Online Appendix of:
Skill-Biased Entrepreneurial Decline

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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

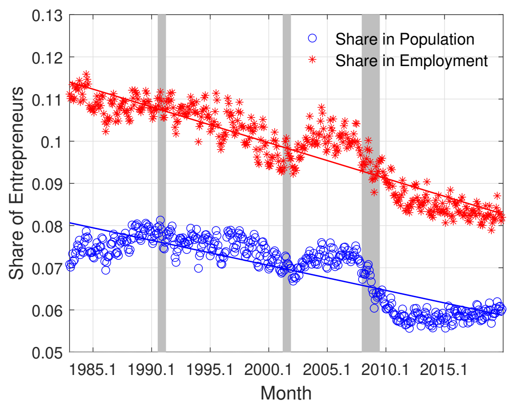
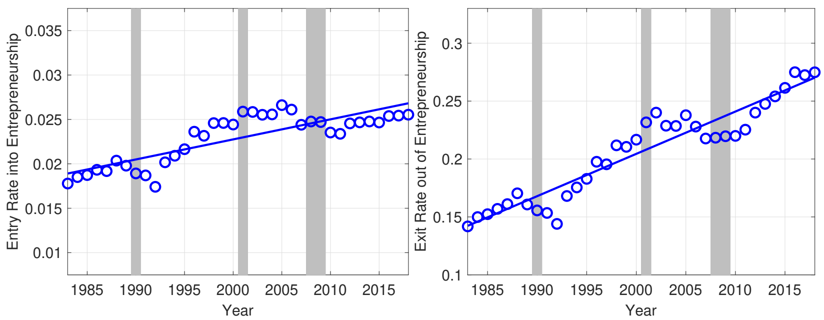


Figure A.1: Share of Entrepreneurs

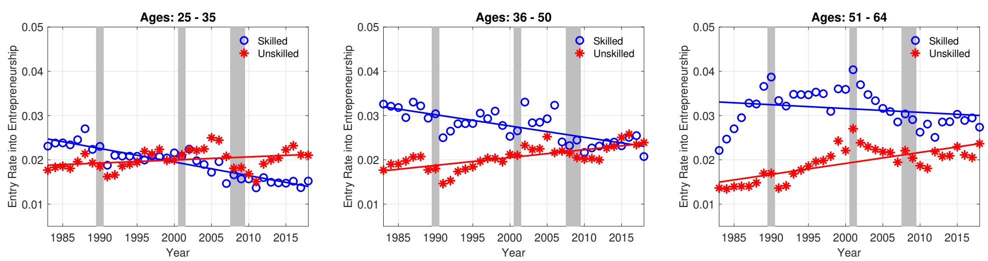
Notes: The figure plots the share of entrepreneurs in the population and the share in total employment. The sample includes full-time, non-agricultural employees, entrepreneurs and all those non-employed aged between 25 and 64. Data is from the Jan. 1983 to Dec. 2019 CPS basic monthly surveys. The shaded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



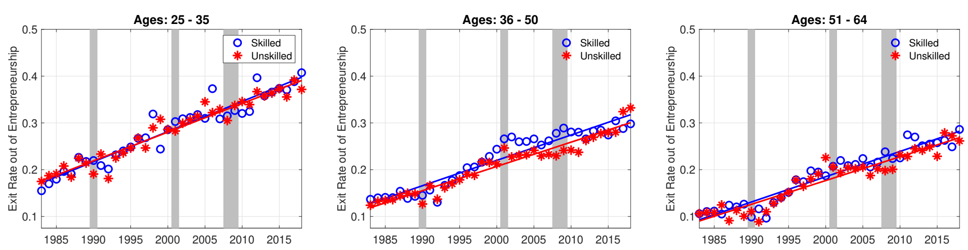
(a) Entry Rate (b) Exit Rate

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.



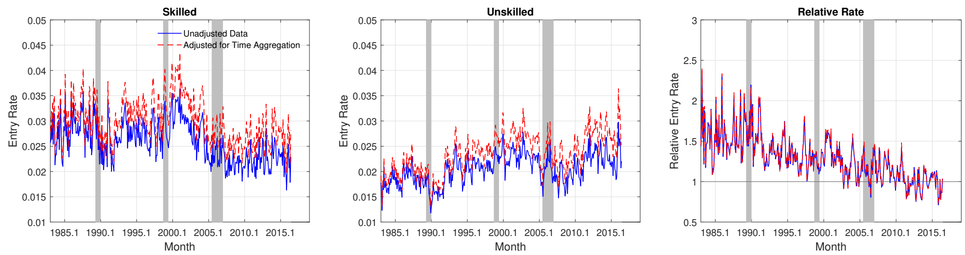
(a) Entry Rate



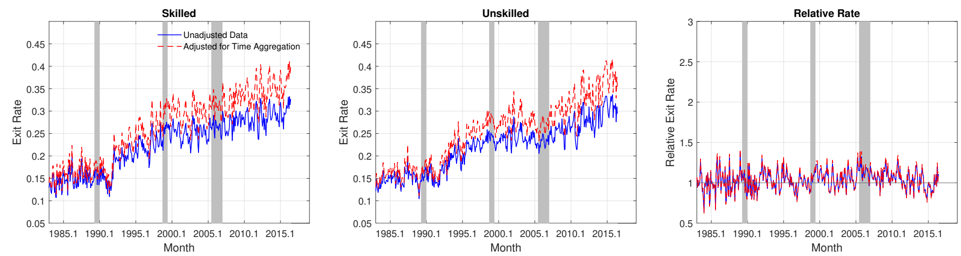
(b) Exit Rate

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).

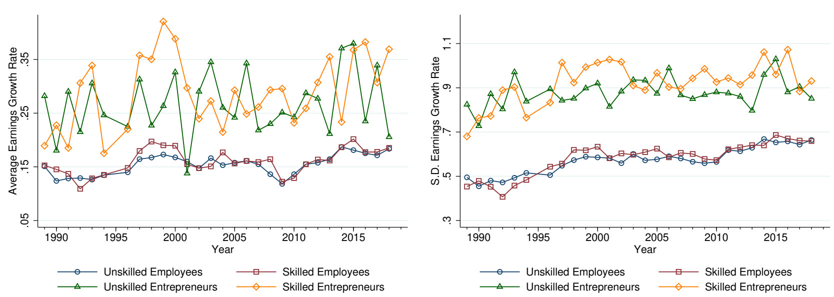


Figure A.5: Average and Standard Deviation of Earnings Growth Rates, by skill

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.

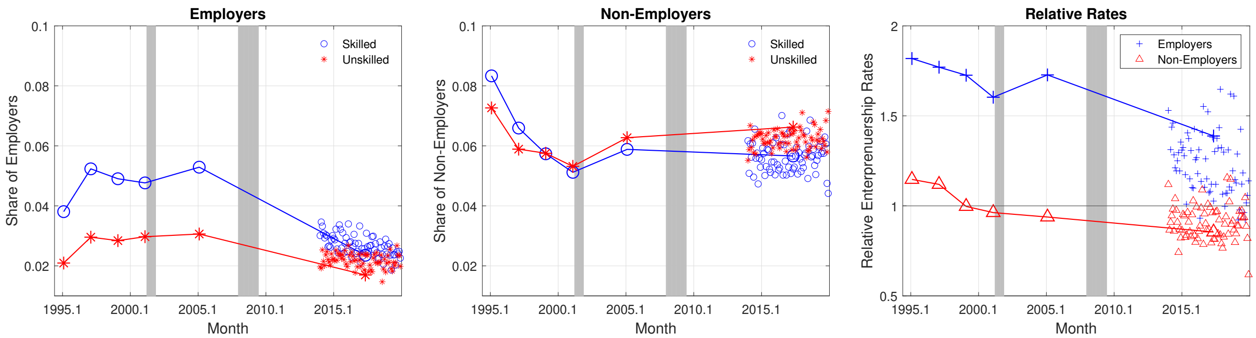
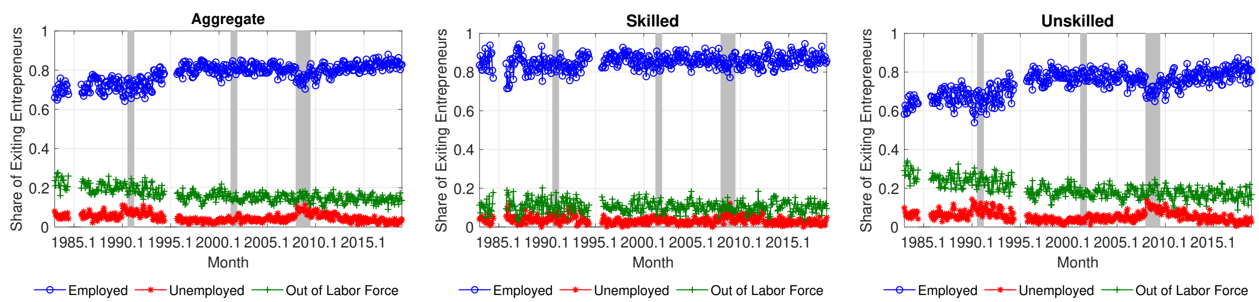


Figure A.6: Entrepreneurship Rates by Employer Status

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.

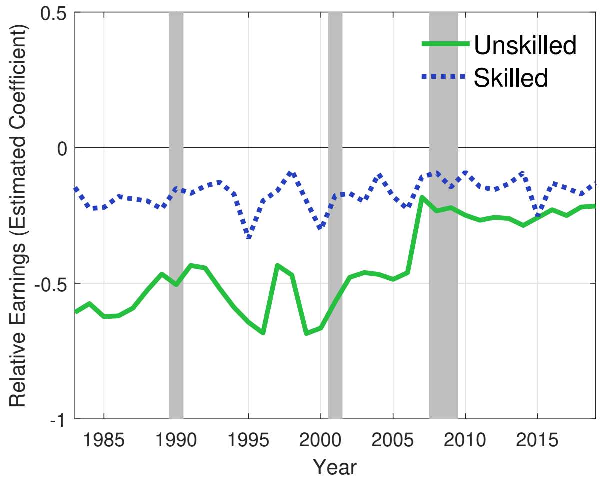


Figure A.8: Relative Earnings for Workers and Entrepreneurs, including controls

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.

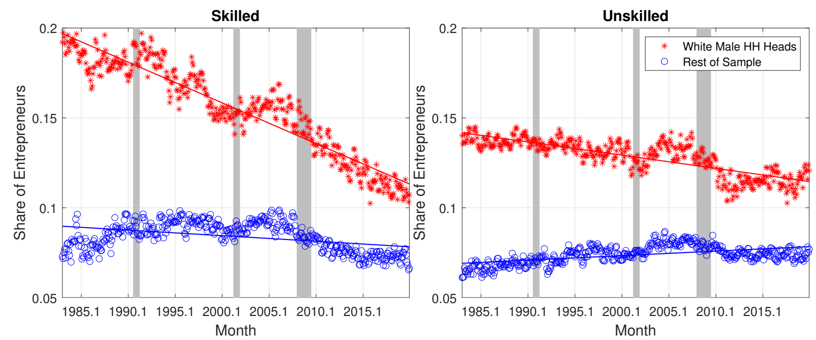
Adjusting for Margin Error Consistent with the literature studying labor market flows, we adjust the observed flows, $\mathbf{p}$, between entrepreneurship and employment so that they are consistent with the observed stocks. This adjustment is referred to as a *margin error adjustment*. As discussed 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.

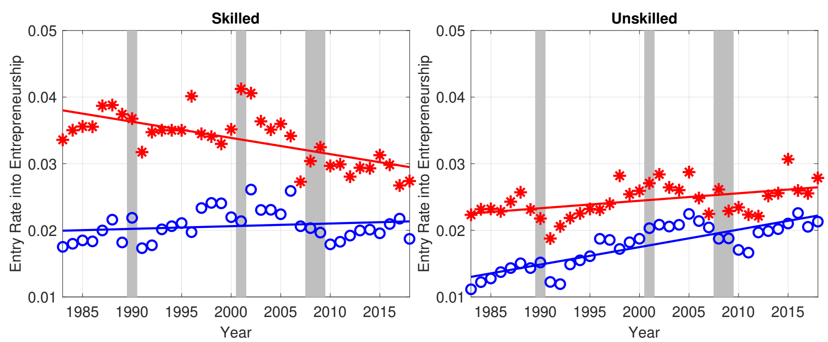
Adjusting for Survey Redesigns Several major and minor redesigns of the CPS have taken place over our sample period which require us to make adjustments to our measures of flows in and out of entrepreneurship.[1] There is a relatively little literature on adjusting for the CPS redesigns with a notable 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

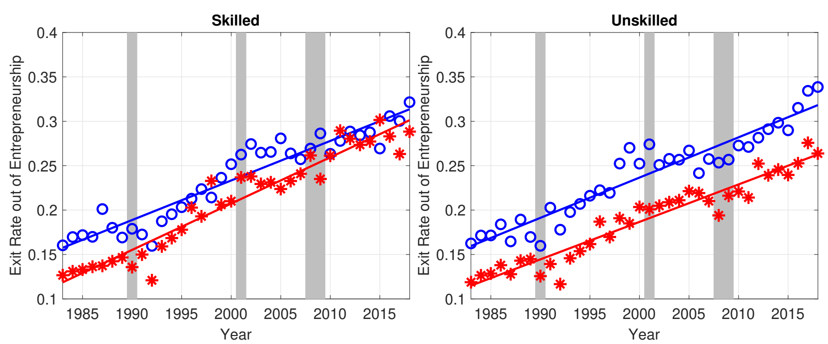
[1] See Polivka and Miller (1998) and Shoemaker (2004) for details on the 1994 and 2004 redesigns respectively.



(a) Entrepreneurship Rate



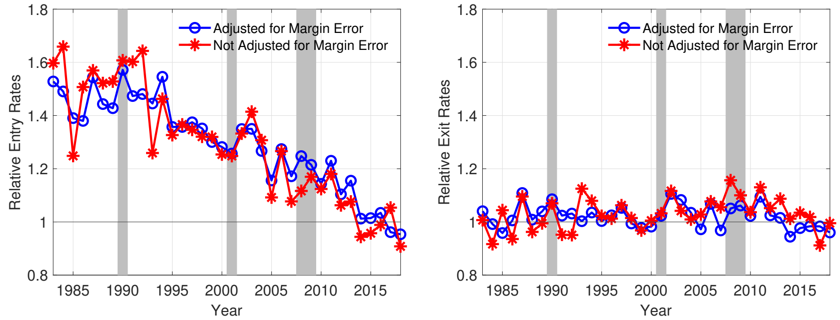
(b) Entry Rate



(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.

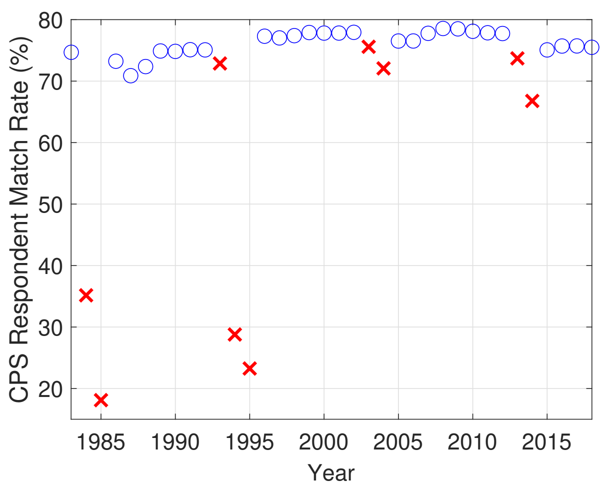


Figure B.3: CPS Respondent Match Rate (%)

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.

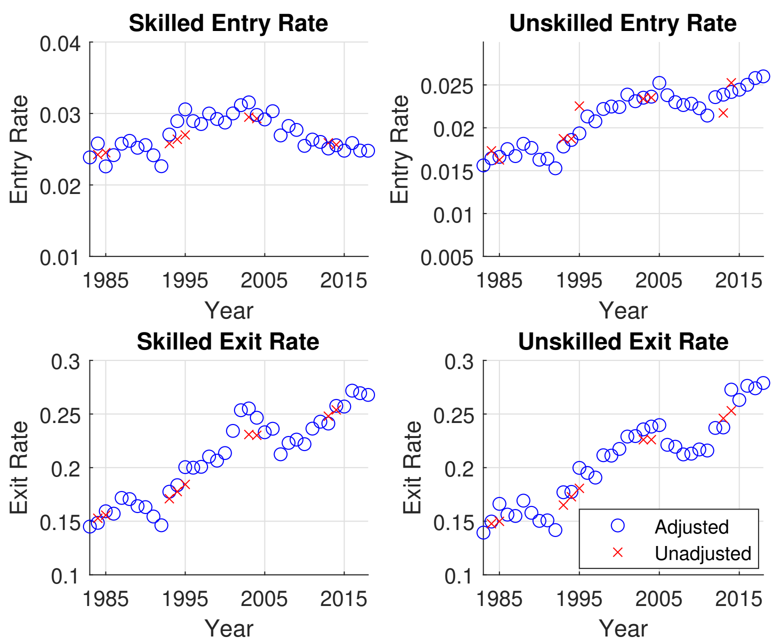


Figure B.4: Adjusted and Unadjusted Entry and Exit Rates

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 $\leq$ 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

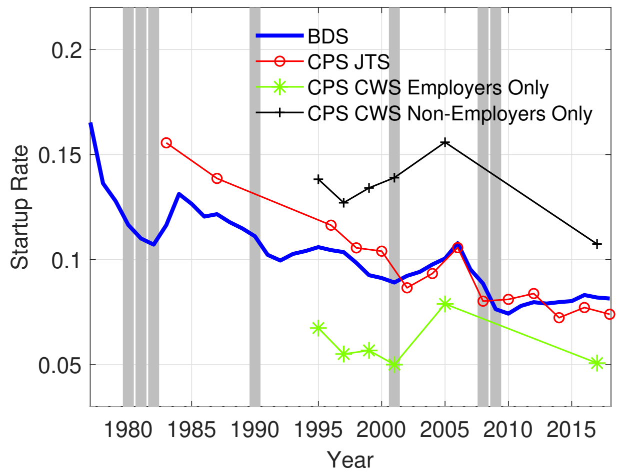


Figure B.5: Startup Rates in the BDS and CPS

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.

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.

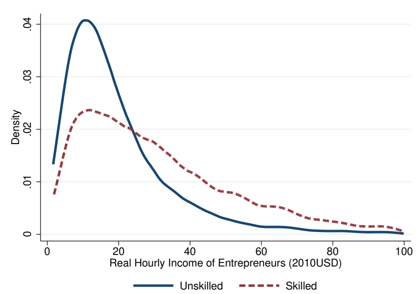


Figure B.6: Distribution of Real Hourly Entrepreneurial Income in the SIPP
Notes: This figure plots the distribution of real hourly entrepreneurial income by skill, in the SIPP.

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.

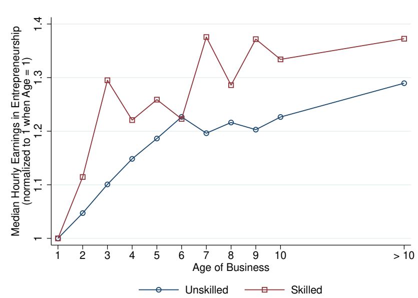


Figure B.7: Growth of Median Hourly Entrepreneurial Income in the SIPP
Notes: This figure shows the median hourly entrepreneurial income by skill, in the SIPP.

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.

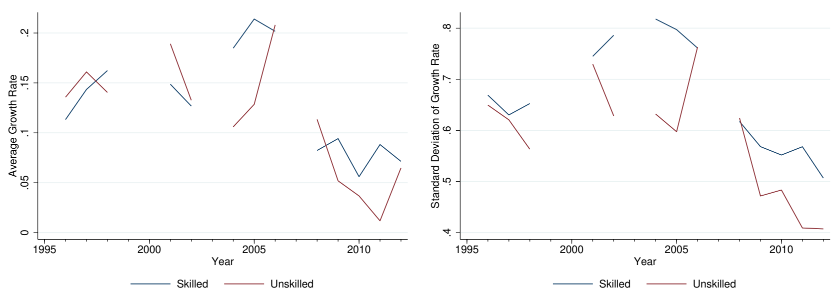


Figure B.8: Average and Standard Deviation of Entrepreneur Earnings Growth

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%.

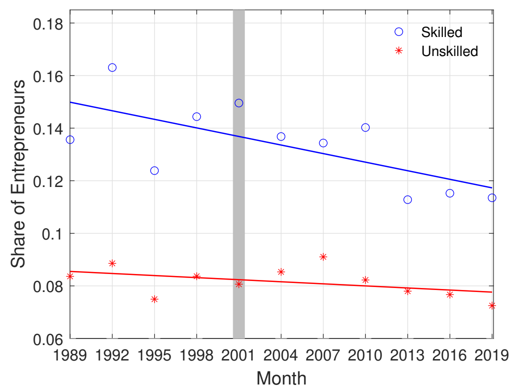


Figure B.9: Share of Entrepreneurs

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

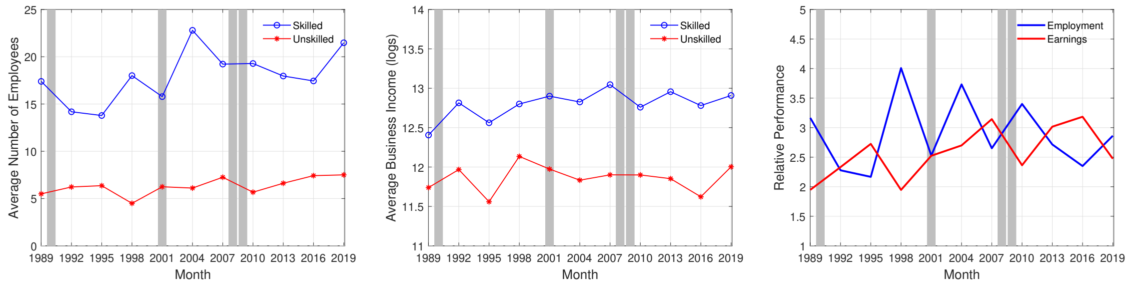


Figure B.10: Entrepreneur Performance by Skill

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.

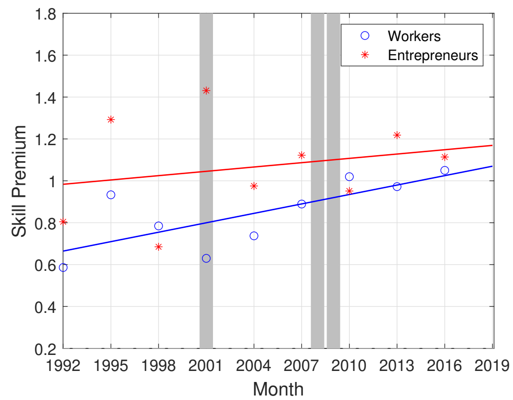


Figure B.11: Skill Premium for Workers and Entrepreneurs in the SCF

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,

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

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

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

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.

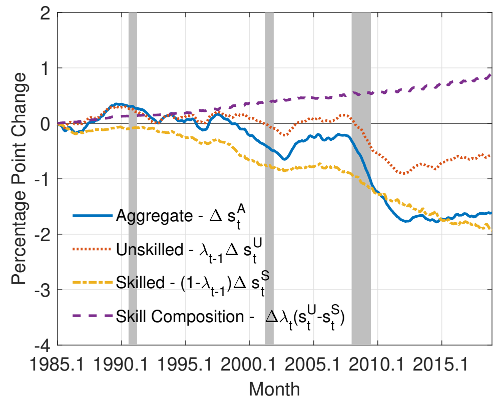


Figure C.1: Skill Group Decomposition of the Aggregate Change in Entrepreneurship Rates

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.

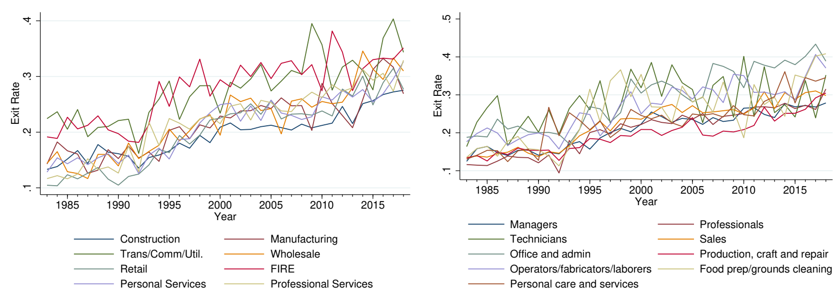


Figure D.1: Exit Rates by Industry and Occupation

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.

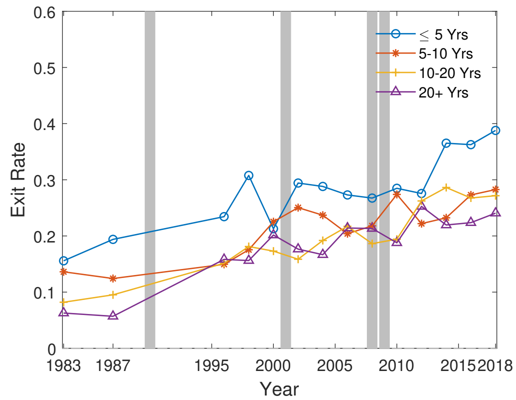


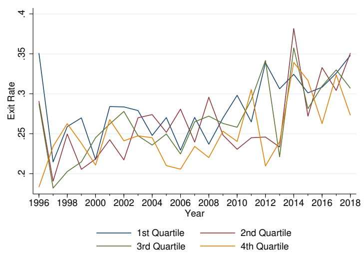
Figure D.2: Exit Rates by Time in Entrepreneurship

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.

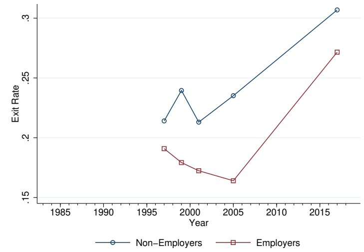
The neutrality of exit rates also precludes the idea of entrepreneurs undertaking riskier investments over time. Such a mechanism is explored in Vereshchagina and Hopenhayn (2009) and more recently Choi (2017) who argue that improved outside options to entrepreneurship encourage entrepreneurs to undertake 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.

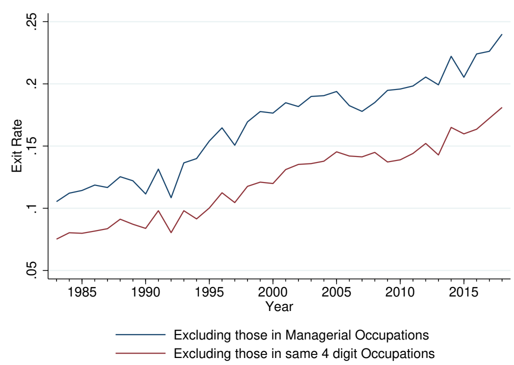


Figure D.4: Alternative Definitions of Exit Rate

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.

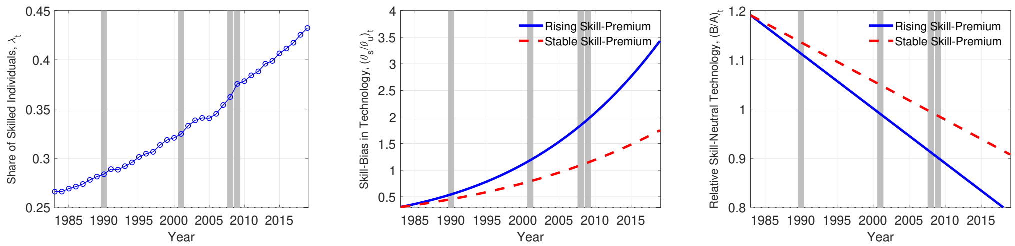
Table E.1: Re-calibrated Parameter Values

	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.

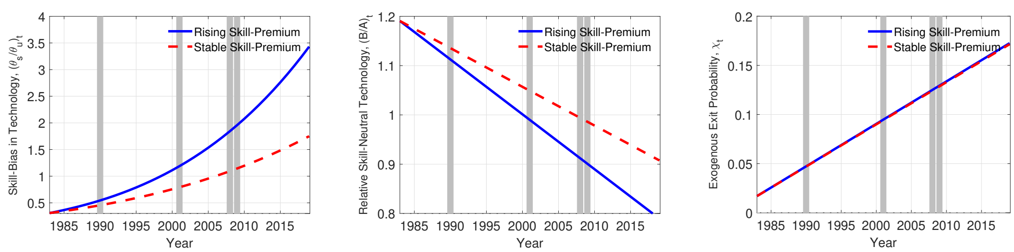
the observed share of college graduates as in the data.

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.

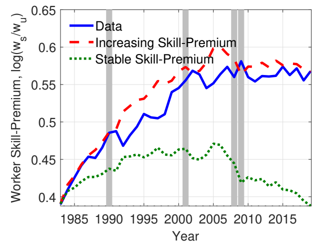
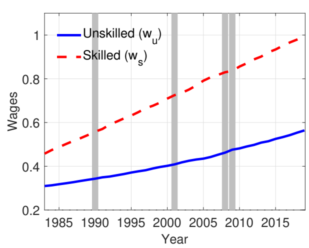
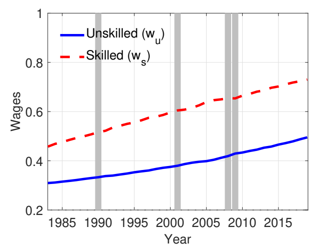


Figure E.3: Transition Dynamics of the skill premium, without increasing exit

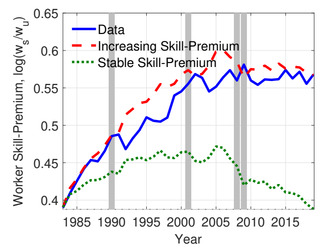
The wages and skill premium when exit rates are increasing is plotted in Figure E.4 and are very similar to those in Figure 15.



(a) Increasing skill premium



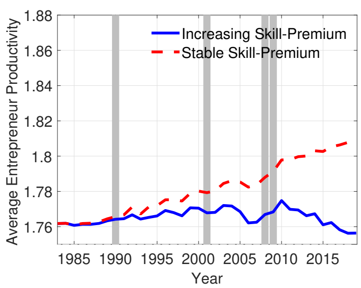
(b) Stable skill premium



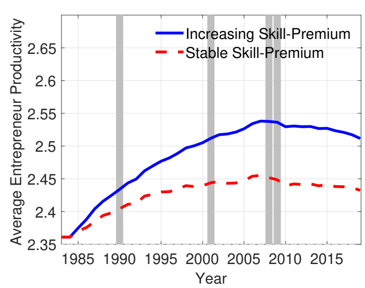
(c) Transition Dynamics of the skill premium

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

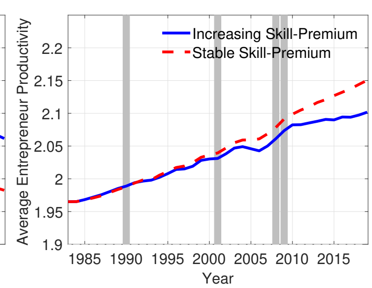
Figure E.5 plots the evolution of average productivity when exit rates increase. These are also very close to the case without increasing exit.



(a) Unskilled Entrepreneurs



(b) Skilled Entrepreneurs

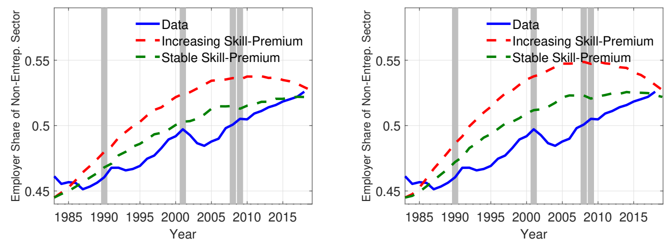


(c) All Entrepreneurs

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



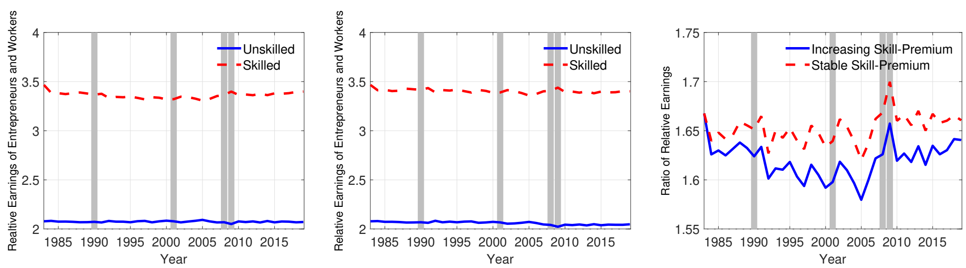
(a) Technological Change Only

(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

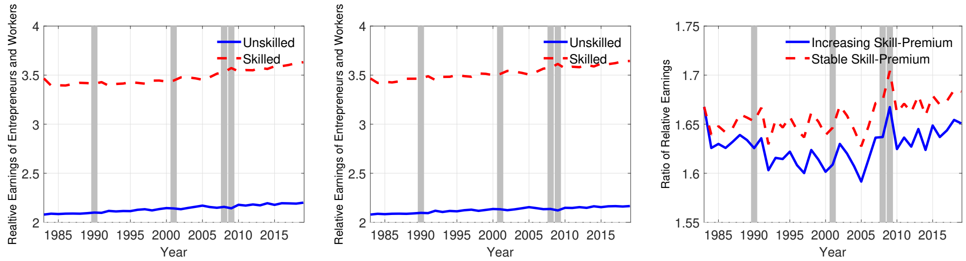
(c) Ratio of Skilled and Unskilled

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)).

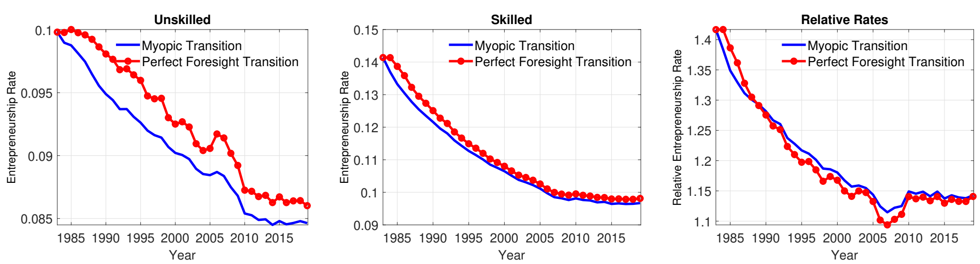


(a) Increasing skill premium (b) Stable skill premium (c) Ratio of Skilled and Unskilled

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

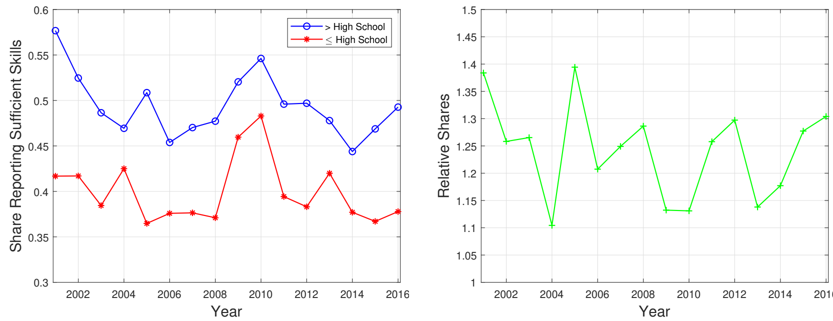
Here, we discuss the sensitivity of our model to changes in other features of the model that might potentially explain the aggregate and skill specific changes in entrepreneurship.

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 -0.001 with an associated p-value of 0.37. The analogous coefficient for those with more than a high school degree is -0.003 with a p-value of 0.14. The trend coefficient on the ratio of shares is -0.004 with p-value of 0.45.

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

	(1)	(2)	(3)
>High School	0.101***	0.117***	0.114***
	(0.008)	(0.015)	(0.015)
Year	-0.002***	-0.001	-0.002
	(0.001)	(0.001)	(0.001)
>High School × Year	-	-0.002	-0.001
	-	(0.002)	(0.002)
Additional Controls	N	N	Y
Observed Probability	0.463	0.463	0.463
N	22,935	22,935	22,935
Pseudo R^2	0.007	0.007	0.025

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.