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Abstract

Over the past half-century, while self-employment has consistently accounted for around one in ten of the United States workforce, its composition has changed. Since 1970, industries with high startup capital requirements have declined from 53% of self-employment to 23%. This same time period also witnessed declines in "hometown" local entrepreneurship and the probability of the self-employed being among top earners. Using 2016 data, we show that high startup capital requirements are linked with lower profitability at small scales. The transition away from high startup capital industries appears most closely linked to changes in small business production functions and less due to advantageous reallocation to other opportunities, growth in returns-to-scale among large businesses, or a worsening of financing conditions and debt levels.

JEL Classification: L26, D24, G51, J11, J24; J62, M13, R11, R13.

Keywords: Self-employment, small business, entrepreneurship, startup investment, occupational choice, financing.

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1 Introduction

Over the past fifty years, about ten percent of the adult U.S. workforce has reported being self-employed. Self-employment is both a significant part of the economy and a challenging phenomenon to describe comprehensively because it is comprised of varied industries, occupations, and experiences. The self-employed provide construction and daycare services and run medical and legal professional practices. They might be independent contractors working from a home office or a repair van, or proprietors of prominent Main Street storefronts passed from parents to children.

The heterogeneity within the category of self-employment has been illuminated by recent academic work examining the motivations and outcomes of the self-employed, as well as their role in local economic development. Hurst and Pugsley (2011, 2018) brought renewed attention and new data to the multiple factors that lead people to be self-employed, including the significant role of non-pecuniary motives like "being your own boss," first suggested by Hamilton (2000).[1] Many authors have also grappled with the greater propensity of self-employed individuals to be in the top and bottom tails of the income distribution (e.g., Asterbo et al. 2011; Levine and Rubinstein 2017). Michelacci and Silva (2007) showed that self-employed individuals are disproportionately working in their region of birth in the United States and Italy; moreover, these local entrepreneurs have higher earnings and perform better than non-local entrepreneurs, generating a "local bias of entrepreneurship."

In this paper, we add to the study of self-employment by documenting a significant, broad transformation of US self-employment from 1970 to 2018. We show a sharp decline in self-employment in industries which require relatively more startup capital such as agriculture, retail trade, hotels, and medical offices. While industries with above-median startup capital intensity accounted for 53% of self-employment in the 1970 Decennial Census, they have since stagnated and only account for 23% of self-employment in the 2014-2018 American Community Survey. (Hereafter, we refer to these samples as 1970 and 2018.) Self-employment has by contrast flourished in low startup capital industries like personal services, construction, childcare, and health services.

Figure 1 highlights the remarkable relationship between declines in self-employment and industry-level startup capital requirements. On the vertical axis is the percentage change in self-employment from 1970 to 2018, measured by the log change in the count of self-employed

[1] Asterbo et al. (2014) review behavioral factors behind entrepreneurial decisions.

individuals. On the horizontal axis is our measure of startup capital intensity: the industry share of self-employed individuals with 0-2 employees who reported raising \$50,000 or more in startup capital (from themselves or others) according to the 2007 Survey of Business Owners (SBO). The negative relationship between startup capital needs and the long-run decline in self-employment is striking, and we later show that it is remarkably robust to considering other traits of industries (e.g., franchising, e-commerce) and other types of financing needs (e.g., expansion capital requirements, investment levels for a 50+ person business).[2]

Inter-industry differences in levels of startup financing are associated with major differences in industry growth in self-employment. A 10% decline in the share of businesses with 0-2 employees needing this level of initial financing (for example, moving from 30% to 20% on the x-axis of Figure 1), links to a 93% higher (0.66 log points) rate of relative industry growth for self-employment. This is not easily explained, even by the rise of transformational "superstar" firms like Walmart and Amazon in the retail industry, or the contemporaneous contraction in employment in sectors like agriculture and manufacturing. In Hurst and Pugsley (2018) framing, the industries with declining self-employment counts, such as agriculture and retail trade, also show a within-sector shift away from self-employment (see Appendix Figure 1). This transformation is pervasive, appearing across education levels, demographics, and both urban and rural settings. While the transformation is strongest among less educated white men in rural settings, it is also present among highly educated non-white women in urban settings.[3]

The remainder of this paper documents the decline in self-employment for high startup capital industries, and we evaluate plausible explanations based on prior literature and theoretical models of self-employment entry decisions.

Section 2 reviews the theoretical models of startup capital intensity and self-employment entry decisions of Evans and Jovanovic (1989) and Hurst and Pugsley (2018). This review identifies four broad factors that could explain the relationship between startup capital requirements and the self-employment entry decision: reduced profitability within a self-employment sector due to changes in the nature of small business, reallocation across self-employment industries towards growing industries with better pecuniary and non-pecuniary returns, reallocation towards wage work that is becoming better compensated, and reallocation due to declines in the financial endowments and lending conditions necessary for startup investments.

[2] See Appendix Table 1 for industry-level data used in Figure 1.

[3] Studies of racial differences in self-employment with links to capital access include Fairlie (1999), Fairlie and Robb (2007), Chatterji and Seamans (2012), Hamilton et al. (2021), and Fairlie et al (2022).

Section 3 introduces our data, which includes Census and American Community Survey data that spans 1970 to 2018 and was retrieved from IPUMS and confidential micro data from the 2007 SBO and the 2016 Annual Survey of Entrepreneurs (ASE) housed at the US Census Bureau. We use the confidential data to develop our measure of initial startup capital needs by industry, which was previewed in Figure 1, and consider alternative financing metrics. We then turn to analyzing the first hypothesis of reduced profitability within some self-employment industries due to industry-level production functions and capital intensity. We find that higher startup financing needs are associated with lower profitability in 2016 for businesses with 0-2 employees, but not for businesses even modestly larger. In colloquial terms, we show that while it is challenging to be profitable as a mom-and-pop bed-and-breakfast, owning a motel of modest size has remained profitable. Using the Business Dynamics Survey, we also show that industries with high startup capital needs have a smaller share of businesses with 1-4 employees.

In Section 4, we turn to an analysis of self-employment dynamics from 1970 to 2018 to evaluate which of the four factors is most consistent with the declines. There is a significant decline from 1970 to present in the share of self-employed who are earning top incomes in high startup capital industries, which is consistent with these industries being more profitable in earlier decades. By contrast, Mincerian income regressions and a cohort entry analysis suggest the second hypothesis of self-employed migrating to other industries for better returns plays a minimal role. Self-employment incomes in both high and low startup capital industries are declining sharply compared to wage work, and the precipitous fall in new cohort entry into self-employment for high startup capital industries is not being compensated for with higher entry rates into low startup capital industries.

We also show that significant differences in the growth of wage worker incomes across regions is not triggering a large-scale reallocation to outside opportunities. For example, wage growth in cities is not disproportionately drawing individuals away from rural self-employment that required high startup investments. Moreover, we use the Business Dynamics Survey to show that these results are not due to a massive change in industry returns-to-scale (e.g., big box retail), but are instead closer aligned with shifts from micro-scale of 0-2 employees to modest sizes of 20 or 50 employees. While it is likely that most of the individuals who could have entered self-employment in high startup capital industries are instead going to wage work, our evidence suggests this is more a "push out" from the self-employment industries than a "pull" from accelerating compensation opportunities from wage work.

Our final analysis turns to the question of financing conditions. While it is difficult to argue that the overall financing environment available to entrepreneurs in 2018 is worse than that of 1970, debt-to-income ratios have risen dramatically in the second half of the twentieth century (Kuhn et al. 2020), and debt obligations like student debt have been shown to discourage contemporary entry into entrepreneurship (Krishnan and Wang 2019). Long-run data from the Survey of Consumer Finances show a strong macro relationship of the debt-to-income levels of cohorts and their propensity to enter high startup capital self-employment. Yet, despite this macro relationship, regional analyses suggest rising debt is not the main factor behind the transition, either due to student debt or escalating housing debt (the principal component of overall debt; Bracke et al. 2018). Rising debt is likely crowding out some forms of entrepreneurship, but the evidence suggest it plays a limited role for the transition that is the focus of this study.

Considering the evidence, we conclude that the profit squeeze on small scale businesses in startup capital intensive industries is the most important factor driving this broad shift in self-employment. Reassuringly, this also aligns with features of the transformation like the marked decline in local entrepreneurship. The phenomenon of local bias of entrepreneurship chronicled by Michelacci and Silva (2007) was attributed to better financing networks and access to capital by hometown entrepreneurs. We document that the tilting of entrepreneurship towards those working in their states of birth has almost entirely disappeared in the United States by 2018 due to this stagnation of high startup capital self-employment. This is consistent with fewer local individuals, who posses better networks and financial access, selecting into self-employment.

There are several important implications of this work. Many studies use industry-level capital intensity to isolate financing constraints or limited access to capital in regressions, building on the work of Rajan and Zingales (1998). Our work suggests we need to be cautious when using this technique with self-employment data (and likely even small entrants more broadly), because capital intensity is tied to profit potential. Explorations in this paper suggest that capital market constraints per se are not the key driver of the dampened entry decisions observed in Figure 1. Instead the challenge is a lack of profit, which carries quite different implications.

More broadly, studies of the evolution of self-employment across these five decades should consider startup capital intensity in their work. This metric alone does not explain everything about self-employment (e.g., the rapid aging of self-employed individuals is mostly due to population aging, not the dynamic we study). But, the startup capital intensity metric is a remarkably strong way of organizing the data, and it can help isolate trends that are otherwise obscured by this large-scale transformation. As an example, this study began as an inquiry into the declining local bias of entrepreneurship, but we could only reliably organize the data once we factored in the startup capital component.

Our work complements the significant attention paid to the dynamics and decline in employer businesses since the 1970s (e.g., Haltiwanger et al. 2013, Decker et al. 2014) and reallocation (e.g., Foster et al. 2008; Acemoglu et al. 2018). In contrast to the continual reduction in the share of new firms among employer businesses, self-employment increased from 7.8% of workers in 1970 to a peak of 10.1% around 2010, before retreating back to 9.3%. These self-employment dynamics have been far less studied but impact as many people as startups among employer businesses.[4] Moreover, we observe that some of the leading explanations for the decline in employer business startups, such as the aging US population (Alon et al. 2018; Karahan et al. 2021; Engbom 2019) or limited tech transfer (Akcigit and Ates 2019), cannot explain the transformation of self-employment that we document.

Looking forward, this transformation may become even more important. Through cohort analyses, we document that the recent decline of US self-employment to 9.3% of working population in 2018 does not appear to be an anomaly. Industry trends suggest the reduction in self-employment in the high startup capital industries is not being compensated for by increases in low startup capital industries. This shortfall was masked through 2010 by an aging US population (as self-employment entry rises with age) but the impending retirements of baby boomers may lead to a sharp decline in self-employment's share of the workforce until the decline in self-employment in high startup capital industries reaches its conclusion.

2 Capital Requirements and Entry Decisions

Evans and Jovanovic (1989) provide the canonical model for considering the relationship between capital requirements and entrepreneurial decisions. This section adapts their framework to motivate factors that shape startup capital needs and self-employment entry decisions. We also incorporate stylized elements from the multi-sector self-employment model of Hurst and Pugsley (2018) and discuss the important logic of their work.

Individuals can choose to work for wage income at a level w^*, which can depend upon education and work experience. Individuals can alternatively choose to be self-employed in an

[4] The business registration data pioneered by Guzman and Stern (2020) provide an important bridge across these forms of entrepreneurship. Bento and Restuccia (2019) model the importance of non-employers for aggregate dynamics, and Kozeniauskas (2018) considers skill biased technical change and fixed costs for entry declines among more educated workers. Cagetti and De Nardi (2006) and Bradley (2016) provide important theoretical models.

industry i, where they produce and sell output

$$y = p\theta k^{\alpha} - c, \tag{1}$$

where p is the sales price of output, θ is an individual's entrepreneurial ability, k is the capital level of the business, α is the elasticity of output to capital investment, and c is a fixed cost. Each of these elements could be indexed by i, as we will contemplate shifts in self-employment across industries, but the extra notation is omitted for simplicity.

Compared to the original Evans and Jovanovic (1989) model, we have retained p (versus setting to one) so that we can conceptually describe the industry-level competition from large companies. We have also introduced the simple fixed cost c that can capture non-linear constraints of operating at small scale. We further introduce a simple utility benefit b to model non-pecuniary advantages of self-employment (Hurst and Pugsley 2011, 2018).

The cost of capital is r, one plus the interest rate. This leads those engaged in self-employment to an optimal capital investment level of

$$k^* = \left(\frac{p\theta\alpha}{r}\right)^{1/(1-\alpha)} \tag{2}$$

and entrepreneurial earnings e^* inclusive of capital costs of

$$e^* = (p\theta)^{1/(1-\alpha)} \left(\frac{\alpha}{r}\right)^{\alpha/(1-\alpha)} - r\,(p\theta)^{1/(1-\alpha)} \left(\frac{\alpha}{r}\right)^{1/(1-\alpha)} - c. \tag{3}$$

The first term on the right hand side is the revenue generated, the second term is the cost of the capital invested, and the last term is the fixed cost. Knowing their entrepreneurial ability θ, individuals select their occupation based upon whether $e^* + b$ exceeds the outside option w^*. In our multi-industry setting, $e^* + b$ could vary across industries, with self-employed choosing the industry with greatest combined pecuniary and non-pecuniary returns.

We use this simple sketch to consider four factors that could shape changes in self-employment decisions:

- **Changes in industry-level production for small businesses** α, c: Holding the rest of the economy as fixed (including the competition from large companies), self-employment could change for an industry due to adjustments in the nature of small business. For example, a sole proprietor gym may today need to invest in more numerous and expensive amenities like swimming pools, or spend more on marketing. In the model, a lower elasticity of output to capital α or higher fixed costs c would make the industry less attractive overall and influence optimal business size for a given entrepreneur's ability θ. As aptitude for self-employment is often industry specific, ranging from early investments (e.g., learning the trade from a parent, attending law school) to accumulated assets with time on the job (e.g., client base for a dental practice, networks for general contractors), some individuals will persist even if the self-employment production function for an industry weakens. But, as their numbers shrink, they will also be increasingly be squeezed for profit.

- **Reallocation due to sector price levels** p: The baseline Evans and Jovanovic (1989) model treats self-employment as a homogeneous sector and thus cannot describe the choice of self-employed over industries. The diminishing-returns-to-scale model is also not equipped to describe big companies operating at a much larger scale. Yet, big box retail and e-commerce have more significantly reshaped self-employment decisions for retail trade than any comparable force for self-employment in construction. These industry-level shifts can be for traded and non-traded goods. If these forces put downward pressure on prices p, the self-employed may reallocate out of an industry even if the small business production function was otherwise unchanged. Individuals who derive a substantial non-pecuniary benefit b from self-employment may seek to stay in self-employment but move to more viable industries.[5]

- **Reallocation due to outside wage options** w^*: If outside wage employment is becoming more lucrative for an individual, this can reduce the attractiveness of self-employment across all industries. Importantly, this comparison point is for an individual based upon her expected earnings for wage work and her entrepreneurial ability θ. High ability individuals who in the 1970s may have set up a local medical practice can be instead drawn to consulting or banking in a big city, whereas individuals closer to the middle of the income distribution will be influenced more by median wages. This broad reallocation effect does not confine itself to industry boundaries but in most cases has a regional component to it. Decisions of an individual close to the middle of the income distribution in Alabama will be mostly shaped by typical wage opportunities in the Southeast compared to the West

[5] Hurst and Pugsley (2018) provide a sophisticated treatment of the development of amenable industry spaces for self-employment due to non-pecuniary motives interacting with differences across industries in returns to scale. Anecdotally, shifts of the self-employed between industries appear common. The authors of this paper have had a husband-wife real estate agent team who previously owned a local bed-and-breakfast; they migrated to real estate to continue working for themselves when the bed-and-breakfast struggled.

Coast.[6]

- **Changes in financial endowments and lending conditions**: To simplify the Evans and Jovanovic (1989) model for this conceptual review, we removed the model's endowment differences across individuals and its constraints on borrowing funds. These factors limited the size of business that people could start compared to optimal k^* in equation (2), especially for poor but high θ people. Constrained individuals might enter at a non-optimal business size, or they may go to wage work instead. Michelacci and Silva (2007) and Hvide and Moen (2010) further expand on access to financing and entrepreneurship, and Holtz-Eakin et al. (1994) considers survival of businesses. In our context, shifts in population wealth levels (e.g., the struggle of Millennials to accumulate wealth) or financial lending access could broadly compress self-employment and differentially impact industries with high startup capital requirements.

These four factors frame our empirical investigation of the shift away from self-employment in high startup capital industries. We start in the next section with some evidence from the 2007 SBO and 2016 ASE about sector-level production functions. Section 4 will then use changes from 1970 to present to quantify how well all four factors align with the data.

Before proceeding, we pause to draw out a few more subtle features to guide future work. First, the model has treated investment as capital k in the production function. When we approach the data, the most consistently available metric on firm size is employment. We have kept to the traditional model in large part to avoid confusion over wage terms. The above discussion is very similar if we alternatively model firm production as $p\theta l^{\alpha}$, with l being the labor hired by the firm at wage cost $\tilde{w}$. What is important to distinguish, however, is that the outside option w^* of the self-employed owner is rarely the wage cost $\tilde{w}$ of the firm. The person deciding to own a childcare center pays $\tilde{w}$ to employees but compares her potential earnings e^* against what she could personally earn in the labor market w^*. Additionally, modeling the input as labor-based requires a slightly more complicated production function to afford the possibility of non-employer self-employed businesses.

More broadly, this segues into an important practical observation that capital needs arise for many reasons. Building and machinery are primary capital requirements in many industries. Even when these inputs are leased, the financial commitment can be substantial. Another

[6] Given the linear utility, most population-wide changes would map onto changes in outside wage options w^*. Examples are universal changes in entrepreneurial ability θ, non-pecuniary benefits b, or self-employment costs c. We believe the wage dimension is the most relevant and will use regional catchments for empirical testing.

significant requirement can be physical inventory, which ranges from raw materials needed for production to finished retail goods for sale. Further capital may be needed for business licenses, marketing, non-production payroll, etc. In short, capital requirements are rather broad-based for small business owners.[7]

A final factor to highlight is that the single period set-up in these types of models makes entry costs (e.g., logo design, early marketing, durables purchases) indistinguishable from ongoing capital needs. Many businesses also sell early goods at reduced prices to build demand (e.g., Foster et al. 2016), which is effectively a form of early marketing. Yet, in reality, these early costs have different financial consequences from ongoing capital needs. When launching a restaurant, entrepreneurs may make expensive one-off leasehold improvements to prepare the physical space in addition to paying ongoing monthly rent. Even if these initial costs are partially capitalized by a bank loan, they weigh heavily in decisions as they often have little value that can recouped if the business fails. In our simple framework, consider separating c into a once-off $\bar{c}$ to enter (leasehold improvements) and an ongoing $\tilde{c}$ thereafter (monthly rent). The self-employed individual must first ensure each period that revenues from operations are sufficient to pay $\tilde{c}$. If initial profits do not also cover $\bar{c}$, she must also believe that the business will persist long enough to recover the investment. A multi-period model where the business may fail at an exogenous rate each period would place large upfront $\bar{c}$ in the center of entry decisions.

3 Startup Investment and Small Scale Profitability

3.1 Data

We analyze publicly available Census and American Community Survey (ACS) data from IPUMS and confidential data from the Census Bureau. Our data on self-employment combine the 1% decennial Census of Population for 1970; the 5% decennial Censuses of Population for 1980, 1990,

[7] The cash flow timing of a business also matters significantly (Barrot 2016; Barrot and Nanda 2020). The Evans and Jovanovic (1989) model, especially with respect to financing constraints due to endowment differences, assumes capital inputs must be assembled in advance of production, creating the external financing need. For example, small manufacturers who supply Walmart are often paid on 90-day terms, which requires that the business have sufficient capital raised to finance the whole operation through the cash conversion cycle given the firm must pay employees and suppliers sooner. By contrast, a company that obtains prepay customers (e.g., lawn care company with prepaid contracts for the summer) can fund its costs out of prepaid cash, significantly lowering external financing needs. In equations (2) and (3), this prepayment is akin to pushing r (which is one plus the interest rate) down toward a value of one or below (as the business can, in fact, earn interest on the prepaid funds before it pays them out). Importantly, the business's economics still depend upon its realized capital intensity—more workers and machinery still reduce profit for a given output level—with the cash cycle modifying realized external capital needs.

and 2000; and the five-year American Community Surveys for 2006-2010 and 2014-2018. For simplicity, we refer to the last two periods by their ending of years of 2010 and 2018, respectively. We focus on individuals aged 18-65 who are not living in group quarters. The class-of-worker variable distinguishes the self-employed from wage workers. When individuals have multiple sources of employment, class of worker is defined based on the work activity in which they spent the most time (so, for example, an academic who independently consults part-time would still be classified as a wage worker). The definition includes both owners of employer firms and sole proprietors and excludes small-scale hybrid entrepreneurship (e.g., Folta et al. 2010).

Our confidential data from the Census Bureau include the 2007 Survey of Business Owners (SBO) and the 2016 Annual Survey of Entrepreneurs (ASE). The SBO collected data from more than two million businesses across America. We use the 2007 SBO to derive estimates of startup capital intensity by industry. As described further below, the depth of the SBO and its timing permit us to explore and disclose financing needs at a detailed level. Our main metric is the share of 0-2 employee business that invested \$50,000 or more in startup financing. This investment capital could come from the personal savings of the entrepreneur, external financing, or both. This measure ranges from 8.7% for legal services to 48.9% for lodging/hotels. In many analyses, we use a split of the industries into above- vs. below-median startup capital intensity at 24%; results are not sensitive to modest shifts in this cut-off.[8] Importantly, while this industry-level measure of capital requirements is only available for 2007, we believe that the broad categorization of industries as high and low capital intensity is unlikely to change much over time. Even if industry-specific capital requirements have shifted since 1970, it has plausibly always been the case, for example, that hotels and food manufacturing require more startup capital than personal services.

The 2016 Annual Survey of Entrepreneurs (ASE) surveyed more than 100,000 business owners about the state of their operations, and included the following question: "For 2016, did this business have profits, losses, or break-even?" We code a response of "losses" as a zero value, "break-even" as a 0.5 value, and "profits" as a unit value. Our analyses below use the profit data to test the first rationale in Section 2's conceptual review on the economics of small businesses. We also use the ASE for information on investments in expansion, whether the business struggles financially, and how the business was acquired. Finally, the ASE allows us to calculate the rate of franchising, e-commerce, and intellectual property use by industry.

[8]Examples of similar empirical strategies include Hurst and Lusardi (2004), Adelino et al. (2015), and Jensen et al. (2021). Robb and Robinson (2014) provide a comprehensive introduction to financing in new businesses.

The Census Bureau has merged to the SBO and ASE several key data from the Longitudinal Business Database (LBD): revenues, payroll, employment, and four-digit NAICS industry. We exclude from the SBO sample records that relate to public companies and records with missing employment, industry, or startup capital data. We use these criteria plus an additional requirement that the business reports profitability data with the ASE. We define firm size through the LBD employment data, often using the buckets of 0-2 employees, 3-9 employees, 10-49 employees, and 50+ employees. The 0-2 employees group is the largest share in the ASE.[9]

Appendix Table 1 lists the 38 industries at the core of this study. We developed these industry categories in two steps. We first identified 43 industries that we could consistently measure across the 1970-2018 Census-ACS data from IPUMS. These industries are large enough to have meaningful self-employment series (which required, for example, combining some small manufacturing industries) while still providing enough granularity to capture material inter-industry differences that may affect self-employment (for example, distinguishing between different types of services like restaurants and personal services). From this original list, we later aggregated up to the 38 industries in Appendix Table 1 to allow disclosure of the underlying financing and profitability values that we developed from the SBO and ASE. These values are contained in Appendix Table 1 and allow empirical replication of most of our work and their use in future studies. Our findings are very similar when using the full 43 industries.

3.2 Trends in Self-Employment

Figures 2a and 2b show the trends of self-employment from 1970 to 2018 for high vs. low startup capital intensity industries, split at the median. Panel A of Figure 2a highlights high startup capital businesses accounted for 53.3% of self-employment in 1970, but declined to 35.8% by 1990 and further to 23.4% by 2018. The absolute count of self-employed in the high startup capital industries has stagnated at around 3.5 million across the five decades, with self-employment in low startup capital industries growing almost four-fold from 3.1 million in 1970 to 11.5 million in 2018.[10]

Panel B of Figure 2a shows this decline for high startup capital self-employment was particularly acute among "local" entrepreneurs living in their state of birth. While local and moving self-employed conform to the broader trends evident in Panel A, the relatively larger impact

[9] We also use publicly available Business Dynamics Survey data derived from the LBD. In these data, the average industry has 47% of firms with four or fewer employees for 1978-2018.

[10] Appendix Tables 2a-2c provide baseline values shown in Figures 2a and 2b, raw counts, and additional disaggregations.

for local entrepreneurs in high startup capital industries will be useful later when considering theories.

Panel C considers ethnic and gender composition. In 1970, white men accounted for 76.4% of self-employed workers, and for white men and other demographic groups self-employment was evenly split between high and low startup capital industries. By 2018, due to the decline in white male self-employment in high startup capital industries and the growth of self-employment by other demographic groups in low startup capital industries, white men were 49.4% of the self-employed.

Figure 2b shows three more breakouts. Panel A parses the series into those with a high school education or less compared to individuals with at least some college attendance. The high startup capital decline is strongest among those not proceeding beyond high school. But, the decline is again present for individuals attending college, which is rather remarkable given that rising education levels in America since the 1970s would naturally push this trend up.

Panel B further show that while the decline in high startup capital industries is especially sharp in rural areas, it also occurs in urban areas. Whereas self-employment in high startup capital industries represented about 43% of urban self-employment in 1970, it had diminished to 22% by 2018.

Panel C illustrates the change in the composition of self-employment of heads of households by homeownership status. The decline in high startup capital self-employment by homeowners is particularly striking.

A final important trend in self-employment is the declining local bias of entrepreneurship in America. A significant literature has considered that entrepreneurs are often disproportionately located in their regions of birth or hometowns and that regions tend to have differential supply of entrepreneurs.[11] Michelacci and Silva (2007) document this "local bias of entrepreneurship" (LBE) in Italian data from the early 2000s, where they also demonstrate that local entrepreneurs are running bigger and stronger businesses than entrepreneurs who move to a region, perhaps due to better financial access and professional networks. The authors also document with the 2000 US Census that self-employed are more likely to be in their state of birth. A full calculation of the LBE is a regression-based comparison to the inter-state mobility of self-employed to wage workers. Appendix Figure 2 shows that the local bias of entrepreneurship has been steeply declining since 1970. It is still present for full-time white men in 2018, but at half of the

[11] For example, Chinitz (1961), Figueiredo et al. (2002), Glaeser et al. (2010), Audretsch et al. (2012), Dahl and Sorenson (2012), and Glaeser et al. (2015).

strength evident in 2000. For the total population, the LBE has disappeared by 2018.

3.3 Startup Financing and Self-Employment Growth

Table 1 presents estimations of the relationship between growth in industry self-employment from 1970-2018 and startup financing requirements using the cross-section of industries. Column 1 starts by documenting the trend line of Figure 1. Industries with a 10% lower share of 0-2 employee businesses in the 2007 SBO needing $50,000 startup capital or more experienced 0.66 log points more growth from 1970 to 2018 in IPUMS self-employment (or a 93% increase). The adjusted R-Squared value of 0.39 is quite high. The contemplated 10% variation is slightly more than one standard deviation of the financing metric (8.5%).[12]

Column 2 extends the growth regression to include the initial self-employment level in 1970 and the growth over the period in total industry employment:

$$\Delta \ln SelfEmp_i = \nu \ln SelfEmp_i^{1970} + \gamma \Delta \ln Emp_i + \beta \text{Financing}\%_i^{0-2} + \varepsilon_i, \tag{4}$$

where i indexes industries. These covariates have explanatory power, showing some reversion over time from initially large self-employment levels and a high correlation of self-employment growth to aggregate industry growth. The adjusted R-Squared of the estimation grows to 0.68 with these controls. These additions, however, do not diminish the explanatory power of $\text{Financing}\%_i^{0-2}$. The negative association of high startup financing to self-employment growth is not due to large-scale industry contraction.[13]

Columns 3-9 present results from the disclosed Census Bureau analysis. The self-employment sample used in the internal Census Bureau work was restricted to US born individuals with hourly wage data. Column 3 shows this sample is very similar in its relationship to startup capital as the full sample.[14] Columns 4 and 5 next consider if our focus on the financing needs of 0-2 employee

[12] Appendix Table 3 provides descriptive statistics on SBO- and ASE-based variables.

[13] Appendix Figure 1 shows that industries with large positive or negative changes in self-employment counts tend to have similar shifts in self-employment shares of industry employment. This backdrop makes our work quite stable to how industry growth or decline is modelled. The heterogeneity in Appendix Figure 1 is also interesting. Some industries like construction, real estate, and personal services grow on both dimensions. Others, most notably legal and medical practices, are growing in count but nonetheless a falling percentage of industry activity. By contrast, a number of manufacturing industries show a flat self-employment growth but growth in sector share due to overall declines in sector employment. Finally, agriculture, retail trade, and food services show very large declines in self-employment counts and shares.

[14] The analytical results in this paper are very similar with and without immigrants engaged in self-employment. After the release of the Census Bureau results, we deemed it most appropriate to base the key descriptive trends in this paper on the full sample that includes immigrants engaged in self-employment. A final disclosure from the Census Bureau, following revisions of the analysis, will encompass both samples.

businesses is reflecting a broad industry need for investment. Column 4 substitutes a metric based on the startup capital needs for businesses employing 50 people or more in 2007. Across industries, the share of 50+ employee businesses reporting raising \$50,000 or more at founding (47.3%) is double the share of 0-2 employee businesses (24.0%). By itself, the financing of 50+ employee businesses has marginal explanatory power. It is modestly statistically significant, but the explanatory power of the regression is cut in half from 0.68 to 0.34. When including both measures in Column 5, the $\text{Financing}\%_i^{0-2}$ measure retains its strength. Columns 6 and 7 show these results are also stable to including broader sector fixed effects or controlling for the importance of franchising, e-commerce, and intellectual property for a sector.[15]

Appendix Table 4 provides an extended set of results testing variations on these SBO financing calculations. We have based our core work on companies designating themselves as "employer firms" in the SBO, although they may not have paid employees at the time of the survey. We obtain similar results with non-employer firms. Second, we value the SBO because it collects initial financing data for businesses founded throughout the decades under study. We obtain quite comparable results when looking at data from entrants during 2003-2007 vs. entrants before 1990, showing the startup financing need is a stable industry attribute through the period we study. We obtain similar conclusions when using log average financing levels, and non-parametric regressions show the particular change at investment amounts exceeding \$50,000.

Finally, Columns 8 and 9 use data from the 2016 ASE to compare startup and expansion investment needs. (The SBO did not collect dollar amounts on expansion investments.) Column 8 presents a combined metric, while Column 9 contrasts startup and expansion investment. The relationship that we have emphasized is most apparent on the startup financing of 0-2 employee businesses.

3.4 Small Scale Profitability and Self-Employment Growth

Having observed the robust relationship of self-employment growth to startup financing requirements across industries, Table 2 turns to exploring the role of small-scale profitability in these findings. We only have data on profitability in 2016 itself, but this analysis helps inform what lies behind the financing relationship and prepares us for Section 4's longitudinal analysis.

[15] The latter variables are calculated from the 2016 ASE as the share of an industry's firms that are franchises, the average share of sales that are e-commerce, and the share of firms in an industry holding a patent, trademark, or copyright.

The first four columns of Table 2 mimic Table 1, but instead consider profitability rates of 0-2 and 50+ employee businesses for each industry. While 80.1% of businesses with 50+ employees report profitability (factoring in the mid-point value assigned to "break-even" businesses), this share is 67.6% for 0-2 employee companies. These differences again have explanatory power in Columns 1-4 of Table 2. A 10% growth in industry profitability at a 0-2 employee scale in 2016 connects to a 0.40 log point growth in IPUMS self-employment from 1970 to 2018. By contrast, even in its isolated estimation in Column 3, profitability at 50+ employee size businesses is negatively correlated to self-employment growth.[16]

Column 5 next introduces the startup financing variables. This joint estimation shows the startup financing metrics retain their strength and account for the variation that was captured in the profit metrics. These estimations suggest high startup financing requirements can dampen self-employment and small-scale entry through lowering the profitability rate of these enterprises. This finding is intuitive, but we are not aware of it being documented previously.

Columns 6 and 7 show two extensions motivated by the model in Section 2. In the Evans and Jovanovic (1989) framework, the elasticity of output to investment (α) in the small business sector shapes the profit maximizing size for a given set of interest rates, prices, and entrepreneurial ability. We can test whether high startup capital is linked to production functions that are particularly profitable at mid-size scale. We evaluate profit maximization for businesses ranging from zero to 100+ employees as captured by the 2016 ASE. (In Section 4, we study returns to scale for larger companies.)

Creating bins of employment sizes that follow 0-2, 3-5, 6-10, 11-15, etc. to 100+, we first calculate the size point for each industry where the profit rate hits its peak. For most industries, this peak is less than the maximum bin of 100+ employees.[17] Second, Viner (1931) emphasizes "minimum efficient scales" for businesses, and we accordingly developed an estimate of the size threshold for each industry after which businesses consistently achieve profitability with 80% likelihood. We introduce these as unreported controls in Column 6. They do not predict self-employment growth well, and the role of $\text{Financing}\%_i^{0-2}$ remains well estimated.

Column 7 takes a second route. We calculate a measure of sales to payroll margin per employee as $(receipts - payroll)/employee$ for firms with 0-2 employees and for their industry

[16] The profit differential is striking when comparing 0-2 and 3+ employee businesses on the financing dimension. As an example, consider the share of all firms in the industry that raised $50,000 at launch (no longer just among those with 0-2 employees). This metric has a -0.367 (0.114)+++ correlation with profit rates for 0-2 employee businesses compared to -0.090 (0.133) for 3+ employee businesses.

[17] Our reported results use the raw bin with the highest observed profit rate, and we also considered parametric versions to calculate an estimated peak point using a quadratic function.

as whole. We use these values to calculate a ratio of this margin over labor costs for 0-2 employee businesses vs. their industry average. This control also proves to be second order to the baseline Financing$\%_i^{0-2}$ metric.[18]

3.5 Extensions and Discussion

Taking stock, we have seen that industry-level decline in self-employment is tightly linked to industries with high startup capital needs for businesses with 0-2 employees. Financing needs at larger scales or for expansionary investments are much weaker predictors of self-employment growth, if at all. As theory and business logic would predict, this appears to be due to a profit squeeze at small scale, and some extensions suggest that this is not connected to industry profitability as a whole. With the caveats appropriate for an industry-level analysis, the relationship of startup financing requirements to self-employment growth is remarkably strong.

One concern with the analysis thus far is that perhaps there is something odd about combining self-employment data across this 48-year time span. In later analyses, we will show the results are consistent with shorter slices of data. In addition, Table 3 shows our result with an alternative dataset. We measure from the Business Dynamics Survey (BDS) the share of firms by industry and year in size categories. Keeping our baseline regression, we model as the outcome variable the changes in firm sizes from 1978 to 2018 across the five columns of Table 3. By definition, the coefficients in the row sum to zero. We see again a significant decline in small firms in industries with high startup capital requirements. A 10% increase in the share of 0-2 employee businesses needing to raise $50,000 or more is associated with a 4.6% decline over 1978 to 2018 in the share of industry firms with four or fewer employees (compared to an

[18] The ASE includes two additional questions regarding access to finance for investment. One question asks respondents whether access to or cost of financial capital hurt profitability, and the other asks whether the respondent believes that a funding gap exists. Interestingly, Appendix Table 3 shows that 0-2 employee businesses are modestly less likely than 3+ employee businesses to report difficulties on these dimensions. For example, 15.8% of 0-2 employee businesses suggest access to or cost of financial capital hurt profitability, compared to 17.4% of 3+ employee firms. Even though the share is lower, there is a greater sensitivity of these reported difficulties to required startup capital investment among the smallest firms. An increase in the industry share of businesses reporting raising $50,000 or more for launch correlates to a 0.248 (0.072)+++ increase in the likelihood of a 0-2 employee business reporting that access to or cost of financial capital hurt profitability. For 3+ employee companies, the comparable correlation is 0.121 (0.076). Thus, a 10% increase in our financing metric, such as moving from 20% of firms raising $50,000 or more to 30%, would predict a 2.5% increase in reported difficulty for 0-2 employee firms (compared to 15.8%) and a 1.2% increase for 3+ employee firms (compared to 17.4%). The pattern of lower averages and greater sensitivity for the smallest firms is also evident for the question regarding the existence of a funding gap. While financial access may play a role in the profit outcomes related to startup capital and self-employment, these data suggest the scope is second order to that of the required investment levels themselves.

industry-level average of 47.0%). This analysis also shows the share has been mostly reallocated to firms with fewer than 100 employees, which we return to in later discussion.

A second reaction might be to ask why there are any small businesses of this size in these industries! Yet that question misses that the largest size category in *almost every industry* is 0-2 employees. Moreover, more than two-thirds of 0-2 employee firms are turning a profit in 2016. Thus small businesses remain viable overall and important for the economy. We suspect that the steep decline from 1970 levels is because it has become ever harder to "make the numbers" work when facing heavy startup investments. While we can't observe an analysis similar to Table 2 for 1970, the next section looks for complementary evidence like where self-employed sit in the income distribution over time. This longitudinal analysis will also provide us an opportunity to consider reallocation forces and changes in financing conditions.[19]

4 Longitudinal Evidence on Self-Employment

This section uses longitudinal data from 1970 to 2018 to consider the four factors described in Section 2. We study the positions of self-employed individuals in the 1970 and 2018 income distributions and explore Mincerian income regressions. We then use cohort entry analyses for each sector to model entrepreneurial transitions through the lifecycle. Finally, we return to an augmented form of the industry analysis in the prior section to consider wage incentives for reallocation and financial constraints/access. We close this section with a discussion of the findings.

4.1 Income Distributions and Mincerian Regressions

The decisions about self-employment built into the Evans and Jovanovic (1989) model center on relative earnings across sectors. Our first step considers income levels over time by profession. We shall observe that the relative incomes for self-employment in high startup capital industries have been dwindling at the same time that their count has been stagnant.

Appendix Table 2b provides tabulations over the full sample of individuals, showing that the declines in self-employment have been particularly strong at the top of the income distribution.

[19] The ASE data also collect how a business originated. Consistent with the stagnation of self-employed counts in high startup capital industries in Appendix Table 2a, a 10% increase in the share of firms requiring the high investment level is correlated with a 10% decline in the share of new businesses that are de novo owner founded (compared to those acquired, inherited, or similar). Holmes and Schmitz (1995) model the turnover of businesses among owners.

In 1970, more than 11% of individuals self-employed in high startup capital industries were among the top 5% of incomes for that year; for low startup capital industries, the share exceeded 14%. These 1970 shares were substantially above the 5% benchmark that would have shown equal representation to wage work among top incomes, and self-employed are similarly positioned if compared to only individuals in their state. By 2018, however, 9.7% of self-employed in high startup capital industries were among the top 5% of incomes. The share of self-employed in low startup capital industries among top incomes declined even more to 6.8%.

To ensure a consistent comparison over time, Figure 3 and Table 4 focus on individuals reporting usually working at least 30 hours per week and 40 weeks per year. We also adjust incomes for inflation to be in year 2000 dollars, and we bottom and top code observations at $0 and $150,000, respectively. The latter is used to correct for changes over time in the maximum reported earnings in IPUMS data.

Figure 3 shows the reduced presence of self-employed individuals in the right tails of the income distribution. The self-employed still have a larger relative mass among very top incomes, but the difference has substantially diminished from 1970, and the density in above average incomes is very similar across worker types.

Table 4 similarly documents Mincerian income regressions by decade. Panel A considers whether incomes are above $50,000 in year 2000 dollars; Panel B considers an indicator for an income above the 95th percentile. We model indicator variables for being self-employed in high and low startup capital industries and for being a wage worker in a high startup capital industry. These indicator variables are measured relative the omitted group of being a wage worker in a low startup capital industry. We control for the demographics of individuals (gender, race, age, and education) and fixed effects for state of residence. Regressions are unweighted and report robust standard errors.

Both panels quantify a decline in the likelihood of self-employed having top incomes relative to wage workers, conditional on individual characteristics. The decline is similar, and perhaps even steeper, among low startup capital industries. These income analyses inform our investigation in two ways. First, while we are unable to mirror the 2016 ASE analysis for earlier decades, the substantial decline in top incomes connected to self-employment suggests that more profitable opportunities may have existed earlier. Second, the contemporaneous decline in top incomes for low startup capital self-employment casts doubt on explanations that center on the self-employed reallocating over industries for better earnings. The cohort analysis in the next section will further confirm this.[20,21]

4.2 Cohort Entry Analysis

We next model the uptake of self-employment by birth cohort. This descriptive analysis deepens our understanding of how the self-employment transition has unfolded and whether it is likely that individuals are moving across self-employment industries.

An important feature of self-employment, dating back to the work of Evans and Leighton (1989), is that self-employment rises with age. There are several factors behind this relationship, ranging from the accumulation of financial assets and experience that enable business entry, to self-employment transitions as a path for partial retirement. Consequently, the aging of the US population over the five decades we study is a natural boost to US self-employment levels.

Figure 4 examines how cohorts age into self-employment by integrating our IPUMS data together to follow birth decades over time. We study individuals as they move from 17-19 years old to being 60-65 years old. The vertical axis in Panel A is the percentage of employed people in the cohort during an age range who are classified as self-employed in a high startup capital industry. Panel B considers entry into a low startup capital industry for self-employment.

All cohorts show a monotonic increase into both types of self-employment as they age. The 1940s cohort peaks at 4.6% and 12.2% in high and low startup capital industries, respectively, by ages 60-65. Ungraphed partial series for the 1920s and 1930s cohorts look quite similar to the 1940s cohort. The most significant increase in self-employment work happens when individuals are in their 30s and 40s. During this age range, individuals have often accumulated the work experience and necessary financial and social capital to become self-employed. This period of life may also see the transfer of family businesses from parents to children, and in some professions

[20] In real 2000 dollars and conditioning on the traits of individuals, we calculate that, relative to wage workers in low startup capital industries, average incomes of the self-employed in high and low startup capital industries were \$3,808 and \$10,500 higher in 1970. For 2018, these differences were \$1,188 and -\$796, respectively. However, the large mass of low incomes makes assessments of average values quite sensitive to bottom and top coding choices, as well as log transformations. Due to this issue, we focus on an approach using indicator variables.

[21] A significant literature discusses the challenges and nuances of comparing entrepreneurial and wage earnings, including the option value of experimentation with self-employment for better lifetime earnings, the heterogeneity of self-employed activities, and the under-reporting of entrepreneurial earnings. Examples include Hamilton (2000), Hurst and Lusardi (2004), Kerr and Nanda (2011), Kerr et al. (2014), Manso (2016), Sarada (2016), Dillon and Stanton (2016), and Levine and Rubinstein (2017). We are not able to model these advanced issues with the repeated cross-sections available in IPUMS, as they require more specialized datasets and/or longitudinal analyses of individuals. IPUMS data also do not allow us great separation of income sources by person. Yet, our main conclusion that self-employed in 2018 are less likely to be among top incomes compared to 1970 are unlikely to be materially affected by alternative techniques and adjustments.

like law and medicine, individuals have completed the schooling and apprenticeships necessary to open their own practices.[22]

Subsequent birth cohorts, however, show a striking difference to those born in the 1940s. They are entering self-employment as they age, but they are increasingly shunning high startup capital industries. Panel B suggests that this lower entry is not being diverted into low startup capital industries. The transition is even sharper if we narrow the sample to white men, and the patterns are robust to inclusion or exclusion of people out of the labor force. In summary, these cohort entry patterns, in combination with the income trends in the prior section, suggest the decline in self-employment in high startup capital industries is not due to self-employment in other industries becoming more attractive.[23]

4.3 Growth Dynamics and Industry Analysis

Our next analyses return to the earlier industry growth model (4), expanding it to consider other potential rationales developed in Section 2 for why self-employment might be weakening.

Panel A of Table 5 first repeats our baseline model with windows of time ranging from 10 years in Column 1 to 48 years in Column 5. As before, unreported controls are for the log of number of self-employed in the initial year (1970 in columns 1-5, 1990 in column 6) and growth in total industry employment through the specified period of time. The negative association between industry self-employment and high startup capital requirements is barely visible by 1980 but then significant by 1990. Thereafter, it more slowly converges to the full gap evident in 2018. The adjusted R-Squared of the model hits its peak in 1970-2010. Recognizing the big jump over 1970-1990, Column 6 also calculates the growth from 1990 to 2018.

In Panel B, we introduce four new variables. Schumpeterian competition from large-scale farming, big box retail, and so on (e.g., Haltiwanger et al. 2010) might operate at a scale well beyond the 0-100 employee range of the ASE profit analysis. We thus calculate from the Business Dynamics Statistics the average firm size by industry from 1978 to 2018. We also calculate the

[22] From small-scale businesses to startups backed by venture capital, Azoulay et al. (2020) show how entry rates peak in many parts of the entrepreneurial spectrum when individuals are close to age 40. This graph of repeated cross-sectional data captures realized levels of self-employment, with greater levels of self-employment entry and exit by individuals underlying the observed net changes. Evans and Leighton (1989) highlight how a persistent rate of entry into self-employment can combine with a lower transition rate out of self-employment into a rising self-employment overall share as cohorts age until a steady state level is achieved.

[23] Appendix Figure 3 provides a combined graph that models overall self-employment entry. By combining years of the General Social Survey (GSS), we chart an almost identical pattern. Moreover, the GSS provides information on whether a respondent's parent is an entrepreneur (e.g., Hvide and Oyer 2021), allowing us to confirm that the pattern is not being driven by changes or delays in the transmission of family businesses (Tsoutsoura 2015).

change in average firm size from 1978 to 2018. These measures provide a test for overall industry returns-to-scale and changes across the full firm size distribution. (Agriculture is removed from this analysis due to a lack of BDS data.)

We also calculate two measures to consider the wage opportunities that might be present for individuals as they consider their occupation. Compared to a Schumpeterian model that operates via competition within industries, this process is more likely to be explained by a Roy (1951) model of occupational choice. We model this occupational choice at a regional level, allowing individuals choices across industries based upon comparisons of income. Our estimator for incomes at the middle of the distribution takes the form:

$$WageExposure_{i,t}^{50} = \sum_{r} Share_{r,i,1970}^{SE} \cdot \frac{Income_{r,t}^{Wage,50}}{Income_{r,1970}^{Wage,50}}, \tag{5a}$$

where i indexes industries and r indexes nine Census regions. $Share_{r,i,1970}^{SE}$ is the portion of self-employment for industry i in 1970 that was contained in region r. $Income_{r,t}^{Wage,50}$ is the median income of a wage worker in the region. The Bartik-like regressor captures whether the geographic distribution of self-employed for an industry placed them into areas that were going to see more rapid median income growth for wage workers than what was likely for other industries. We similarly construct a measure for income trends at the 95th percentile. (These measures are tightly correlated for the first ten years, and so we analyze spans beginning with 1970-1990.)

Introducing these four variables into Panel B does little to our estimate of the association between high startup capital intensity and lower self-employment. There is some evidence that growing average firm size also predicts less self-employment growth since 1990, but it does not explain our key relationship. While we structured this analysis to stay with the industry framework, we have derived the same conclusions from a more complicated regional-industry-year panel estimation. That analysis shows all of the important variation occurs across industries rather than regions, and so we developed the Bartik estimators to simplify the exposition.

Table 6 repeats our core estimation with different outcomes. The impact was evident among the self-employment of white men by 1980, and thereafter it is present for white men and other demographic groups. Linking our various analyses, we also see reduced self-employment as a share of an industry's workforce and among top earners.

4.4 Wealth and Debt Exploration

Our final set of analyses explore the fourth factor outlined in Section 2: that changes in financial endowments and/or lending conditions could have stymied self-employment in high startup capital industries. The canonical Evans and Jovanovic (1989) model emphasized borrowing constraints capping self-employment entry, and work like Michelacci and Silva (2007) further linked factors like the local bias of entrepreneurship to financial access. Could the shift away from self-employment in high startup capital sectors be due to declines in wealth accumulation or adverse lending conditions?

Of the four factors outlined in Section 2, the contribution of wealth and debt are the most difficult to test due to data limitations. This section reports one macro fact that is consistent with wealth and debt playing a role, but we also describe several more detailed empirical exercises that cast significant doubt. Our conclusion is that the available evidence leans against this factor.

One macro relationship signals the importance of considering wealth and debt as a candidate for lower self-employment in high startup capital industries. Using data from the Survey of Consumer Finances (SCF+) harmonized by Kuhn et al. (2020), Appendix Figure 4 displays changes in self-employment rates and total debt-to-income ratios across birth cohorts during peak working years. We plot the share of working individuals by birth cohort engaged in self-employment in high and low startup capital industries, respectively, against the age-adjusted average total debt to average total income for each cohort.[24] The macro relationship is striking: rising debt levels among recent birth cohorts move almost monotonically with shifts in self-employment, and the correlations between debt-to-income ratios by cohort-year and self-employment behavior are statistically significant.

Yet, there are several factors that suggest the macro relationship is spurious. Figure 2a, for example, showed two of the most significant transitions are declines in shares for white men and for local businesses. Indeed, Michelacci and Silva (2007) further provided extensive evidence that the local bias of entrepreneurship originated from better access of these groups to local financial networks. Even with rising debt levels, we find it difficult to construct a scenario where these wealthier and more advantageously positioned groups as a whole have suffered adverse declines

[24] We compute these values by calculating the debt-to-income ratios for heads of household aged 30-64 in the SCF+. In order to adjust for the age composition of different cohorts (e.g., that the 1980s cohort is only observed relatively early in their working life), we then regress the debt-to-income ratios on indicator variables for birth cohorts and age bins (ages 30-39, 40-49, 50-59, and 60+). The values shown in the graph are the coefficients on the cohort dummies, representing the average total debt to total income for heads of household of that birth cohort after partialling out age.

in their ability to raise startup financing. Instead, the link to the declining income advantages shown in Figure 3 appears to be the stronger candidate.

Along these lines, Appendix Figure 5 shows the projected net wealth levels (inclusive of debt) of the demographic groups in 1970 who comprised self-employed and wage worker. We first divide the 1970s self-employed and wage workers into six groups: whites and non-whites who are under thirty years of age, aged 30-49, and 50-64 years of age. We then multiplied the share of self-employed and wage workers in each of these six groups by the average actual wealth observed for that group in the SCF+ in the years 1970, 1983, 1992, 2001, 2010, and 2016. Household wealth is expressed in year 2016 dollars. The demographic groups that were initially more disposed to self-employment show greater wealth and slightly stronger relative wealth gains over the ensuing decades.

In Panel B of Table 5, we considered regional distributions of industries to test wage reallocation hypotheses. We undertake a similar strategy to consider debt. We access debt data from the New York Federal Reserve's Consumer Credit Panel, which is compiled from a nationally representative random sample of consumer credit reports (Lee and van der Klaauw, 2010). Debt information is exceptionally scarce, and these data are only available for 2003-2018. Lacking information for 1970, we make the necessary assumption that debt levels are similar in 1970 across regions and consider only the debt level evident in 2003-2018:

$$DebtExposure_i = \sum_r Share^{SE}_{r,i,1970} \cdot DebtRatio^{03-18}_r, \tag{6a}$$

where $DebtRatio^{03-18}_r$ is regional average debt (from the consumer credit reports) to average total incomes of individuals working full time (from the census data). In one variant, we alternatively use the 1990 industry distribution for self-employment. We construct these metrics for total debt (which is mostly comprised of housing debt) and student debt.

When we introduce these factors in Panel C of Table 5, they do not impact our core results. The debt regressors themselves do not exhibit much of a relationship to self-employment dynamics, although there is an interesting positive correlation in Column 6 among recent years. Because the vast majority of debt is housing debt, we also investigated whether the decline in self-employment for high startup capital industries was disproportionately large in geographic areas where entrepreneurs face more housing debt-related pressure.[25] Our analysis considered

[25] Fairlie and Krashinsky (2012) extend the Evans and Jovanovic (1989) model to consider home price growth, debt reductions, and self-employment decisions. Bracke et al. (2018) model the difficult balance entrepreneurs face for optimal asset allocation given that homes and businesses can both be large, nondiversifiable assets.

household heads working full time, and we ranked metro areas based on the share of these individuals who own their homes, the median ratio of house value to total income, and the share of individuals in the metro area who own a home valued at three times or more their income. We then compared the change in self-employment in high housing pressure areas like Santa Barbara and New York City compared to low housing pressure areas like Beaumont-Port Arthur, Texas and Flint, Michigan. This analysis shows very similar declines in high startup capital self-employment for high- and low-pressure areas.

4.5 Discussion and Implications

Considering our theories, the analyses documented in this paper suggest that the most likely explanation for the decline in self-employment in high startup capital industries was a shift in the nature of the production function for small businesses. As we cannot observe the production function in 1970, we cannot fully document this. But, this theory is consistent with evidence assembled: the weak profit opportunities in the 2016 ASE in these sectors for 0-2 person businesses, the BDS shift in activity from 1-4 employee firms to 5-100 employee firms since 1978, and the decline in the share of this group among top incomes since 1970.

Turning to the second theory, we suspect that some individuals who greatly valued self-employment activity shifted away from high startup capital industries to less intensive ones. However, our evidence leans against a theory where large numbers of self-employed moved to low startup capital industries due to exciting opportunities and better earnings. To begin, self-employment earnings in the low startup capital industries have also declined relative to wage work. Moreover, the cohort entry graph does not show a substantial reallocation over self-employment industries.

Our third theory dealt with transition to wage work due to improving outside wage options. While we suspect that most of the "missing self-employed" in high startup capital industries are instead engaged in wage work, the regional wage analysis suggests this is more likely to have been due to a "push" from self-employment's lower prospects rather than due to a "pull" from exciting new wage opportunities. The origin of the transition appears to lie within the self-employment sector and its production technologies, not outside opportunities.

Our final theory deals with potential financing constraints. Despite the macro relationship discussed, the weight of the evidence suggests rising US debt levels are not responsible for the transition in self-employment away from high startup capital industries. Debt is important for entrepreneurial entry decisions, but the regional evidence and the prominence of the transition away from high startup capital industries among those least likely to face financing constraints, such as wealthier white men, suggests declines in industry attractiveness are more important.

5 Conclusions

While self-employment has been a relatively stable share of the workforce over the past fifty years, we document in this paper a substantial shift away from industries requiring relatively more startup capital. This transition is substantial, representing 30% of self-employment, and robust to considering other features of industries. Guided by a simple model of the entry decision for self-employment, our analysis considered the relative importance of four factors in explaining this transformation: changes in the industry-level production function for small businesses, reallocation of self-employment between industries, reallocation due to outside wage options, and changes in financial endowments and lending conditions. The accumulated evidence favors the first factor as the most important explanation.

This transformation has implications for the US workforce and industry structure. The self-employed are around 10 percent of the workforce, a share comparable to the share of the workforce working in manufacturing, and businesses with 0-2 employees are the largest category of firm in almost every industry. Future work about the self-employed (and likely small businesses more generally) should consider the role of capital requirements in the entry decision. Moreover, scholars should carefully consider whether capital requirements per se are driving entrepreneurial decisions, or whether there is a relationship between startup capital requirements and profitability which could confound causal interpretations of capital needs.

The implications of declining transition rates by cohort deserve more research. While self employment rates rose from 1970 to 2010, in stark contrast to declining entry rates for employer businesses, this increase was mostly because an aging US population increasingly weighted the higher self-employment propensities of older individuals. Consequently, through 2018 the United States mostly maintained a consistent level of self-employment, but its self-employed population was aging rapidly. The smaller recent cohorts will be increasingly important for aggregate self-employment as the larger, older cohorts retire. In a simple extrapolation, had recent birth cohorts displayed the same rate of self-employment by age as the 1940s cohort, self-employment in 2018 would have been almost a full percentage point higher in 2018. The future evolution of this important part of the economy could look quite different than recent decades.

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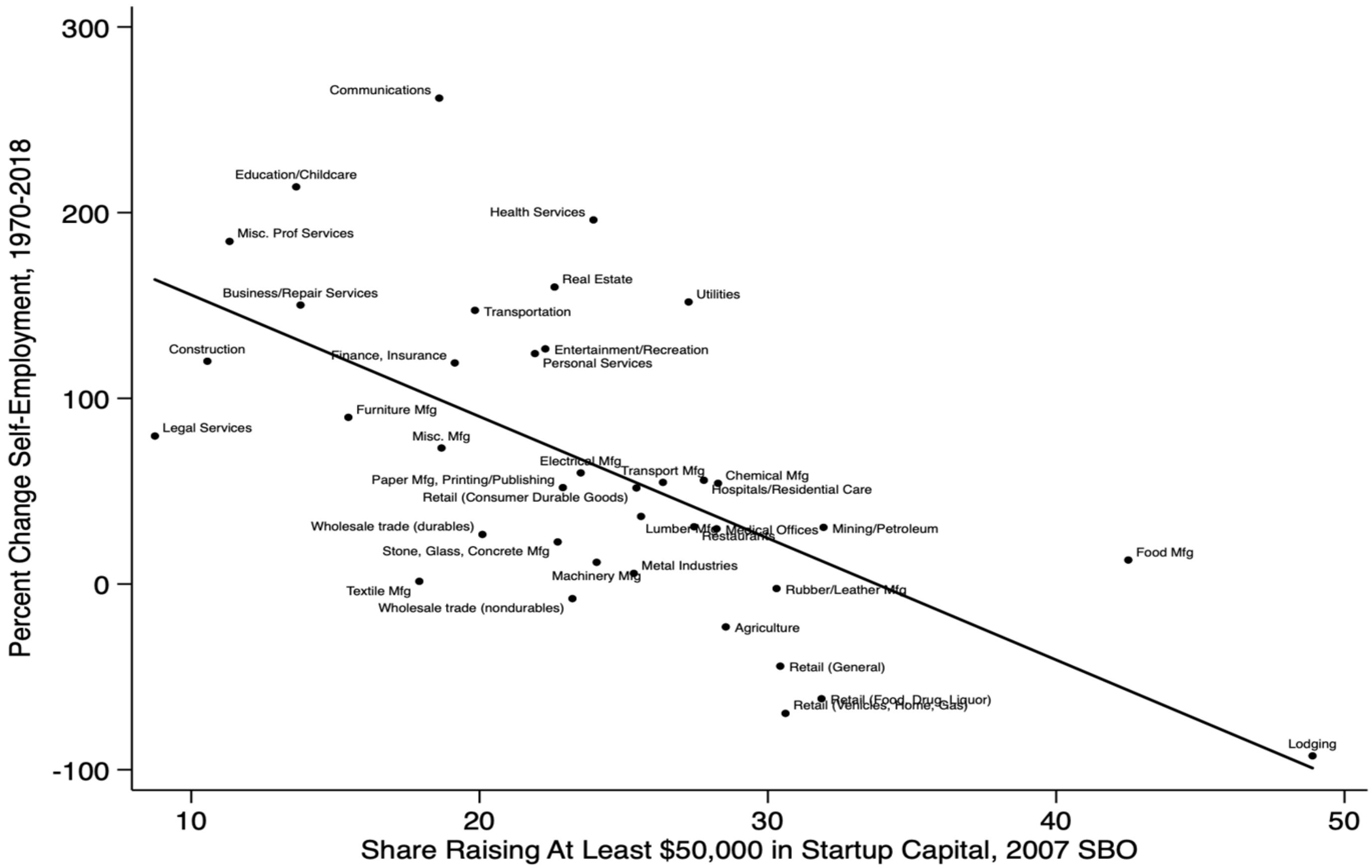
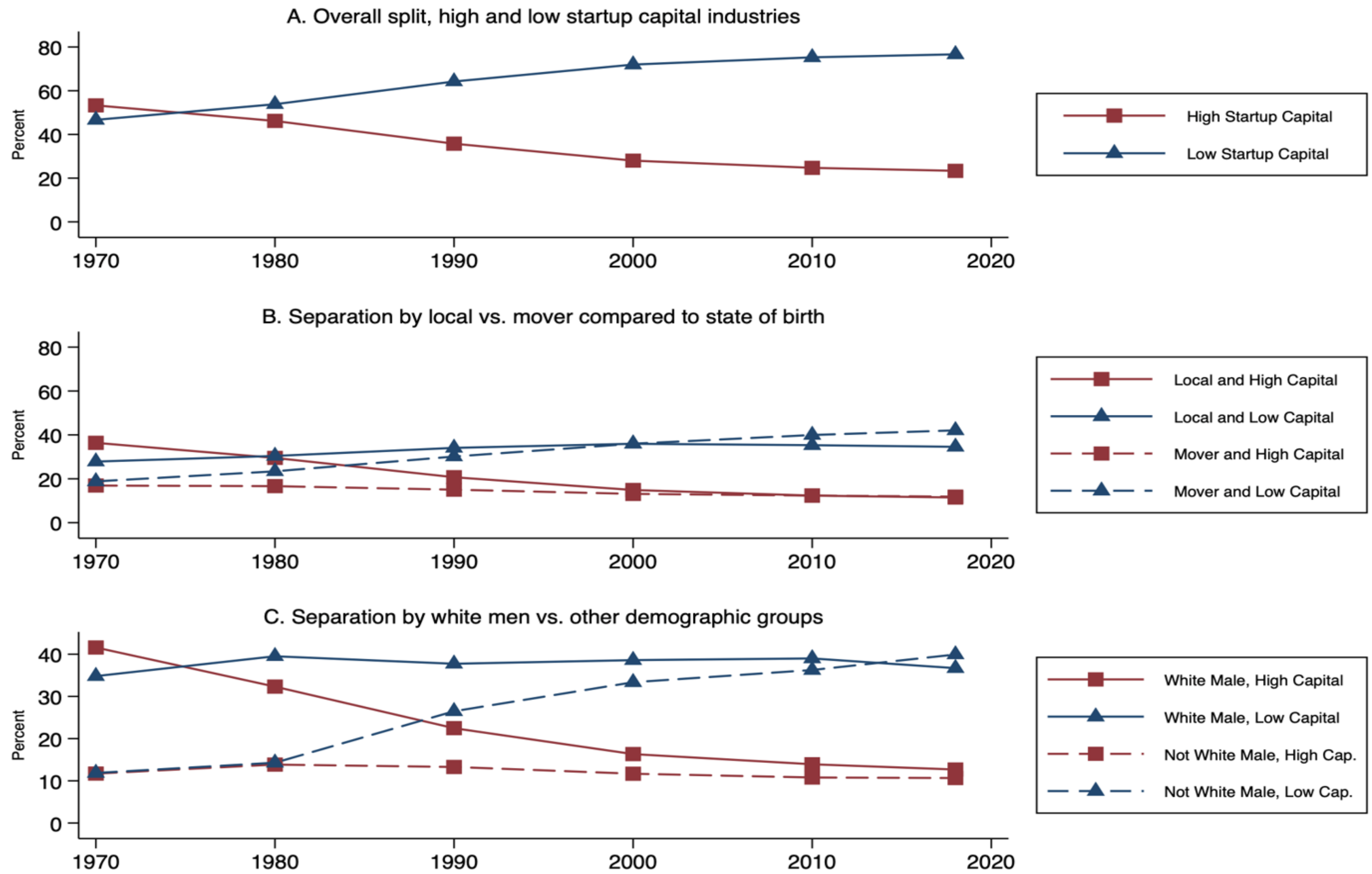
Figure 1: 1970-2018 log growth in self-employment counts
vs startup financing for 0-2 employee businesses



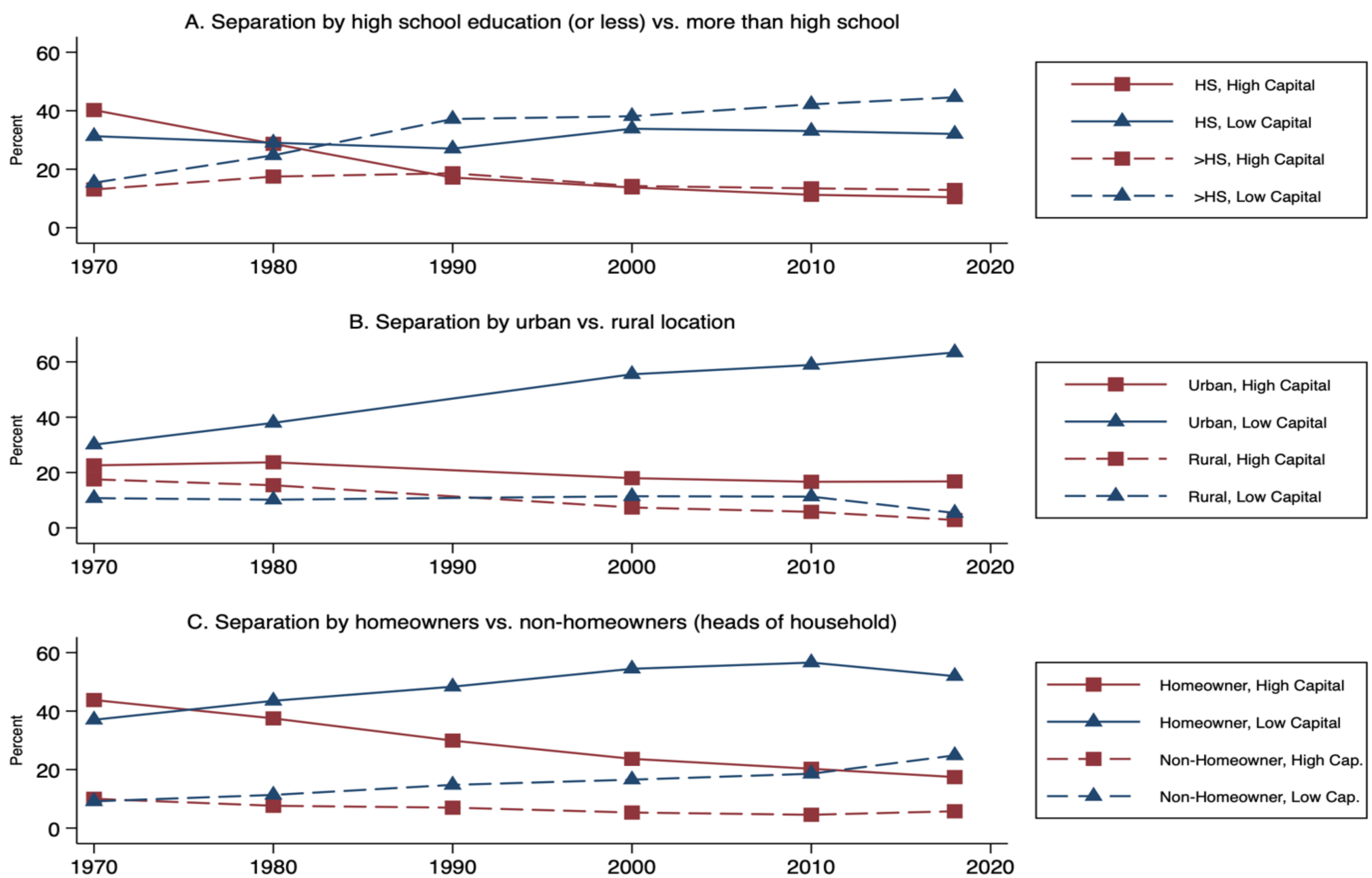
Notes: Vertical axis is the log change in the count of self-employed individuals from 1970 to 2018 taken from IPUMS data using 1970 Decennial Census and the 2014-2018 American Community Survey. Horizontal axis is the share by industry of self-employed individuals with 0-2 employees in the 2007 Survey of Business Owners who reported raising $50,000 or more in startup capital. Values are documented in Appendix Table 1.

Figure 2a: Trends in US self-employment by startup capital intensity



Notes: Data combines Decennial Censuses from 1970-2000 with 2006-2010 and 2014-2018 ACS. Appendix Tables 2a-2c provide baseline values and additional disaggregations.

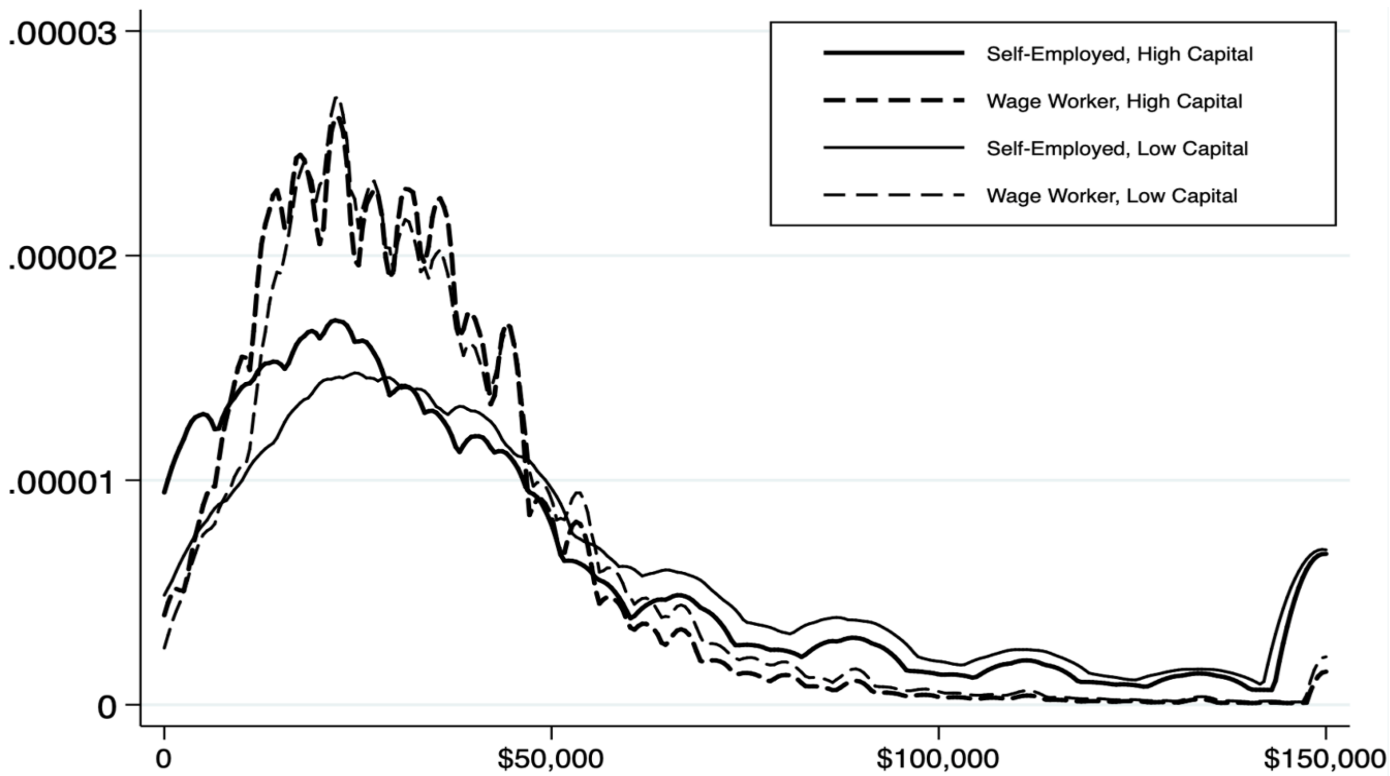
Figure 2b: Trends in US self-employment by startup capital intensity, continued



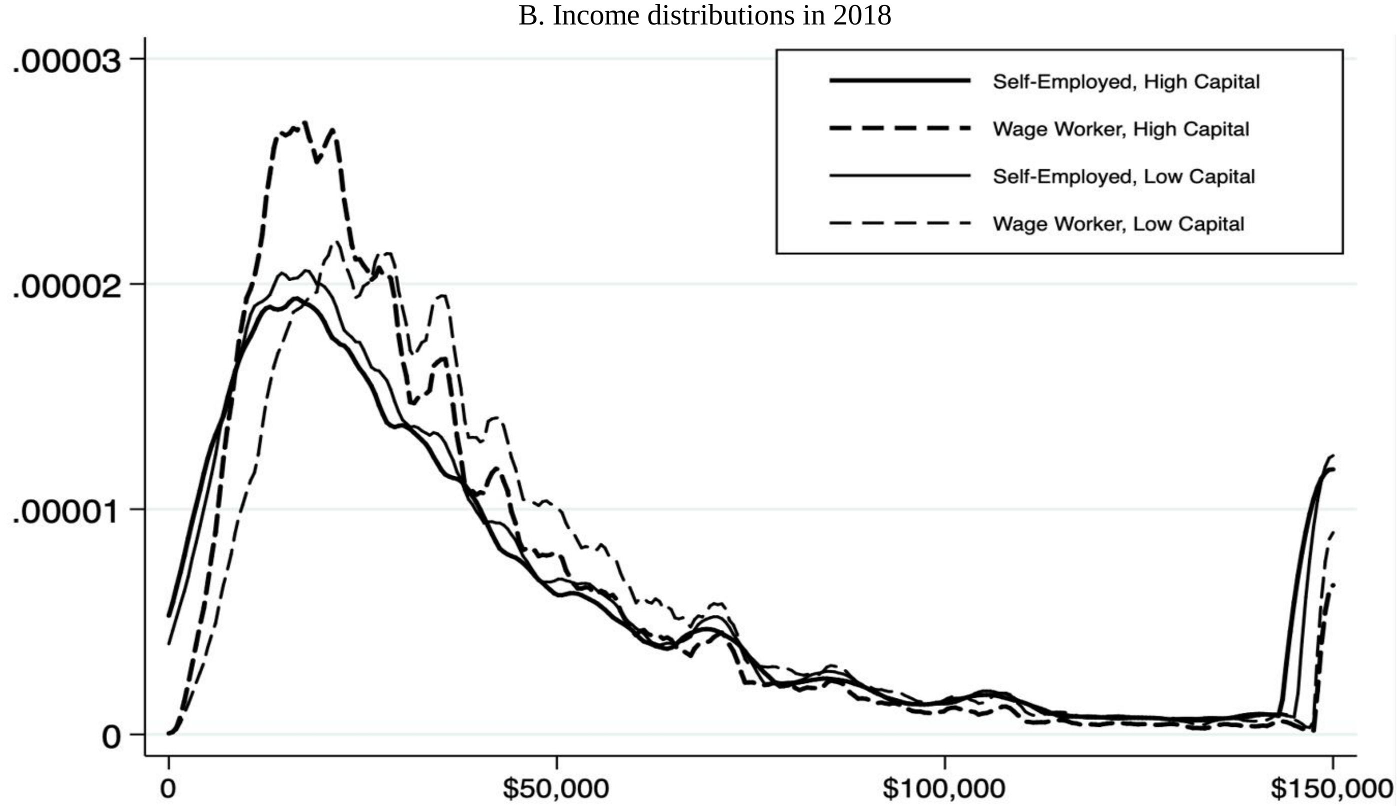
Notes: See Figure 2a.

Figure 3: Income distributions

A. Income distributions in 1970



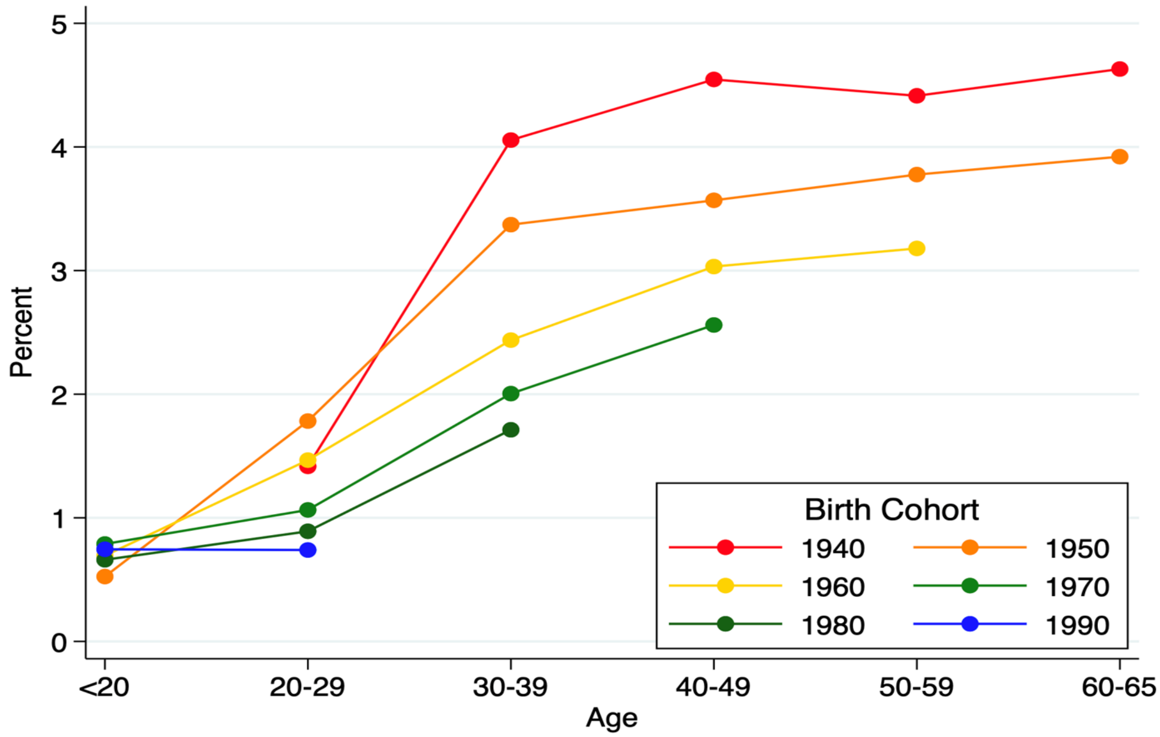
B. Income distributions in 2018



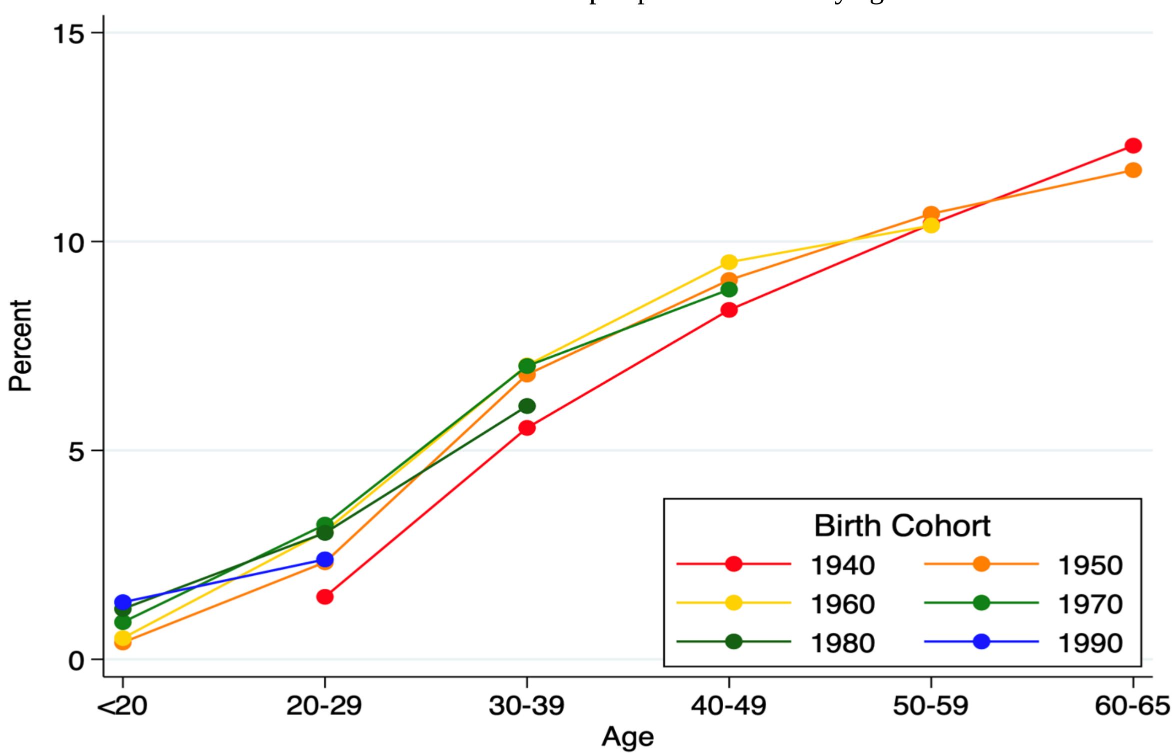
Notes: Figure show density plots of total income from the 1970 decennial census (top panel) and the 2018 five-year ACS. Total income is converted into year 2000 dollars, bottom-coded at zero, and top-coded at $150,000.

Figure 4: Transition rates by birth cohorts into types of self-employment as they age

A. Percent in high startup capital industries by age



B. Percent in low startup capital industries by age



Notes: Vertical axis is the share of working individuals from a birth cohort engaged in the indicated self-employment. Data for cohorts are combined across Decennial Censuses from 1970-2000 with 2006-2010 and 2014-2018 ACS.

Table 1: Estimations of 1970-2018 growth in industry self-employment on startup financing requirements

	Full Sample		Restricted Sample of US born individuals in Census Bureau analysis						
	Baseline correlation (shown in Figure 1)	Adding initial conditions and aggregate industry growth	Column 2 with restricted demographic sample	Instead examining 50+ employee financing	Including both 0-2 and 50+ employee financing	Incorporating sector fixed effects	Controlling for franchising, ecommerce and IP levels in industry	Using ASE data to calculate startup and expansion investment	Column 8 with separated startup and expansion investment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	DV: Log 1970-2018 growth in industry self-employment								
Log 1970 self-employment count		-0.263+++	-0.282+++	-0.272+++	-0.288+++	-0.250+++	-0.273+++	-0.250+++	-0.247+++
		(0.076)	(0.077)	(0.094)	(0.075)	(0.070)	(0.083)	(0.078)	(0.085)
Log growth in industry total employment		0.590+++	0.541+++	0.646+++	0.547+++	0.367++	0.553+++	0.542+++	0.508+++
		(0.076)	(0.078)	(0.120)	(0.078)	(0.142)	(0.104)	(0.079)	(0.093)
Share of 0-2 empl. firms raising >$50k for startup purposes	-0.066+++	-0.062+++	-0.065+++		-0.062+++	-0.057+++	-0.062+++		
	(0.012)	(0.011)	(0.011)		(0.011)	(0.015)	(0.013)		
Share of 50+ empl. firms raising >$50k for startup purposes				-0.034+	-0.017	-0.017	-0.017		
				(0.020)	(0.013)	(0.013)	(0.016)		
<u>ASE DATA:</u>									
Share of 0-2 empl. firms raising >$50k for startup or expansion purposes								-0.042+++	
								(0.005)	
Share of 50+ empl. firms raising >$50k for startup or expansion purposes								-0.002	
								(0.013)	
Share of 0-2 empl. firms raising >$50k for startup purposes									-0.039+++
									(0.009)
Share of 50+ empl. firms raising >$50k for startup purposes									-0.003
									(0.007)
Share of 0-2 empl. firms raising >$50k for expansion purposes									0.001
									(0.016)
Share of 50+ empl. firms raising >$50k for expansion purposes									-0.008
									(0.009)
Adjusted R-Squared value	0.390	0.676	0.681	0.342	0.685	0.772	0.656	0.715	0.695

Notes: The dependent variable is the log change in the count of self-employed individuals from 1970 to 2018 taken from IPUMS data using 1970 Decennial Census and the 2014-2018 American Community Survey. IPUMS data is also used to measure initial industry self-employment in 1970 and the total growth in industry employment from 1970 to 2018. In Column 1-7, the 2007 SBO data is used to calculate the share of businesses by size bin in an industry raising $50,000 or more in startup capital. Columns 8-9 use comparable data from the 2016 ASE. Sample includes 38 industries. Regressions are unweighted and report robust standard errors. + p<.1, ++ p<.05, +++ p<.01

Table 2: Estimations of 1970-2018 growth in industry self-employment on startup financing and profitability

	Baseline correlation	Adding initial condition and aggregate industry growth	Instead examining 50+ employee profitability	Including both 0-2 and 50+ employee profitability	Incorporating financing variables	Column 5 controlling for max profitability size and the minimum size required to achieve 80% profitability rate	Column 5 controlling for ratio of sales to payroll margin per employee in 0-2 empl. firms compared to industry average
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	DV: Log 1970-2018 growth in industry self-employment						
Log 1970 self-employment count		-0.289+++	-0.261++	-0.299+++	-0.291+++	-0.279+++	-0.288+++
		(0.101)	(0.102)	(0.100)	(0.077)	(0.074)	(0.076)
Log growth in industry total employment		0.574+++	0.655+++	0.579+++	0.555+++	0.539+++	0.539+++
		(0.110)	(0.120)	(0.094)	(0.075)	(0.087)	(0.110)
Share of 0-2 empl. firms profitable	0.040+++	0.034++		0.043++	0.002		
	(0.014)	(0.015)		(0.017)	(0.020)		
Share of 50+ empl. firms profitable			-0.009	-0.015++	-0.007		
			(0.008)	(0.007)	(0.006)		
Share of 0-2 empl. firms raising >$50k for startup purposes					-0.061+++	-0.064+++	-0.062+++
					(0.010)	(0.011)	(0.011)
Share of 50+ empl. firms raising >$50k for startup purposes					-0.017	-0.015	-0.017
					(0.014)	(0.015)	(0.014)
Adjusted R-Squared value	0.052	0.338	0.342	0.358	0.675	0.671	0.675

Notes: See Table 1.

Table 3: Estimations of 1978-2018 change in the firm size distribution for industries

	Change in share of 1-4 employee firms	Change in share of 5-19 employee firms	Change in share of 20-99 employee firms	Change in share of 100-999 employee firms	Change in share of 1000+ employee firms
	(1)	(2)	(3)	(4)	(5)
Share of 0-2 empl. firms raising >$50k for startup purposes	-0.458+++	0.259++	0.139+	0.049	0.011
	(0.163)	(0.107)	(0.074)	(0.043)	(0.013)
Initial conditions and industry growth	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared value	0.333	0.195	0.172	0.125	0.347

Notes: See Table 1. Outcome variables are changes in firm size distribution for industries taken from Business Dynamics Survey. The five columns sum to zero.

Table 4: Mincerian regressions for income across sectors

	1970	1980	1990	2000	2010	2018
	(1)	(2)	(3)	(4)	(5)	(6)
	A. DV is (0,1) for incomes of $50,000 or more in real 2000 dollars Reference group is wage workers in low startup capital industries					
(0,1) Self-employed in high startup capital industry	0.0516+++	0.0645+++	0.0226+++	0.0203+++	-0.0010	-0.0039+++
	(0.0018)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
(0,1) Self-employed in low startup capital industry	0.1208+++	0.0957+++	0.0455+++	0.0326+++	0.0018++	-0.0161+++
	(0.0020)	(0.0011)	(0.0009)	(0.0008)	(0.0007)	(0.0008)
(0,1) Wage worker in high startup capital industry	-0.0237+++	-0.0045+++	-0.0065+++	-0.0090+++	-0.0093+++	-0.0081+++
	(0.0007)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Individual covariates and state fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,057,041	3,279,392	3,972,891	4,668,001	4,919,731	5,070,247
	B. DV is (0,1) for above 95th percentile in income Reference group is wage workers in low startup capital industries					
(0,1) Self-employed in high startup capital industry	0.0890+++	0.1019+++	0.0780+++	0.0665+++	0.0747+++	0.0674+++
	(0.0013)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
(0,1) Self-employed in low startup capital industry	0.1217+++	0.1070+++	0.0710+++	0.0499+++	0.0513+++	0.0421+++
	(0.0016)	(0.0009)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
(0,1) Wage worker in high startup capital industry	-0.0001	0.0010+++	0.0001	0.0007+++	0.0021+++	0.0040+++
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Individual covariates and state fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,057,041	3,279,392	3,972,891	4,668,001	4,919,731	5,070,247

Notes: Estimations use data from the 1970-2000 Decennial Censuses and the 2006-2010 and 2014-2018 ACS. Sample is limited to individuals who report usually working at least 30 hours per week, at least 40 weeks/year. Estimations include unreported controls for gender, race, education, and age and fixed effects for states. Regressions are unweighted and report robust standard errors. + p<.1, ++ p<.05, +++ p<.01

Table 5: Estimations of 1970-2018 growth in industry self-employment on explanatory factors

	1970-1980	1970-1990	1970-2000	1970-2010	1970-2018	1990-2018
	(1)	(2)	(3)	(4)	(5)	(6)
			A. Baseline model			
Share of 0-2 empl. firms raising >$50k for startup purposes	-0.009	-0.042+++	-0.052+++	-0.059+++	-0.062+++	-0.027+++
	(0.006)	(0.008)	(0.008)	(0.009)	(0.011)	(0.006)
Initial conditions and industry growth	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.333	0.630	0.713	0.723	0.676	0.546
			B. Panel A adding industry size changes and regional wage growth			
Share of 0-2 empl. firms raising >$50k for startup purposes	n.a.	-0.045+++	-0.051+++	-0.056+++	-0.055+++	-0.025+++
		(0.010)	(0.011)	(0.010)	(0.012)	(0.007)
Log average size of firms in sector in BDS		0.054	0.023	-0.004	-0.061	-0.103
		(0.127)	(0.130)	(0.165)	(0.186)	(0.118)
Log change in average size from 1978 to 2018 in BDS		0.039	-0.057	-0.201	-0.354+	-0.335++
		(0.168)	(0.158)	(0.170)	(0.173)	(0.162)
Growth of regional median wage incomes weighted by industry distribution		0.030	0.005	0.018	0.024	0.024
		(0.114)	(0.056)	(0.069)	(0.066)	(0.069)
Growth of regional 95th wage incomes weighted by industry distribution		-0.074	0.007	0.005	0.067	0.114
		(0.136)	(0.088)	(0.075)	(0.081)	(0.068)
Initial conditions and industry growth		Yes	Yes	Yes	Yes	Yes
Adjusted R-squared		0.569	0.658	0.684	0.655	0.616
			C. Panel A adding industry size changes and regional debt growth			
Share of 0-2 empl. firms raising >$50k for startup purposes	n.a.	n.a.	-0.055+++	-0.058+++	-0.060+++	-0.025+++
			(0.010)	(0.010)	(0.012)	(0.007)
Log average size of firms in sector in BDS			0.059	0.030	-0.016	-0.110
			(0.122)	(0.155)	(0.180)	(0.108)
Log change in average size from 1978 to 2018 in BDS			-0.016	-0.163	-0.262	-0.292++
			(0.149)	(0.156)	(0.158)	(0.143)
Growth of regional total debt weighted by industry distribution			0.126	0.171	0.272	0.130+
			(0.145)	(0.140)	(0.194)	(0.074)
Growth of regional student debt weighted by industry distribution			-0.028	-0.079	-0.197	-0.111
			(0.178)	(0.146)	(0.163)	(0.095)
Initial conditions and industry growth			Yes	Yes	Yes	Yes
Adjusted R-squared			0.681	0.706	0.669	0.586

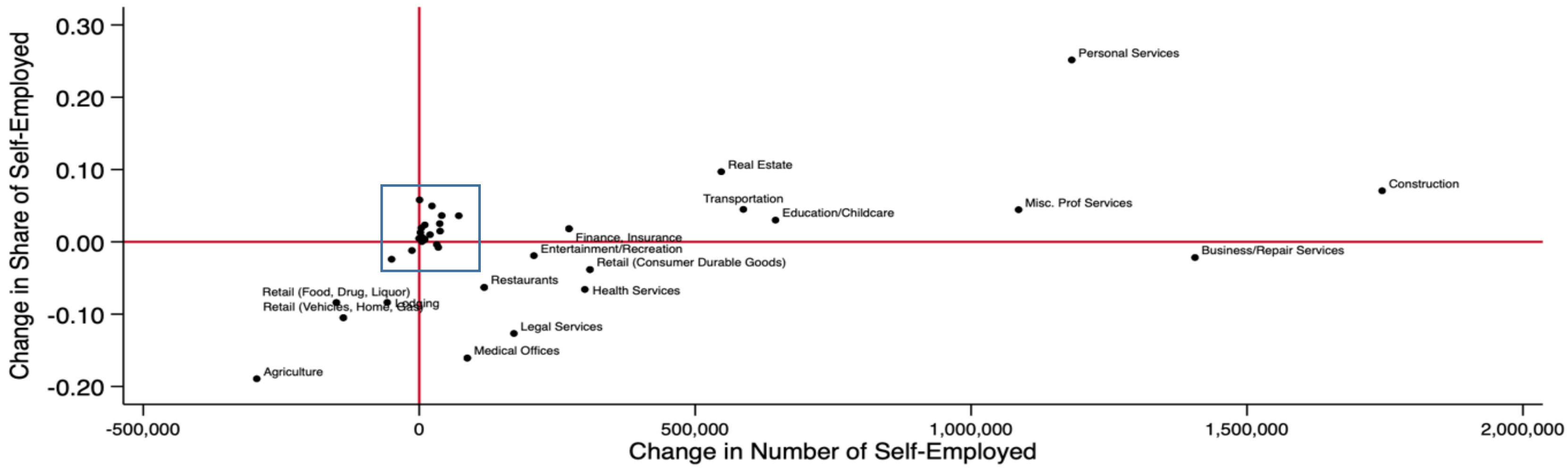
Notes: Estimations use data from the 1970-2000 Decennial Censuses and the 2006-2010 and 2014-2018 ACS. Estimations include unreported controls for log initial self-employment and log total change in industry employment. Regressions are unweighted and report robust standard errors. + p<.1, ++ p<.05, +++ p<.01

Table 6: Extensions on Table 5's baseline model to additional outcomes

	1970-1980	1970-1990	1970-2000	1970-2010	1970-2018	1990-2018
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Log change in self-employment					
Share of 0-2 empl. firms raising >$50k for startup purposes	-0.009	-0.042+++	-0.052+++	-0.059+++	-0.062+++	-0.027+++
	(0.006)	(0.008)	(0.008)	(0.009)	(0.011)	(0.006)
Initial conditions and industry growth	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.333	0.630	0.713	0.723	0.676	0.546
	B. Log change in self-employment for white men					
Share of 0-2 empl. firms raising >$50k for startup purposes	-0.015+++	-0.030+++	-0.042+++	-0.051+++	-0.056+++	-0.032+++
	(0.003)	(0.006)	(0.007)	(0.008)	(0.011)	(0.008)
Initial conditions and industry growth	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.746	0.691	0.774	0.777	0.723	0.568
	C. Log change in self-employment for other groups					
Share of 0-2 empl. firms raising >$50k for startup purposes	-0.006	-0.051+++	-0.064+++	-0.069+++	-0.072+++	-0.027+++
	(0.006)	(0.011)	(0.009)	(0.010)	(0.014)	(0.006)
Initial conditions and industry growth	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.078	0.561	0.636	0.654	0.619	0.518
	D. Change in share of industry workforce that is self-employed					
Share of 0-2 empl. firms raising >$50k for startup purposes	-0.046	-0.243+++	-0.340+++	-0.359+++	-0.355+++	-0.165++
	(0.060)	(0.078)	(0.106)	(0.120)	(0.130)	(0.070)
Initial conditions and industry growth	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	-0.031	0.275	0.212	0.168	0.166	0.010
	E. Change in share of top earners that is self-employed					
Share of 0-2 empl. firms raising >$50k for startup purposes	-0.228++	-0.475+++	-0.630+++	-0.497+	-0.577+	-0.270
	(0.108)	(0.164)	(0.205)	(0.267)	(0.324)	(0.194)
Initial conditions and industry growth	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.139	0.457	0.485	0.339	0.391	0.147

Notes: See Table 5.

Appendix Figure 1: 1970-2018 change in self-employment share of industry employment vs 1970-2018 change in self-employment count by industry

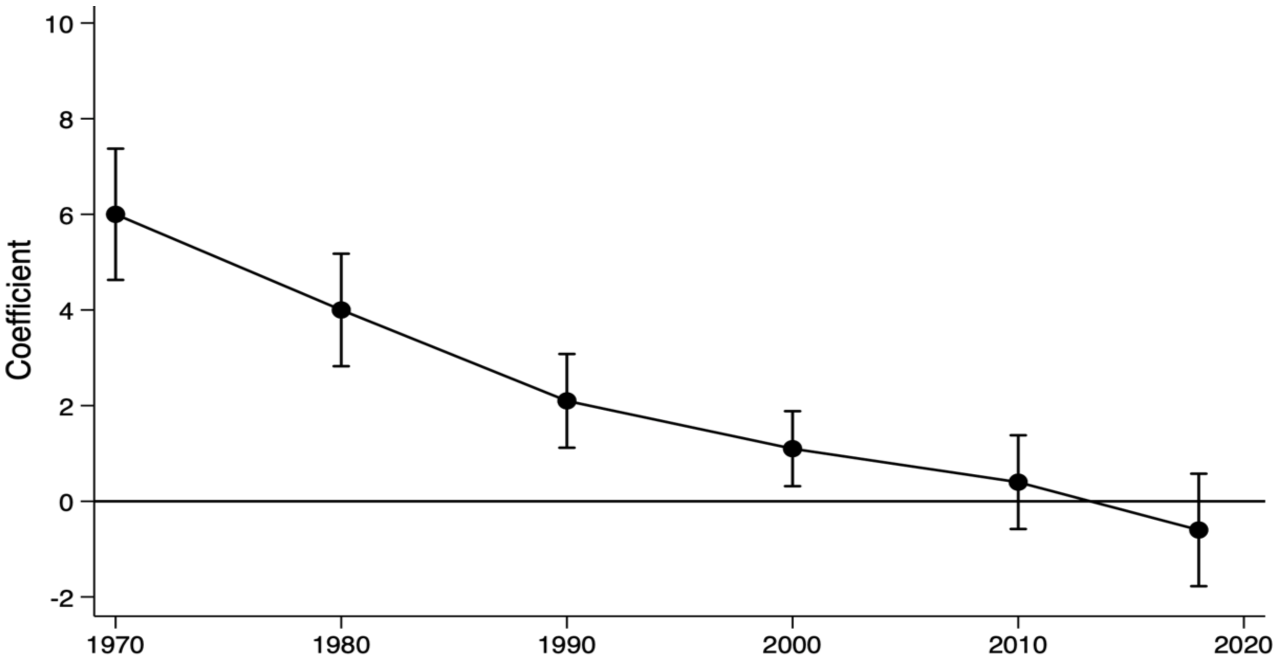


Interior box:

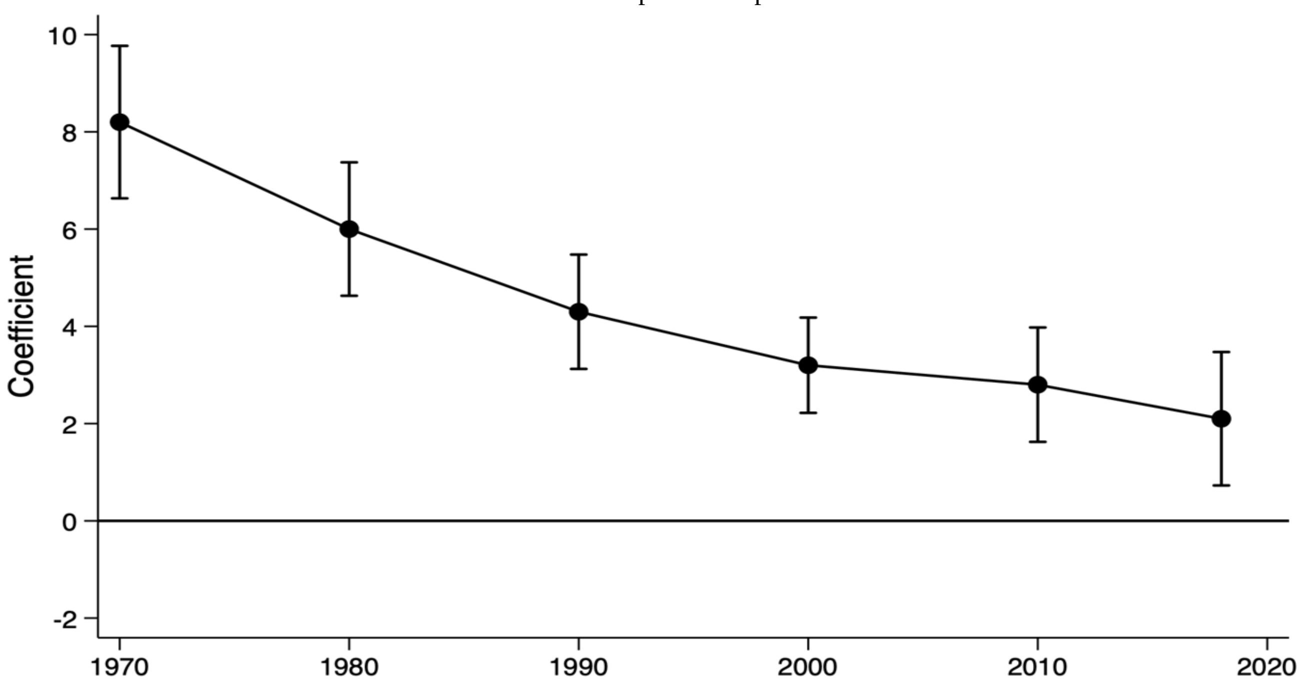
Notes: Vertical axis is the change in the share of self-employed individuals for industry workforce from 1970 to 2018 taken from IPUMS data using 1970 Decennial Census and the 2014-2018 American Community Survey. Horizontal axis is change in the count of self-employed individuals from 1970 to 2018 by industry from the same data. The bottom panel zooms on the unlabeled dots in the top panel.

Appendix Figure 2: Local bias of entrepreneurship

A. Local bias of entrepreneurship for full sample

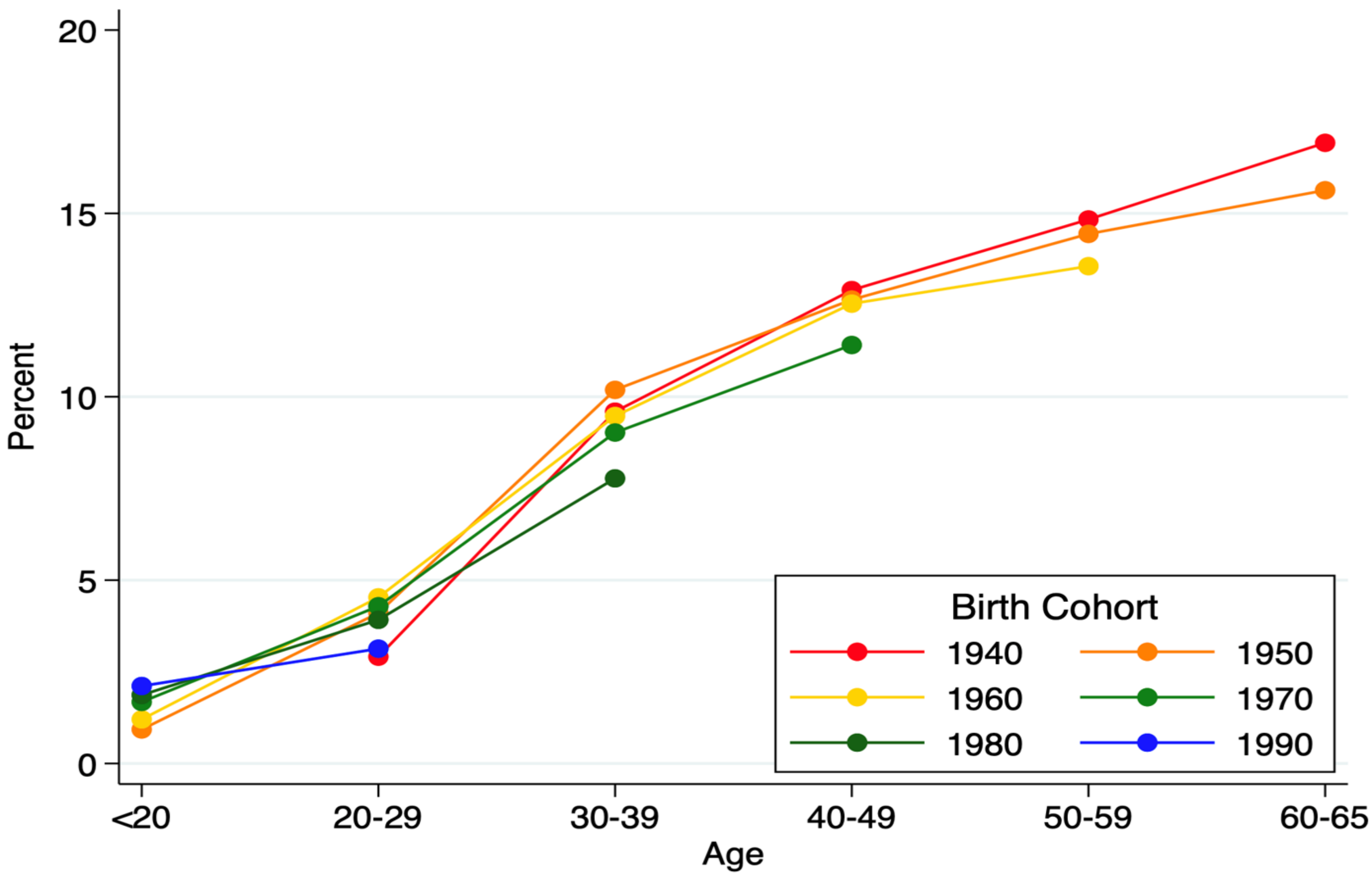


B. Local bias of entrepreneurship for white men



Notes: Figure displays the decline in the local bias of entrepreneurship among US-born individuals. The top panel presents results for all US-born individuals, and the bottom panel restricts the analysis to US-born white males. The local bias of entrepreneurship is defined as the additional probability that self-employed individuals are living in their state of birth, relative to wage workers. For example, a coefficient of 4 in the figures represents a 4% higher rate of living in one's state-of-birth, relative to wage workers (baseline is approximately 70% in 2000, for reference). This estimate is obtained by regressing an indicator variable for living in one's state of birth on an indicator variable for being self-employed, controlling for sex and gender (in the top panel) as well as age, education, marital status, number of children and region of birth (in both panels). The coefficient and 95% confidence interval on the self-employment indicator is plotted in the figure. Data combines Decennial Censuses from 1970-2000 with 2006-2010 and 2014-2018 ACS.

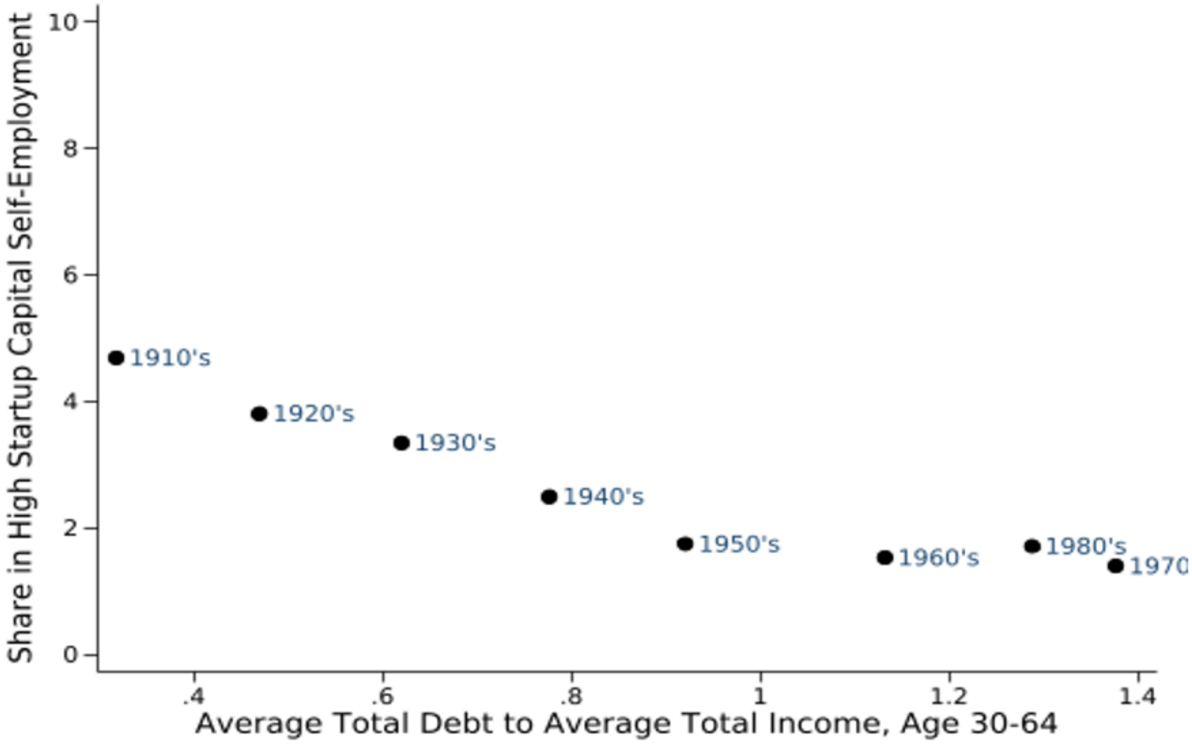
Appendix Figure 3: Transition rates by birth cohorts into self-employment as they age



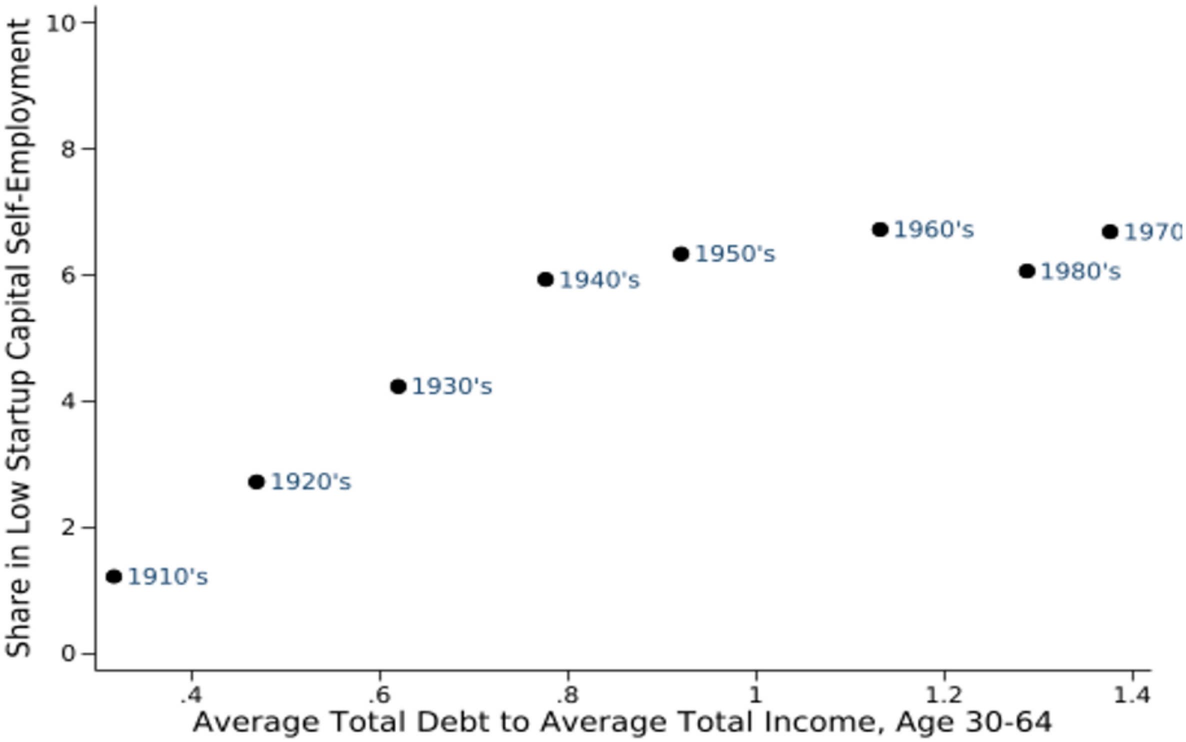
Notes: See Figure 4.

Appendix Figure 4: Cohort self-employment rate and debt-to-income levels

A. High startup capital industries

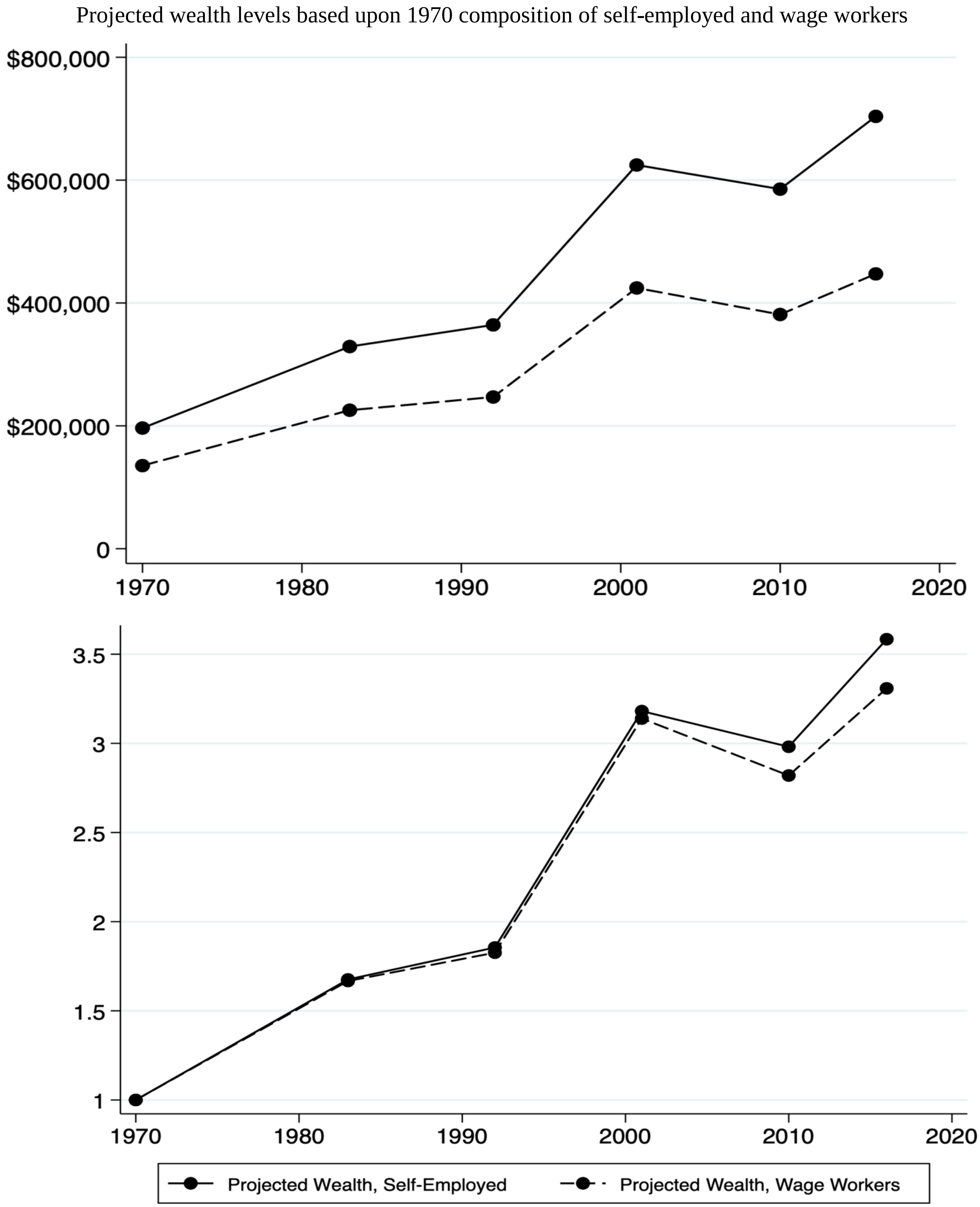


B. Low startup capital industries



Notes: Vertical axis is the share of working individuals from a birth cohort engaged in the indicated type of self-employment. Data for cohorts are combined across Decennial Censuses from 1970-2000 with 2006-2010 and 2014-2018 ACS. Horizontal axis the age-adjusted average total debt to average total income for each cohort from the Survey of Consumer Finances (SCF+) harmonized by Kuhn et al (2021). Debt-to-income ratios are calculated for heads of household ages 30-64.

Appendix Figure 5: Projected wealth levels using Survey of Consumer Finance



Notes: Figure calculates the projected wealth for self-employed and wage workers holding their 1970 compositions fixed. Calculations divided the self-employed and wage workers into six groups: whites and non-whites who are under thirty years of age, aged 30-49, and 50-64 years of age. We then multiplied the share of self-employed and wage workers in each of these six groups by the average actual wealth observed for that group in the SCF+ in the years 1970, 1983, 1992, 2001, 2010, and 2016. Household wealth is expressed in year 2016 dollars. The Survey of Consumer Finances (SCF+) is harmonized by Kuhn et al (2021).

Appendix Table 1: Industry data on US self-employment and small business financing/profitability

Industry	Count of self-employed in 2018 (thousands)	Log growth of self-employed from 1970 to 2018	Share of businesses in 2007 SBO reporting $50,000 or more startup financing		Average profitability rate of businesses in 2016 ASE (see App. Table 3)	
			0-2 empl.	50+ empl.	0-2 empl.	3+ empl.
Agriculture, Landscape/Horticulture, Forestry, Fishing	1,133,744	-0.231	28.5	46.2	67.7	65.3
Mining and Petroleum Refining	33,788	0.305	31.9	50.9	55.1	55.3
Construction	2,497,086	1.200	10.6	41.8	73.0	77.4
Food Manufacturing	41,022	0.129	42.5	46.3	61.5	69.6
Textile Manufacturing	40,170	0.014	17.9	43.1	69.0	64.5
Paper Mfg, Printing, Publishing, and Allied Industries	100,772	0.519	22.9	48.1	63.9	63.1
Chemicals and Allied Products	19,953	0.542	28.3	46.3	70.0	72.7
Rubber and Leather Manufacturing	11,761	-0.024	30.3	47.2	66.7	77.0
Lumber and Wood Products Manufacturing	33,314	0.364	25.6	53.7	69.5	82.3
Furniture Manufacturing	39,018	0.898	15.5	47.9	68.4	73.7
Stone, Clay, Glass and Concrete Manufacturing	19,316	0.227	22.7	42.8	62.7	77.6
Metal Industries Manufacturing	39,868	0.057	25.4	50.5	63.8	74.8
Machinery Manufacturing	48,446	0.117	24.1	49.2	63.8	74.5
Computing and Electrical Equipment Manufacturing	43,487	0.599	23.5	46.1	59.0	65.7
Transportation Equipment Manufacturing	24,199	0.547	26.4	51.2	65.8	75.0
Miscellaneous Manufacturing	71,669	0.733	18.7	40.8	66.4	69.5
Transportation	761,839	1.474	19.8	38.8	64.5	67.1
Communications	77,355	2.617	18.6	43.4	65.9	60.7
Utilities	48,420	1.519	27.3	48.6	68.2	75.2
Wholesale Trade - Durable Goods	147,515	0.267	20.1	53.4	68.2	75.9
Wholesale Trade - Nondurable Goods	161,285	-0.078	23.2	50.0	66.0	77.9
Retail Trade - General Merchandise	89,883	-0.442	30.4	41.7	62.9	75.4
Retail Trade - Food, Drug, Liquor	175,512	-0.618	31.9	46.8	67.6	75.9
Retail Trade - Vehicles, Home Supply, Gasoline	136,513	-0.697	30.6	56.6	67.8	76.4
Retail Trade - Consumer Durables (Mostly)	765,984	0.517	25.4	35.2	63.8	68.4
Retail Trade - Restaurants	443,573	0.308	27.4	59.2	60.8	70.9
Finance, Insurance	390,048	1.191	19.1	62.4	80.9	83.8
Real Estate	685,912	1.599	22.6	42.8	77.4	78.4
Business and Repair Services	1,808,193	1.503	13.8	41.6	71.0	74.7
Personal Services - Lodging	38,049	-0.925	48.9	47.4	68.5	75.0
Personal Services - Beauty/Barber + Misc Personal	1,663,233	1.241	21.9	43.5	69.7	72.0
Entertainment and Recreation	289,328	1.266	22.3	53.4	65.5	62.0
Medical Professional Offices	338,685	0.297	28.2	48.2	77.7	81.8
Hospitals + Residential Care Facilities	74,401	0.559	27.8	51.7	61.5	69.5
Health Services Unspecified	349,203	1.961	24.0	42.7	67.2	65.2
Legal Services	312,210	0.797	8.7	40.9	84.4	85.7
Professional Services - Education and Childcare	731,745	2.139	13.6	47.5	67.3	71.0
Misc. Professional Services	1,289,909	1.845	11.3	49.1	76.5	83.1

Notes: Industries developed by authors to consistently model IPUMS industries over time and have sufficient sample size to pass Census Bureau disclosure statistics. Industries with greater than 24% of businesses in 2007 SBO reporting $50,000 or more startup financing are above median in financing requirements.

Appendix Table 2a: Trends in US self-employment

							Considering local self-employed vs. mover self-employed			
		Total count	High startup capital	Low startup capital	High startup capital share	Low startup capital share	Local and high capital	Local and low capital	Mover and high capital	Mover and low capital
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Non WM	1970	1,571,400	780,650	790,750	0.497	0.503	0.293	0.275	0.203	0.229
Non WM	1980	2,564,660	1,261,940	1,302,720	0.492	0.508	0.271	0.258	0.222	0.250
Non WM	1990	4,718,879	1,575,996	3,142,883	0.334	0.666	0.161	0.324	0.173	0.342
Non WM	2000	6,208,368	1,610,379	4,597,989	0.259	0.741	0.110	0.332	0.149	0.408
Non WM	2010	7,325,814	1,679,307	5,646,507	0.229	0.771	0.089	0.320	0.140	0.450
Non WM	2018	7,579,452	1,597,576	5,981,876	0.211	0.789	0.083	0.318	0.128	0.471
White Men	1970	5,092,950	2,772,700	2,320,250	0.544	0.456	0.386	0.280	0.159	0.176
White Men	1980	6,547,700	2,945,640	3,602,060	0.450	0.550	0.305	0.322	0.145	0.228
White Men	1990	7,145,784	2,667,866	4,477,918	0.373	0.627	0.238	0.352	0.135	0.274
White Men	2000	7,572,690	2,252,163	5,320,527	0.297	0.703	0.181	0.382	0.116	0.320
White Men	2010	8,243,194	2,169,237	6,073,957	0.263	0.737	0.154	0.382	0.109	0.355
White Men	2018	7,396,956	1,899,539	5,497,417	0.257	0.743	0.148	0.374	0.109	0.369
Total	1970	6,664,350	3,553,350	3,111,000	0.533	0.467	0.364	0.278	0.169	0.188
Total	1980	9,112,360	4,207,580	4,904,780	0.462	0.538	0.295	0.304	0.167	0.234
Total	1990	11,864,663	4,243,862	7,620,801	0.358	0.642	0.207	0.341	0.150	0.301
Total	2000	13,781,058	3,862,542	9,918,516	0.280	0.720	0.149	0.360	0.131	0.360
Total	2010	15,569,008	3,848,544	11,720,464	0.247	0.753	0.123	0.353	0.124	0.400
Total	2018	14,976,408	3,497,115	11,479,293	0.234	0.766	0.115	0.346	0.119	0.421

Notes: Calculated from IPUMS data.

Appendix Table 2b: Trends in US self-employment

		Considering top earners (95th+) vs. non-top earners				Considering low, middle, and high education levels					
		Top and high capital	Top and low capital	Non-top and high capital	Non-top and low capital	Low ed and high capital	Low ed and low capital	Mid ed and high capital	Mid ed and low capital	High ed and high capital	High ed and low capital
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Non WM	1970	0.015	0.013	0.482	0.491	0.402	0.362	0.078	0.123	0.017	0.019
Non WM	1980	0.018	0.015	0.474	0.493	0.324	0.287	0.133	0.175	0.034	0.046
Non WM	1990	0.015	0.018	0.319	0.648	0.167	0.294	0.132	0.319	0.035	0.053
Non WM	2000	0.013	0.024	0.246	0.717	0.133	0.361	0.096	0.302	0.031	0.077
Non WM	2010	0.012	0.025	0.217	0.746	0.104	0.337	0.094	0.345	0.031	0.088
Non WM	2018	0.012	0.025	0.199	0.765	0.088	0.318	0.091	0.371	0.032	0.101
White Men	1970	0.075	0.083	0.469	0.373	0.402	0.298	0.089	0.113	0.053	0.045
White Men	1980	0.069	0.085	0.381	0.465	0.272	0.292	0.114	0.182	0.064	0.076
White Men	1990	0.052	0.080	0.322	0.546	0.175	0.255	0.139	0.294	0.060	0.078
White Men	2000	0.039	0.077	0.259	0.625	0.141	0.320	0.106	0.290	0.050	0.093
White Men	2010	0.034	0.074	0.229	0.663	0.120	0.325	0.101	0.322	0.042	0.091
White Men	2018	0.029	0.067	0.228	0.676	0.122	0.323	0.101	0.332	0.035	0.087
Total	1970	0.061	0.066	0.472	0.400	0.402	0.313	0.086	0.115	0.044	0.039
Total	1980	0.054	0.065	0.407	0.473	0.287	0.291	0.119	0.180	0.055	0.067
Total	1990	0.037	0.056	0.321	0.587	0.172	0.271	0.136	0.304	0.050	0.068
Total	2000	0.027	0.053	0.253	0.666	0.138	0.339	0.102	0.296	0.041	0.086
Total	2010	0.024	0.051	0.223	0.702	0.113	0.331	0.098	0.333	0.037	0.089
Total	2018	0.020	0.046	0.213	0.721	0.104	0.321	0.096	0.352	0.033	0.094

Notes: See Appendix Table 2a.

Appendix Table 2c: Trends in US self-employment

		Considering urban vs rural				Homeowners vs. non-homeowners (heads of household only)			
		Urban and high capital	Urban and low capital	Rural and high capital	Rural and low capital	Homeowner and high capital	Homeowner and low capital	Non-owner and high capital	Non-owner and low capital
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Non WM	1970	0.257	0.327	0.154	0.115	0.392	0.383	0.105	0.120
Non WM	1980	0.287	0.370	0.139	0.090	0.402	0.397	0.090	0.111
Non WM	1990	.	.	.	.	0.265	0.496	0.069	0.170
Non WM	2000	0.186	0.591	0.053	0.104	0.203	0.545	0.057	0.196
Non WM	2010	0.172	0.628	0.041	0.098	0.183	0.565	0.046	0.206
Non WM	2018	0.167	0.675	0.019	0.046	0.155	0.524	0.056	0.265
White Men	1970	0.217	0.293	0.182	0.105	0.450	0.372	0.095	0.083
White Men	1980	0.217	0.383	0.160	0.107	0.379	0.443	0.071	0.107
White Men	1990	.	.	.	.	0.311	0.500	0.062	0.126
White Men	2000	0.175	0.525	0.090	0.123	0.252	0.573	0.045	0.129
White Men	2010	0.162	0.554	0.073	0.126	0.223	0.596	0.040	0.141
White Men	2018	0.170	0.593	0.038	0.062	0.205	0.560	0.051	0.183
Total	1970	0.226	0.301	0.175	0.107	0.436	0.375	0.097	0.092
Total	1980	0.237	0.380	0.154	0.102	0.386	0.430	0.076	0.108
Total	1990	.	.	.	.	0.293	0.499	0.065	0.144
Total	2000	0.180	0.555	0.074	0.114	0.230	0.561	0.050	0.159
Total	2010	0.167	0.589	0.058	0.113	0.204	0.582	0.043	0.171
Total	2018	0.168	0.634	0.029	0.054	0.180	0.542	0.054	0.224

Notes: See Appendix Table 2a.

Appendix Table 3: Descriptive statistics on Census Bureau data

Variable	Source	Mean	SD
Share raising >$50k in start-up financing, employer firms	SBO	33.2	8.5
… 0-2 employees	SBO	24.0	8.0
… 3-9 employees	SBO	36.0	7.9
… 10-49 employees	SBO	44.8	6.6
… 50+ employees	SBO	47.3	5.6
… 3+ employees	SBO	40.9	7.0
… 0-2 employees, recent entrants (2003-2007)	SBO	44.9	14.8
… 0-2 employees, older entrants (pre 1990)	SBO	29.7	12.6
Share raising >$50k in start-up financing, non-employer firms	SBO	8.2	5.2
Share raising $5-25k	SBO	16.6	4.7
Share raising $25-50k	SBO	8.1	1.4
Share raising $50k-$1m	SBO	28.8	6.8
Share raising $1m+	SBO	4.4	2.8
Log average start-up capital level in thousands	SBO	4.0	0.7
Expansion or startup capital exceeds $50k	ASE	61.5	12.1
… 0-2 employees	ASE	48.6	12.6
… 50+ employees	ASE	84.6	9.5
Startup capital exceed $50k	ASE	46.5	13.9
… 0-2 employees	ASE	34.6	13.2
… 50+ employees	ASE	68.3	13.2
Expansion capital exceed $50k	ASE	41.6	7.8
… 0-2 employees	ASE	32.1	8.1
… 50+ employees	ASE	61.1	9.9
Access to or cost of financial capital hurt profitability	ASE	16.5	3.9
… 0-2 employees	ASE	15.8	4.7
… 3+ employees	ASE	17.4	3.9
Share of businesses reporting a funding gap exists	ASE	17.2	4.2
… 0-2 employees	ASE	14.9	3.6
… 3+ employees	ASE	19.5	4.9
Business was profitable (0="loss", 0.5="break-even", 1="profits")	ASE	70.7	5.7
… 0-2 employees	ASE	67.6	5.9
… 3-9 employees	ASE	69.9	8.0
… 10-49 employees	ASE	74.9	6.8
… 50+ employees	ASE	80.1	11.0
… 3+ employees	ASE	72.7	6.9
Share franchised	ASE	5.5	6.4
Share of sales via ecommerce	ASE	5.6	4.6
Share holding IP (patent, copyright, trademark)	ASE	14.9	11.8
Share founded by owner	ASE	74.6	11.2

Notes: Values calculated from micro data of 2007 SBO and 2016 ASE. Tabulation weights aggregate the data into 38 NAICS groups listed in Appendix Table 1. Means and standard deviations are across these 38 groups.

Appendix Table 4: Extensions on measuring startup investment in SBO

DV: Log 1970-2018 growth in industry self-employment
Estimations control for covariates in Column 5 of Table 1

A. Baseline regression (Column 5 of Table 1)		
Share of 0-2 empl. firms raising >$50k	-0.062+++	(0.011)
Share of 50+ empl. firms raising >$50k	-0.017	(0.013)
B. Using non-employer firms		
Share of non-employer firms raising >$50k	-0.056++	(0.025)
Share of 50+ empl. firms raising >$50k	-0.024	(0.023)
C. Using recent entrants from 2003-2007		
Share of 0-2 empl. firms raising >$50k	-0.037+++	(0.006)
Share of 50+ empl. firms raising >$50k	-0.012	(0.011)
D. Using older entrants from before 1990		
Share of 0-2 empl. firms raising >$50k	-0.037+++	(0.005)
Share of 50+ empl. firms raising >$50k	-0.012	(0.015)
E. Including four size categories		
Share of 0-2 empl. firms raising >$50k	-0.055+++	(0.018)
Share of 3-9 empl. firms raising >$50k	0.013	(0.020)
Share of 10-49 empl. firms raising >$50k	-0.040+	(0.022)
Share of 50+ empl. firms raising >$50k	-0.004	(0.017)
F. Combining all size categories		
Share of firms raising >$50k	-0.067+++	(0.012)
G. Combining all size categories and using log amounts		
Log average start-up capital level in thousands	-0.912+++	(0.139)
H. Combining all size categories and using binned investment levels (omitted is <$5k)		
Share of firms raising $5-25k	-0.061	(0.048)
Share of firms raising $25-50k	0.075	(0.065)
Share of firms raising $50k-$1m	-0.091+++	(0.020)
Share of firms raising $1m+	-0.110++	(0.044)

Notes: See Tables 1 and 2.