
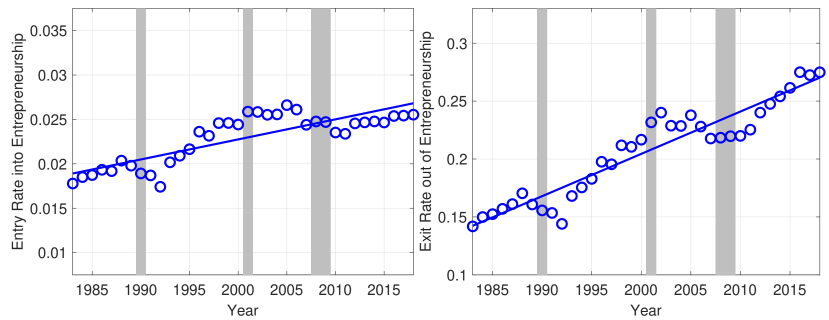


Figure A.1: Share of Entrepreneurs

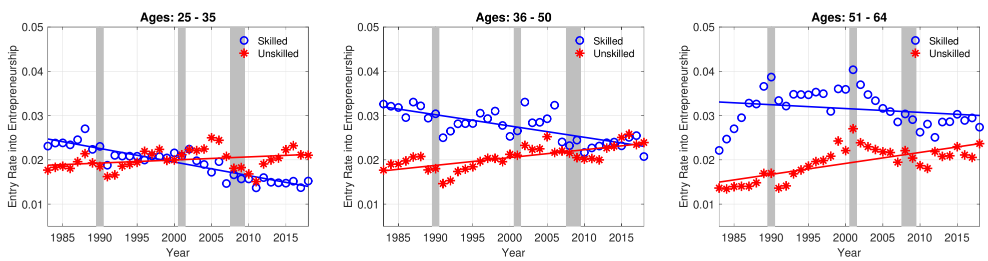
Notes: The figure plots the share of entrepreneurs in the population and the share in total employment. The sample includes full-time, non-agricultural employees, entrepreneurs and all those non-employed aged between 25 and 64. Data is from the Jan. 1983 to Dec. 2019 CPS basic monthly surveys. The shaded bars indicate recessions as determined by the National Bureau of Economic Research (NBER).



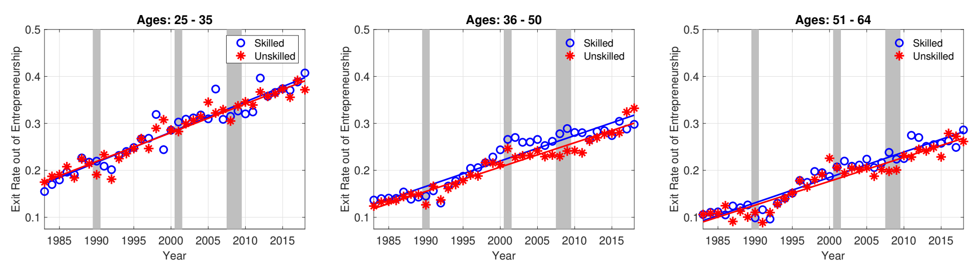
(a) Entry Rate (b) Exit Rate

Figure A.2: Aggregate Entry and Exit Rates

Notes: Panel (a) plots the share of employees that transition into entrepreneurship over a 12 month period, while Panel (b) plots the share of entrepreneurs that transition into employment. Entry and Exit rates have been adjusted to account for margin error and CPS redesigns. Data is from a sample of full-time, non-agricultural employees and entrepreneurs aged between 25 and 64 from the Jan. 1983 to Dec. 2019 CPS basic monthly surveys.



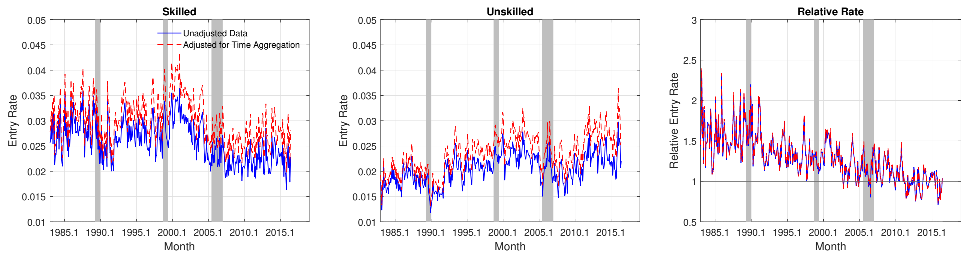
(a) Entry Rate



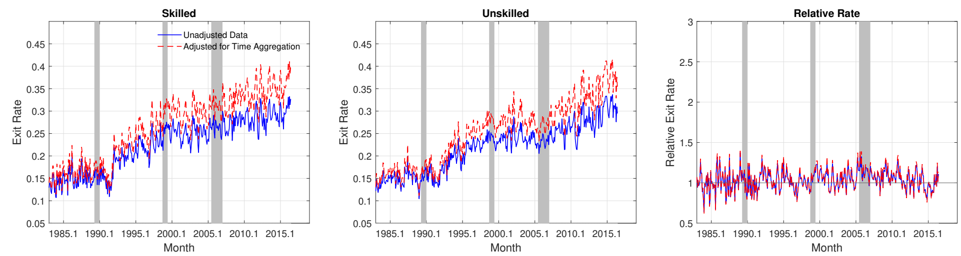
(b) Exit Rate

Figure A.3: Entry and Exit Rates by Age Groups

Notes: Panel (a) plots the of share of workers that transition into entrepreneurship over a 12 month period. Panel (b) plots the share of entrepreneurs that transition into employment. Data comes from matching respondents in the CPS Monthly Surveys over a 12 month period.



(a) Entry Rate



(b) Exit Rate

Figure A.4: Adjusting Flows for Time Aggregation Bias

Notes: The figure plots raw entry and exit rates and those that have been adjusted for time aggregation bias. The leftmost figure in Panels (a) and (b) plot the ratios of skilled and unskilled entry and exit rates, respectively. The unadjusted data (solid blue lines) are the raw entry and exit rates as calculated from the CPS that have not been adjusted for the CPS redesigns. The adjusted entry and exit rates (dashed red lines) are constructed by first using the annual transition rates to extrapolate corresponding monthly transition rates following Gomes (2015). These monthly rates are then used to compute the implied continuous time transition rates as in Shimer (2012).

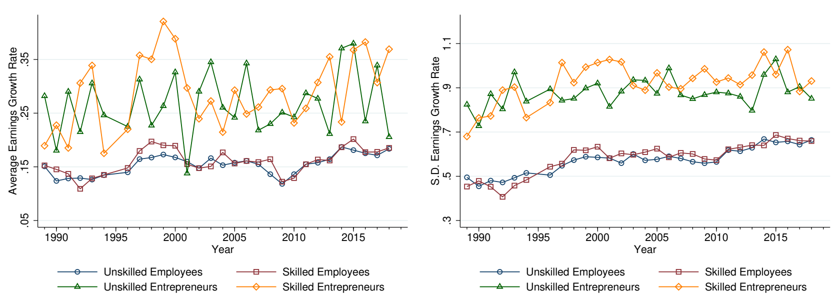


Figure A.5: Average and Standard Deviation of Earnings Growth Rates, by skill

Notes: The figure reports the average, standard deviation of earnings growth among continuing entrepreneurs and workers, by skill, in the CPS. Earnings growth is calculated as percentage change in earnings for continuing entrepreneurs. The top and bottom 1% growth rates are excluded when calculating the average and standard deviation of growth rates.

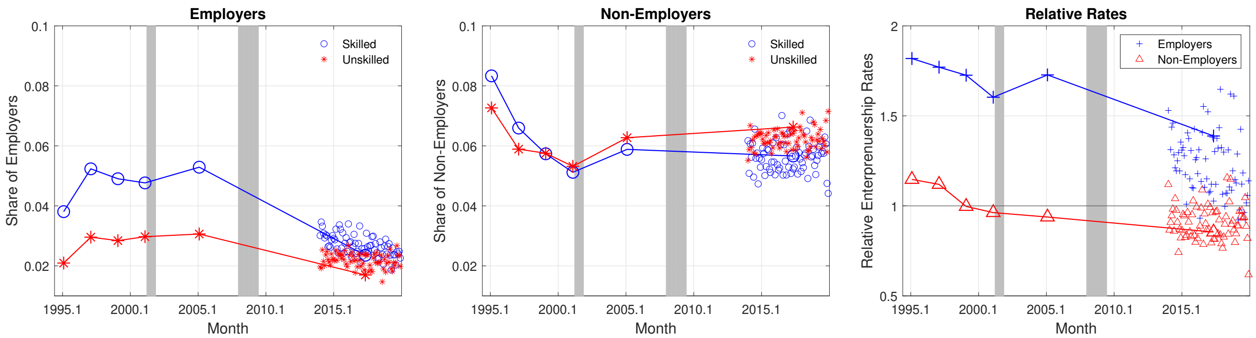


Figure A.6: Entrepreneurship Rates by Employer Status

Notes: The figure plots, by skill, the share of employers among total non-agricultural employment from the Contingent Worker Supplement (CWS) of the CPS (large markers with connected line) and the the Outgoing Rotation Group Sample (ORG) of the CPS (small markers scatter plot). Data on employer status is available in the CWS from 1995 while data on employer status in the ORG sample is available from 2014.

(a) Sources of Entering Entrepreneurs

(b) Destinations of Exiting Entrepreneurs

Figure A.7: Sources and Destinations of Entrepreneurs

Notes: Panel (a) reports the share of new entrepreneurs by their occupation in the previous year. Panel (b) reports the share of exiting entrepreneurs by their occupation in the current year. Data is from the monthly CPS and includes both employed and non-employed.

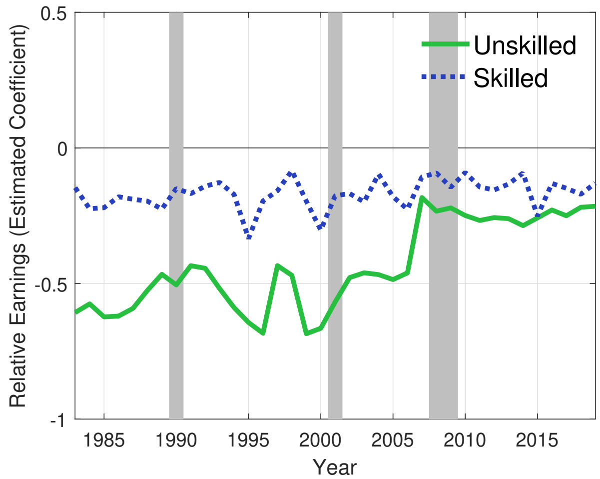


Figure A.8: Relative Earnings for Workers and Entrepreneurs, including controls

Notes: The figure plots the coefficient obtained from an OLS regression of log income on an indicator variable identifying those with that are entrepreneurs and those that are workers. The reference category is workers. The regression is performed separately for skilled and unskilled individuals and includes a quartic in years of experience, gender, race and census region dummies. Sample includes full-time, non-agricultural workers and entrepreneurs aged between 25 and 64 from the March Supplement of the CPS. The shaded bars indicate recessions as determined by the NBER.

B Data Appendix

B.1 CPS Basic Monthly Surveys

Participants in the CPS Basic Monthly Surveys are interviewed 8 times over a period of 16 months. The rotating panel design is such that individuals are surveyed for 4 consecutive months, then not interviewed for 8 months, and then surveyed for a final 4 months. This design allows us to match individuals across interviews over months, quarters or years. We link individuals across a 12 month period – a year. That is, we match responses from interview n to interview $n+4$ in the same month the following year for $n \in \{1, 2, 3, 4\}$ to compute annual transition rates. Whenever possible, matches from all n interviews are included so the same individual will be included in the final sample at most four times. Using only a single interview pair $(n, n+4)$ to match individuals yields similar results while decreasing our sample size. The average annual matching rate is around 70% and the final sample includes 6.7 million matched interviews from 2.1 million unique individuals. Rivera Drew et al. (2014) includes technical details on linking respondents using the IPUMS CPS monthly files.

To measure the entry rate into entrepreneurship we construct a binary variable $d_{i,a,t}$ for each individual i of skill type a that is a worker (i.e. not self-employed) in period t. We set $d_{i,a,t}$ equal to 1 if this individual is self-employed in period $t+1$ (12 months later) and 0 if this individual remains a worker. The entry rate is simply the share of workers that transition from employment to entrepreneurship – the average of the variable $d_{i,a,t}$. The exit rate is analogously constructed where a binary variable for all self-employed in period t identifies transitions from self-employment in time t to employment in time $t+1$. We report entry and exit rates at an annual frequency by taking the average of annual transition rates for all months in a given year.

Table B.1 reports the characteristics of our sample for i) employees, ii) all entrepreneurs as well as entering and exiting entrepreneurs for the entire sample. Notice, the demographic composition and

Table B.1: Summary Characteristics of Sample

	Employees	Entrepreneurs	Entrants	Exiters
Age	41.6	45.0	42.5	43.4
White	0.817	0.883	0.835	0.835
Male	0.560	0.727	0.586	0.587
HH Head	0.585	0.654	0.595	0.595
$\leq$ HS	0.402	0.376	0.384	0.386
LTC	0.261	0.250	0.259	0.259
College+	0.337	0.374	0.257	0.255
Incorporated	-	0.379	0.405	0.573
N (in 1000s)	19,387	2,190	122	130

Notes: The table shows the average age, and share of sample by its demographic characteristics. $\leq$ HS and LTC denote the share of the sample with at most a high school degree and the share with less than a college degree, respectively. The first two columns, report data from the unmatched CPS monthly data while the last two columns show data from the matched CPS sample.

sample size here differ significantly from the PSID sample used in Salgado (2019). The CPS results in a much larger sample size and include a higher shares of non-white and female respondents. This distinction is not without consequence. As shown in Figure B.1, the overall share and flow in and out of self-employment for white, male, heads of households – the primary component in the Salgado's sample – exhibits much steeper declines (increase) in overall and entry (exit) into self-employment relative to the rest of the sample.

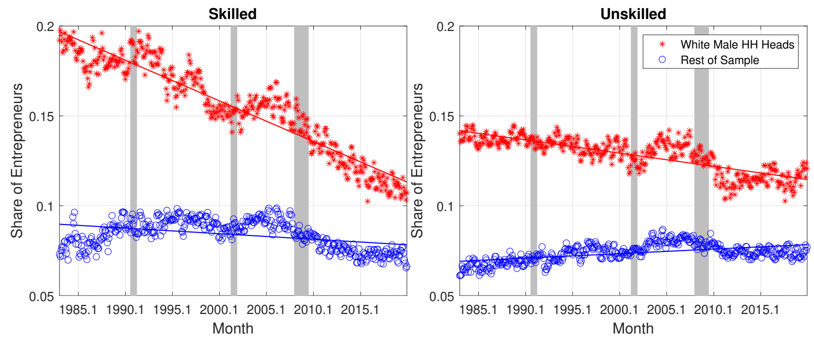
Adjusting for Margin Error Consistent with the literature studying labor market flows, we adjust the observed flows, $\mathbf{p}$, between entrepreneurship and employment so that they are consistent with the observed stocks. This adjustment is referred to as a *margin error adjustment*. As discussed by Elsby et al. (2015), inconsistencies between observed stocks and those implied by flows may be due to several reasons. These include attrition of survey respondents due to say, death, immigration or movements in and out of age range of 25 to 64 that we focus on.

We apply the process described in Elsby et al. (2015) in making the adjustment to entry and exit rates. This adjustment process involves choosing adjusted flows $\hat{\mathbf{p}}$ to minimize a weighted difference between $\mathbf{p}$ and $\hat{\mathbf{p}}$ subject to the adjusted flows being consistent with the evolution of stocks observed in the data. Details can be found in Appendix A.2. of Elsby et al. (2015). As shown in Figure B.2, the margin-error adjustment has very little impact on relative entry and exit rates.

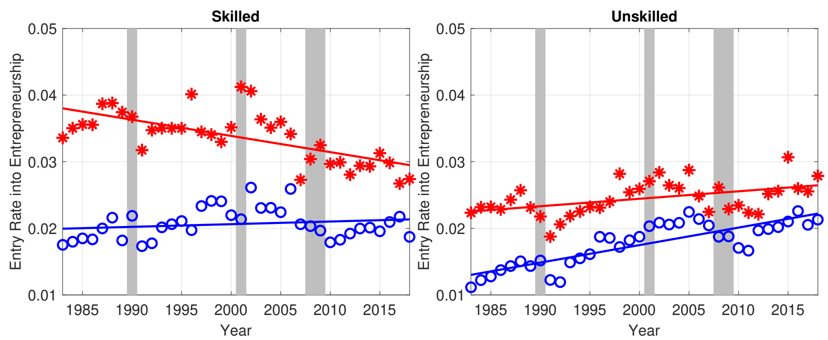
Adjusting for Survey Redesigns Several major and minor redesigns of the CPS have taken place over our sample period which require us to make adjustments to our measures of flows in and out of entrepreneurship.[1] There is a relatively little literature on adjusting for the CPS redesigns with a notable exception being Polivka and Miller (1998) who provide multiplicative adjustment factors for various aggregate labor market measures derived to adjust for the major 1994 redesign. These adjustment factors cannot be applied to our work as they do not include subgroups relevant to this paper such as entrepreneurs.

Instead, along the lines of Polivka and Miller (1998), we exploit the slow phase-in of the redesigns in the CPS to justify the assumptions that underlie our adjustment process. In particular, since

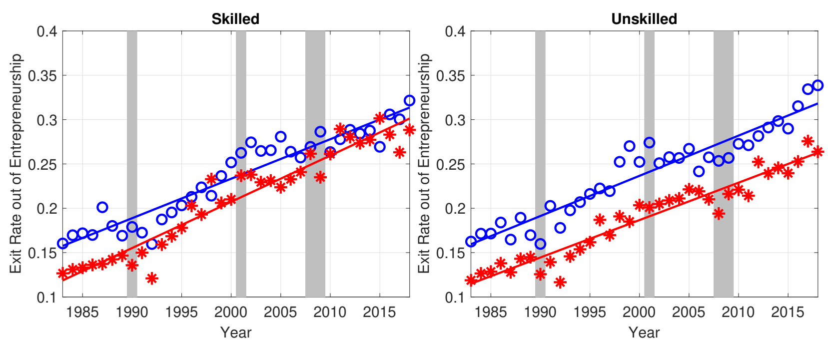
[1] See Polivka and Miller (1998) and Shoemaker (2004) for details on the 1994 and 2004 redesigns respectively.



(a) Entrepreneurship Rate



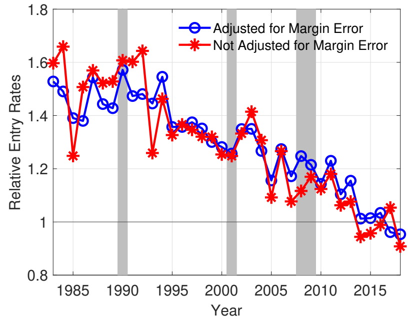
(b) Entry Rate



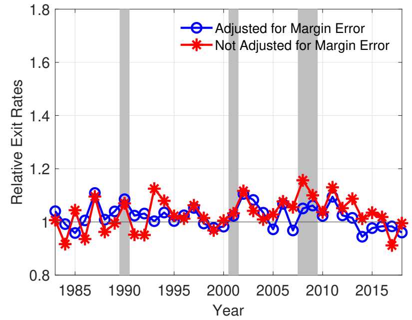
(c) Exit Rate

Figure B.1: Measures of Entrepreneurship for White Male HH Heads and the Rest of Sample

Notes: The figure plots entrepreneurship rate (Panel (a)), entry rate (Panel (b)), exit rate (Panel (c)) for white male household heads and the rest of sample. Sample includes full-time, non-agricultural employees aged between 25 and 64 with at least a high school degree from the basic monthly CPS files. The self-employment rate is the share of the sample that is identified as self-employed.



(a) Relative Entry Rates



(b) Relative Exit Rates

Figure B.2: Relative Entry and Exit Rates

Notes: Panel (a) compared the ratio of skilled and unskilled entry rates when flows have and have not been adjusted for margin-error. Panel (b) reports the ratio of skilled and unskilled exit rates when flows have and have not been adjusted for margin-error. Data is from the matched monthly CPS sample.

changes in the CPS are incorporated slowly over a number of months it is still possible to match respondents across months during the redesign phase-in periods. However, since a subset of a given sample will be surveyed with the new questionnaire in the following period, the respondent match rate is lower during the phase-in periods. Naturally the number of respondents is also lower during these periods. Figure B.3 shows the share of the sample that is matched over a 12 month period. The figure reports the annual match rate which is constructed by taking the average of the match rate for all months in a given year.

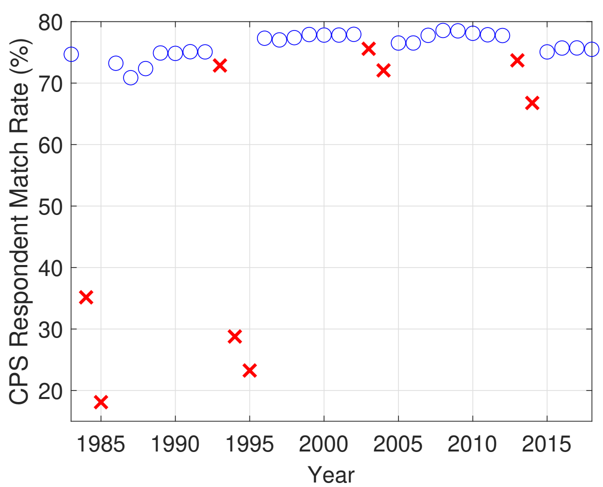


Figure B.3: CPS Respondent Match Rate (%)

To make our adjustment we assume that the entry and exit rates experience only a temporary *level* shift during those years affected by the redesign. To justify this, consider five years of raw survey data labeled $\{s_1, s_2, x, t_4, t_5\}$ where s_i and t_j represent redesigned surveys conducted in years i and j and survey x represents the transition year which, similar to the CPS, includes a mix of type s and t respondents. Label the resulting matched sample as $\{s_{12}, s_2x, xt_4, t_{45}\}$. The data sets s_2x and xt_4 are potentially impacted by the redesign while s_{12} and t_{45} are not. Although the s and t type questionnaires may be different, as long as the variable definitions and methods of measurement are consistent across the two surveys, the transition rates from the matched samples s_{12} and t_{45} will be comparable over time.[2] Although the 1994, and to a lesser extent the 1984/2004/2014, redesigns were significant they do not alter the definitions and measurements of the variables of interest in this paper. For instance, the 1994 redesign introduced additional educational attainment categories yet both the pre- and post- redesign education variables allow us to identify skilled and unskilled individuals as defined above in a consistent manner. Given this, we take as given that the entry and exit rates prior to and following the redesign are comparable and do not need to be adjusted. All that remains is to address the potentially incomparable transition year data; s_2x and xt_3. Since we only match t type respondents in xt_3 and s type respondents in s_2x it is possible that measures derived from these data are comparable across time. However, for this to be true it must be the case that that phase-in samples are designed so that all subgroups of interest, say self-employed with at least a college degree, are randomly assigned to s and t type questionnaires. As outlined in footnote 4 in Polivka and Miller (1998) this is not how the redesign took place. Instead following an initial introduction of the new survey to subgroups of respondents, the older survey was completely phased out over consecutive months. As we pool monthly data at the annual level it is a certainty that subgroups of interest will not be randomly assigned across s and t type questionnaires during the transition period. As such, measures derived from the matched data s_2x and xt_3 may have unpredictable level shifts from the *true* measure of flows. Notice that these level difference are not due to a changes in variable definitions but due to differences in sample sizes as represented in the match rate.

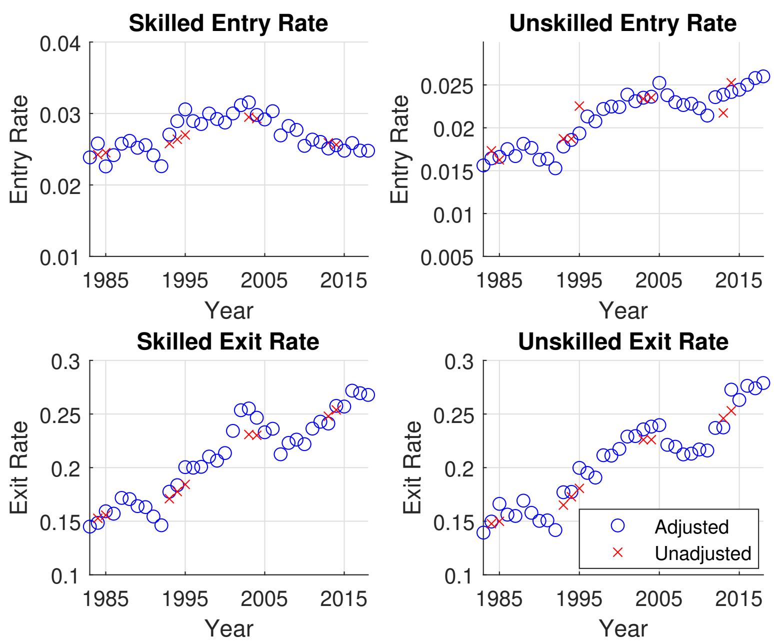


Figure B.4: Adjusted and Unadjusted Entry and Exit Rates

Notes: This figure plots the adjusted and unadjusted entry and exit rates in the matched monthly CPS data.

To adjust for these level shifts we perform a simple regression on, say, the entry rate $e_{i,t}$ and include dummies for those years impacted by the redesign. We also include dummies for those

[2] As an example, consider the CPS prior to 1983. During this time it was only possible to identify the unincorporated self-employed while after 1983 it became possible to identify both the incorporated and unincorporated self-employed. This constitutes a permanent and significant change in the definition of who is self-employed. So when we compare, say, the entry rate into self-employment prior to and following the redesign we will observe a permanent level shift following the redesign.

years immediately prior to and after the implementation of the redesign. For example, for the 1994 redesign we include dummies for 1992,93,94, 95 and 96 and for the 2004 redesign we include dummies for 2002, 03, 04 and 05. The marginal effect of these dummies are then subtracted from the unadjusted entry rate $e_{i,t}$. This impacts the expected predicted entry rate only for those years that are effected by the redesign. Figure B.4 plots the unadjusted and adjusted entry rate and exit rate from the matched monthly CPS data. The discrepancies between the adjusted and unadjusted entry rates is larger than that for exit rates. This is intuitive as the entry rate captures a smaller subgroup, transitions into self employment, across surveys and this population is less likely to be evenly distributed across surveys during the phase-in period. Additionally, the more comprehensive redesign in 1994 requires a larger adjustment than other redesigns.

Comparison with BDS Much of the current literature studying business dynamism and declining firm startups uses aggregated data such as firm-level data from the Business Dynamics Statistics (BDS). Indeed, a well established fact in this literature is the trend decline in new firm startup rate. The startup rate – also referred to as the firm entry rate and not to be confused by the entry rate discussed in this paper – is measured as the share of young (age ≤ 1 year old firms) firms among all firms. Here, we construct a measure of the startup rate using only individual level CPS data and show that the CPS and BDS startup rates exhibit strikingly similar trends. We take this to suggest that despite covering individuals, not firms, the CPS is suitable for studying and capturing aggregate trends that have previously only been documented using firm level data.

We begin by describing the key differences between the CPS and BDS. The BDS records information on the universe of employer firms including firm age as of the week of March 12th each year. The entrepreneurs that we study in the basic monthly CPS sample includes both employers and non-employers. Further, the basic monthly CPS survey does not ask respondents how long they have been self-employed and we cannot distinguish new entrepreneurs from incumbent entrepreneurs.

Fortunately, this information is periodically elicited in the Job Tenure Supplements (JTS) of the CPS. Much like the March ASEC supplement, the JTS asks additional questions for a share of respondents (on average around 50%) that are in the basic monthly surveys. Note, this is not a different set of respondents but rather includes additional information from (a subset of) the same respondents as those in the basic monthly CPS data. Using this data, we can measure the share of entrepreneurs that have been in operation for no more than a year among all entrepreneurs.[3] This is exactly analogous to the definition of the firm startup rate from the BDS.

Figure B.5 compares the startup rate from the BDS (blue line) with the startup rate from the JTS (red line). The two measures correlate remarkably well both in terms of changes over time but also in levels. However, this startup rate from the JTS includes both employer and non-employer entrepreneurs.[4] To overcome this limitation, we use another supplement to the CPS, the Contingent Worker Supplement (CWS). The CWS includes information on both business age and the employer

[3]We use the IPUMS variable `jtyears` which "gives the number of years the respondent has worked in his/her current job."

[4]The fact that the BDS and JTS startup rates are similar despite the JTS including non-employers suggests that there is no significant trend in the share of employers/non-employer share among all entrepreneurs. To see why this holds, define the BDS startup rate at time t as $\frac{e_t^0}{\Sigma e_t^a}$ where e_t^a is the number of employer firms of age a at time t. Let the JTS startup rate be defined similarly as $\frac{s_t^0}{\Sigma s_t^a}$ where s_t^a is the number of entrepreneurs with businesses of age a comprised of a number of employers $\tilde{e_t^a}$ and non-employers $\tilde{n^a}_t$. If we assume that the CPS is representative of the number of employers then we can write $\tilde{e_t^a} = \chi e_t^a$ where χ is some constant. Then, we can rewrite the JTS startup rate as $\frac{\chi e_t^0 + \tilde{n^a}_t}{\Sigma \chi (e_t^a + \tilde{n^a}_t)}$. Rearranging this gives the JTS startup rate as a product of the BDS startup rate $\frac{e_t^0}{\Sigma e_t^a}$ and the

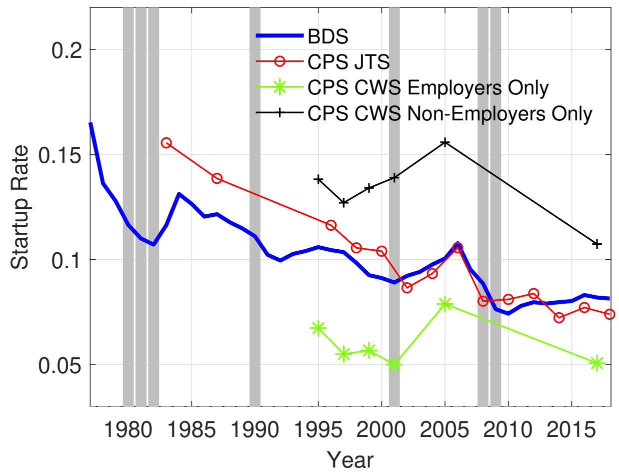


Figure B.5: Startup Rates in the BDS and CPS

Notes: The figure plots startup rates from 1977 to 2018 as computed in the BDS and CPS. The BDS startup rate is the number of all employer firms that have been in operation for under a year, as a share of all firms. Data for 1977 is from the legacy (pre-2018) BDS time series. The CPS JTS startup rate is computed using the CPS Job Tenure Supplement and is the number of entrepreneurs that have been in operation under a year, as a share of all entrepreneurs. The CPS CWS rates are computed analogously for the sample of employers and non-employers only using the CPS Contingent Worker Supplement. We employ the same sample restrictions to the JTS and CWS as in the CPS monthly sample and results are weighted using the provided supplement weights.

status of entrepreneurs. Using the CWS, we can construct the startup rate for employers and non-employers separately. It should be noted, that the CWS does *not* ask respondents how long they have been employing others but rather how long they have been self-employed. Since most young businesses do not employ others (less than 20% of young businesses in the CWS sample) we expect the employer startup rate from the CWS to be much lower than the non-employer startup rate. The black and green lines show the startup rate for non-employers and employers, respectively. As expected, the employer only startup rate is much lower than the JTS startup rate which also includes non-employers while the non-employers startup rate is higher. The time path of the CWS startup rates also lines up well with the BDS although the data is available for a much smaller sample period.

Taken together, Figure B.5 suggests that despite only covering individuals, the CPS data is able to replicate and capture the time path of the much studied firm level startup rate.

Next, we discuss whether the worker to entrepreneur transition rates we construct – the entry rate – can be used to construct a measure of the startup rate that is consistent with the BDS.

From Panel (b) of Figure A.2, the entry rate from employment into entrepreneurship has increased slightly over time. If we assume that each transitioning worker creates a new startup of age ≤ 1 years, then the number of startups would simply be the (relatively constant) entry rate θ_t multiplied by the total number of workers E_t at time t. Then, the startup rate would be $\frac{\theta_t E_t}{S_t}$ where S_t is the total number of self-employed. The declining share of entrepreneurs among total employment leads the ratio $\frac{E_t}{S_t}$ to be increasing over time while θ_t is fairly stable. As a result, this startup rate computed using flows of workers into entrepreneurship is also increasing. Over our sample period, this measure increases from around 16% in 1983 to 24% in 2019.

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term $\frac{1+\frac{\tilde{n}_t^0}{e_t^0}}{1+\frac{N_t}{E_t}}$ where $\frac{N_t}{E_t}$ is the ratio of all non-employers to all employers.

This is clearly inconsistent with the declining startup rate in the BDS and the CPS supplements in Figure B.5. The reason for this discrepancy is that that our assumption of a transitioning worker creating a startup does not hold in practice. To see this, we merge the matched CPS sample with the JTS and consider the number of years a respondent reports working in his/her current job among the sample of transitioning workers. If each transitioning worker creates a new startup, then we would expect all switchers to report working ≤ 1 years in their current job. However, we find that only around 25% of switching respondents report working ≤ 1 years and 70% report working ≤ 10 years.

Why might workers that switch into entrepreneurship report working such a long time as an entrepreneurs? We think there are two likely reasons for this result. First it may be that respondents pursue the same type of work in entrepreneurship as in employment. For example, a restaurant manager switches to operating their own restaurant. Hence, they may interpret the question of how many years they have worked in their "current job" as the number of years they have been doing their current type of work. In this case, reporting a large number of years worked does not imply that the respondent did not create a startup.

A second reason could be that, while employed, individuals pursue a less involved form of self-employment. This could involve applying for a business licenses or conducting market research etc while still an employee. Then at some point they choose to switch entirely into self-employment. Similarly, individuals may switch frequently between employment and self-employment depending on market conditions and report the years since their first switch to entrepreneurship.[5] In such cases, the information on number of years worked for switching workers could include not only the length of time since switching into self-employment but also the length of time while employed. With this interpretation, a high number of reported years worked in current job does indeed imply that the respondent did not create a startup.

It is likely that both scenarios hold in reality and there is strong evidence to support the second interpretation (see for example, Folta et al. (2010) and Hincapié (2020)). As such, we cannot use the entry rate – the share of workers that switch into entrepreneurship – alone to infer the number of new startups in the economy. If we believe that the likelihood of respondents misinterpreting the question on years in current job is low, then a lower bound on the number of startups can be taken as the number of switching workers that also report working ≤ 1 year in their current job. That is, $\frac{\theta_t E_t}{S_t} \times \mathbb{I}_{\text{Startup,t}}$ where $\mathbb{I}_{\text{Startup,t}}$ is the share of switching workers that report working ≤ 1 years from the JTS. This measure declines by half since 1987 from around 6% to 3% in 2018 with a correlation of 0.64 with the BDS startup rate.

B.2 CPS March Supplement

The Annual Social and Economic Conditions (ASEC) supplement to the CPS – conducted each March – includes information on income earned in the prior year and is used to measure the skill premium.

Skill Premium and Top-Coding We follow Acemoglu and Autor (2011) closely in constructing the worker skill premium. Our measure of income is weekly earnings which is computed by dividing annual earnings (the IPUMS variable `incwage`) and the total number of weeks worked

[5] We confirm that switches between employment and non-employment with spells of under one month in an occupation are uncommon in the CPS.

in a year.[6] We restrict our sample to include full-time, full-year workers by excluding all those that worked less than 40 weeks over the year and are classified as full-time workers in the CPS. We further drop those workers that earned less than half the minimum wage.[7] Prior to 1996, earnings of respondents are top-coded such that any earnings above a certain threshold level are reported as being equal to that threshold. After 1996, there is instead a threshold earnings level such that earnings above the threshold are replaced with the average earnings of other high income earners with the same demographic characteristics. To adjust for this top-coding we multiply top-coded/replaced earnings by 1.5 as in Acemoglu and Autor (2011).[8] Following this adjustment, the reported measure of skill premium is the coefficient on a dummy variable for those with at least a bachelor's degree in an OLS regression of log weekly earnings with a variety of controls. The controls are, (1) a quartic in years of potential experience, (2) gender dummy , (3) race (white/non-white) dummy, (4) interactions between race and gender dummies (5) state dummies (6) additional dummies for educational categories. The state-level skill premia is computed analogously with the exception that we do not include state dummies. Years of potential experience $E = age - S - 6$ is defined by assuming that an individual's schooling starts after age six and years of schooling, S, are inferred using the IPUMS variable `educ`. This variable reports the highest level of educational attainment of a respondent. Our correspondence between years of schooling and this variable is detailed in Table B.2.

Table B.2: Years of Schooling in March CPS, 1965-2014

`educ`	Years (S)	Share (%)	`educ`	Years (S)	Share (%)
None or preschool	0	0.3	12th grade, diploma unclear	12	16.0
Grades 1, 2, 3, or 4	2.5	0.3	High school diploma or equivalent	12	17.8
Grade 1	1	0.1	1 year of college	13	2.6
Grade 2	2	0.1	Some college but no degree	13.5	10.0
Grade 3	3	0.2	2 years of college	14	3.4
Grade 4	4	0.3	Associate's degree, occupational/vocational	14	2.9
Grades 5 or 6	5.5	0.8	Associate's degree, academic program	14	2.8
Grade 5	5	0.3	3 years of college	15	1.2
Grade 6	6	0.7	4 years of college	16	5.4
Grades 7 or 8	7.5	0.7	Bachelor's degree	16	12.1
Grade 7	7	0.7	5 years of college	17	1.2
Grade 8	8	2.3	6+ years of college	18	2.8
Grade 9	9	2.3	Master's degree	18	4.6
Grade 10	10	3.0	Professional school degree	18	1.0
Grade 11	11	2.7	Doctorate degree	21.5	0.9
12th grade, no diploma	12	0.6			

The skill premium for entrepreneurs is constructed analogously. The relevant measure of income for entrepreneurs is the IPUMS variable `incbus` which reports annual business income. For incorporated entrepreneurs, we use the sum of `incwage` and `incbus`. The lowest 1% of earners are dropped after which only around 3% of entrepreneurs in our sample report negative earnings. Our measure of the entrepreneur skill premium is computed with the assumption that those reporting non-positive income are assumed to have log income equal to 0. We also compute the skill premium by i) excluding entrepreneurs with non-positive earnings and ii) adding a positive constant to entrepreneurial earnings such that log earnings are strictly positive. Neither assumption significantly alters the evolution of the entrepreneur's skill premium. As with workers, top-coded/replaced earnings for entrepreneurs are assumed to be 1.5 times the top-code.[9]

[6] Information on usual weekly hours worked is only available after 1975 after which hourly earnings can be constructed in a similar manner. All earnings are deflated using a Personal Consumption Expenditure (PCE) index available from the US BEA.

[7] That is, those that earned less than 136 2008$, as in Acemoglu and Autor (2011).

[8] We use the top-code/replacement value threshold for `incwage` to adjust the variable `incwage`. For additional details on how top-coding/replacement values are implemented in the IPUMS data see `https://cps.ipums.org/cps/topcodes_tables.shtml`.

[9] To determine the replacement value threshold for the variable `incbus`, we use the sum of the top-code/replacement

Entrepreneurship We also construct measures of the entrepreneurship, entry and exit rates using the March CPS sample and sample restrictions that are identical to those used with the basic monthly surveys. We use the same method to match CPS March respondents and estimate entry and exit rates as in the basic monthly files. However, since only the March surveys are of relevance individuals appear only once in the sample and are matched from their n^{th} interview to their $(n+4)^{th}$ interview where $n \in \{1,2,3,4\}$ is their first March interview. Unlike the monthly files it is not possible to match individuals during those years when the CPS underwent major redesigns in 1984 and 1994.

B.3 ACS and Census Data

Data from the American Community Surveys (ACS) between 2000 to 2017 and data from the 1990 Census is used to rank occupations by average wages to study polarization in entrepreneurship.

We begin by creating a consistent set of occupations following Autor and Dorn (2013) and then use the ACS/Census provided weights to construct measures of labor supply and real hourly earnings. Labor supply is measured as annual hours worked – the product of usual weeks and hours worked in a year. Real hourly earnings are the ratio of annual earnings and annual hours worked. The supply of self-employed when using the ACS is constructed analogously and entrepreneurs are grouped according to their stated occupation as an entrepreneur to produce Figure 9. This figure plots changes in the share of self-employment against the average earnings of occupations which are grouped into percentiles. More concretely, if the share of self-employed in occupation o at time t is $e_{o,t}$ the figure plots,

$$100 \times (e_{o,t+1} - e_{o,t})$$

Wage changes are computed similarly.

By contrast, Figure 10 plots the percentage change in the share of new entrepreneurs that originate from occupation o' as a worker. So, if for an occupation o' there are a total of $L_{o'}$ employees and $E_{o'}$ of them become entrepreneurs in a given period t, we measures changes in the share $\frac{E_{o'}}{L_{o'}}$. That is, the share of former employees of occupation o' that become entrepreneurs. To obtain this measure, we compute $\frac{E_{o'}}{\Sigma_{o'} E_{o'}}$ in the CPS data and then divide this with the share of employees in a given occupation among all employees: $\frac{L_{o'}}{\Sigma_{o'} L_{o'}}$. The result is $\left(\frac{E_{o',t}}{L_{o',t}}\right) \div \left(\frac{\Sigma_{o'} E_{o',t}}{\Sigma_{o'} L_{o',t}}\right)$. Figure 10 reports log differences in this ratio between period t and period $t+h$ that is:

$$100 \times \left(\log\left(\frac{E_{o',t+h}}{L_{o',t+h}}\right) - \log\left(\frac{E_{o',t}}{L_{o',t}}\right) + \Omega\right)$$

where Ω is the change change in entry rate between the two periods $\left(\log\left(\frac{\Sigma_{o'} E_{o',t}}{\Sigma_{o'} L_{o',t}}\right) - \log\left(\frac{\Sigma_{o'} E_{o',t+h}}{\Sigma_{o'} L_{o',t+h}}\right)\right)$.

Notice, Ω is a level shifter and impacts all occupations in the same manner. In particular, it does not impact the relationship between changes in entry rate and the skill percentile but allows us to incorporate changes in the composition of employment between t and $t+h$.

value thresholds of IPUMS variables `inclongj` and `oincbus` which are the two variables that comprise `incbus`. Prior to 1996, no more than 3.8% of entrepreneurs in our sample have earnings top-coded. After 1996, no more than 2.5% entrepreneurs have replacement values.

B.4 SIPP Data

The Survey of Income and Program Participation (SIPP) is used to complement the findings from the CPS monthly and March data. The SIPP has the advantage of being a longitudinal survey which features detailed information on incomes and hours worked of respondents. We use this data to identify those individuals that are earning income as both an employee and self-employed and classify an individual as an employee or wage worker based on the occupation in which they earn the most and work more hours. To measure the entrepreneurship and entry rates, we use data from all waves of the 1996, 2001, 2004 and 2008 SIPP panels. All sample restrictions are identical to those used with the CPS monthly data. Figure B.6 shows the distribution of entrepreneurial income for both skilled and unskilled individuals in the combined sample. The figure shows that skilled entrepreneurship earn more than their unskilled counterparts.

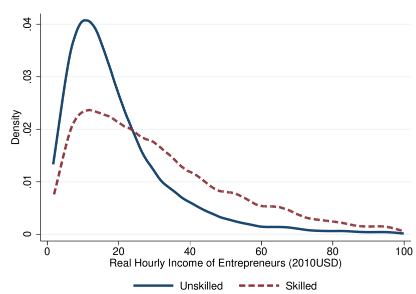


Figure B.6: Distribution of Real Hourly Entrepreneurial Income in the SIPP
Notes: This figure plots the distribution of real hourly entrepreneurial income by skill, in the SIPP.

Figure B.7 shows the cross-sectional growth of hourly earnings over the life cycle of an entrepreneurs business separately by skill. The figure shows that the businesses of skilled entrepreneurs – conditional on survival – grow faster than the businesses of unskilled entrepreneurs. Indeed, after 10 years in operation, the median unskilled entrepreneurs has grown their earnings by around 23% compared to around 32% for skilled entrepreneurs. This along with Figure B.6 shows that skilled entrepreneurs perform better than their unskilled counterparts – consistent with evidence in Levine and Rubinstein (2016), among others.

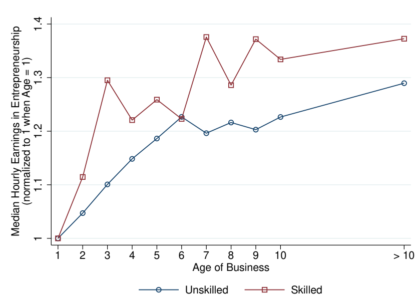


Figure B.7: Growth of Median Hourly Entrepreneurial Income in the SIPP
Notes: This figure shows the median hourly entrepreneurial income by skill, in the SIPP.

The method used to estimate entry and exit rates from the SIPP is slightly different from that used for CPS data. Each SIPP panel includes multiple waves which cover information for four consecutive reference months. To measure the entry rate, we consider all employees and only consider them to have transitioned into self-employment if they remain self-employed for at least a quarter. To avoid the well known seam-bias in the SIPP, we use information from the last month of a given wave along with the next three months of the following wave to determine if a respondent continue to remain in entrepreneurship across two waves. To measure the exit rate, we classify respondents as entrepreneurs by using information in the first two waves of a SIPP panel. In particular, we only classify respondents as entrepreneurs if they report being self-employed in reference month 4 of wave 1 and in reference months 1 to 3 of wave 2. We then track the share of this group that remain self-employed in successive appearances. Table 4 reports the share of these entrepreneurs that are employees by their 16th reference month in a SIPP panel – that is one year from wave 1, reference month 4.

We also use information on the level and growth of entrepreneurial income in the SIPP to shed light on changes in the risk associated with entrepreneurship. In particular, we compute growth in real hourly business earnings for continuing entrepreneurs over a 12 month period. We restrict the sample to only include those entrepreneurs that earn above the federal minimum wage then measure the growth rate in earnings across a 12 month period. Before computing the mean and standard deviation of earnings growth we trim the top and bottom 1% of growth rates. Figure B.8 reports the average and standard deviation of earnings growth rates for entrepreneurs in the SIPP sample. We only report information from years in which we observe more than 1,000 continuing entrepreneurs. Prior to the Great Recession in 2008, the coefficient of variation in earnings growth for both skilled and unskilled entrepreneurs is stable, exhibiting no statistically significant relationship over time. After 2008, both the average and standard deviation of earnings growth decreases.

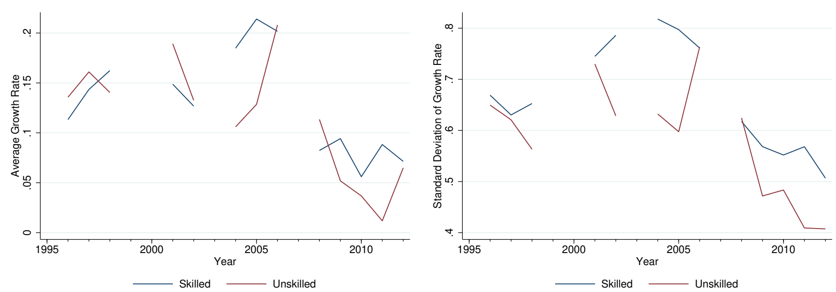


Figure B.8: Average and Standard Deviation of Entrepreneur Earnings Growth

Notes: The figure reports the average, standard deviation of earnings growth among continuing entrepreneurs in the SIPP. Earnings growth is calculated as percentage change in earnings for continuing entrepreneurs. The top and bottom 1% growth rates are excluded when calculating the average and standard deviation.

B.5 SCF Data

In this section, we use data from the Survey of Consumer Finances (SCF) to provide additional evidence on the skill-biased decline in entrepreneurship and discuss potential selection issues. The SCF is a triennial household survey that includes detailed information on household balance sheets, earnings and other demographic characteristics. Unlike CPS or SIPP, the SCF oversamples wealthy and high income households which allows us to overcome the top-coding concerns with the CPS data. The SCF also includes detailed information on the business performance of entrepreneurs. We use this information to explore whether there have been changes in the relative performance of skilled and unskilled entrepreneurs. We begin our analysis in 1989 as data from earlier years is less reliable.

We focus on heads of households between the ages of 25 and 64 who are employed in non-agricultural occupations. As with the CPS sample, we divide the sample into skilled and unskilled based on the highest education level achieved (variables `X5901` from 1989 to 2013 and `X5931` for 2016 and 2019). With sample restrictions, there are around 160 thousand observations covering data from 1989 to 2019.

We begin by establishing a skill-biased decline in the entrepreneurship rate shown in Figure B.9. That is, the share of skilled entrepreneurs declines by around 3pp from 14% in 1989 to 11% in 2019, while the analogous measure of unskilled entrepreneurs declines by around 1pp from 8% to 7%.

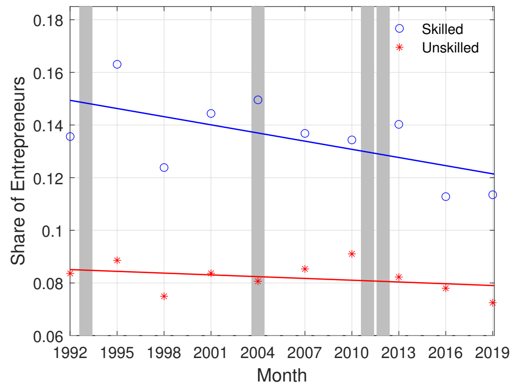


Figure B.9: Share of Entrepreneurs

Notes: This figure shows the evolution of entrepreneur share over time. Following Michelacci and Schivardi (2016) we define entrepreneurship based on two criteria: (1) whether she is self-employed in her primary job using the variable `X4106`, and (2) whether she has an active management role in at least one privately owned business using the variable `X3104`.

Next, we explore measures of entrepreneur performance by skill. We show that businesses owned by skilled individuals tend to perform better as illustrated in Figure B.10. The left panel shows the average number of employees while the middle panel reports average business income. The levels of both average employment and earnings are higher for skilled entrepreneurs. Indeed, on average skilled entrepreneurs hire around 3 times as many workers and their business income is around 2.5 times higher than their unskilled counterparts.

Focusing on relative performance over time, the right panel of Figure B.10 shows that the employment gap between skilled and unskilled entrepreneurs has remained roughly stable over time while the relative gap in earnings exhibits a statistically weak (p-value =0.06) and positive time trend.

The SCF also allows us to estimate the skill premium of workers and entrepreneurs with the advantage the there is very little top-coding in this data. Indeed, the SCF minimizes top-coding by oversampling the wealthiest and richest households. [10]

To estimate the skill premium, we use the same regression as in with the CPS. More specifically, we regress log real income on a indicator variable of skill and control for household characteristics such as age, gender, race, and marital status. The coefficient on the skill indicator is our measure of the skill premium which is shown in Figure B.11.[11] Both worker and entrepreneurs experience

[10] The SCF implements two techniques of random sampling which are detailed in Rodriguez et al. (2002). First, the survey uses the standard multistage area-probability sampling method. Second, the survey selects a supplemental sample to disproportionately include wealthy and high income households, drawn from a list of statistical records based on tax returns (excluding Forbes 400). By oversampling the richest households, the SCF is able to minimize the errors of top-coding and capture the right tail of the wealth distribution. Bricker et al. (2016) and Bricker et al. (2017) provide detailed descriptions on the SCF sampling process and top-end coverage.

[11] We exclude the 1989 survey when measuring the skill premium as it employs a different sampling and interview

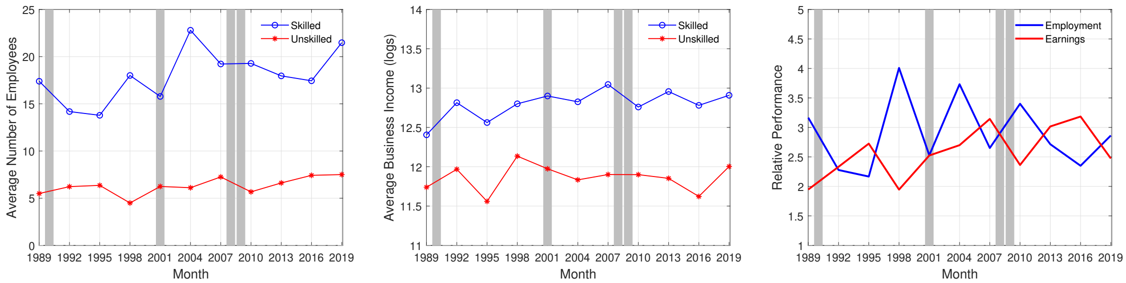


Figure B.10: Entrepreneur Performance by Skill

Notes: Panel (a) plots the average number of employees for skilled and unskilled entrepreneurs. Panel (b) plots the average (log) business income of entrepreneurs. Panel (c) plots the ratio of performance measures in Panels (a) and (b). The variables `X3111` and `X3132` are used to measure business employment and pre-tax net income respectively. To compute average earnings, we trim the bottom and the top 1 percent of business income.

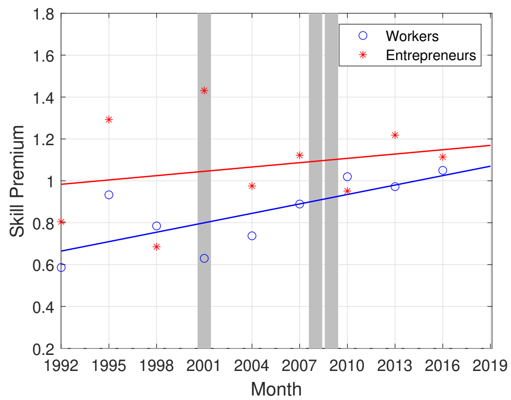


Figure B.11: Skill Premium for Workers and Entrepreneurs in the SCF

Notes: The figure shows the evolution of skill premium for workers and entrepreneurs over time. Variables `X4112` and `X3132` are used to construct income for workers and entrepreneurs respectively. We regress real log earnings on the education group dummy, controlling for household characteristics such as age (`X14`), gender (`X8021`), race (`X8023` and `X6809`), and marital status (`X8023`).

an increase in the skill premium, with a more pronounced increase for workers. The modest trend increase in the entrepreneur skill premium is not observed in the analogous measure using CPS data which, may in part, be due to the top-coding in the CPS data. Having said this, as in the CPS data, the increase in the skill premium remains more pronounced for workers.

C Flow Decomposition Details

We closely follow the non-steady state flow decomposition of Elsby et al. (2019) which generalizes Elsby et al. (2015). These works focus on flows between unemployment, out of the labor force and employment (excluding entrepreneurs) while we study transitions between stocks of i) entrepreneurs, ii) employees and iii) the non-employed. Below, we briefly describe the derivation of a flow decomposition expression which allows us to decompose changes in the stock of entrepreneurs

procedures relative to later year. In particular, there is a larger mass of middle-income workers in this sample which leads to a very high value of the worker skill premium. The trend for the skill premium declines when including this outlier observation, a result that is at odds with evidence from other surveys.

into changes in the inflows and outflows of all three occupational status.

Define the vector of occupational states in period t as $[W, N, E]_t$ where W_t is the share of employees, N_t is the share of non-employed and E_t is the share of entrepreneurs in the population so that $W_t + N_t + E_t \equiv 1$. Then, the mapping between occupation stocks in period $t-1$ to period t is simply given by a transition matrix whose elements $p_{ij,t}$ are the probabilities of switching from occupation i to j between $t-1$ and t,

$$\begin{bmatrix} W \\ N \\ E \end{bmatrix}_t = \begin{bmatrix} 1 - p_{WE} - p_{WN} & p_{NW} & p_{EW} \\ p_{WN} & 1 - p_{NW} - p_{NE} & p_{EN} \\ p_{WE} & p_{NE} & 1 - p_{EW} - p_{EN} \end{bmatrix}_t \begin{bmatrix} W \\ N \\ E \end{bmatrix}_{t-1}$$

Since the share of entrepreneurs satisfies $1 - W_t - N_t$, we can summarize the state of occupations as $s_t = [W, N]_t$ and transform the above mapping into,

$$\Delta s_t = \underbrace{\begin{bmatrix} -p_{WE} - p_{WN} - p_{EW} & p_{NW} - p_{EW} \\ p_{WN} - p_{EN} & -p_{NW} - p_{NE} - p_{EN} \end{bmatrix}_t}_{\tilde{P}_t} \underbrace{\begin{bmatrix} W \\ N \end{bmatrix}_{t-1}}_{s_{t-1}} + \underbrace{\begin{bmatrix} p_{EW} \\ p_{EN} \end{bmatrix}_t}_{d_t}$$

$$\Delta s_t = \tilde{P}_t s_{t-1} + d_t$$

where $\Delta s_t = s_t - s_{t-1}$ and the the implied steady state $\bar{s}_t$ given transition probabilities $\tilde{P}_t$ and d_t is,

$$\bar{s}_t = -\tilde{P}_t^{-1} d_t$$

As described in Elsby et al. (2019), we can express changes in the vector of occupation states Δs_t as,

$$\Delta s_t = \tilde{P}_t \left(\mathbb{I} + \tilde{P}_{t-1}\right) \tilde{P}_t^{-1} \Delta s_{t-1} + \tilde{P}_t \left(\tilde{P}_t + \tilde{P}_{t-1}\right)^{-1} \times \left[2\Delta d_t + \Delta \tilde{P}_t \left(\bar{s}_t + \bar{s}_{t+1}\right)\right] \tag{C.1}$$

where $\mathbb{I}$ is the identity matrix, $\Delta d_t = d_t - d_{t-1}$ and $\Delta \tilde{P}_t = \tilde{P}_t - \tilde{P}_{t-1}$.

Since the share of entrepreneurs is $\left(1 - \begin{bmatrix} 1 & 1 \end{bmatrix}' s_t\right)$, we can use (C.1) and a time series of flow probabilities $\tilde{P}_t$ and d_t to decompose changes in the share of entrepreneurs into changes in flow probabilities and changes in *all three* occupation stocks. With this decomposition *prior* changes in the stock of, say, non-employed has a role in determining the share of entrepreneurs in the *current* period.

To operationalize this decomposition, we compute transition probabilities from the CPS where $p_{ij,t}$ is the share of those in occupation i in time $t-1$ that move to occupation j in time t. We restrict attention to those between the ages of 25 and 64 and for employees or entrepreneurs, we exclude those engaged in agricultural or part-time employment. The non-employed are all those unemployed or out of the labor force. The resulting flow probabilities are adjusted to ensure that they are consistent with the observed evolution of stocks. This '"margin-error" adjustment is common in the labor flows literature and we follow Elsby et al. (2015) in making the adjustment. Since we focus on annual transitions, the change in occupation states Δs_t is the change between month m in year $y-1$ and month m in year y, that is $\Delta s_t = s_{m,y} - s_{m,y-1}$. The monthly change in stocks $(s_{m-1,y} - s_{m,y})$ is approximated by dividing the annual change by 12. In the text, we report for each month τ, the cumulative changes in the share of entrepreneurs, $(s_\tau - s_0) = \sum_{t=0}^{\tau} \Delta s_t$ where the initial period is Jan. 1985.

We conduct the flow decomposition separately for three subgroups of the population; the aggregate population A, unskilled U and skilled individuals S. The aggregate change in occupation stocks Δs_t^A can be decomposed into changes in occupation stocks of each skill group (Δs_t^U and Δs_t^S) and changes in the composition of skill in the aggregate population. To see this, note that the occupation stock in the aggregate can be written as,

$$s_t^A = s_t^U \lambda_t + s_t^S \eta_t$$

where λ_t and $\eta_t \equiv (1 - \lambda_t)$ is the share of unskilled and skilled individuals in the population, respectively.

Changes in the occupations shares in the aggregate population are,

$$\begin{aligned}
\Delta s_t^A &= s_t^A - s_{t-1}^A \\
\Delta s_t^A &= \left[s_t^U \lambda_t + s_t^S \eta_t\right] - \left[s_{t-1}^U \lambda_{t-1} + s_{t-1}^S \eta_{t-1}\right] \\
\Delta s_t^A &= \left[s_t^U \lambda_t - s_{t-1}^U \lambda_{t-1}\right] + \left[s_t^S \eta_t - s_{t-1}^S \eta_{t-1}\right] \\
\Delta s_t^A &= \left[s_t^U \lambda_t + s_t^U \lambda_{t-1} - s_t^U \lambda_{t-1} - s_{t-1}^U \lambda_{t-1}\right] + \left[s_t^S \eta_t + s_t^S \eta_{t-1} - s_t^S \eta_{t-1} - s_{t-1}^S \eta_{t-1}\right] \\
\Delta s_t^A &= \left[s_t^U (\lambda_t - \lambda_{t-1}) + \lambda_{t-1}\left(s_t^U - s_{t-1}^U\right)\right] + \left[s_t^S (\eta_t - \eta_{t-1}) + \eta_{t-1}\left(s_t^S - s_{t-1}^S\right)\right] \\
\Delta s_t^A &= \lambda_{t-1} \Delta s_t^U + \eta_{t-1} \Delta s_t^S + \Delta \lambda_t s_t^U + \Delta \eta_t s_t^S
\end{aligned}$$

Using $\eta_t \equiv 1 - \lambda_t$ we have,

$$\Delta s_t^A = \underbrace{\lambda_{t-1} \Delta s_t^U}_{\text{Change in Unskilled Stocks}} + \underbrace{(1 - \lambda_{t-1}) \Delta s_t^S}_{\text{Change in Skilled Stocks}} + \underbrace{\Delta \lambda_t \left(s_t^U - s_t^S\right)}_{\text{Change in Composition}} \tag{C.2}$$

Equation (C.2) provides the decomposition of aggregate changes in occupation stocks into components due to i) changes in occupation stocks within the unskilled, Δs_t^U, weighted by the share of unskilled, ii) changes in occupation stocks within the skilled, Δs_t^S, weighted by the share of skilled and iii) the changes in skill composition $\Delta \lambda_t$ weighted by relative stocks of skilled and unskilled occupations. Figure C.1 plots the aggregate change Δs_t^A as well as each of its three components in the monthly CPS sample which includes the non-employed.

By combining (C.2) and (C.1) we can decompose aggregate changes in entrepreneurship into skill specific inflows and outflows as in Figure 4.

D Additional Evidence on Exit Rates

A striking finding from our analysis of flows in and out of entrepreneurship is the trend increase in transitions from entrepreneurship to employment. In this section, we explore the rise in exit rates in further detail. This analysis is particularly useful to test potential mechanisms that might be driving this trend. Complementing the findings in the main text, we find that the increase in exit rates is a secular trend that is observed similarly across the economy, across types of entrepreneurs and is present using alternative measures of exit. The neutrality of exit rates help us to preclude many economic mechanisms as the potential cause behind rising exit rates as they would bias trends in exit towards a particular subgroup of entrepreneurs.

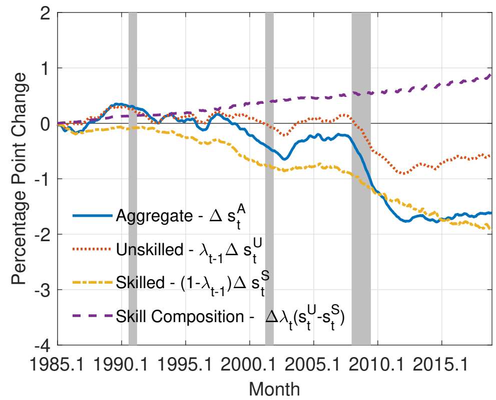


Figure C.1: Skill Group Decomposition of the Aggregate Change in Entrepreneurship Rates

Notes: The figure plots the percentage point change aggregate entrepreneurship rate relative to Jan. 1985 as well as each of the components of equation (C.2). Monthly changes are computed as annual changes divided by 12. Data is from the monthly CPS sample and includes both employed and non-employed.

Occupation and Industry As discussed in the main text, the trend increase in exit rates is similar for skill groups across industries (Table 5). Figure D.1 plots the exit rate by the stated industry and stated occupation of entrepreneurs. The figure shows that the trend increase in exit is evident and similar across all industries and occupations - roughly doubling over our sample period. While there are some level differences, the exit rates display strong co-movements to each other. For instance, the average of the correlations between exit rates for managers and the remaining occupations is around 0.80.

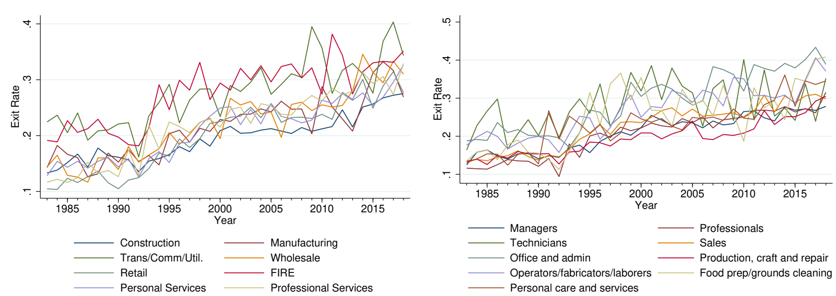


Figure D.1: Exit Rates by Industry and Occupation

Notes: The figure plots the share of entrepreneurs that transition to employment within a give year based on the industry (Panel (a)) and occupation (Panel (b)). Data is from the matched CPS sample and occupations are grouped following Autor and Dorn (2013). Due to small sample size, protective service occupations are not shown.

Length of Time in Entrepreneurship Next, we study the exit rate of entrepreneurs based on their stated length of time as an entrepreneur. Exit rates by business age are particularly instructive as they can help narrow down the theories behind rising exit rate. For instance, a rise in exit rates could be due to faster learning of entrepreneur's own ability over time in a model of passive learning, occupational choice and industry dynamics as in Jovanovic (1982). However, such a mechanism would predict that the increase in exit rate has been more pronounced for newer businesses – that is entrepreneurs that have spent only a little time in entrepreneurship. On the other hand, a theory which includes vintages of technology, such as Chari and Hopenhayn (1991) could generate higher exit rates by assuming faster generation of new technology in which case exit rates would increase most for older businesses.

Using data from the Job Tenure supplements of the CPS and matching it to the CPS basic monthly data, Figure D.2 shows that the trend increase in exit rate is similar regardless of how long an entrepreneur has been in business. As expected, we do observe that older businesses are less likely to exit. However, there is no significant difference in the time trends of older versus younger businesses. This goes against mechanisms of improved learning or vintage capital/technology where we expect the trend change in exit to be biased based on how long an entrepreneur has been in business.

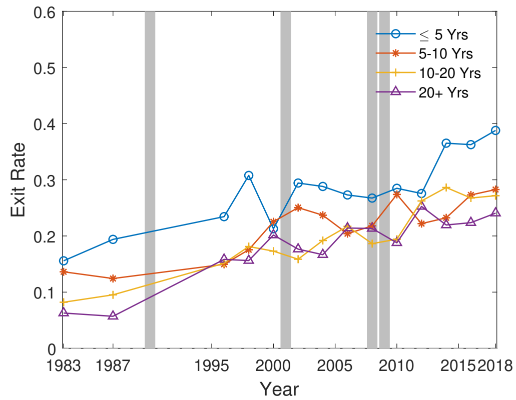


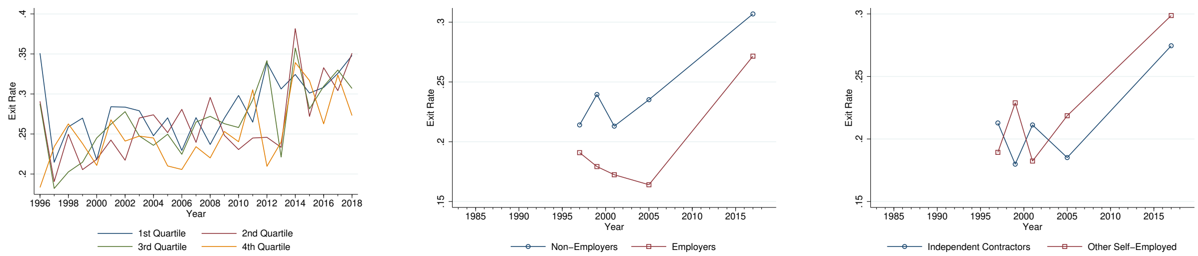
Figure D.2: Exit Rates by Time in Entrepreneurship

Notes: The figure plots the share of entrepreneurs that transition to employment within a give year based on their stated length of time in entrepreneurship. Data is from the CPS Job Tenure Supplement and the basic monthly surveys.

The neutrality of exit rates also precludes the idea of entrepreneurs undertaking riskier investments over time. Such a mechanism is explored in Vereshchagina and Hopenhayn (2009) and more recently Choi (2017) who argue that improved outside options to entrepreneurship encourage entrepreneurs to undertake riskier investments which in turn would lead to an increase in exit rates. Using administrative data, Choi (2017) finds that this mechanism is present primarily for new entrepreneurs suggesting that if the trend increase in exit rate is indeed driven by riskier investments in response to improved outside options, then the trend increase rise in exit rates would be strongest for new entrepreneurs.

The secular trend increase in exit rates in Figure D.2 is an important finding as it suggests that mechanisms present in alternative occupational choice models such as those just discussed are likely not the primary contributors of increasing exit rates.

Type of Entrepreneurship Next, we consider exit rates for different types of entrepreneurs. First, by matching CPS March Supplement respondents over time, we plot the exit rate of entrepreneurs based on their position in the entrepreneurs earnings distribution. Panel (a) of Figure D.3 shows that both rich and poor entrepreneurs exhibited similar trend increases in exit over time. Second, using data from the Contingent Worker Supplement merged with the basic monthly surveys, we show in Panel (b) that the exit rate for employers and non-employers evolves similarly. Related to this, Panel (c) uses the same data to show that the exit rate for self-employed independent contractors and all other self-employed evolves similarly over time. Taken together, Figure D.3 shows that the trend increase in exit rate is similar for different types of entrepreneurs.



(a) By Earnings Quartile (b) By Employer Status (c) By Independent Contractor Status

Figure D.3: Exit Rates by Type of Entrepreneurship

Notes: The figure shows the exit rate from entrepreneurship to employment for different types of entrepreneurs. Panel (a) plots the share of entrepreneurs that transition to employment within a given year by their earnings quartile in the distribution of entrepreneurial earnings. Data is from the matched March CPS sample. Panels (b) and (c) uses data from the CPS Contingent Worker Supplement and matches it to the CPS basic monthly surveys to measure the exit rate by entrepreneur type.

Alternative Measures of Exit Given the uniformity with which exit rates increase over time for different sub-samples, we next consider whether the rising trend in exit is due to changes in measurement of occupations over time in the CPS. For example, classifying entrepreneurs and employees may have become less precise over time. We test for this idea by constructing two alternative measures of exit rates. First, we redefine the exit rate as the share of entrepreneurs that transition to a non-managerial occupation. Second, we consider the exit rate to be the share of entrepreneurs that switch to employment in a 4-digit occupation that is different from their stated occupation in entrepreneurship. Figure D.4 shows that the trend increase in exit rates persists even for these alternative definitions of exit.

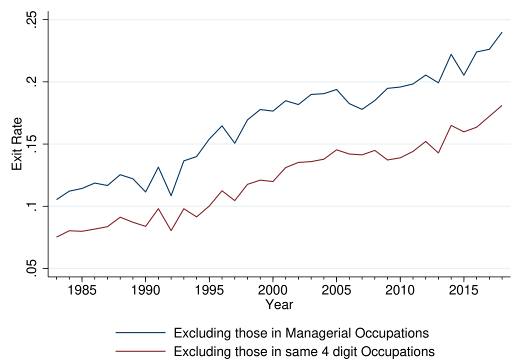


Figure D.4: Alternative Definitions of Exit Rate

Notes: The figure plots two alternative measure of the exit rate using the matched monthly CPS sample.

There may also have been increased mis-classification of occupational status over time. To check this we measure the share of "high frequency" switchers between entrepreneurship and wage employment over time. We define a high frequency switch as one in which an entrepreneur switches to employment for only one month and then returns back to entrepreneurship. For example, if an individual is self-employed in month 1, the possible labor market sequences for the next 3 months are SSS, SSE, SEE, EEE, SES, ESE, ESS, EES with the sequences SES, ESE, ESS considered as high frequency switches and where S and E represents self-employment and employment, respectively.

We find that since 1994 the share of high-frequency switchers (among all switchers) rose by around 7pp. It is initially relatively stable at around 7%. and in 2008 this share jumps to 12%. Since then, the share of high-frequency switchers has remained high fluctuating between 10 and 14%. So, while the share of high frequency switchers has increased since 1994 it accounts for a small fraction – under 14% – of all measured exit. Indeed, if we exclude all high frequency switches from our measure of exit, exit rates would have increased by around 73% rather than the observed 83% since 1994. As such, increased mis-classification is not the primary driver of the trend increase in exit rates. Further, high frequency switches need not necessarily be taken as evidence of spurious transitions when studying flows between employment and entrepreneurship. As entrepreneurship involves risk and experimentation, frequent switches are to be expected. Further still, an underlying increase in exit probabilities will also manifest in increased prevalence of high frequency switches.

Expected Time in Entrepreneurship Finally, we show that the length of time entrepreneurs expect to remain in entrepreneurship has declined over time. To do this, we use data from the Contingent Worker Supplement of the CPS which asks respondents how long they expect to remain in their occupation. Using this information, we estimate the coefficient on year dummies on a regression where the dependent variable is the length of time (in log years) an entrepreneur expects to remain self-employed. Controls include race, gender, gender, marital status, a quartic in years of experience, 2-digit industry controls and census region controls.

Table D.1 shows that relative to 1995, entrepreneurs in 2005 and 2015 expected to spend around 4.9% and 5.4% fewer years in entrepreneurship, respectively. This effect is significant and represents around an expected decrease of 1 year in entrepreneurship. Further, this finding is consistent with an increase in the exogenous probability of exit which we introduce in our benchmark model.

Table D.1: Estimated Coefficient on Year Dummies (rel. to 1995) on Expected Time in Entrepreneurship

	Coefficient	p-value
1997	-0.007	0.74
1999	-0.031	0.11
2001	-0.088	0.00
2005	-0.049	0.01
2017	-0.054	0.01

Notes: The table reports the coefficient β_t from the regression, $l_{it} = \alpha + \Sigma_{t=1995}^{2015} \beta_t t + \mathbf{X_i} + \epsilon_i t$, where l_{it} is the log years entrepreneur i expects to remain in entrepreneurship. t is the year with the excluded year 1995. $\mathbf{X_i}$ is a vector of controls for race, gender, gender, marital status, a quartic in years of experience, 2-digit industry controls and census region controls. Data is from the Contingent Worker Supplement of the CPS.

Overall, the evidence presented in this section shows that the trend increase in transitions from entrepreneurship to employment is ubiquitous. It is observed uniformly across the economy, across different types of entrepreneurs, is robust to more restrictive definitions of exit and not driven by survey mis-classification. Further, it is accompanied by a decrease in the length of time individuals expect to remain in entrepreneurship. The ubiquity and skill-neutrality of increasing exit rates allow us to preclude several candidate economic mechanisms as potential drivers of rising exit. These mechanisms include changes in individual learning, technology vintages and investment behaviour as they would predict more pronounced changes in exit for some subgroups of entrepreneurs rather than the uniform increase that we document since 1983.

Given this, we generate an increase in exit rates in our quantitative analysis by increasing the probability of exogenous entrepreneur exit χ.

E Quantitative Analysis Appendix

This appendix includes details of the quantitative analysis as well as additional quantitative results. We also discuss the sensitivity of the model to alternate changes in parameters.

E.1 Calibration Details

The Impact of an Increasing Skill Premium

Starting from our baseline economy which matches the 1983 U.S. economy, our first quantitative exercise introduces i) a rising supply of skilled workers $\{\lambda_t\}$ and ii) technological change $\left\{\left(\frac{B}{A}\right)_t, \left(\frac{\theta_s}{\theta_u}\right)_t\right\}$ over time t. We assume that agents are myopic, being surprised each period with an updated set of parameters and study the resulting impact on measures of entrepreneurship on the transition path from the baseline economy.

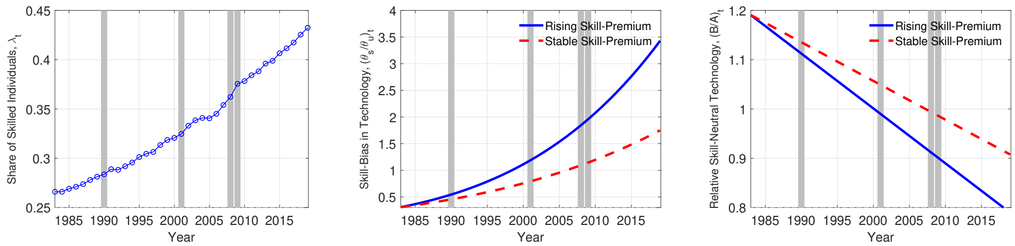
Table E.1: Re-calibrated Parameter Values

	λ	$\frac{\theta_s}{\theta_u}$	$\frac{B}{A}$
Baseline (1983 values)	0.27	0.31	1.19
Benchmark: Increasing skill premium (2019 values)	0.43	3.40	0.83
Counterfactual: Stable skill premium (2019 values)	0.43	1.72	0.95

Notes: The first row of the table reports baseline parameter values. The second row reports parameter values from a joint calibration such that the skill premium and employment share of non-entrepreneurial sector match the observed levels in 2019. The third row reports parameter values from a joint calibration such that the employment share of non-entrepreneurial sector matches the observed levels in 2019 while the the skill premium remains stable at 1983 levels. In our calibration we continue with the normalization that $A = 1$ and $\theta_u = 1$.

The time path $\{\lambda_t\}$ is the share of colleges graduates in the CPS. The time paths for the parameters governing technological change are calibrated. In particular, we solve for the stationary equilibrium of the model by taking all other parameters as fixed and setting the supply of skills to be as in 2019. Then, we jointly calibrate $\left(\frac{B}{A}\right)$ and $\left(\frac{\theta_s}{\theta_u}\right)$ so that the model equilibrium matches, respectively, the worker skill premium and the employment share of the non-entrepreneurial sector in 2019. In our counterfactual analysis, which aims to quantify the impact of the change in the worker skill premium, we re-calibrate the technology parameters such that the skill premium remains stable while the non-entrepreneurial sector matches the size observed in 2019. The time paths of $\left\{\left(\frac{B}{A}\right)_t, \left(\frac{\theta_s}{\theta_u}\right)_t\right\}$ are simple monotonic interpolations between the baseline parameter value and the calibrated 2019 values.

Table E.1 reports these re-calibrated parameter values and contrasts them with the baseline values. To generate an increasing or stable skill premium between 1983 and 2019, the parameter θ_s increases (relative to θ_u). That is, there is skill-biased technological change which serves to raise the demand for skilled workers to counteract the concurrent increase in the supply of skilled workers. In the



(a) Share of College Graduates, λ_t

(b) Skill-Biased Productivity, $\frac{\theta_s}{\theta_u}$

(c) Skill-Neutral Productivity, $\frac{B}{A}$

Figure E.1: Time Path of Parameters, with technological change

data, the employment share of the non-entrepreneurial sector increases by around 6pp since 1983 from around 46% to 52%.[12] In order for the model to match this increase in employment share (jointly with a rising θ_s), the relative aggregate productivity term $\frac{B}{A}$ *declines*. That is, the skill-neutral component of entrepreneur productivity increases relative to the skill-neutral component of non-entrepreneurial productivity.

To understand why B declines relative to A, consider the calibration where the term $\frac{B}{A}$ is held constant and we introduce only skill-biased technological change via an increase in $\frac{\theta_s}{\theta_u}$. Since the non-entrepreneurial sector does not feature a limited span of control, the same change in θ_s(relative to θ_u) leads to a much larger increase in the overall productivity in the non-entrepreneurial sector relative to the entrepreneurial sector. That is, the constant returns to scale non-entrepreneurial sector can leverage changes in skill specific productivity much more so than the decreasing returns to scale entrepreneurial sector. Indeed, if we re-calibrate only θ_s to match the skill premium, the employment share of the non-entrepreneurial sector increases to around 90%. So, in order to match the observed changes in non-entrepreneurial sector, the model implies skill-neutral technological changes that improves the relative productivity of the entrepreneurial sector. These changes can be interpreted as represented the sector-specific but skill-neutral impact of recent technological advances that have led to the declining cost of information technology (IT).

The share of college graduates and the parameters governing technological change that are fed in to the model to generate the transition dynamics in response to technological change are shown in Figure E.1. The change in the share of college graduates is exactly the data counterpart from the CPS. We impose a linear interpolation in the time path of skill-neutral productivity and a strictly monotonic convex interpolation for skill-biased productivity. To construct this time path, we take the initial and final parameter values $\left(\frac{\theta_s}{\theta_u}\right)_{1983}$, $\left(\frac{\theta_s}{\theta_u}\right)_{2019}$ and construct a linear interpolation between $\left(\frac{\theta_s}{\theta_u}\right)_{1983}^{\Xi}$ and $\left(\frac{\theta_s}{\theta_u}\right)_{2019}^{\Xi}$. We then take this linear interpolation and raise it to the power of $\frac{1}{\Xi}$. We set $\Xi = 0.20$ and this value is chosen so that the model closely tracks the observed evolution of the skill premium over time.

The Impact of Increasing Exit Rates

In the exercise with rising exit rates, we jointly re-calibrate $\left\{\frac{B}{A}, \frac{\theta_s}{\theta_u}, \chi\right\}$ to match the size of the non-entrepreneurial sector, skill premium and aggregate exit rate in 2019, respectively, while imposing

[12]Since the BDS only includes data up to 2018, we apply the 2018 measure of the employment share of large firms (>500 employees) when calibrating the model.

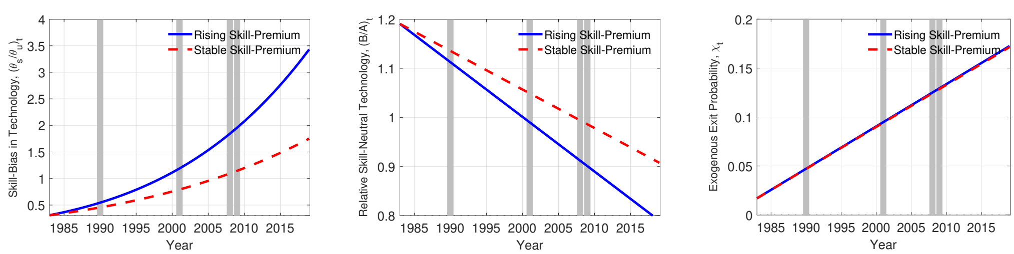
the observed share of college graduates as in the data.

Table E.2: Re-calibrated Parameter Values, with Increasing Exit

	λ	$\frac{\theta_s}{\theta_u}$	$\frac{B}{A}$	χ
Baseline (1983 values)	0.27	0.31	1.19	0.02
Benchmark: Increasing skill premium (2019 values)	0.43	3.43	0.79	0.17
Counterfactual: Stable skill premium (2019 values)	0.43	1.75	0.91	0.17

Notes: The first row of the table reports baseline parameter values. The second row reports parameter values from a joint calibration such that the skill premium, employment share of non-entrepreneurial sector and aggregate exit rate matches the observed levels in 2019. The third row reports parameter values from a joint calibration such that the employment share of non-entrepreneurial sector and the aggregate exit rate matches the observed levels in 2019 while the the skill premium remains stable at 1983 levels. In our calibration we continue with the normalization that $A = 1$ and $\theta_u = 1$.

Table E.2 reports the re-calibrated parameter values. Compared to Table E.1, the estimated values governing technological change are quite similar when the exogenous exit rate increases. The estimated increase in χ is around 15pp between 1983 and 2018 this is roughly equal to the observed change in aggregate exit rates (from 14% in 1983 to 28% in 2019).



(a) Skill-Biased Productivity, $\frac{\theta_s}{\theta_u}$

(b) Skill-Neutral Productivity, $\frac{B}{A}$

(c) Exit Probability, χ_t

Figure E.2: Time Path of Parameters, with technological change and increasing exit rates

The time paths for the parameters in the quantitative exercise with both technological change and increasing exit rates are plotted in Figure E.2. We apply the same process as in the case with only technological change to generate the time path of $\frac{\theta_s}{\theta_u}$. The change in exit probability χ_t is simply a linear interpolation between the initial and final calibrated values.

E.2 Additional Quantitative Results

Figure E.3 plots the evolution of the skill premium and shows that the benchmark economy closely tracks the data. Notice, in the counterfactual economy, we only impose that the skill premium in 2019 and 1983 be the same. Along the transition path of the counterfactual economy, the skill premium increases slightly before returning to its original value. A calibration which ensures a stable skill premium at each point along the transition path yields identical implications regarding the interaction of the skill premium and the skill-biased decline in entrepreneurship.

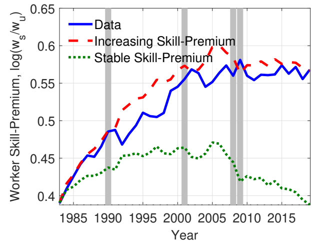
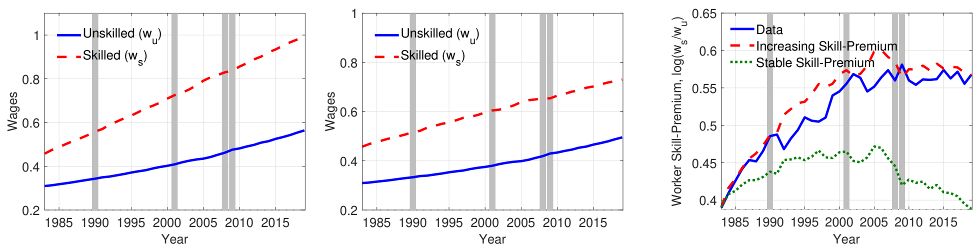


Figure E.3: Transition Dynamics of the skill premium, without increasing exit

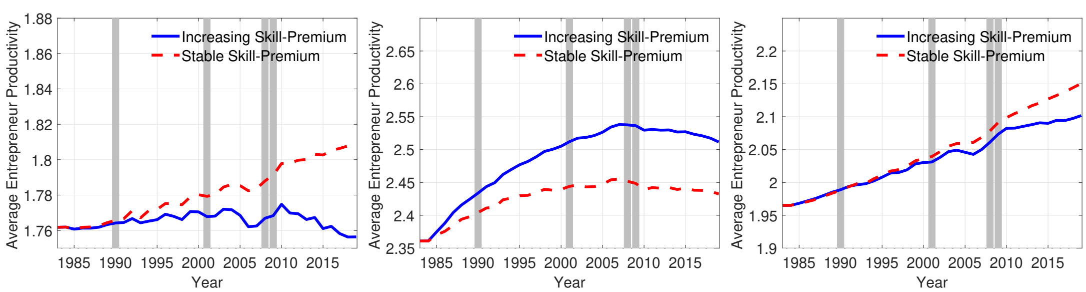
The wages and skill premium when exit rates are increasing is plotted in Figure E.4 and are very similar to those in Figure 15.



(a) Increasing skill premium (b) Stable skill premium (c) Transition Dynamics of the skill premium

Figure E.4: Wages and the skill premium, with increasing exit

Figure E.5 plots the evolution of average productivity when exit rates increase. These are also very close to the case without increasing exit.

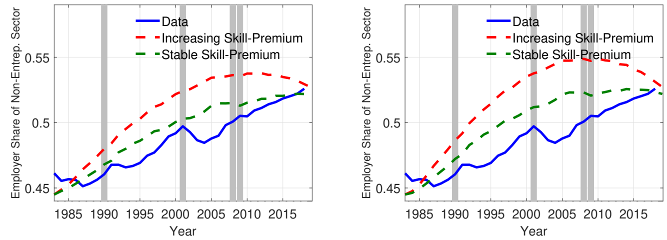


(a) Unskilled Entrepreneurs (b) Skilled Entrepreneurs (c) All Entrepreneurs

Figure E.5: Transition Dynamics of Average Entrepreneur Productivity, with increasing exit

We also report the model implied size of the non-entrepreneurial sector in Figure E.6. It shows that the model slightly overestimates the employment share of the non-entrepreneurial sector along the transition path. Imposing non-linear time paths for $\frac{B}{A}$ would improve the fit of the model without significantly changing the results of our analysis.

Relative Earnings In Panels (a) and (b) of Figures E.7 and E.8, we plot the ratio of the average earnings of entrepreneurs and workers as implied by the model with technological and



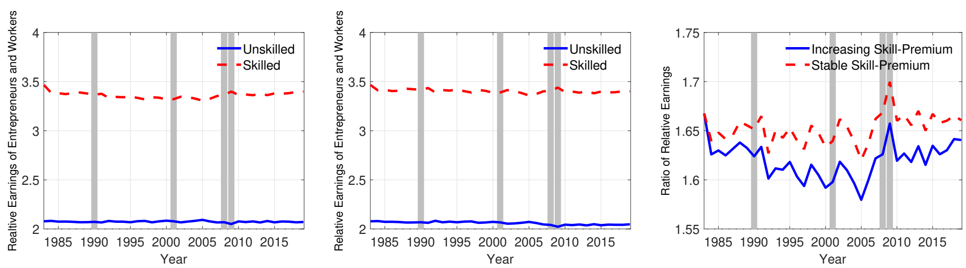
(a) Technological Change Only

(b) Technological Change and Increasing Exit

Figure E.6: Employment Share of Non-Entrepreneurial Sector

Notes: Data is from the 2018 vintage of the Business Dynamics Statistics and reports the employment share of firms with over 500 employees.

the model with technological change and increasing exit, respectively. These measures correspond roughly to the relative earnings shown in Figure 6. Qualitatively, the model matches the higher relative earnings for skilled individuals. Quantitatively, the model over-estimates the levels of relative earnings. This is consistent with a model that abstracts from the non-pecuniary motives for entrepreneurship – as emphasized in Hamilton (2000).



(a) Increasing skill premium

(b) Stable skill premium

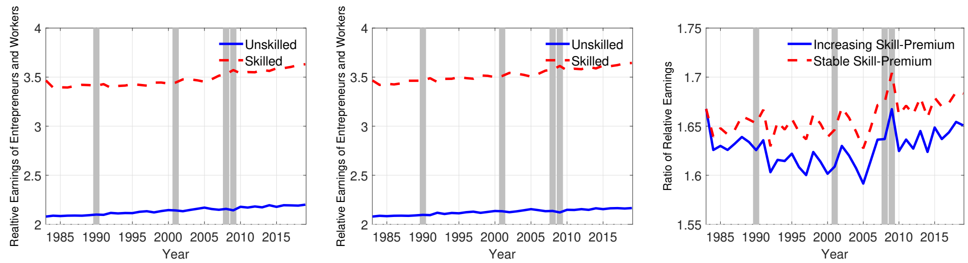
(c) Ratio of Skilled and Unskilled

Figure E.7: Relative Average Earnings of Entrepreneurs and Workers, with Technological Change

Notes: Panels (a) and (b) plots the ratio of average earnings of entrepreneurs to average earnings of workers by skill in the benchmark increasing skill premium and counterfactual stable skill premium economies, respectively. Panel (c) plots the ratio of skilled and unskilled relative earnings.

In the data, we see convergence in relative earnings for both skilled and unskilled entrepreneurs. To help evaluate whether the model implies similar convergence, Panel (c) of Figures E.7 and E.8 plot the ratio of relative earnings of skilled and unskilled individuals. From these panels, there is evidence of convergence in the benchmark economies (solid blue line in Panel (c)) – particularly prior to 2008.

When the skill premium is stable, the ratio of relative earnings is also stable. When the worker skill premium increases, the earnings of skilled *workers* increase relative to the unskilled. On the other hand, technological changes that are responsible for the skill premium impact both skilled and unskilled *entrepreneurs* in the same manner as operation of the production function is skill-neutral. As a result, the ratio of skilled entrepreneurs to skilled worker earnings declines relative to the ratio of unskilled entrepreneur earnings to unskilled worker earnings. When the skill premium is stable, both skilled and unskilled workers earnings change similarly as do their returns to entrepreneurship leading to a stable ratio of relative earnings (dashed red line in Panel (c)).

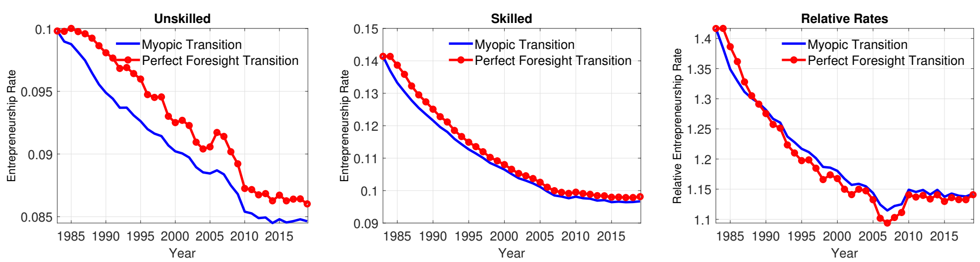


(a) Increasing skill premium (b) Stable skill premium (c) Ratio of Skilled and Unskilled

Figure E.8: Relative Average Earnings of Entrepreneurs and Workers, with Technological Change and Increasing Exit

Notes: Panels (a) and (b) plots the ratio of average earnings of entrepreneurs to average earnings of workers by skill in the benchmark increasing skill premium and counterfactual stable skill premium economies, respectively. Panel (c) plots the ratio of skilled and unskilled relative earnings.

Perfect Foresight Transition We also compute transition dynamics assuming that agents have perfect foresight about the time path of parameters. We find that this has very little impact on our results. Indeed, equilibrium wages in the model with perfect foresight are almost exactly equal to equilibrium wages with myopic agents. To illustrate the similarity in results, Figure E.9 show the skill specific entrepreneurship rate in response to technological change with an increasing skill premium (benchmark economy). The implied share of entrepreneurs correlates well for both skilled and unskilled individuals as do the relative rates.



(a) Unskilled (b) Skilled (c) Relative Rates

Figure E.9: Transition Dynamics with Perfect Foresight

E.3 An Alternative Decomposition

Here, we conduct an alternative decomposition exercise which is instructive for understanding the impact of each one of the parameter changes introduced in our quantitative analysis. To do this, we start with the baseline 1983 calibration and change the value of only one parameter at a time while holding all other parameter values fixed. In particular, we change the baseline parameter values – one at a time – to those reported in the second row of Table E.2. We then compare the stationary equilibrium measures of entrepreneurship to their baseline values. Table E.3 reports the results of this exercise.

Share of College Graduates The first row shows that an increase in the only the share of college graduates leads to an increase in the aggregate entrepreneurship rate. The entrepreneurship rates for unskilled and skilled individuals move in opposite directions, increasing by 53% for skilled and decreasing by 34% for the unskilled. Entry and exit rates mirror the entrepreneurship rates.

Increasing the supply of skilled individuals or equivalently lowering the supply of unskilled individuals puts upward pressure on unskilled wages and downward pressure on skilled wages. With no other changes in the model economy, an increase in college graduates leads to differential shifts in the wages of skilled and unskilled workers, which lowers unskilled entrepreneurship rates and increases skilled entrepreneurship rates. Combined with the shift in the composition of the population toward skilled individuals, this (general equilibrium) response of wages raises aggregate entrepreneurship and pushes against the skill-biased decline in entrepreneurship.

Table E.3: Measures of Entrepreneurship, Baseline Calibration = 1

	Entrepreneurship Rate			Entry Rate			Exit Rate		
	Aggregate	Unskilled	Skilled	Aggregate	Unskilled	Skilled	Aggregate	Unskilled	Skilled
Share of College Graduates, λ	1.18	0.66	1.53	1.18	0.67	1.63	1.10	0.82	1.19
Skill-Biased Technological Change, $\frac{\theta_s}{\theta_u}$	0.13	0.14	0.11	0.12	0.14	0.10	1.04	1.04	1.03
Skill-Neutral Technological Change, $\frac{B}{A}$	1.71	1.84	1.45	1.89	2.04	1.58	1.01	1.01	1.01
Probability of Exit, χ	0.74	0.71	0.78	1.41	1.31	1.62	1.95	1.90	2.13

Skill-Biased Technological Change Next, we increase the parameter which governs skill-bias in technology, $\frac{\theta_s}{\theta_u}$, increasing it from a baseline value of 0.31 to 3.43 as in our quantitative analysis.[13] In the model economy, this increase enhances the overall productivity of the production function. That is, for the same innate ability z and idiosyncratic demand shock κ, agents are able to produce more output, thus raising the returns to entrepreneurship and encouraging agents to pursue it.

However, since the non-entrepreneurial sector does not have a limited span of control, the same improvement of the production function is much more beneficial to this sector thus raising demand for workers from the non-entrepreneurial sector, increasing wages and discouraging the pursuit of entrepreneurship. Further, as this parameter change is inherently skill-biased, the increase in wages is larger for skilled workers.

The second row of Table E.3 shows that the entrepreneurship and entry rates decline dramatically while the exit rate increases very slightly when we increase $\frac{\theta_s}{\theta_u}$. This suggests that the increase in worker demand from the non-entrepreneurial sector sufficiently outweighs the improvement in entrepreneur's production function resulting in a rightward shift of the entrepreneur productivity threshold. Indeed, in the model, the employment share of the non-entrepreneurial sector doubles to around 93%. As a result, aggregate, unskilled and skilled entrepreneurship rates decline by 87, 86 and 89%, respectively. Due to the skill-biased nature of technological change, the decline in entrepreneurship is also slightly biased towards the skilled.

Skill-Neutral Technological Change The third row of Table E.3 shows the response of the model economy when there is only skill-neutral technological change. That is, we decrease B relative to A from 1.19 to 0.79 as in our quantitative analysis. In response to this change, the share of entrepreneurs and entry rates increase while exit rates remain stable.

[13] Note that since the change in $\frac{\theta_s}{\theta_u}$ is not accompanied by an increase in the supply of college graduates, the rise in the skill premium following this change is much larger than that observed in the data.

This is intuitive; as the entrepreneurial sector becomes relatively more productive, it encourages lower productivity z agents to pursue entrepreneurship. At the same time, worker demand from the non-entrepreneurial sector declines lowering wages. Both forces push the threshold at which agents become entrepreneurs to decline. As a result, entrepreneurship and entry rates increase.

Notice, the increase in entrepreneurship is larger for the unskilled since the decline in wages of unskilled workers is larger. The reason for this is that the skill premium does not change when there is only skill-neutral technological change. As such, when worker wages decline, they must decline more for the unskilled to maintain a stable skill premium.

Comparing these results to those with only changes in $\frac{\theta_s}{\theta_u}$ shows that these two parameter changes move the entrepreneurship (and entry) rates in opposite directions. Further, both these changes introduce a skill bias in measures of entrepreneurship − exactly due to their interaction with the skill premium. As such, considering both forms of technical change together is important when evaluating the evolution of entrepreneurship.

Increase in Exit Rates Finally, the last row of Table E.3 reports the impact of increasing only the probability of exogenous exit χ. Intuitively, as χ increases, it lowers the value of entrepreneurship since agents are more likely to switch to wage work which yields lower utility. This discourages entrepreneurship. By design, the exit rate should increase which should also encourage more entry from those experiencing exit. The response of the model is in line with this intuition. Entrepreneurship rates decline, in a largely skill-neutral manner while entry and exit rates increase.

E.4 Sensitivity Analysis

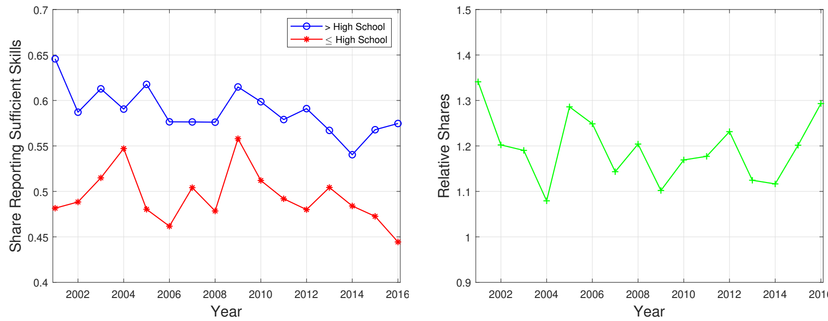
Here, we discuss the sensitivity of our model to changes in other features of the model that might potentially explain the aggregate and skill specific changes in entrepreneurship.

Changes in Entrepreneur Productivity In our quantitative analysis, we calibrate the productivity distributions $G_a(z)$ for $a \in \{u, s\}$ to match entrepreneurship rates in 1983 and then keep these distributions fixed over time. It may be possible that there have been changes in these distributions over time. Indeed, one aspect of skill-biased technical change may have involved skill-biased changes in the abilities of individuals to pursue entrepreneurship.

This possibility is compelling as it could fully explain the skill-biased decline in our empirical findings while implying a minimal role for the income structure of workers. From the standpoint of our theory it would mean that the distributions $G_a(z)$ are changing over time so as to exactly match the observed share of entrepreneurs. Given the potential explanatory power of this story, we think it is important to utilize empirical evidence to discipline such changes. However, we do not find evidence supporting the idea that those with post-secondary education are relatively less prepared to engage in entrepreneurship. We discuss this evidence below.

First, conditional on selecting into entrepreneurship, the evolution of the entrepreneurial skill premium − as documented in our empirical evidence − suggests that there have not been significant skill-biased changes in returns to entrepreneurship.

The more interesting possibility is that there have been skill-biased changes in the ability (perceived or actual) of individuals to pursue entrepreneurship which has discouraged entry into entrepreneurship. Such changes could take many forms, such as post secondary education no longer providing an advantage in starting a business. To test this idea, we use data from the Global Entrepreneurship



(a) Share Reporting Sufficient Skills to Start Business

(b) Relative Shares

Figure E.10: Perception of Entrepreneurial Capability

Notes: The figure uses data from the 2001 to 2016 Global Entrepreneurship Monitor Individual Adult Population Surveys for the U.S. Sample includes those aged between 25 and 64 that do not operate their own business. Panel (a) plots the share of respondents, by education, that report having sufficient "*knowledge, skill and experience required to start a new business?*". Panel (b) plots the ratio of the shares in Panel (a). The micro-data can be found at https://www.gemconsortium.org/data

Monitor (GEM) which conducts an annual survey designed to document perceptions towards entrepreneurship. Since 2001, the GEM Individual Adult Population Survey has asked respondents, "*Do you have the knowledge, skill and experience required to start a new business?*". Importantly, this survey question is asked of those that are *not* entrepreneurs and also includes information on educational attainment. We can use this survey question to measure the perceived entrepreneurial capabilities of skilled and unskilled respondents and test the idea that skilled individuals are relatively less prepared to engage in entrepreneurship now compared to the past.

Panel (a) of Figure E.10 plots the share of respondents that report having sufficient "*knowledge, skill and experience required to start a new business*", by respondents' educational attainment.[14] The figure shows that for both education groups perceived entrepreneurial ability is trending down. That is, respondents in both education categories have felt less capable of pursuing entrepreneurship over time. Panel (b) plots the ratio of the shares in Panel (a) and shows that the relative perceived capabilities does not display a significant time trend.[15]

Table E.4, shows the results from a similar analysis where we estimate differences in time trends by educational status using a probit regression. The key message remains the same – there is no significant difference by education in the share of respondents that report having sufficient skills to operate a business.

Taken together, the evidence presented here does not provide strong empirical support for the hypothesis of skill-biased changes in entrepreneurial ability. As such, we keep this fixed over time in our quantitative analysis.

Changes in Risk Consistent with the stable mean and dispersion of entrepreneurial earnings growth in Figure 7, we keep the AR1 process governing demand shocks κ to be fixed over time.

[14]The reporting of education in the GEM survey does not allow us to apply the same skilled-unskilled definition as in our paper.

[15]The trend coefficient for respondents with at most a high school degree is -0.002 with an associated p-value of 0.26. The analogous coefficient for those with more than a high school degree is -0.004 with a p-value of 0.01. The trend coefficient on the ratio of shares is -0.003 with p-value of 0.50.

Table E.4: Marginal Effect of Education on Perceived Entrepreneurial Capability

	(1)	(2)	(3)
>High School	0.237***	0.226***	0.244***
	(0.0169)	(0.0191)	(0.0193)
Year	-0.006***	-0.00338	-0.00380
	(0.002)	(0.00280)	(0.00282)
>High School × Year		-0.00407	-0.00256
		(0.00346)	(0.00348)
Additional Controls	N	N	Y
Observed Probability	0.554	0.554	0.554
N	31,407	31,407	31,407
Pseudo R^2	0.006	0.006	0.027

Notes: The table shows the marginal effects estimated on a probit regression from observations in the GEM Individual Adult Population Surveys,

$$d_{it} = \alpha + \beta e_i + \gamma t + \nu\,(e_i \times t) + \sigma X_{it} + \epsilon_{it}$$

where the dependent variable is an indicator d_{it} equal to 1 if respondent i reports having sufficient skills to start a new business and is 0 otherwise. The independent variables include i) education status e_i defined as a dummy variable equal to 0 for those with at most a high school degree 1 otherwise, ii) a time trend variable t which is equal to 1 in the year 2001, 2 in 2002 and so on, iii) an interaction term $e_i \times t$. Additional controls X_{it} include a gender dummy and a quadratic in age. Robust standard errors are reported in parentheses. *** indicates statistical significant at the 1% confidence level.

However, recent work by Decker et al. (2020) argues that the dispersion of shocks faced by businesses have increased. This study also finds that responsiveness to shocks has declined more so (due to, for example adjustment costs) which could explain the stable volatility we document. While the study of shocks versus responsiveness is beyond the scope our paper, it is instructive to analyze the impact of an increase in the variance of idiosyncratic shocks in our model. In particular, we evaluate whether rising dispersion can help explain the aggregate or skill-biased declines in entrepreneurship. To do this, we keep the model parameters fixed at their baseline level and increase the parameter ν by 25% from a value of 0.16 to 0.20.[16]

The first row of Table E.5 reports the measures of entrepreneurship, relative to the baseline economy, following an increase in the variance of shocks. The model economy exhibits a modest and skill-neutral decrease in the entrepreneurship rate and skill-neutral increases in entry and exit rates. These results are intuitive; an increase in the dispersion of κ shocks leads to higher exit rates as the probability of receiving a bad shock increase. The entry rates increase accordingly. The modest decline in the share of entrepreneurs is due to a decrease in the expected value of entrepreneurship as bad draws become more likely and (re)entry is associated with an entry cost. Notice, an increase in ν leads to skill-neutral changes in entrepreneurship which gives us confidence that changes in the process governing κ do not generate skill-biased changes in entrepreneurship.

Changes in Span of Control The span of control parameter, η governs the earnings and employment level of entrepreneurs. It is calibrated to match the top 5% earnings share in 1983 and is kept fixed in our quantitative analysis. However, there have been significant increases in earnings inequality over the period we study. This corresponds to increases in the span of control parameter in our model. We study the impact of increasing η by increasing it 5% from the baseline value of

[16]This is a significant change and the model implied dispersion of entrepreneur earnings growth increase by almost 50%.

Table E.5: Measures of Entrepreneurship, Baseline Calibration = 1

	Entrepreneurship Rate			Entry Rate			Exit Rate		
	Aggregate	Unskilled	Skilled	Aggregate	Unskilled	Skilled	Aggregate	Unskilled	Skilled
Increase in ν	0.98	0.98	0.98	1.11	1.11	1.11	1.13	1.14	1.13
Increase in η	0.88	0.85	0.94	0.90	0.88	0.94	1.05	1.06	1.01
Increase in τ	0.78	0.74	0.86	0.44	0.40	0.53	0.58	0.56	0.63

0.62 to 0.65.[17]

The second row of Table E.5 reports the measures of entrepreneurship in response to this change. The aggregate entrepreneurship rate declines by 12% with a strong decliner for unskilled individuals (15% vs. 6%). Increases in η shift the composition towards skilled entrepreneurs rather than the unskilled. The entry rate also exhibits similar percentage declines while exit rates increase moderately – more so for the unskilled. As η increases, entrepreneurs are able to manage more workers increasing the demand and price of workers. Further, η makes the returns to entrepreneurship more convex in productivity, these two changes, in general equilibrium, lead to a rightward shift in the productivity threshold at which agents pursue entrepreneurship. This mechanism is present in standard models of occupational choice (see for example Figure 2 in Garicano and Rossi-Hansberg (2015)).

Changes in Entry Costs Finally, we consider the role of changing entry costs. Recent work has argued that there have been increases in entry costs in the form of more onerous regulation or other costs associated with starting a business (see for example Bollard et al. (2016)). We evaluate the implications of such increases in our model by changing the share of profits paid at entry into entrepreneurship, τ. In particular, we double the value of τ from around 0.25 to 0.50 and report the resulting measures of entrepreneurship in the third row of Table E.5.

Increasing the cost of entry lowers the entrepreneurship rate, particularly so for the unskilled. The decline in entry and exit rates is much more pronounced with the aggregate entry (exit) rate falling by over 50 (40)%. The decline in entry rates in response to an increase in entry costs is straightforward to understand. As it becomes costlier to enter, fewer agents choose to do so. Similarly, increasing entry costs also lowers the option value of exiting since agents would have to pay a higher cost if they choose to re-enter. This leads to a lower exit rate. As a result, an increase in entry costs also lowers the value of entrepreneurship which leads to fewer agents pursuing it. Overall, while increasing entry costs could explain the aggregate decline in entrepreneurship, it would fail to account for the skill-biased declines we observe in the data.

[17] As in most occupational choice model, the model in our paper is quite sensitive to changes in the span of control parameter. Hence, we adjust this parameter by a relatively small amount to illustrate the model's response to such changes.