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Grown-up Business Cycles*

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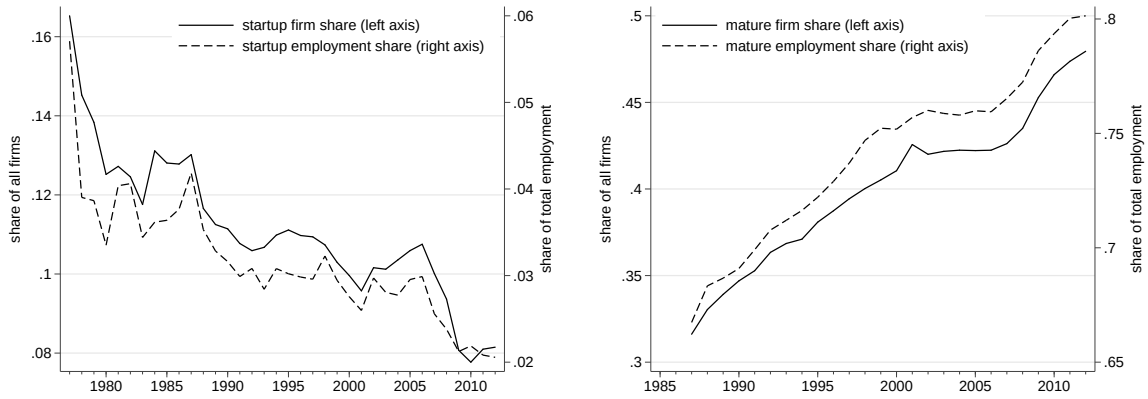
Abstract

We document two striking facts about U.S. firm dynamics and interpret their significance for aggregate employment dynamics. The first observation is the steady decline in the firm entry rate over the last thirty years, and the second is the gradual shift of employment from younger to older firms over the same period. Both hold across industries and geography. We show that despite these trends, firms' lifecycle dynamics and their business cycle properties have remained virtually unchanged. Consequently, the reallocation of employment towards older firms results entirely from the cumulative effect of the 30-year decline in firm entry. This "startup deficit" has both an immediate and a delayed (by shifting the age distribution) effect on aggregate employment dynamics. Recognizing this evolving heterogeneity is crucial for understanding shifts in aggregate behavior of employment over the business cycle. With mature firms less responsive to business cycle shocks, the cyclical component of aggregate employment growth diminishes with the increasing share of mature firms. At the same time, the trend decline in firm entry masks the diminishing cyclicality in contractions and reinforces it during expansions, which generates the appearance of jobless recoveries where aggregate employment recovers slowly relative to output.

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1 Introduction

There have been two significant changes in U.S. firm demographics in the past thirty or more years. The first is the dramatic decline in business formation. Figure 1a shows the declines in two common measures of business formation. The *startup rate*, which is the number of age 0 employer firms (what we refer to as *startups*) as a fraction of the overall stock of employer firms, has declined from an average of about 13 percent in the early 1980s to a recent level near 8 percent. The *startup employment share*, which measures employment at age 0 firms as a fraction of all private sector employment, plotted as the broken line against the right axis has fallen by almost half, from 4 percent to just above 2 percent.[1] As Figure 1b shows in the early 1980s, only around one-third of firms were 11 or more years old (what we call *mature firms*), while by 2012 almost half of all firms were 11 or more years old. The employment share of mature firms increased from about 65 percent in the late 70s to almost 80 percent by 2012. These patterns are broad-based across sectors and geographic areas and are not due to a compositional shift in economic activity.



(a) Startup shares from 1977 to 2012

(b) Mature (ages 11+) shares from 1987 to 2012

Figure 1: Firm and employment share of startups and mature firms

Note: U.S. Census Bureau Business Dynamics Statistics. Left panel: number of age 0 employer firms as fraction of number of employer firms of all ages (left axis) and total employment at age 0 firms as fraction of total employment at firms of all ages (right axis). Series begins in 1977 because age 0 employers are not left censored. Right panel: number of age 11+ employer firms as fraction of number of employer firms of all ages (left axis) and total employment at age 11+ firms as fraction of total employment at firms of all ages (right axis). Series begins in 1987 because firms aged 11+ are left censored from 1977 to 1986.

While these two observations are closely related, they do not necessarily imply each other. For example, the decline in firm entry could coincide with a shift towards higher quality entrants with higher survival probabilities or higher expected employment growth offsetting the declining entrant share. To isolate the margins of change, we provide a decomposition framework where employment shares by firm age are determined by the history of firm survival and employment growth by firm

[1] The average startup employment has remained roughly constant over this period, while the overall average firm size has slightly increased, so the employment share of startup firms has declined even faster than the startup rate.

age in addition to the entire history of firm entry. The empirical counterparts to these measures are readily available in Census Bureau Business Dynamics Statistics (BDS) database. Aside from cyclical and other higher frequency fluctuations, we show that the survival and growth margins have remained relatively stable over the long-run. In other words, despite the pronounced decline in the startup rate, conditional on age, the dynamics of incumbent firms are approximately stationary. Consequently, the shift in employment shares of young and mature firms over this period is entirely determined by the cumulative effects of the decline in the startup rate. We refer to this shortage of entrants as the *startup deficit*. This observation also holds across states and industries. When we apply our decomposition to 50 U.S. states and 7 broad industry groups separately, we find that the decline in the startup rate accounts for almost all the increase in the employment share of mature firms across states and industries.

These shifts in firm-level demographics have had a significant effect on aggregate employment dynamics. The rest of the paper traces the direct and indirect effects of the startup deficit on the behavior of aggregate employment. To put things into context, we first decompose employment growth into three components using data from the BDS: startup, young and mature firm employment growth contributions. We show that aggregate employment growth has always been dominated by startups' contribution, which has been gradually diminishing from declines in entry. The contribution from incumbent firms is on-net negative. Cohorts of new firms attrit early on in their lifecycle, before eventually stabilizing. The high growth rate of surviving young firms is not enough to compensate for their higher exit rates. While employment growth rates have been stable for incumbent young and mature firms, the importance of mature firms has been increasing over time. These observations, put together with the declining entry and maturing of firms, is suggestive of a change in trend employment growth.

Before we quantify this effect, we examine the cyclicality of employment growth rates by firm age to understand the business cycle implication of the growing startup deficit. We do so by exploiting the aggregate time series variation on U.S. business cycles as well as cross state variation in local economic conditions. We proxy for business cycle conditions using four different measures: (i) log differences in annual real personal income, (ii) log differences in annual real gross domestic or state output, (iii) changes in annual average of monthly unemployment and (iv) annual averages of monthly cyclical unemployment fluctuations.[2] Across all of these measures we find that the growth rate of both startups and young incumbents covaries much more strongly with the overall economy than the growth rate of mature firms. The greater cyclical sensitivity of young firm employment than of mature firm employment is a robust finding in the data. In particular, this finding is robust to (i) exploiting time series vs. state-level variation; (ii) using different proxies for business cycles; (iii) using more disaggeragated firm age groups; (iv) controling for industry fixed effects; (v) considering survival and conditional employment growth margins separately. In addition we find that the relative cyclicality by firm age remained fairly stable over time. This observation resonates

[2] These last two requirements are consistent with the conclusions of Haltiwanger, Jarmin, and Miranda (2013) and Fort, Haltiwanger, Jarmin, and Miranda (2013), who using the same population of firms establish the higher average growth rate among young businesses as well as relatively stronger cyclical growth rates relative to older firms.

with our findings about the stability of survival and growth margins by firm age over time. Despite the large changes in the firm age distribution, firm survival rates, employment growth rates, and relative cyclical sensitivies by firm age remained essentially unchanged in the last 30 years. This finding provides the foundation for the the counterfactual exercise that we conduct in the last section of our paper.

As suggested by our findings, the effect of the startup deficit—both its direct effect and its cumulative indirect effect vis-a-vis the growing share of mature firms—on aggregate employment dynamics is important in both the trend and the cyclical components of employment growth. We first consider the trend growth rate of employment. The trend decline in startups has an immediate *negative* impact on employment due to the outsized role firm entry plays in net employment creation. In addition, it has a delayed *positive* impact by gradually shifting the distribution of employment towards mature firms, which actually have higher growth rates than young incumbents because of a much lower exit rate. To quantify the importance of the startup deficit on employment, we compute counterfactual employment paths keeping the startup rate at its 1980-85 average and the age distribution of firms at their 1987 level. Our analysis shows that the negative immediate effect is overwhelmingly larger than the delayed positive effect thereby causing a decline in the trend growth rate of employment. We find that the effect is quantitatively significant re-emphasizing the well-known role of startups in employment growth.

We then examine how the startup deficit reshaped employment dynamics over the business cycle. There are two related effects. The first is the gradual aging of firms which acts to decrease the cyclical sensitivity of employment, implying milder recessions and slower recoveries. The second is the decline in employment contribution from firm entry which amplifies the response of employment to output contractions and dampens employment growth during expansions. While these two forces act in opposing directions during recessions, our counterfactual analysis shows that the effect of the declining startups is quantitatively larger, causing more severe declines in employment during recessions. For recoveries, both effects reinforce each other implying a decoupling of employment and output growth during recoveries. This disconnect between employment and output increases as the startup deficit cumulates. Therefore its effect is more significant for the Great Recession. Our experiment shows that increasing the pace of startups to its 1980-85 average and reallocating the pool of businesses to its 1987 distribution would result in an employment recovery (at least to the pre-recession peak) a full two years ahead of the current recovery.

Our paper is closely related to the emerging literature on the declining pace of reallocation in the U.S. economy. Decker, Haltiwanger, Jarmin, and Miranda (2014), Davis and Haltiwanger (2014), and Hathaway and Litan (2014) also document the decline in firm startups and emphasize that aging of firms accounts for a substantial decline in the overall pace of reallocation, i.e. gross job flows. Hyatt and Spletzer (2013) and Lazear and Spletzer (2012) also find secular declines in gross labor market flows. Instead, our work considers the effect of declining startups and aging of firms on net employment growth. This allows us to provide a new perspective on jobless recoveries by linking the changes on firm dynamics to the changing cyclical behavior of employment growth.

In that sense, our work is closely related to the literature on jobless recoveries and complements the structural change explanations (Groshen and Potter, 2003, and Jaimovich and Siu, 2012) and reorganization and adjustment costs-based explanations (Bachmann, 2011, Berger, 2012, and Koenders and Rogerson, 2005).

Our work also builds on the literature that considers the differential impact of business cycles on different types of firms to study the propagation and impact of business cycle shocks. See for example Moscarini and Postel-Vinay (2012), Gertler and Gilchrist (1994). While most of the earlier literature focused on firm size, our focus is on firm age similar to a recent study by Fort, Haltiwanger, Jarmin, and Miranda (2013). While we believe that firm size can captures some of the differences in growth potential, credit access, or size of consumer base for firms, firm age is a better proxy as discussed by Haltiwanger, Jarmin, and Miranda (2013). Some of our findings also resonate with the small literature that analyzed the effect of aging of the work force on business cycle volatility. In particular, Gomme, Rogerson, Rupert, and Wright (2005), Clark and Summers (1981), Ríos-Rull (1996), Jaimovich and Siu (2009), and Lugauer (2012) examined how the aging of the labor force acts as a stabilizing force for business cycle volatility. While we find a similar stabilizing effect through the shift of employment from younger to mature firms, we uncover an additional effect that has an opposite effect, which is the decline in firm entry.

Collectively our findings suggest that simply comparing the experiences of employment dynamics across recent business cycles may be misleading. Each business cycle in the last thirty years has shocked a different age distribution of employer firms. Even for roughly comparable business cycle shocks, it would be surprising if the outcomes were the same! Increasingly jobless recoveries are understandable when we account for the shifts in entry and its cumulative effects on the stock of incumbent firms.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework and introduces a statistical model of firm and employment dynamics. Section 3 describes the data. Section 4 performs the decomposition analysis and analyzes the margins of adjustment in firm dynamics in the long-run. Section 5 estimates the cyclicality of employment at startups, young, and mature firms using time-series and state-level variation. Section 6 examines the effects of the startup deficit on aggregate employment dynamics in light of the findings of the earlier sections. Section 7 concludes.

2 A Framework for Decomposing Firm Dynamics by Age

We present a decomposition framework to understand the key margins driving the reallocation of employment towards older firms. Although our framework is only a statistical model of firm dynamics, it could be interpreted as the reduced form of an equilibrium model. Formulated this way, it will also pose a set of restrictions that an equilibrium model of firm dynamics would need to satisfy in order match U.S. data.

Our framework assigns a central role to firm age for understanding differences in firm dynamics.

There are many other dimensions along which firms may differ that are also relevant for firm dynamics, such as firm size. We focus on firm age for three reasons. First, empirical studies of firm and employment dynamics find firm age to be a principal determinant of growth and survival, even conditioning on firm size. Early work by Evans (1987) and Dunne, Roberts, and Samuelson (1988) had identified the key role of firm age in firm survival and growth in the manufacturing sector.[3] Recently, Haltiwanger, Jarmin, and Miranda (2013) document similar patterns for all private sector firms and emphasize the key role of firm age over firm size for explaining employment growth. Second, product market and financial market frictions that make firm-level heterogeneity relevant for aggregate fluctuations may be more closely related to firm age than to firm size. For example, in their influential paper on the role of firm size in the propagation of monetary policy shocks Gertler and Gilchrist (1994) argue that the relevant financial frictions are closer linked to firm age and use small firms as a proxy for young firms. Finally, relative to the dramatic shifts in the firm age distribution in Figure 1, the firm size distribution conditional on firm age has remained relatively stable over the period we study.[4] Our framework allows us to interpret the aggregate significance of this shift in firm age.

2.1 The Basic Framework

We distinguish three key margins that determine the dynamics of firms and the distribution of employment across firms of varying ages. First is the entry margin where we measure total employment E_t^0 at age 0 firms or "startups" and label it as

$$S_t \equiv E_t^0 \ .$$

Total startup employment is the product of the number of startups F_t^0 and their average employment size N_t^0. Fluctuations in S_t reflect changes along both the entry (extensive) and average entrant size (intensive) margins, but this distinction is not important for the current analysis.[5,6] The second margin is the survival rate x_t defined as

$$x_t^a \equiv \frac{F_t^a}{F_{t-1}^{a-1}} \ ,$$

[3] Dunne, Roberts, and Samuelson (1988) focus on plant-level rather than firm-level behavior.

[4] Within age group, the firm size distribution appears even more stable, so that gradual shifts in the overall firm size distribution appear to also be driven by the shifts in firm age. See the online appendix for a more detailed discussion of firm age and firm size.

[5] See Sedlacek and Sterk (2014) for a thoughtful analysis of fluctuations in the average size of entrants over the same period.

[6] Although we focus on the behavior of S_t, there are several alternative measures of the entry margin. When S_t is normalized by the total quantity of employment E_t, we refer to S_t/E_t as the *startup employment share*. This measure, plotted as a broken line in Figure (1a) from the introduction, is equivalent to the product of the *startup rate* F_t^0/F_t which is plotted as the solid line in the same figure and the average startup employment size relative to the overall average firm size N_t^0/N_t. Over the period we study overall average firm size (along with the share of mature firms) has gradually increased, while the average size of entrants has remained relatively steady, so the startup employment share has declined slightly faster than the startup rate.

which is the number of surviving firms F_t^a in age group cohort $a \geq 1$ as a fraction of the number of firms F_{t-1}^{a-1} from that age group cohort the previous year. The third and final margin is the growth in average size within the age group cohort a. We refer to this as the *conditional growth rate* n_t and define it as

$$1 + n_t^a \equiv \frac{N_t^a}{N_{t-1}^{a-1}} \ ,$$

where N_t^a is the average employment size of age group a firms in period t, and N_{t-1}^{a-1} is the average size of that same cohort in the previous year. Higher order moments of the size and growth rate distribution are also important for the rich heterogeneity within cohorts, but it will be enough for our purposes to work in terms of averages. Since by construction $E_t^a = x_t^a \left(1 + n_t^a\right) E_{t-1}^{a-1}$ the *unconditional* employment growth rate $g_t^a \equiv E_t^a / E_{t-1}^{a-1} - 1$ for incumbent firms $a \geq 1$ is the product of an age group's survival and conditional growth

$$1 + g_t^a = x_t^a \left(1 + n_t^a\right) \ .$$

Keeping track of S_t, x_t and n_t over time determines the entire age distribution of employment in each year. This formulation also has the advantage that these variables are all easily measured in the Census data.

We can write the law of motion for the distribution of employment across age groups as an exact decomposition by firm age. However, for simplicity we use only three age groups of firms: *startups* (age 0) S_t, *young* (ages 1 to 10) $E_t^y \equiv \sum_{a=1}^{10} E_t^a$, and *mature* (ages 11+) $E_t^m = \sum_{a \geq 11} E_t^a$. The mature grouping is straightforward. After 10 years much of the dynamism in a firm's lifecycle documented in Haltiwanger, Jarmin, and Miranda (2013) subsides and at least in terms of their dynamics firms begin to look more alike across ages. The young age group definition of ages 1 to 10 needs some explanation. Although this definition is broad and aggregates much of the rich heterogeneity and dynamism among young firms into a single category, it turns out to be a reasonable simplification for our analysis. The reason is that the relative differences within the young age group have remained more or less stable. We have repeated the decomposition exercises with more disaggregated age groups for young firms with little change from our main results.[7]

The exact law of motion of the distribution of employment across these larger age groups depends on the age a specific survival and growth rates. For example for young firms

$$E_t^y = \sum_{a=1}^{10} E_{t-1}^{a-1} x_t^a \left(1 + n_t^a\right) \ .$$

However, we can reformulate the law of motion entirely in terms of broader age group employment

[7] In our online appendix we include results with more disaggregated age groups. We also provide the decomposition by exact age group, which we use with the restricted access microdata to verify that our conclusions are unchanged.

shares and growth rates.[8] To do this we need to be careful of compositional changes across age groups since young firms that were age 10 in year $t-1$ become old firms in year t. For this purpose we introduce notation q_{t-1}^{y} to identify the fraction of age group y employment in year $t-1$ that remains in the y age group in year t.[9,10] Then

$$q_{t-1}^{y} E_{t-1}^{y} = \sum_{a=1}^{9} E_{t-1}^{a} \ ,$$

and for young firms we can write

$$E_{t}^{y} = \left(S_{t-1} + q_{t-1}^{y} E_{t-1}^{y}\right) x_{t}^{y} \left(1 + n_{t}^{y}\right). \tag{1}$$

Similarly, for the mature (ages 11+) group we have

$$E_{t}^{m} = \left(\left(1 - q_{t-1}^{y}\right) E_{t-1}^{y} + E_{t-1}^{m}\right) x_{t}^{m} \left(1 + n_{t}^{m}\right) \ . \tag{2}$$

If we use $\mathbf{E}_t = \left(S_t, E_t^y, E_t^m\right)'$ to label the vector of employment across firm age groups we can define a transition matrix P_t

$$P_t \equiv \begin{bmatrix} 0 & x_t^y \left(1 + n_t^y\right) & 0 \\ 0 & q_{t-1}^y x_t^y \left(1 + n_t^y\right) & \left(1 - q_{t-1}^y\right) x_t^m \left(1 + n_t^m\right) \\ 0 & 0 & x_t^m \left(1 + n_t^m\right) \end{bmatrix}$$

and write the law of motion for the employment distribution

$$\mathbf{E}_t = P_t^{'} \mathbf{E}_{t-1} + (1,0,0)' \, S_t \ . \tag{3}$$

Writing (3) as a moving average

$$\mathbf{E}_t = \sum_{j=0}^{\infty} \left(\prod_{k=0}^{j-1} P_{t-k} \right) (1,0,0)' \, S_{t-j}$$

[8] Note that

$$x_t^y \left(1 + n_t^y\right) = \frac{\sum_{a=1}^{10} F_t^a}{\sum_{a'=1}^{10} F_{t-1}^{a'-1}} \frac{\sum E_t^a}{\sum F_t^a} \Big/ \frac{\sum E_{t-1}^{a-1}}{\sum F_{t-1}^{a-1}} = \frac{\sum_{a=1}^{10} E_t^a}{\sum_{a'=1}^{10} E_{t-1}^{a'-1}} = \sum_{a=1}^{10} \frac{E_{t-1}^{a-1}}{\sum_{a'=1}^{10} E_{t-1}^{a'-1}} x_t^a \left(1 + n_t^a\right) \ .$$

[9] This grouped decomposition framework could be equivalently formulated as the reduced form of a model of firm dynamics with entry and exit and a stochastic lifecycle component where $1 - q_{t-1}^y$ is the probability a young firm in $t-1$ becoming a mature firm.

[10] In our online appendix, we provide more detail on the behavior of q_{t-1}. This variable serves a dual purpose in our framwork. In addition to representing the share of young employment that remains young the following year, the q_{t-1} variable also ensures stock flow consistency. Because of measurement issues in the administrative data, the change in stocks does not in general equal the measured flows, as explained in Jarmin and Miranda (2002). These stock/flow corrections are small from year to year, but would accumulate over time using our law of motion.

emphasizes how the employment age distribution in any year depends exclusively on the history of startup employment $\{S_t\}$ and sequences of firm survival and growth encoded in $\{P_t\}$.

Any equilibrium model of firm dynamics, such at the workhorse Hopenhayn (1992) model, has a statistical representation analogous to (3). Our framework emphasizes the importance of heterogeneity in firm age as opposed to heterogeneity in firm-level productivity for example in Hopenhayn (1992). As formulated by (3) the empirical behavior of P_t places important restrictions on age dependence in models of firm dynamics.[11] We use this framework to argue in Section 4 that P_t is stationary and further that fluctuations in survival and growth are second order to a trend decline in S_t in explaining the growth of the mature-firm employment share.

2.2 Incorporating Business Cycle Fluctuations

Even if P_t is stationary, its components still fluctuate with the business cycle and other aggregate shocks. To identify the cyclical component of P_t we extend the model in order to allow the margins to depend on a business cycle shock Z_t, which we formulate as a mean zero shock. For simplicity, we work in terms of the *unconditional* growth rates g_t^a, but it is straightforward to introduce business cycle fluctuations separately to both survival x_t^a and conditional growth n_t^a rates. Rather than applying a filter to g_t^a in order to identify fluctuations at business cycle frequencies, we project the age group growth rates individually on Z_t

$$g_t^a \quad = \quad \bar{g}^a + \beta^a Z_t + \varepsilon_t^a \qquad a = y, m \tag{4}$$

where ε_t^a represents the component of g_t that cannot be predicted by Z_t. Decomposed in this way, if g_t^a is stationary then $\bar{g}^a$ captures the trend or long run average component of employment growth, and $\beta^a Z_t$ captures the component that covaries with the business cycle shock. We refer to each age group's β^a as its *cyclical elasticity*. We state that young firms are more *cyclical* than mature firms if they load more heavily on the business cycle variable, i.e. when $|\beta^y| > |\beta^m|$.

Beyond the components of P_t, we also allow the entry margin S_t to depend on the business cycle. To do this we define a growth rate for startup employment

$$g_t^s \equiv \frac{S_t - S_{t-1}}{S_{t-1}},$$

and project *startup growth* g_t^s on Z_t, while allowing its mean to drift

$$g_t^s = \mu_t^s + \beta^s Z_t + \varepsilon_t^s \ . \tag{5}$$

Note that whereas the growth rates for the young and old age groups are the growth rates of employment within each cohort, startup growth g_t^s is the growth rate of the startup process, and not growth within startups. Also, even absent a trend decline in μ_t, if average startup growth is insufficient to keep pace with overall employment growth, the *startup employment share* $s_t = S_t/E_t$

[11] One recent example of a model with explicit age heterogeneity is Sedlacek and Sterk (2014).

will decline. For the period we study, not only is μ_t^s is not high enough to keep startups' employment share constant, it is also declining. Relative to a pace that keeps the startup employment share constant, we label the long run shortage of startup growth captured by drift μ_t^s as the *startup deficit*.

2.3 Dynamics of Aggregate Employment

The dynamics of aggregate employment follow immediately from aggregating over the dynamics by age group. Aggregate employment is

$$E_t = S_t + E_t^y + E_t^m \ .$$

In growth rates, aggregate employment growth is the sum of a *startup employment contribution* $s_{t-1}\left(1+g_t^s\right)$ and an employment share weighted average of incumbent growth rates

$$g_t = s_{t-1}\left(1+g_t^s\right) + \left(1-\omega_{t-1}\right) g_t^y + \omega_{t-1} g_t^m \ . \tag{6}$$

The startup employment contribution is the gross growth rate of the startup employment process $1+g_t^s$, weighted by the startup share of employment in the previous year

$$s_{t-1} = \frac{S_{t-1}}{E_{t-1}} \ .$$

For incumbents, weight ω_{t-1} refers to the previous year employment share of the current mature cohort

$$\omega_{t-1} = \frac{E_{t-1}^m + \left(1-q_{t-1}\right) E_{t-1}^y}{E_{t-1}} \ . \tag{7}$$

Because the current young group includes last year's startups the incumbent lagged employment weights sum to exactly 1. From this formulation it is clear that the startup deficit has an immediate effect on aggregate g_t through g_t^s. In addition, if $g_t^s \neq g_t^y \neq g_t^m$ it has a lagged and growing effect through increases in the incumbent mature employment share ω_{t-1} and declines in the startup employment share s_{t-1}.

Using our decomposition framework, we can write (6) in terms of its trend and cyclical components

$$\begin{aligned} g_t \ = \ & \underbrace{s_{t-1}\left(1+\mu_t^s\right) + \left(1-\omega_{t-1}\right)\bar{g}^y + \omega_{t-1}\bar{g}^m}_{\text{Trend component}} \\ & + \underbrace{\left(s_{t-1}\beta^s + \left(1-\omega_{t-1}\right)\beta^y + \omega_{t-1}\beta^m\right) Z_t}_{\text{Cyclical component}} \\ & + s_{t-1}\varepsilon_t^s + \left(1-\omega_{t-1}\right)\varepsilon_t^y + \omega_{t-1}\varepsilon_t^m \ . \end{aligned} \tag{8}$$

Here the startup deficit has an effect on both the trend (through μ_t^s, ω_{t-1} and s_{t-1}) and cyclical

(through only ω_{t-1} and s_{t-1}) components of aggregate employment growth. We later apply this decomposition to U.S. employment growth in order to properly isolate the cyclical component in light of the full effects of the startup deficit embedded in the history of μ_t^s.

3 Data Description

3.1 Measuring firm dynamics

We use data on employer businesses from the U.S. Census Bureau Longitudinal Business Database (LBD) and its public use data product the Business Dynamics Statistics (BDS).[12] This administrative database covers nearly every employer business in the U.S.. The data are based on a longitudinally-linked version of the Census Bureau's business register that includes all private-sector establishments with paid employees. Multiple establishments owned by the same firm are linked through their ownership records. This is an important detail, since we are interested in true firm startups rather than new locations (new establishments) of an existing firm. The data report the total employment of each firm on March 12 of each calendar year from 1977 through 2012. Age is recorded for all firms founded during this years. Firms founded prior to 1977 are part of the database, but their age is left censored.[13]

Throughout, firm age is the age of the oldest establishment measured from the year the establishment first reported positive employment. We further aggregate the firm age measure into three categories: startups (age 0), young, (ages 1 to 10) and mature (ages 11+). As Haltiwanger, Jarmin, and Miranda (2013) show, rich employment dynamics at new firms continue through about 10 years. Although our definition of *young* aggregates away some of this heterogeneity, our results are not sensitive to this choice.[14] For our analysis, we use aggregations of employment and net job creation by year, our firm age groups, one-digit sectors, and state. For each of these cells, we measure the survival rates and conditional growth rates as defined in Section 2.1. We also focus primarily on employment shares rather than firm shares. The reasons are twofold: first the link between the behavior of aggregate employment and firm age is more straightforward; second employment is better measured in the administrative data than establishments and firms.[15]

In Table 1 we summarize the data from the BDS. The upper panel reports the summary statistics computed over the national data. These are time series averages over the period from 1987 to 2012, for which we can distinguish young and old firms. Young firm survival rate x_t^y is 88.5 percent and conditional on survival, young firms grow on average at almost 9 percent. As we discuss below, the

[12]The results included in this draft are from the Business Dynamic Statistics (BDS), which is a public use aggregation of the LBD by firm size and age. Our results from the firm-level LBD are not yet approved for disclosure as of this writing. We include qualitative descriptions of the LBD results when appropriate. A description of the BDS and the data are available for download at http://www.census.gov/ces/dataproducts/bds/.

[13]For a detailed description of the LBD see Jarmin and Miranda (2002)

[14]In our work with the underlying microdata we use much more detailed age measures.

[15]Establishments may be over- or under-measured as very small establishments hire or fire a single employee and go out of scope. We thank John Haltiwanger for pointing out the susceptibility of establishment and firm counts to measurement error for this reason.

lower survival rate more than offsets the higher conditional growth rate, so that cohorts of younger firms are expected to shrink over time. When the surviving young firms eventually become mature firms their employment stabilizes. Mature firms survival rate is close to 95 percent and conditional on survival mature firms grow roughly 5 percent on average. Young firms are also more volatile than mature firms, both on the survival (about 2x) and the growth (about 1.5x) margins. The lower panel of Table 1 computes these same statistics by state and reports the employment weighted distribution of these statistics across states. Within the interquartile range, the state level survival rates and conditional growth rates are very close to their national counterparts. In the top panel, we report the standard deviation of the detrended startup growth rate.

[INSERT TABLE 1 (BDS SUMMARY) ABOUT HERE]

3.2 Measuring business cycle shocks

As a proxy for business cycle shock Z_t we consider mean deviations of four measures: (i) log differences in annual personal income, (ii) log differences in annual gross domestic or state output, (iii) changes in annual average of monthly unemployment and (iv) annual averages of monthly cylical unemployment.

Our preferred measure is the log differences in annual real personal income. This measure has several advantages over its alternatives. First, it is highly correlated with real GDP growth. Although we cannot observe the true business cycle shock Z_t, what we have in mind are shocks to output. Employment based measures, while also correlated with real GDP growth are less ideal since the mapping between output and employment is in part the object we are investigating. Second, personal income, like GDP, is available at quarterly frequency, allowing us to match the timing of employment in the Census Data, which is measured annually at the March 12 levels.[16] Finally, unlike annual measures of gross state output, which we also consider, personal income is available at the quarterly frequency even at the state level.[17] For robustness we also consider two unemployment based proxies. The first is the change in the annual average of monthly unemployment. This is the preferred measure in Fort, Haltiwanger, Jarmin, and Miranda (2013) and Foster, Grim, and Haltiwanger (2013). We use the annual average of the cyclical component of monthly unemployment obtained by first HP filtering the monthly data with a smoothing parameter of 8.1 million.[18] Moscarini and Postel-Vinay (2012) use this measure to compare the cyclicality of large and small employers. Both unemployment-based (counter-) cyclical proxies also have the advantage of being available at high frequency even at the state level. Our results are for the most part similar across all four measures.

[16] When possible, we compute all annual measures over a time-shifted year that ends in March in order to correspond to the timing of the Census data. For more details on the business cycle shock variables see the Appendix.

[17] At the state level real GSP is only available at an annual frequency so the GSP proxy for Z_t is measured over the calendar year.

[18] The high smoothing parameter leaves some medium run fluctuations in the cyclical component and is suggested by Shimer (2005).

In Table 2 we summarize the four annual business cycle measures measured at the national and state level.

[INSERT TABLE 2 (Z_t SUMMARY) ABOUT HERE]

4 Long Run Stability of the Margins of Adjustment

Age is a crucial source of heterogeneity in firm dynamics, and in this section we show persistent differences in firm behavior by age that change little over time. Applying the framework from Section 2.1 we decompose shifts in the distribution of employment over time into contributions from the sequence of startup employment S_t, survival rates x_t^a and conditional growth rates n_t^a by age group.[19] Despite cyclical (and other) fluctuations in the survival and growth margins encoded in P_t, the primary determinant of the expanding mature employment share has been the cumulative effect of the decline in startups since the 1980s.

4.1 Incumbent Survival and Growth

In Figure 2 we plot the one-year probability of survival x_t of firms from year $t-1$ to t by age group. Consistent with early evidence on selection in Evans (1987) and Dunne, Roberts, and Samuelson (1988) for the manufacturing sector, the exit hazard for U.S. firms overall declines predictably with age.[20] Measured over the 1987 to 2012 period, the within age group survival probabilities are 88.5 percent for younger firms and 95 percent for mature firms.[21] The survival rates are also mildly procyclical, showing dips in recession years.

Even with this cyclicality, the within-age group survival rates are remarkably stable over the long run. We confirm this stability in Table 3 where we fit a linear trend to survival rates x_t by age group. Columns (1) to (3) report the estimated coefficient on the linear trend when using just annual aggregates, annual aggregates by sector, and annual aggregates by state.[22] The estimated coefficients are almost all both statistically and quantitatively insignificant. The high R^2 even for the national data with no fixed effects confirms the stability of survival rates around their long run averages. Fitting a simple linear trend from the raw time series for survival rates may be sensitive to the time period. However, we find the same results even when first filtering the data to remove business cycle and higher frequency fluctuations before estimation.[23]

[INSERT TABLE 3 (TRENDS IN X AND N) ABOUT HERE]

[19] The fraction q_{t-1}^y also adjusts with shifts in survival, growth, and startups to reflect the shifting age composition within the young age group.

[20] In the Appendix Figure A.1a we show that the same pattern holds even within the disaggregated young age group.

[21] These results are virtually identical if we exclude years 2008 to 2012.

[22] The online appendix replicates this table controlling additionally for firm size, with little change in the results.

[23] In Appendix Table A.2 we repeat the same state level estimation after having first removed business cycle and higher frequency variation with an HP filter.

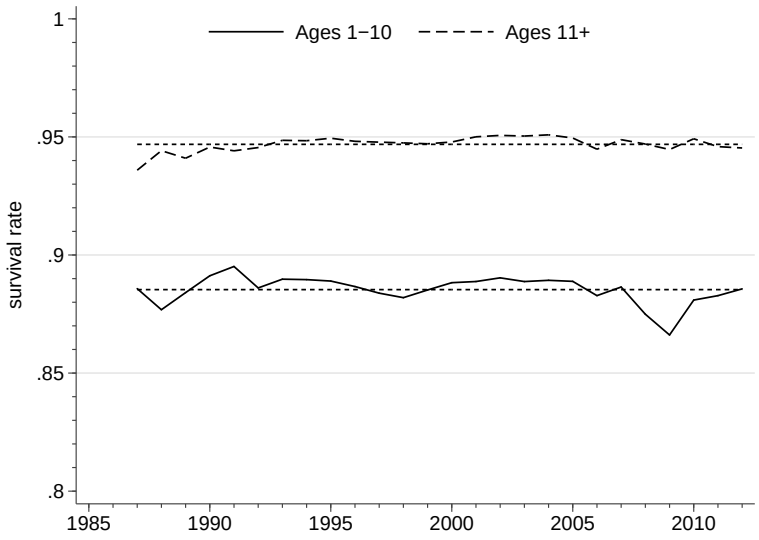


Figure 2: One-year survival rates x_t of young (ages 1 to 10) and mature (ages 11+) firms

Note: U.S. Census Bureau Business Dynamics Statistics. Fraction of young and mature cohorts that survived from previous year. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Although statistically insignificant and quantitatively small in Table 3, Figure 2 does appear to show a slight downward trend in young firm survival starting in the mid-2000s. This decline results from a recent shift in the survival rates of very young firms. The young age group combines the first 10 years of a firm's life, a period with substantial heterogeneity and selection. We disaggregate the young age group and examine the survival rates more closely. We plot the survival rates by these age groups in Figure A.1a, and in Table A.1 we estimate the same linear trends using disaggregated individual ages 1 to 5 and a medium age group of ages 6 to 10. In both the figure and the regression results, we find some evidence for a persistent decline in both early (age 1) and medium term survival. Although it is of independent interest, this recent decline appears isolated and has very little effect on our results.

The relationship between firm age and conditional employment growth rate is also stable. In Figure 3 we plot the one-year growth rate in average firm size by age group. The conditional growth rate of young firms fluctuates around its average value of 8.5 percent. Mature firms similarly fluctuate around their average conditional growth rate of 4.9 percent. Similar to survival rates, Table 3 columns (4) to (6) report the estimated coefficient on a linear trend in n_t by age group. For the U.S. overall, within sector, and within state, the estimated trend coefficients are all statistically and quantitatively insignificant. Again, this is robust to alternative methods of removing cyclical fluctuations.

Table 1 shows that mature firms have both a lower conditional growth rate and volatility roughly half of their younger counterparts. The first observation is consistent with Haltiwanger, Jarmin, and Miranda (2013) who show that conditional on survival young firms grow on average faster than old firms. The same patterns hold even within the disaggregated young age group. Figure



Figure 3: One-year conditional growth rate n_t at young (ages 1 to 10) and mature (ages 11+) firms

Note: U.S. Census Bureau Business Dynamics Statistics. Conditional growth rate is the one year growth rate of average employment size for the current age group from the same cohort in the previous year. Average size in previous year also includes cohort's firms that do not survive. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

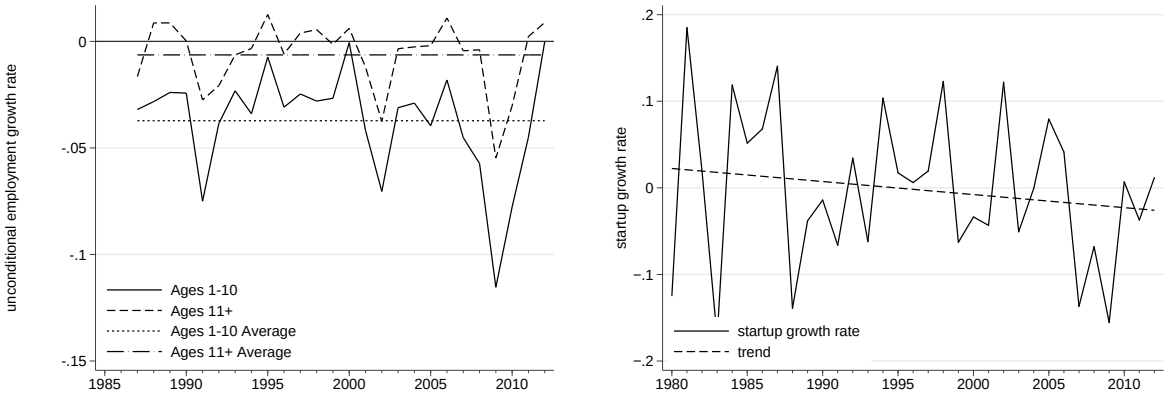
A.1b plots the conditional growth rate by age, and Figure A.2 plots the average size. Although much more volatile, the disaggregated conditional growth rates show no evidence of a trend over this period. Even more remarkable is that over a thirty-year period, startups and young firms (conditional on survival) tend to have roughly the same number of employees.[24]

The stability of the survival and conditional growth margins for each age group carries over to the unconditional growth rates. In panel (a) of Figure 4 we plot the unconditional growth rate for young g_t^y and mature firms g_t^m. Several observations are evident in the time series. First, the growth rates of young and mature age groups are on average negative. These growth rates reflect both employment destroyed at exiting firms and growth conditional on survival. [25] Finally, both components not surprisingly comove strongly with the business cycle. Young firms appear to fluctuate more strongly with the business cycle. We quantify the extent of this additional cyclicality in the next section using several sources of identification.

The main takeaway is that amidst large changes in the age composition of firms, the lifecycle dynamics are remarkably stable over time. Growth and survival rates fluctuate as one would expect over the business cycle (a point we take up in detail in Section 5), but they fluctuate around steady averages with no sign of a trend. Interpreted through the decomposition framework in section

[24] Average employment in mature firms increases since old firms remain old until they exit and the flow in of smaller young to old businesses diminishes over this period.

[25] When startup employment is excluded from the young age group, the unconditional growth rate of young firms is lower (more negative) than the growth rate of mature firms because of their higher exit rate. In **Figure** A.3 we plot the growth rate of young firms inclusive of the startup contribution.



(a) Young g_t^y and mature g_t^m from 1987 to 2012

(b) Startup growth g_t^s from 1980 to 2012

Figure 4: Unconditional incumbent growth rates and startup employment growth

Note: U.S. Census Bureau Business Dynamics Statistics. Unconditional growth rate is the growth rate of employment within an age group. Startup employment growth is the growth rate in level of startup employment from the previous year. Incumbent growth rate series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986. Startup employment growth begins in 1980 because of large outliers for level of startup employment in 1977 and 1978.

2.1, the matrix P_t appears stationary and procyclical. Put differently, the two components of the aggregate employment growth rate in (6) that are due to incumbent firms have been stable over time. The evident stationary of P_t contrasts starkly with the behavior of the startup employment share which we turn to next.

4.2 Startup Deficit

In contrast to the unconditional growth rates of young and mature firms, there has been a marked decline in startup employment. In panel (b) of Figure 4 we plot the growth rate for startup employment, g_t^s, defined as $(S_t/S_{t-1}) - 1$. While startups account for the majority of employment growth, their contribution has been diminishing. As the figure shows, g_t^s was positive in the earlier periods but has moved to the negative territory since early 2000s. Due to the gradual decline in firm entry, startup employment has started to shrink even in absolute terms, causing a gradual decline in startups' contribution to employment growth as well as their overall employment share. This marked decline is in contrast to the employment growth rates of the young and mature age groups which although volatile appear to fluctuate around a steady average. The trend in the startup growth contribution imparts a trend to the aggregate time series which is attenuated somewhat by an increasing mature age group share.

4.3 Aging is a Cumulative Effect of the Startup Deficit

A corollary of the long run stability of the incumbent survival and growth rate margins is that the growing mature employment share follows almost entirely from the cumulation of startup deficits

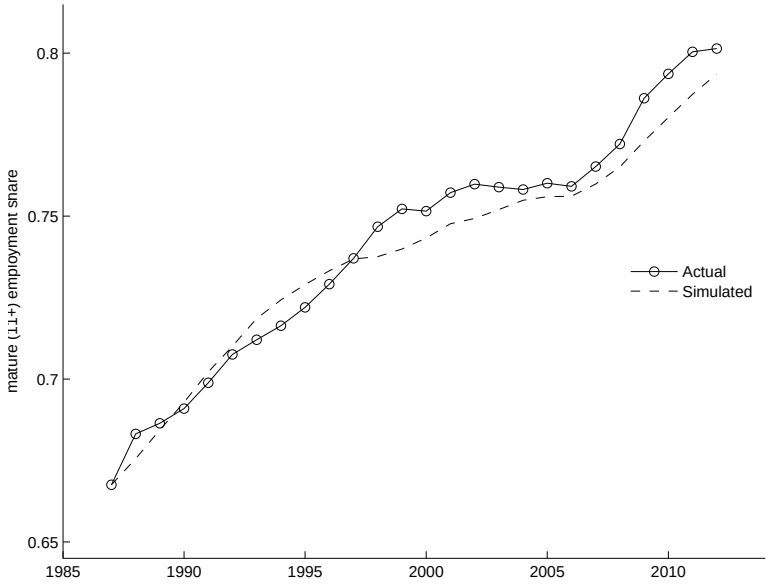


Figure 5: Mature employment share from 1987 to 2012 and its predicted path from constant survival and growth.

Note: U.S. Census Bureau Business Dynamics Statistics. Actual is the mature employment shares from 1987 to 2012 measured in the BDS. The simulated mature employment share is simulated using actual sequence of startup employment and constant growth and survival rates in the law of motion. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

since the early 1980s. Each successive year brings a relatively smaller share of entrants, but they behave exactly as the cohorts that preceded them. The shortage of entrants gradually tilts the composition towards older firms. To make this point we remove all fluctuations in the sequences of survival rates and growth rates by setting

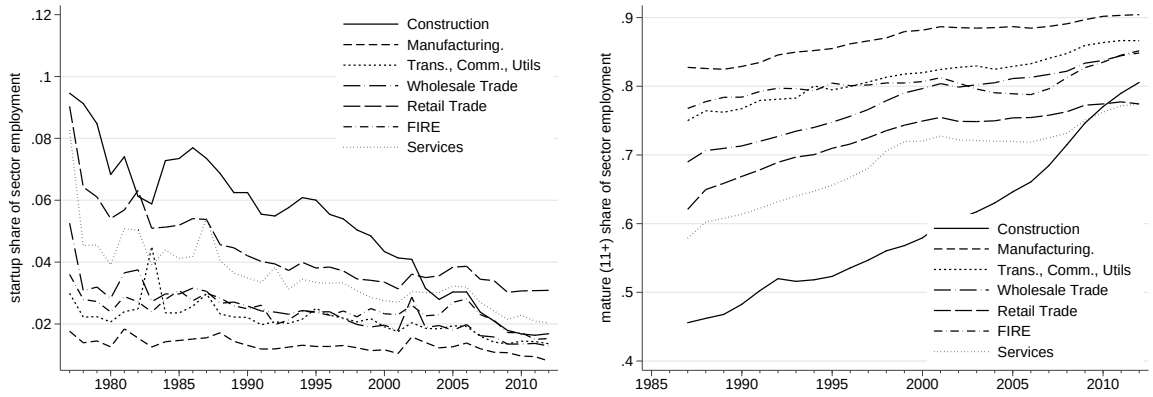
$$P_t = \bar{P},$$

constructed by replacing survival and growth rates with their long run averages. Then we simulate (3) using only the history of startup employment $\{S_t\}$.

In Figure 5 we plot the simulated mature employment share with constant survival and growth. It nearly perfectly replicates the actual evolution of the actual share, showing that the entry margin is the sole driver of the shift of employment towards older firms. Fluctuations in survival and growth over this period have almost no effect on the shifts in employment shares. Because the growth and survival margins are stable, the startup deficit drives the shifts in the age distribution of employment.

4.4 Startup deficit and stability hold within sectors and states

The startup deficit and stability of the survival and growth margins are also evident across sectors and states suggesting little room for compositional changes driving the patterns we observe. In



(a) Startup employment share by sector 1977 to 2012 (b) Mature firm employment share by sector 1987 to 2012

Figure 6: Startup (age 0) and mature (ages 11+) employment shares by sector

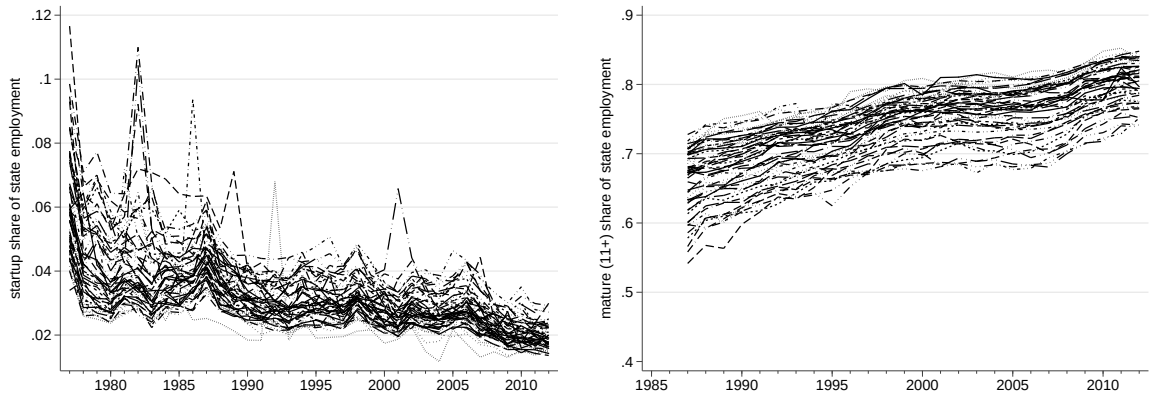
Note: U.S. Census Bureau Business Dynamics Statistics. Startup (age 0) and mature (ages 11+) firm employment in each sector as share of total sector employment. Mature employment series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986. Agriculture and mining sectors are omitted.

Figure 6a we replicate the original figure in terms of employment share within seven different sectors. Almost every sector exhibits a similar decline. We see similar trends using more narrow industry classifications and within metropolitan areas using the firm-level microdata. As one would expect, we observe an increase in the mature firm employment share within each sector as well. In Figure 6b we plot the employment share measure computed within broad sector for the same time period.[26] In all years, there is considerable variation across sectors in the employment shares of mature firms. Manufacturing is the most mature sector, and construction is least. Nevertheless, within each industry, there is a pronounced upward trend. The mature employment share increases in almost all sectors at roughly the same pace. Interestingly, the construction sector, which started with the lowest share of mature employment in 1977, experienced the steepest increase in mature employment.

We repeat the same exercise with states instead of sectors in Figures 7a and 7b. Again, there is considerable variation across states, but there is a striking comovement in employment shares of startups. Employment share of age 0 firms averaged around 0.04 in the early part of the sample, while it was below 0.04 for all states by 2012. Aging is also a common trend across states. Employment share of mature firms varied between 0.55 to 0.75 in 1987 while it increased to 0.7 to 0.85 in 2012.

As in the national data, because the survival and growth margins are relatively stable, the accumulation of startup deficits drives the increase in the mature employment share. We separately simulate (3) using $\bar{P}$ and $\{S_t\}$ for each sector and for each state. Figure 8 plots for each sector

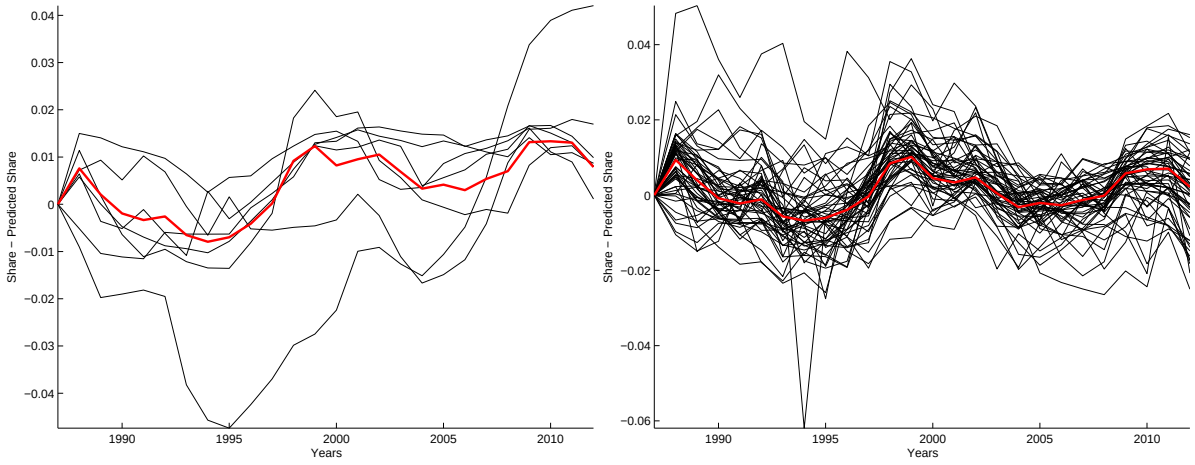
[26] In the appendix Figures A.4a and A.4b we provide the same plots using firm share rather than employment share. The trends are the same.



(a) Startup employment share by state 1977 to 2012 (b) Mature firm employment share by state 1987 to 2012

Figure 7: Startup (age 0) and mature (ages 11+) employment shares by state

Note: U.S. Census Bureau Business Dynamics Statistics. Startup (age 0) and mature (ages 11+) firm employment in each state as share of total state employment. Mature employment series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.



(a) Within sector (b) Within state

Figure 8: Difference between actual and predicted mature employment share by sector and state

Note: US Census Bureau Business Dynamics Statistics. Startup employment share from 1977 to 2012 and young and mature employment shares from 1987 to 2012 are actual data and measure in the BDS. The model-based employment shares are predicted using actual sequence of sector (state) startup shares and constant state growth and survival rates in the law of motion. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

(left panel) and for each state (right panel) the difference between the actual mature employment share and the share predicted only from the shifts in the entry rate. The thick line is for the entire U.S., computed from the shares plotted in Figure 5. As in the national data, the predicted mature share from stable state or sector survival and growth closely follows the actual evolution of the mature share. In the left panel, the sector with the largest deviations is the construction sector, which accounts for about 5 percent of total employment. Additionally, since the startup deficit and growing mature share are widespread across industries and geography, we will be able to use cross industry and cross state variation as additional sources of identification for the behavior of the margins of adjustment.

5 Cyclicality of Employment Growth

In this section we measure the cyclicality of young and old firms using the extension of the framework described in Section 2.2. First we estimate the age group β^a using only the time series variation. To do this we estimate for each incumbent age group $a = y, m$

$$g^a_{njt} = \alpha^a + \gamma^a_n + \phi^a_j + \beta^a Z_t + \varepsilon^a_{njt} \tag{9}$$

using the growth rates computed from the BDS. This formulation differs slightly from equation (4) since here we allow for sector ϕ and firm size γ fixed effects. Table 4 panel A reports the estimated β^a for each incumbent age group using four alternative measures for business cycle shock Z_t. We estimate equation 9 over the full sample of 1987 to 2012 for the first three measures of Z_t. For the HP filtered unemployment shock we estimate over only 1987 to 2007 to avoid any issue from isolating cyclical frequencies near the endpoint.[27] These specifications do not include firm size or sector fixed effects, which both have almost no impact on our results.[28] Young firms are noticeably more cyclical than mature firms in the annual time series in Table 4. For all but the HP filtered unemployment proxy in column (4) young firms are quantitatively and statistically more cyclical than mature firms, ranging from roughly 30 percent to almost 100 percent larger. The table reports an estimated p-value of a test for equality of $\beta^y = \beta^m$. The relatively high R^2, even without the size group fixed effects, shows us that for both age groups the majority of growth rate fluctuations are predicted by the business cycle.

[INSERT TABLE 4 (CYCLICALITY) ABOUT HERE]

Table 5 shows the results for alternative specifications using personal income, our preferred measure. Young firms are noticeably more cyclical than mature firms in all specifications. The second column uses data disaggregated into three firm employment size groups: less than 20 employees, 20 to 499 employees, and 500 or more employees. The estimation includes fixed effects for each size group and clusters the standard errors by year. The time series estimates are nearly identical and

[27] Results are nearly identical if we estimate the HP filtered specification over the entire filtered time series.
[28] Table 5 reports estimates using personal income for Z_t with and without firm size and sector fixed effects.

imply that for any business cycle shock, young firm growth rates respond roughly 40 percent more than mature firms. These estimates are not specific to this time period or age grouping.[29] The relatively high R^2, even without the size group fixed effects, shows us that for both age groups the majority of growth rate fluctuations are predicted by the business cycle.

The greater cyclicality of young firms is also robust to alternative sources of identification. Identifying the age group β is a lot to ask of twenty-five annual observations spanning three business cycles (one of which is the Great Recession). As an alternative to aggregate time-series variation we use cross state s variation in the business cycle variable Z_{st} and the growth rates g_{st}. Here we project the age group growth rates on a constant, dumies for year t, state s, (optionally) size group n, and finally on a business cycle variable Z_{st} and estimate

$$g^a_{nst} = \alpha^a + \gamma^a_n + \theta^a_s + \lambda^a_t + \beta^a Z_{st} + \varepsilon^a_{nst} \tag{10}$$

This specification identifies the parameter β from the within year and across state differences in state level business cycles, time averaged over 1987 to 2012 and adjusting for permanent differences in growth rates across states. Table 4 in lower panel reports the estimated β^a for each incumbent age group using four alternative measures for business cycle shock Z_t. Results are very similar to the ones computed exploiting time series variation. Young firms' employment growth rates covary more strongly with all business cycle indicators we consider.

Columns (3) and (4) in Table 5 present the separately estimated β for young (panel A) and mature (panel B) firms, with and without size group fixed effects using personal income. Again β^y is signficantly above β^m. Quantitatively, young firms load similarly on cross-state variation in Z_{st} as they do on time-series variation in Z_t. Mature firms, however respond less than would have been predicted from the time-series, which amplifies the contrast in cyclicality between young and mature firms. In states with larger changes in macroeconomic conditions relative to other states, we expect the differences in the growth rate of young firms to be nearly twice as large as the differences in the growth rate of mature firms.

5.1 Properties of β^s

We next consider the cyclical properties of the growth rate of the startup employment process, by projecting *startup growth* g^s_t on Z_t, while allowing its mean to drift $g^s_t = \mu^s_t + \beta^s Z_t + \varepsilon^s_t$. For brevity we only report the estimation results using personal income as a proxy for business cycle conditions in Table 6 Columns (1) and (2) show the estimated cyclical sensitivity using time series variation. While the estimates suggest that β^s is positive, estimates are not statistically significant. Columns (3) and (4) exploit richer variation through state-level data and show that estimates of β^s are positive and statistically significant. These estimates are also higher than the cyclical sensitivites of incumbent young and mature firms as comparisons with Columns (3) and (4) in Table 5 show.

[29] They are similar to Fort, Haltiwanger, Jarmin, and Miranda (2013), who estimate the difference between β^y for small firms and β^m for large firms. In the robustness appendix we compare our estimates against Fort, Haltiwanger, Jarmin, and Miranda (2013) for alternative sample restrictions.

Startups' employment growth moves procyclically over the business cycle and it also responds more strongly to business cycle conditions than incumbent firms, i.e., $|\beta^s| > |\beta^y| > |\beta^m|$.

5.2 Time Variation in Cyclical Sensitivity of Employment by Firm Age:

The relative cyclicality of employment in firms of different ages is a robust finding in the data independent of time period. One might expect that as firm entry declined and the business age distribution has tilted towards mature firms, general equilibrium effects might shift the cyclical properties within age group. Interestingly, this does not appear to be the case. To test the stability of the cyclical covariance term, we look for a first order shift over time in the sensitivity of either age group's growth rate to the business cycle indicator. The idea is to use the same within year and across state variation in Z_{st} and allow the identified β_t to depend on time through a linear time trend

$$\beta_t = \beta_0 + \beta_1 t \ . \tag{11}$$

We re-estimate equation (10) where we allow β to include a trend component as in (11). Table 7 reports the estimated linear trend component β_1 separately estimated for young (in the first two columns) and mature (in the second two columns) firms. Columns (2) and (4) use additional variation across firm size groups and condition on firm size fixed effects. In all columns, the point estimates show a small increase in the cyclical sensitivity from 1987 to 2012, but it is statistically indistinguishable from zero.

We also re-estimate equation (5) to include a trend component to check whether the cyclicality of startup employment growth rate changed over time. Columns (5) and (6) of Table 7 reports the estimated linear trend component β_1 for startups and shows that there is no statistically significant change in the cyclical sensitivity of startup employment.

5.3 Robustness

Disaggregated Age Groups: The cyclical volatility of employment growth also declines reliably with firm age. The results in table 5 may mask interesting dynamics by binning together firms as old as 10 years with the very young. In Figure 9 we plot the β estimated for more finely disaggregated age groups. The vertical bars indicate 95 percent confidence intervals. Here the pattern of diminishing cyclicality with firm age is especially clear. The growth rates of very young firms in particular are strongly correlated with the business cycle, and the point estimates for β decline gradually with firm age. The estimated cyclical elasticities for very young firms are statistically indistinguishable until reaching the 6-10 age group and the mature ages 11+ group.[30] The similar cyclical properties of most of the young age group lends support to our choice of aggregation groups.

Role of Extensive and Intensive Margins in Differences in Cyclicality by Firm Age:

[30] An F test for the equality of β for ages 1 to 5 has a p-value of 0.7121 when errors are clustered by state. When equality with the 6-10 age group is added as an additional restriction, the p-value drops to 0.0093.

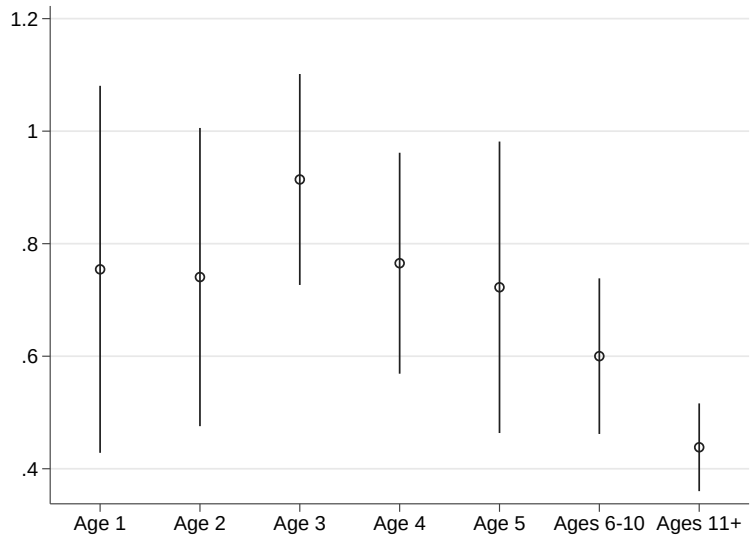


Figure 9: Plot of β on state level log difference in annual personal income by disaggregated age group

Note: U.S. Census Bureau Business Dynamics Statistics. Estimated β on change in state level log difference in annual personal income using state level employment growth by age group from 1987 to 2012.

The additional cyclicality of young firms extends to the extensive and intensive determinants of the unconditional growth rate. Our decomposition of the shifts in employment shares relied on an alternative formulation of the unconditional growth rate, namely

$$1 + g_t = x_t \left(1 + n_t\right) \ ,$$

where we express the unconditional growth rate as the product of the cohort's firm survival rate x_t, and the conditional growth rate n_t which is gross growth rate of cohort's average firm size.[31] In Table 8 we separately estimate versions of equations (9) where instead of the unconditional growth rates g_t we use survival rates x_t and conditional growth rates n_t on the left hand side. Identified off of both time series Z_t and cross sectional Z_{st} variation, the conditional growth rates of the young firms are more cyclically sensitive than those for mature firms. The magnitudes are smaller than Table 5 since the unconditional growth rates include the contributions of the survival rate, which is also procyclical. Columns (1)-(4) report the estimated β for x_t. Although the evidence for procyclicality is weak in the time series, the survival rates for both young and old are notably cyclical when identified off the across state variation in Z_{st}. Not surprisingly, the survival rate of young firms is markedly more sensitive to the business cycle than the survival rate of mature firms. Columns (5)-(8) report the estimated β for young and mature firms for their conditional growth rates n_t. The higher sensitivity of g_t for young firms in Table 5 is not entirely due to the

[31]The growth in average firm size reflects both the growth rate at the cohort's survivors and a selection effect of the difference in average firm size between survivng and exiting firms.

survival margin. Even conditional on survival, the growth rates of young firms are more sensitive to the business cycle than those of mature firms. Nevertheless, the relative sensitivity of young survival to mature survival (anywhere from 5 to almost 15 times) is much more pronounced than for conditional growth rates (roughly 0.4 times). This is not just because young firms are more likely to exit than mature firms. Even given their higher propensity to exit, young firms are especially more likely to exit than mature firms from business cycle fluctuations.

Classification of startups Another concern is that the classification of startups as only age 0 employers may leave very young firms–as young as one year and one day–in the young category. This may be especially important since since the mid 2000s there has been a sharp decline in the survival rate of startups into their first year that would be reflected in the young survival and unconditional growth rates. We repeat the analysis for the young group with a more restrictive definition of 2 to 10 years old and find similar results.[32]

Detailed industry controls and variation by industry Using within year, cross state variation of a cyclical shock and growth rates by age group raises two concerns. First is that industry compositional changes within states may also be driving the results. Second is a reverse causality concern that the changes in the state-level cyclical shock are mechanically related to age group employment. Although we are careful in any causal interpretation of the age group business cycle elasticities–we are interested foremost in shifts in the aggregate covariance structure–it would be preferrable to place some more distance between fluctuations of the cyclical shock at the state level and fluctuations in employment by age group by further conditioning on industry.

The public-use BDS data do not allow us to condition on both state and sector, and even if possible the sector measures are very broad. An alternative data source with a similar population of firms is the Census Bureau Quarterly Workforce Indicators (QWI).[33] These are public-use tabulations of the Census Longitudinal Employer Household Dynamics (LEHD) database. The matched employer-employee data are collected from from state-run unemployment insurance programs. Since 2005 all states and the District of Columbia have participated with the exception of Massachusetts. Many states have participated since the mid 1990s. The QWI release tabulations of employment growth by state and firm-age, but subject to some additional caveats. The age group bins do not allow us to distinguish age 0 and age 1 firms and the employment growth measures are closed to our conditional growth rate measure n_t. With those caveats in mind we re-estimate the cyclical elasticities using the QWI further conditioning on industry j

$$g^a_{jst} = \alpha^a + \phi^a_j + \theta^a_s + \lambda^a_t + \beta^a Z_{st} + \varepsilon^a_{jst} \ .$$

The QWI is tabulated by either age or by size, so we cannot further condition on firm size. With

[32]For brevity, we do not include all of the tables in the main text. Detailed results are available upon request and will be included in our online robustness appendix.

[33]See http://ledextract.ces.census.gov/ and a detailed description in our online robustness appendix

this specification we estimate cyclical elasticities very similar to those in Table 8. Again, young firms are reliably more cyclical than mature firms. Detailed results are available upon request and will be included in our online robustness appendix.

6 Grown-up Business Cycles

The startup deficit has reshaped aggregate employment dynamics through both its immediate impact on job creation and its long run cumulative effect on the employer age distribution. In this section we show how the startup deficit is slowing employment component of economic recoveries. The argument rests on two premises. First is the outsized role startups play in net employment creation as we have shown in Figure 4. This is a point emphasized by Haltiwanger, Jarmin, and Miranda (2013), although they combine startups with other young firms. The second is the more pronounced cyclicality of startups and young firms that we have shown in Table 4.

6.1 Startup deficit and employment growth

Our decomposition of the growth rate of employment into its trend and cyclical components, repeated here from equation (8), is a good starting point to understand the effects of the startup deficit on aggregate employment dynamics:

$$\begin{aligned} g_t \;=\; & \underbrace{s_{t-1}\left(1+\mu_t^s\right)+\left(1-\omega_{t-1}\right)\bar{g}^y+\omega_{t-1}\bar{g}^m}_{\text{Trend component}} \\ & +\underbrace{\left(s_{t-1}\beta^s+\left(1-\omega_{t-1}\right)\beta^y+\omega_{t-1}\beta^m\right)Z_t}_{\text{Cyclical component}} \\ & +s_{t-1}\varepsilon_t^s+\left(1-\omega_{t-1}\right)\varepsilon_t^y+\omega_{t-1}\varepsilon_t^m \;. \end{aligned}$$

This equation highlights the dependence of growth rate of employment on shifts in the age distribution through s_{t-1} and ω_{t-1} and on the shifts in the trend component μ_t of startup employment growth. We first focus on the trend and cyclical components separately to discuss how they have changed as a result of the startup deficit:

Trend component The startup deficit has both an immediate (through μ_t^s) and a lagged (through weights s_{t-1} and ω_{t-1}) effect on the trend component of employment growth. The declines in μ_t^s clearly reduce the trend contribution to employment growth, but their lagged effect through age distribution is ambiguous. As we showed above $\bar{g}^m > \bar{g}^y$ because of the high exit hazard of young firms. So the increase in ω_{t-1} place more weight on mature firms, resulting in less net drag (since both trend growth rates are negative) from incumbents in aggregate growth. However, the contribution

from startup employment must always be positive (there is no job destruction) so $1 + \mu_t^s \gg \bar{g}^m$. Because of this, the declines in s_{t-1} will further reduce the contribution from startups to trend growth. Since these are opposing effects, the total effect on employment growth is ambiguous in general. However, as we will show, in the U.S. the negative effect is quantitatively much larger, implying a declining trend growth rate of employment.

Cyclical component The cyclical component of employment growth is reshaped only through changes in the age distrubtion. As we showed above, startups and young firms have a higher cyclical elasticity than mature firms

$$\beta^s \geq \beta^y > \beta^m \ ,$$

and that these age group cyclical elasticities have not shifted over time. Consequently, the declining weight of startups and young firms implies a decline in the aggregate cyclical elasticity of employment growth with respect to the business cycle shocks, represented by Z_t.

In the next subsection we show for the U.S. the extent of the changes in both the trend and cyclical components of employment growth due to the startup deficit.

6.2 Quantifying the effect of the startup deficit on employment growth

This subsection makes use of the framework we developed and computes the evolution of aggregate employment in an identical economy but for the assumption of a stable startup rate. We replace the linear declining trend in the startup employment growth rate, μ_t^s, with its 1980-85 average of 0.02, leaving the exact sequence of cyclical and other shocks in place.[34] Since the counterfactual economy has a different path for the firm entry rate, the evolution of the age distribution of firms is also affected. We use our model to compute the evolution of the employment shares by age, as represented by s_t^c and ω_t^c by solving equation (3) forward from $\mathbf{E}_{1987}$ using the actual P_t and the counterfactual sequence of startup employment S_t^c without a startup deficit. This imposes for the counterfactual economy a path of aggregate growth rates determined by

$$\begin{aligned} g_t^c \quad = \quad & \underbrace{s_{t-1}^c \left(1 + 0.02\right) + \left(1 - \omega_{t-1}^c\right) \bar{g}^y + \omega_{t-1}^c \bar{g}^m}_{\text{Trend component}} \\ & + \underbrace{\left(s_{t-1}^c \beta^s + \left(1 - \omega_{t-1}^c\right) \beta^y + \omega_{t-1}^c \beta^m\right) Z_t}_{\text{Cyclical component}} \\ & + s_{t-1}^c \varepsilon_t^s + \left(1 - \omega_{t-1}^c\right) \varepsilon_t^y + \omega_{t-1}^c \varepsilon_t^m \ . \end{aligned}$$

starting in 1987. As the above formulation shows, both the average age-specific growth rates $(\bar{g}^y, \bar{g}^m)$, cyclical sensitivities $(\beta^s, \beta^y, \beta^m)$, and orthogonal growth rate shocks ε_t^s, ε_t^y and ε_t^m are

[34] The 2 percent startup growth trend also corresponds to a rate at which the startup employment share would be stable under 2 percent aggregate employment growth.

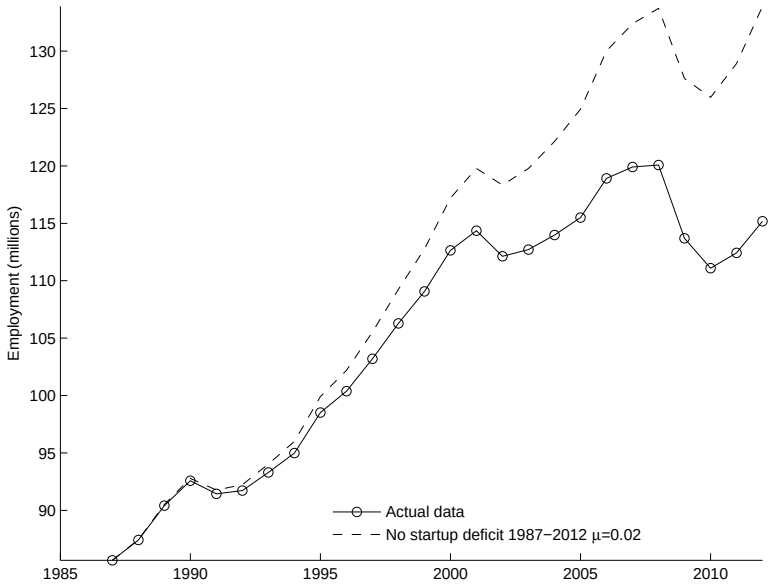


Figure 10: Actual and counterfactual paths for aggregate employment

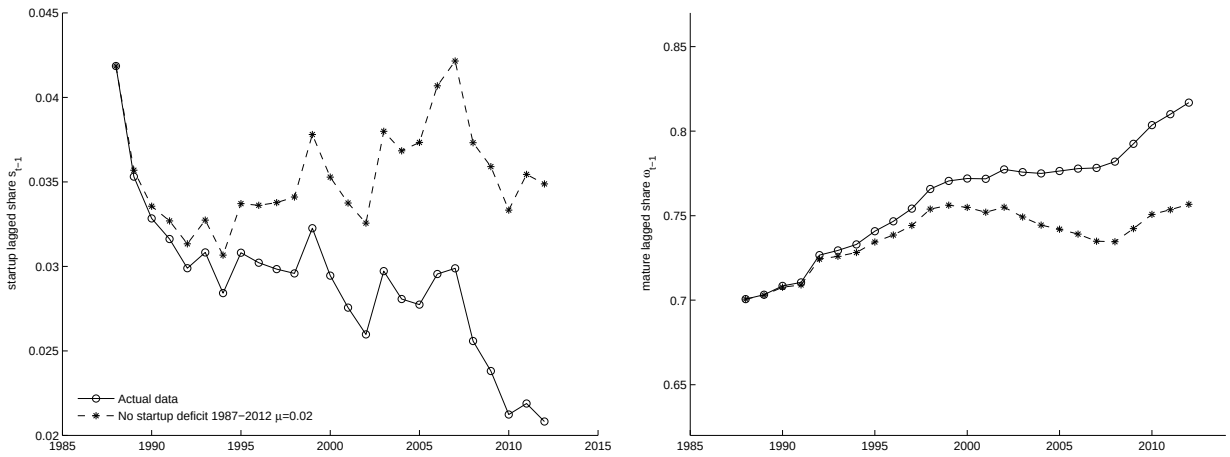
Note: [NOTES]

unchanged in the counterfactual exercise. This choice is motivated by the stability of the average growth rates and the cyclical responsiveness of employment growth that we have shown earlier.

Figure 10 shows the paths of actual and counterfactual aggregate employment for the 1987-2012 period. Counterfactual employment starts from the same level as the actual employment, but grows faster. This discrepancy in actual and counterfactual growth rates creates a gradual divergence between two paths. The effect of startup deficit starts small in the early 1990s and increases gradually to quantitatively significant levels in 30 years. The peak employment levels, which are obtained after eliminating the startup deficit, are 0.2, 4.8, and 11.4 percent higher than the actual employment levels in 1990, 2001 and 2008, respectively.

Aggregate employment growth is a weighted average of startup employment and the growth rates incumbent young, and mature firms with weights varying over time as a consequence of the startup deficit. Figure 11a and 11b show the evolution of the lagged startup employment, s_t and mature employment employment shares, ω_{t-1} in the data and our counterfactual economy. The counterfactual startup employment share fluctuates around 3.5 percent instead of gradually declining from around 4 percent in 1987 to roughly 2 percent in 2012. Eliminating the startup deficit affects the age distribution, undoing almost all the rise in employment share of mature firms in the actual data. Since the age distribution of employment is stable, the trend component of employment growth also becomes stable in the counterfactual economy instead of following a declining trend.

Figure 12 plots the difference between actual and counterfactual for the startup and incumbent growth contributions. Specifically, the lower line plots $[s_{t-1}(1+\mu_t^s)] - [s_{t-1}^c(1+0.02)]$ and the upper line plots $[(1-\omega_{t-1})g_t^y + \omega_{t-1}g_t^m] - [(1-\omega_{t-1}^c)g_t^y + \omega_{t-1}^c g_t^m]$. The counterfactual economy



(a) Actual and counterfactual s_{t-1} (b) Actual and counterfactual ω_{t-1}

Figure 11: Startup and mature incumbent employment weights

Note: [NOTE].

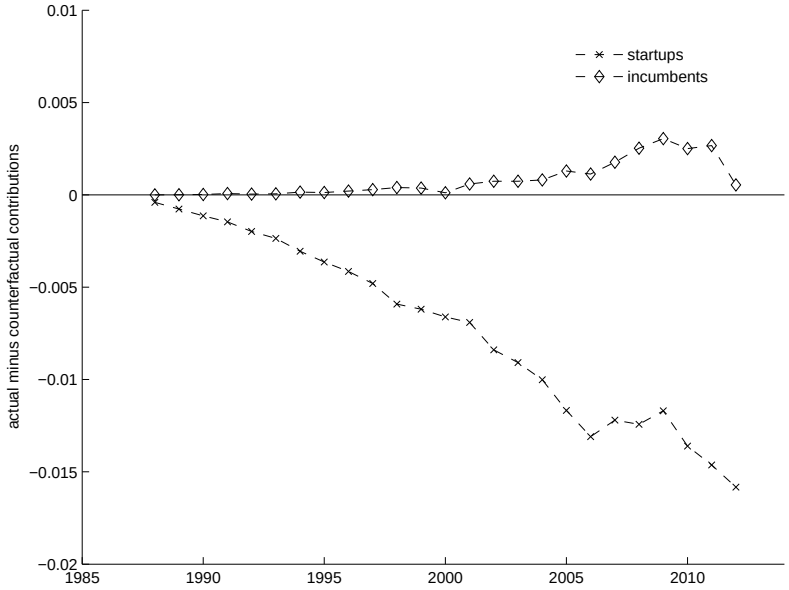


Figure 12: Actual minus counterfactual startup and incumbent growth rate contributions

Note: [NOTES]

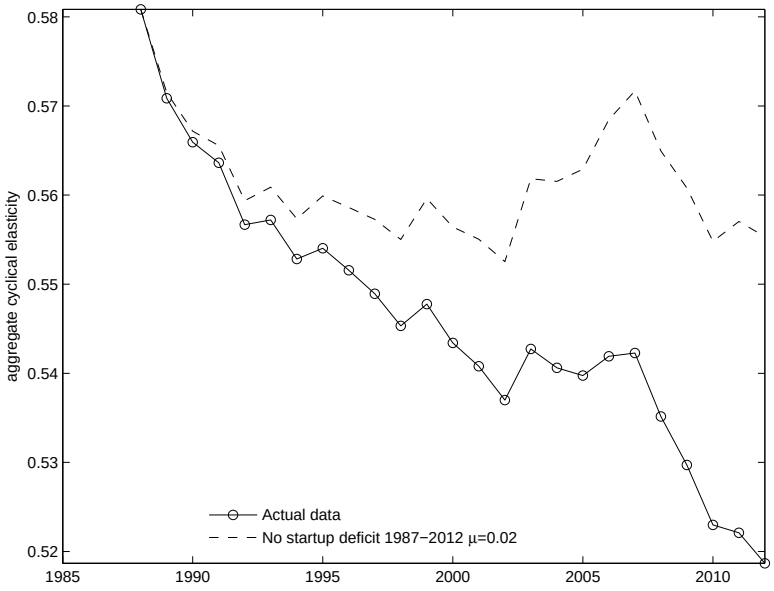


Figure 13: Actual and counterfactual aggregate cyclical elasticity β

Note: [NOTES]

has a substantially higher growth contribution from startups, which is the main source of discrepancy between the actual and counterfactual economies. There is also an opposing effect due to the higher share of young firms in the counterfactual economy. Since young firms have more negative unconditional growth rates than mature firms, the higher weight that the counterfactual economy assigns to them creates a bigger drag on employment. However, as the figure shows, the positive effect on employment due to the decreasing weight of young firms is quantitatively negligible relative to the negative effect of the declining startups. Put together, our counterfactual experiment shows that the startup deficit caused a gradual slow down in trend employment growth over the last 30 years mostly due to the decreasing employment contribution of firm entry.

In addition to the stark decline in trend employment growth, the startup deficit also affected the cyclical responsiveness of employment growth. The cyclical response of employment growth to business cycle shocks, which we formulated as $s_{t-1}\beta^s+(1-\omega_{t-1})\,\beta^y+\omega_{t-1}\beta^m$ is plotted in Figure 13 for both the data and the counterfactual economy. As we have discussed in the previous subsection, the movement towards a more mature firm structure, caused a gradual decline in this elasticity from around 0.59 to 0.53, roughly a 10 percent decline. Put differently, employment response in the current economy to a business cycle shock of the same magnitude is now 10 percent lower in the incumbent firms than in 1987. This decline in cyclical responsiveness of employment is much smaller in the counterfactual economy since the elimination of the startup deficit undoes most of the shift of employment towards less cyclical mature firms. This gradual decline in the cyclical responsiveness of employment implies a decoupling of employment and business cycle shocks, consistent with the emergence of jobless recoveries.

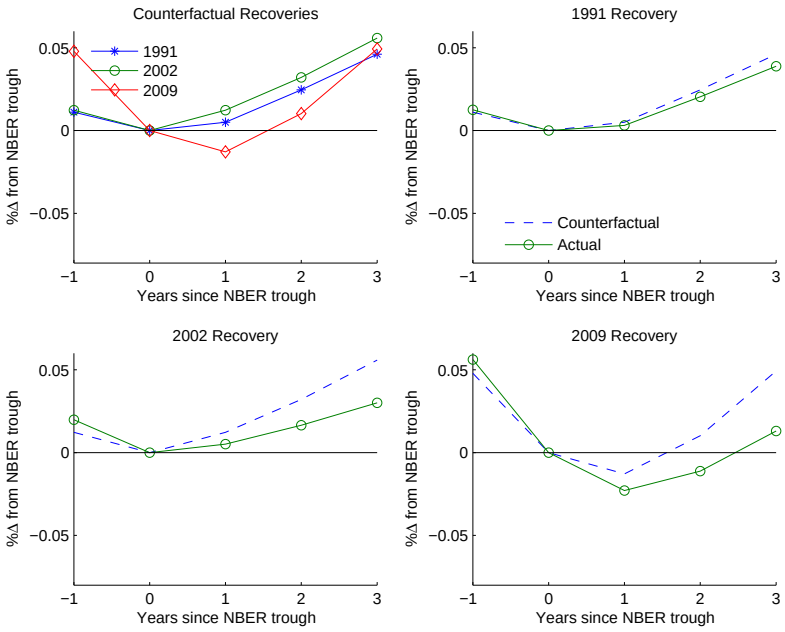


Figure 14: Actual and counterfactual recovery employment dynamics

Note: [NOTES]

6.3 Grownup business cycles

Finally we consider what the employment dynamics of recessions and recoveries might have looked like absent the startup deficit using our counterfactual economy. In particular, we normalize employment to NBER troughs and measure employment response during contraction and recovery for each business cycle starting with the 1990-91 recession. Figure 14 shows that the startup deficit had a notable effect on recession-recovery employment dynamics. The recessions are deeper and the recoveries are slower in the actual economy when compared to the counterfactual one. The effect of the startup deficits grew over time, creating a bigger wedge between the actual and counterfactual employment. In addition, its quantitive effect is more pronounced for recoveries than recessions. This asymmetry is due to the interaction of trend and cyclical components of employment growth. The decline in cyclical sensitivty of employment would have implied milder recessions and slower recoveries since its effect is symmetric. However in addition to the decline in sensitivity, trend employment growth has been declining due to the trend decline in startup employment growth. This trend decline more offsetted the moderation of employment declines in incumbent firms causing larger employment declines during recessions over time. For the recoveries, the declining sensitivity and the trend decline reinforced each other, both causing slower employment recoveries over time.

7 Conclusions

In this paper we examined the effects of the gradual decline in firm entry and the gradual aging of firms on aggregate employment dynamics. The framework we developed to link these two observations together revealed that these two changes are indeed closely related and the aging of firms is a direct consequence of the gradual decline in firm entry. Aside from these two changes, little has changed in life cycle dynamics and cyclical behavior by firm age in the last thirty years. While the relative employment behavior by firm age has been stable, there has always been substantial heterogeneity in employment dynamics of young and mature firms. Startups typically account for majority employment growth and employment growth at these firms has also been more cyclical than incumbent firms. Among incumbents, young firms had lower unconditional growth rates and more cyclical employment growth than mature firms. Put together with the substantial decline in entry and the aging of firms, these observations imply a decline in trend employment growth and a decoupling of employment and output during recoveries, both causing slower recoveries in employment over time. We have shown that these effects grew over time and became quantitatively significant in the last two business cycles.

A natural question, especially considering the robustness of the startup deficit is why has the startup rate declined so much over this period? This is an active area of research for us and the subject of a new paper. We think that the low frequency demographic shifts in the U.S. labor force over this period might have depleted the pool of potential entrepreneurs and lower wage workers for new firms. The second and related trend is the rising real wage of potential business founders. An implication of Lucas's original span of control model in Lucas Jr (1978) is the sensitivity of the selection into entrepreneurship to the wage compensation as an employee. As productivity gains have raised the real wage, they may have also raised the threshold for starting a profitable business. This of course puts restrictions on the path of marginal businesses over time, which can be tested.

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Table 1: Summary statistics from Business Dynamics Statistics (BDS) sample

	Startups	Young			Mature		
	$\tilde{g}_t^s$	g_t^y	x_t^y	n_t^y	g_t^m	x_t^m	n_t^m
	A. Overall U.S.						
Mean	0	-0.037	0.885	0.087	-0.006	0.947	0.049
S.D.	0.089	0.025	0.006	0.026	0.016	0.003	0.018
N	35	26	26	26	26	26	26
	B. Within U.S. States						
Mean							
p25	0	-0.041	0.882	0.080	-0.008	0.950	0.041
p50	0	-0.036	0.889	0.083	-0.004	0.952	0.046
p75	0	-0.030	0.895	0.089	-0.001	0.954	0.049
S.D.							
p25	0.113	0.028	0.007	0.029	0.019	0.003	0.020
p50	0.131	0.034	0.008	0.033	0.021	0.004	0.022
p75	0.167	0.038	0.010	0.038	0.024	0.005	0.025
N	1836	1326	1326	1326	1326	1326	1326

Note: U.S. Census Bureau Business Dynamics Statistics. Survival rate x_t^a is fraction of young and mature cohort that survived from previous year. Conditional employment growth rate n_t^a is the growth rate of cohort's average employment size. Statistics in panel A are computed over time using national data. Statistics in panel B are computed within each state. Quantiles of the state-employment weighted distribution of these state level measures are reported. Startup growth series $\tilde{g}_t^s$ are residuals after removing a linear trend and measured from 1980 to 2012. Incumbent growth and survival series are measured from 1987 to 2012. Young and mature series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Table 2: Alternative measures of business cycle shock Z_t

	Overall U.S.			Within U.S. States				
	$\text{Corr}(Z_t, Y_t)$	N	S.D.	$\text{Corr}(Z_t, Y_t)$	N	S.D.		
						p25	p50	p75
Personal Inc	0.805	33	0.014	0.6173	1683	0.019	0.022	0.026
Gross Output	1	33	0.019	1	1683	0.032	0.037	0.041
ΔUnemp	-0.900	33	0.993	-0.481	1683	0.849	1.026	1.183
HP Unemp	-0.319	33	1.18	-0.371	1683	1.011	1.237	1.449

Note: U.S. Census Bureau Business Dynamics Statistics. Survival rate is fraction of young and mature cohort that survived from previous year. Conditional employment growth rate is the growth rate of cohort's average employment size. Data are equally weighted across years and weighted by employment across sectors or states within years. In columns (2) and (5) standard errors are clustered by sector, and in columns (3) and (6) standard errors are clustered by state. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Table 3: Estimated linear trend in survival rates x_t and conditional employment growth rates n_t by age group

	Survival Rate x_t			Conditional Employment Growth Rate n_t		
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Young Firms (Ages 1-10)					
Trend	-0.0003	-0.0002	-0.0002***	-0.0007	-0.0009***	-0.0008***
	(0.0002)	(0.0001)	(0.00008)	(0.0008)	(0.0002)	(0.0002)
R^2	0.12	0.79	0.59	0.04	0.17	0.08
N	26	234	1,326	26	234	1,326
	B. Mature Firms (Ages 11+)					
Trend	0.0002*	0.0001	0.0002***	-0.0005	-0.0007***	-0.0005***
	(0.0001)	(0.0001)	(0.00004)	(0.0005)	(0.00009)	(0.00008)
R^2	0.19	0.84	0.59	0.05	0.40	0.12
N	26	234	1,326	26	234	1,326
Years	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012
Sector FE	-	Yes	-	-	Yes	-
State FE	-	-	Yes	-	-	Yes

Note: US Census Bureau Business Dynamics Statistics. Survival rate is fraction of young and mature cohort that survived from previous year. Conditional employment growth rate is the growth rate of cohort's average employment size. Data are equally weighted across years and weighted by employment across sectors or states within years. In columns (2) and (5) standard errors are clustered by sector, and in columns (3) and (6) standard errors are clustered by state. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Table 4: Estimated cyclical sensitivity β of net employment growth rates by age group using alternative output and employment based business cycle variables

	(1) Personal Inc	(2) GDP/GSP	(3) Change in U	(4) Cyclical U
	A. National Measures			
$\hat{\beta}^y$	0.984***	1.249***	-2.056***	-0.0675
	(0.340)	(0.222)	(0.539)	(0.332)
$\hat{\beta}^m$	0.546**	0.813***	-1.462***	-0.410*
	(0.220)	(0.137)	(0.380)	(0.227)
p-value of $\beta^y = \beta^m$	0.014	0.002	0.021	0.140
	B. State Level Measures			
$\hat{\beta}^y$	0.717***	0.436***	-2.058***	-0.942***
	(0.0716)	(0.0598)	(0.210)	(0.163)
$\hat{\beta}^m$	0.438***	0.277***	-1.156***	-0.700***
	(0.0388)	(0.0291)	(0.119)	(0.0870)
p-value of $\beta^y = \beta^m$	0.000	0.000	0.000	0.083
Years	1987-2012	1987-2012	1987-2012	1987-2007

Note: US Census BDS, Bureau of Economic Analysis, Bureau of Labor Statistics. Estimated projection by age group of net employment growth rate on the indicated business cycle measures. Unemployment rate and HP filtered unemployment averaged- and personal income and gross domestic product summed- over retimed year of April to March to correspond to BDS March 12 employment measure. Gross state product is measured over previous calendar year. Data are equally weighted across years and weighted by employment across states within years. In Panel B results, standard errors are clustered by state. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Table 5: Estimated cyclical sensitivity β of net employment growth rates by age group using change in personal income as business cycle measure

	(1)	(2)	(3)	(4)
	A. Young Firms (Ages 1 to 10)			
$\hat{\beta}^y$	0.984***	0.965***	0.717***	0.723***
	(0.337)	(0.337)	(0.0716)	(0.0662)
R^2	0.24	0.82	0.68	0.75
N	26	78	1,326	3,946
	B. Mature Firms (Ages 11+)			
$\hat{\beta}^m$	0.546**	0.541**	0.438***	0.434***
	(0.218)	(0.219)	(0.0388)	(0.0379)
R^2	0.18	0.69	0.71	0.76
N	26	78	1,326	3,978
Size FE	-	Yes	-	Yes
Year FE	-	-	Yes	Yes
State FE	-	-	Yes	Yes
Years	1987-2012	1987-2012	1987-2012	1987-2012

Note: U.S. Census Bureau Business Dynamics Statistics. Estimated projection by age group of net employment growth rate on the log difference of annual personal income. Personal income summed over retimed year of Q2 to Q1 to correspond to BDS March 12 employment measure. Data are equally weighted across years and weighted by employment across states and sizes within years. Standard errors in columns (3) and (4) are clustered by state. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Table 6: Estimated cyclical sensitivity β of startup growth rate using change in personal income as business cycle measure

	(1)	(2)	(3)	(4)
$\hat{\beta}^s$	0.571	0.0797	1.412***	0.929***
	(1.104)	(1.099)	(0.434)	(0.265)
R^2	0.01	0.00	0.30	0.30
N	33	33	1,683	1,683
Year FE	-	-	Yes	Yes
State FE	-	-	Yes	Yes
Detrending	Linear	HP 100	Linear	HP 100
Years	1980-2012	1980-2012	1980-2012	1980-2012

Note: U.S. Census Bureau Business Dynamics Statistics. Estimated projection of the startup growth rate on the log difference of annual personal income. Personal income summed over retimed year of Q2 to Q1 to correspond to BDS March 12 employment measure. Data are equally weighted across years and weighted by startup employment across states and sizes within years. Standard errors in columns (3) and (4) are clustered by state. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Table 7: Estimated linear trend of cyclical sensitivity β_t of net employment growth rates by age group using change in personal income as business cycle measure

	(1)	(2)	(3)	(4)	(5)	(6)
	Young Firms		Mature Firms		Startups	
Trend $\hat{\beta}$	0.0013	-0.0033	-0.0098**	-0.0097**	-0.072	-0.058
	(0.0093)	(0.0081)	(0.0041)	(0.0039)	(0.050)	(0.040)
R^2	0.68	0.75	0.71	0.76	0.30	0.30
N	1,326	3,946	1,326	3,978	1,683	1,683
Size FE	-	Yes	-	Yes	-	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Years	1987-2012	1987-2012	1987-2012	1987-2012	1980-2012	1980-2012
Detrending	-	-	-	-	Linear	HP 100

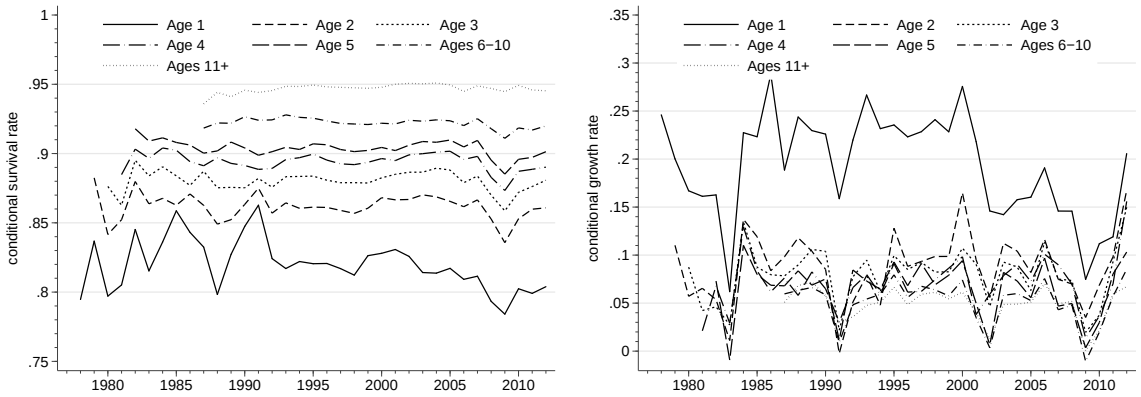
Note: U.S. Census Bureau Business Dynamics Statistics. Estimated projection by age group of net employment growth rate on the log difference of annual personal income. Personal income summed over retimed year of Q2 to Q1 to correspond to BDS March 12 employment measure. Data are equally weighted across years and weighted by employment across states and sizes within years. Standard errors in columns (3) and (4) are clustered by state. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Table 8: Estimated cyclical sensitivity β of survival and conditional growth rates by age group using change in annual personal income as business cycle measure

	Survival Rate x_t				Conditional Employment Growth Rate n_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Young Firms (Ages 1 to 10)							
$\hat{\beta}^y$	0.122	0.0826	0.241***	0.135***	0.966***	1.003**	0.524***	0.669***
	(0.0928)	(0.0523)	(0.0229)	(0.0128)	(0.328)	(0.372)	(0.0588)	(0.0600)
R^2	0.07	0.99	0.82	0.98	0.22	0.17	0.69	0.32
N	26	78	1,326	3,946	26	78	1,326	3,946
	B. Mature Firms (Ages 11+)							
$\hat{\beta}^m$	-0.00533	0.0180	0.0650***	0.0118***	0.583**	0.527**	0.392***	0.431***
	(0.0481)	(0.0306)	(0.00672)	(0.00153)	(0.238)	(0.232)	(0.0377)	(0.0382)
R^2	0.00	0.98	0.85	0.99	0.18	0.20	0.73	0.52
N	26	78	1,326	3,978	26	78	1,326	3,978
Size FE	-	Yes	-	Yes	-	Yes	-	Yes
Year FE	-	-	Yes	Yes	-	-	Yes	Yes
State FE	-	-	Yes	Yes	-	-	Yes	Yes
Years	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012

Note: U.S. Census Bureau Business Dynamics Statistics. Estimated projection by age group of survival rate x_t and conditional growth rate n_t, which are defined in text on the log difference of annual personal income. Personal income summed over retimed year of April to March to correspond to BDS March 12 employment measure. Data are equally weighted across years and weighted by employment across states and sizes within years. Standard errors are clustered by state. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

A Additional Tables and Figures



(a) One-year survival rates

(b) One-year conditional growth rates

Figure A.1: Survival and conditional growth rates of detailed ages 1 to 5, middle age group (ages 6 to 10) and mature age group (ages 11+) firms

Note: US Census Bureau Business Dynamics Statistics. Fraction of each cohort's firms that survived from previous year. Growth rate of average employment size of same cohort from previous year to current year. Average size in previous year also includes cohort's firms that do not survive. The middle (ages 6 to 10) and mature (ages 11+) groups are left censored from 1977 to 1986.

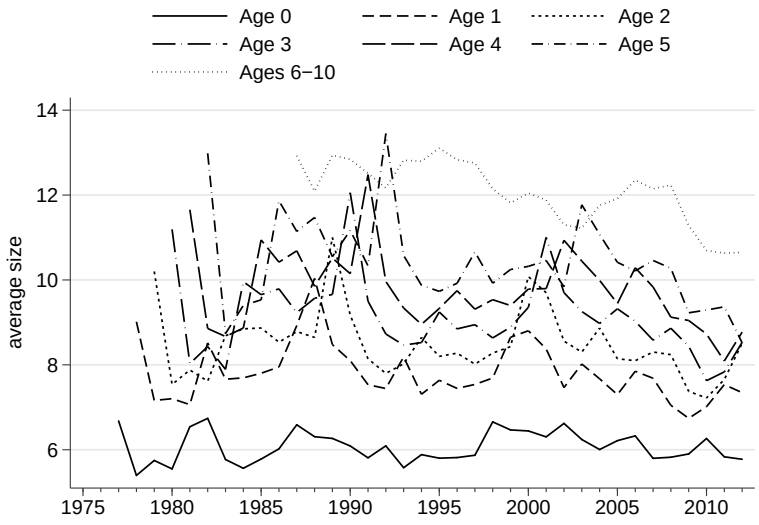


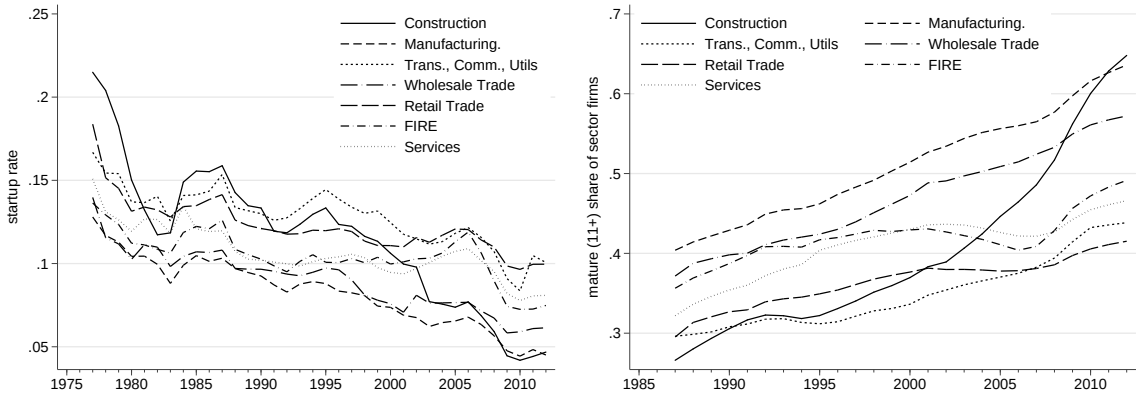
Figure A.2: Average employment by detailed age groups

Note: US Census Bureau Business Dynamics Statistics.



Figure A.3: Unconditional growth rates of combined young and new firms (ages 0 to 10) and mature (ages 11+) firms

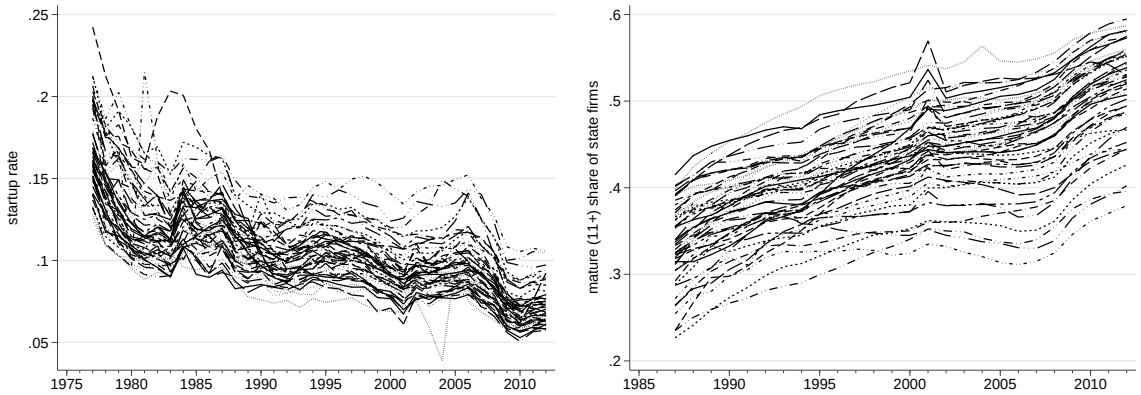
Note: US Census Bureau Business Dynamics Statistics. Growth rate of young and new firms is total employment at young and new firms relative to the total employment of the young cohort in the previous year. Series begins in 1987 because firms aged 11+ are left censored from 1977 to 1986.



(a) Startup rate within each sector 1977 to 2012 (b) Mature firm share within each sector 1987 to 2012

Figure A.4: Startup (age 0) and mature (ages 11+) firm shares by sector

Note: US Census Bureau Business Dynamics Statistics. Startup rate is number of sector's startup (age 0) firms as fraction of total sector firms in each year. Mature firm share is number of sector's mature (age 11+) firms as fraction of total sector firms in each year.



(a) Startup rate within each state 1977 to 2012 (b) Mature firm share within each state 1987 to 2012

Figure A.5: Startup (age 0) and mature (ages 11+) firm shares by state

Note: US Census Bureau Business Dynamics Statistics. Startup rate is number of sector's startup (age 0) firms as fraction of total sector firms in each year. Mature firm share is number of state's mature (age 11+) firms as fraction of total state firms in each year.

Table A.1: Estimated linear trend in survival rates x_t and conditional employment growth rates n_t by detailed age group

	Survival Rate x_t			Conditional Employment Growth Rate n_t		
	(1)	(2)	(3)	(4)	(5)	(6)
Linear Trend						
Age 1	-0.0014**	-0.00090**	-0.0013***	-0.0043***	-0.0047**	-0.0041***
	(0.00041)	(0.00021)	(0.00013)	(0.0011)	(0.0013)	(0.00031)
Age 2	-0.00011	-0.000022	-0.000070	0.00063	0.00031	0.00044
	(0.00024)	(0.00011)	(0.00010)	(0.0011)	(0.00037)	(0.00036)
Age 3	-0.00016	-0.00016	-0.00014	-0.00011	-0.00031	-0.00032
	(0.00019)	(0.00012)	(0.000095)	(0.00095)	(0.00029)	(0.00029)
Age 4	-0.00017	-0.00019	-0.00016	0.00061	0.00053*	0.00057*
	(0.00017)	(0.00011)	(0.000084)	(0.00093)	(0.00020)	(0.00025)
Age 5	-0.00018	-0.00020	-0.00016	-0.00056	-0.00061*	-0.00063**
	(0.00015)	(0.00012)	(0.000079)	(0.00077)	(0.00019)	(0.00022)
Ages 6-10	-0.00023*	-0.00027	-0.00023***	-0.00053	-0.00062***	-0.00051**
	(0.00010)	(0.00012)	(0.000058)	(0.00067)	(0.000070)	(0.00015)
R^2	0.95	0.93	0.91	0.72	0.63	0.45
N	156	1,404	7,956	156	1,404	7,956
Years	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	-	Yes	-	-	Yes	-
State FE	-	-	Yes	-	-	Yes

Note: US Census Bureau Business Dynamics Statistics. Survival rate is fraction of young and mature cohort that survived from previous year. Conditional employment growth rate is the growth rate of cohort's average size. Data are equally weighted across years and weighted by employment across sectors or states within years. Age group is fully interacted with trend and fixed effects. Robust standard errors, clustered by sector in columns (2) and (5) and by state in columns (3) and (6). Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

Table A.2: Estimated linear trend in HP filtered survival rates x_t and conditional employment growth rates n_t by age group

	Survival Rate x_t			Conditional Employment Growth Rate n_t		
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Young Firms (Ages 1-10)					
Trend	-0.0003**	-0.0002	-0.0002***	-0.0003**	-0.0002	-0.0002***
	(0.00010)	(0.0001)	(0.00008)	(0.00010)	(0.0001)	(0.00008)
R^2	0.30	0.89	0.77	0.30	0.89	0.77
N	26	234	1,326	26	234	1,326
	B. Mature Firms (Ages 11+)					
Trend	0.0002**	0.0001	0.0002***	0.0002**	0.0001	0.0002***
	(0.00008)	(0.0001)	(0.00004)	(0.00008)	(0.0001)	(0.00004)
R^2	0.26	0.90	0.69	0.26	0.90	0.69
N	26	234	1,326	26	234	1,326
Years	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012
Sector FE	-	Yes	-	-	Yes	-
State FE	-	-	Yes	-	-	Yes

Note: US Census Bureau Business Dynamics Statistics. Survival rate is fraction of young and mature cohort that survived from previous year. Conditional employment growth rate is the growth rate of cohort's average size. Business cycle and higher frequency fluctuations removed with HP filter using smoothing parameter 6.25. Data are equally weighted across years and weighted by employment across sectors or states within years. Robust standard errors, clustered by sector in columns (2) and (5) and by state in columns (3) and (6). Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.