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Abstract

We document two striking facts about U.S. firm dynamics and interpret their significance for employment dynamics. The first is the dramatic decline in firm entry and the second is the gradual shift of employment toward older firms since 1980. We show that despite these trends, the lifecycle dynamics of firms and their business cycle properties have remained virtually unchanged. Consequently, aging is the delayed effect of accumulating startup deficits. Together, the decline in the employment contribution of startups and the shift of employment toward more mature firms contributed to the emergence of jobless recoveries in the U.S. economy.

Key words: firm dynamics, employment dynamics, business cycles, entrepreneurship

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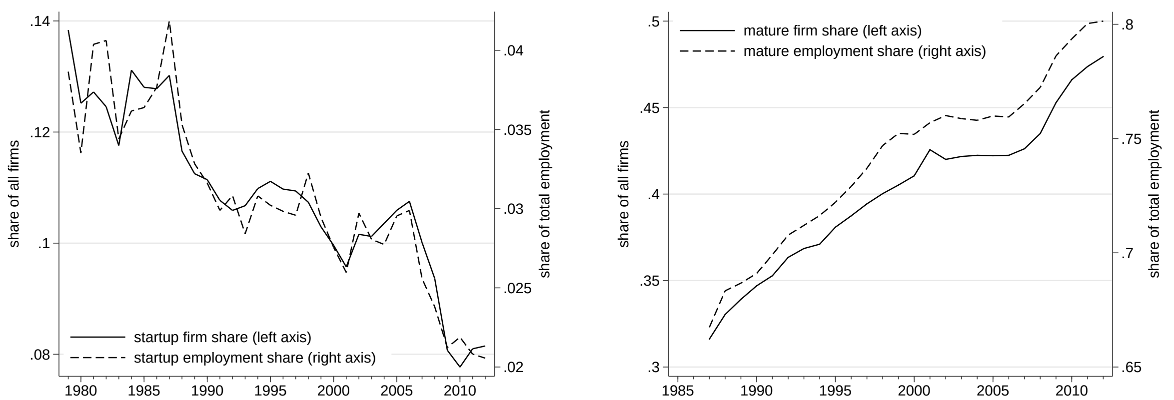
1 Introduction

There have been two significant changes in U.S. firm demographics in the past 30 years. The first is a dramatic decline in business formation. Figure 1a shows the declines in two common measures of business formation. The *startup rate* (left axis) is the number of age 0 employer firms or *startups* as a fraction of the overall stock of employer firms, and it has declined from about 13 percent in the early 1980s to about 8 percent by 2012. Another measure of firm entry, the *startup employment share* (right axis) measures employment at age 0 firms as a fraction of all private sector employment and has fallen by almost half, from 4 percent to just above 2 percent over the same period. The second significant change is an increase in the share of older businesses. Figure 1b shows analogous measures for *mature firms*, which are 11 or more years old. The share of mature firms (left axis) has increased from one-third in 1987 to almost one-half of all firms by 2012, while their employment share (right axis) has increased from around 65 percent to almost 80 percent. These patterns for both startups and mature firms are broad-based across sectors and geographic areas and are not due to a compositional shift in economic activity.



(a) Startup shares from 1979 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 (a): number of (employment at) age 0 employer firms as fraction of number of (employment at) employer firms of all ages. Right panel (b): number of (employment at) age 11+ employer firms as fraction of number of (employment at) employer firms of all ages (left axis). Series begin 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 have coincided with a shift towards higher quality entrants with higher survival probabilities or higher expected employment growth that would have offset the declining startup 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 entry, survival and employment growth. 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 by age group have remained remarkably 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* and show that an immediate implication of the startup deficit is a net decline in trend growth rate of employment. While the indirect effects of the startup deficit on the age distribution actually increase trend employment growth—gradually shifting the distribution of employment towards mature firms with far lower exit rates than young incumbents—we show that this positive effect is dominated by the negative direct effect of the startup deficit on employment growth. Because of substantial churning among incumbents and especially young incumbents, gross job creation from entrants is essential for aggregate net employment growth. This contribution has been gradually diminishing from declines in entry, more than offsetting any gains from the shift towards older employers.

We then examine the cyclicality of employment growth rates by firm age. 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 a variety of measures, and 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. In addition we find that the cyclicality of young firms has remained relatively stable, while the cyclicality of mature firms has, if anything, slightly weakened. These findings together with the shift towards older firms imply a *lower* aggregate cyclical elasticity of employment to business cycle conditions.

Finally, we use the same decomposition framework to quantify how the startup deficit reshaped employment dynamics over the business cycle. By holding trend growth in startup employment at its early 1980s average of 2 percent, we compute a counterfactual employment path that is subject to the same sequence of shocks as the actual data, but purged of the total effects of the startup deficit. Relative to the counterfactual path of employment, we observe the following: first, the decline in firm entry amplifies the response of employment to output contractions and dampens employment growth during expansions; second, the gradual shift in the age distribution towards older firms decreases the aggregate cyclical sensitivity of employment, implying milder recessions and slower recoveries for a given business cycle shock. While these two forces act in opposing directions during recessions, the effect of the declining startups is quantitatively larger, causing more severe declines in employment during recessions. However, both effects reinforce each other during recoveries implying a decoupling of employment and output growth. This disconnect between employment and output increases as the startup deficit accumulates. Therefore its effect is more significant for the Great Recession. Our experiment shows that restoring the trend pace of startups to its 1980-85 average and the reallocation of employment towards younger firms it implies 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 dynamism in the U.S. economy. Recent papers by Lazear and Spletzer (2012), Hyatt and Spletzer (2013), Decker, Haltiwanger, Jarmin, and Miranda (2014b) and Davis and Haltiwanger (2014) document ongoing declines in several measures of job and worker reallocation. Reedy and Strom (2012) were the first to our knowledge to document the aggregate decline in employer firm and establishment entry. Along with our paper, contemporaneous work by Decker, Haltiwanger, Jarmin, and Miranda (2014a) and Hathaway and Litan (2014) also document both declines in the share of new firms nationwide and within sectors or markets, and the accompanying increasing share of older firms. Both papers suggest the two trends may be related. Our further contribution is to directly examine the margins underlying the shifts in the age distribution. By establishing the stability of the survival and growth margins conditional on age, we are the first to show that these opposing trends of a declining new firm share of employment and a rising old firm share of employment are both entirely manifestations of the same underlying startup deficit. Although explaining the decline in business formation is not the focus of this paper, the approximate stationarity of the incumbent margins places strong restrictions on potential explanations.

Our work also builds on the literature that considers the varying impact of business cycles on different types of firms to study the propagation and impact of business cycle shocks. While most of the earlier literature focused on firm size, see for example Gertler and Gilchrist (1994) and more recently Moscarini and Postel-Vinay (2012), our focus is on firm age.[1] While we believe that firm size can capture some of the differences in growth potential, credit access, or size of consumer base for firms, firm age is the first order determinant of firm and employment dynamics.[2] For example, Fort, Haltiwanger, Jarmin, and Miranda (2013) consider employment cyclicality across both firm age and size groups and show that considering differences across size groups alone can be misleading.[3] In a different context, Adelino, Ma, and Robinson (2014) show that firm age is an important determinant of the employment response to investment opportunities from local demand shocks. Our analysis adds to this literature by showing that sensitivity to business cycle shocks depends crucially on firm age *and* highlighting the stability of these differences over time.

Our finding that the decline in firm entry and the aging of firms imply a decline in trend employment growth and a decoupling of employment and output during recoveries also provides 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 structural change explanations (Groshen and Potter (2003), and Jaimovich and Siu (2012)) as well as reorganization and adjustment costs-based explanations

[1] In earlier studies firm size was to some extent used as a proxy for firm age and the choice of firm size over firm age was mostly motivated by availability of better data on firm size. For example, Gertler and Gilchrist (1994) noted in their paper that the informational frictions that add to the costs of external finance apply mainly to younger firms.

[2] See Haltiwanger, Jarmin, and Miranda (2013) for an in-depth discussion of the competing roles of firm size and firm age in firm and employment dynamics.

[3] While almost all new and young firms are small, there are still many older small firms. As shown by Hurst and Pugsley (2011) the vast majority of young small firms that survive become old small firms. As a result, Fort, Haltiwanger, Jarmin, and Miranda (2013) show that the additional cyclicality of large relative to small employers documented by Moscarini and Postel-Vinay (2012) is only found among older employers.

(Bachmann (2012), Berger (2012), and Koenders and Rogerson (2005)). Increasingly jobless recoveries are understandable when we account for the shifts in entry and its cumulative effects on the stock of incumbent firms. 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!

2 A Framework for Decomposing Firm Dynamics by Age

We first 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.[4] 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 primarily 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.[5] 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. The first is the entry margin, which we measure by employment E_t^0 at age 0 firms or "startups" and label it as

$$S_t \equiv E_t^0.$$

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

[5] Gradual shifts in the unconditional firm size distribution appear to also be driven by the shifts in firm age. We include a more detailed discussion of firm age and size in appendix B.1.

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 because the average entrant size has remained stable, this distinction is not important for the current analysis.[6] The second margin is the survival rate x_t defined as

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

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) stabilizes and firm dynamics begin to look more alike across ages. The young age group definition of ages 1 to 10 aggregates much of the rich heterogeneity and dynamism among young firms into a single category, but 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 stable. As we discuss in section 4 we have repeated the decomposition exercises with more disaggregated age groups for young firms with little change

[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 has gradually increased (because of the shift towards older firms), while the average size of entrants has remained relatively steady, so the startup employment share has declined even faster than the startup rate.

from our main results.

The exact law of motion for 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 shares and growth rates. 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.[7,8] 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 for each year 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

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

[7] 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.

[8] In appendix A, we provide more detail on the behavior of q_{t-1}. This variable serves a dual purpose in our framework. 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.

Writing (3) as a moving average

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

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 $\{P_t\}$.

Many equilibrium models of firm dynamics, such at the workhorse Hopenhayn (1992) model, have 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. 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 may still fluctuate with the business cycle. To identify the cyclical component of P_t we extend the model in order to allow the margins to depend on a mean zero business cycle shock Z_t. 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^a 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 group's β 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^s, if average startup growth is insufficient to keep pace with overall employment growth, the *startup employment share* $s_t = S_t/E_t$ must decline. For the period we study, not only is μ_t^s is not high enough to keep startups' employment share constant, but it may also be slowly declining. The aggregate time-series is too noisy to estimate the magnitude of a decline with a reasonable level of confidence. Relative to a sequence of μ_t^s that keeps the expected 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

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

Formulated in growth rates, aggregate employment growth is

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

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

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

The second two terms constitute the *incumbent growth contribution.* For incumbents, weight ω_{t-1} refers to the employment share of the current year t mature cohort in the *previous* year $t-1$

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

Because the current young group includes last year's startups the incumbent lagged employment weights sum to exactly 1. This weight evolves according to the law of motion in equation (3). 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

$$\begin{aligned} g_t \quad = \quad & \underbrace{s_{t-1}\left(1+\mu_t^s\right)+\left(1-\omega_{t-1}\right)\bar{g}^y+\omega_{t-1}\bar{g}^m}_{\text{Trend component}} \\ & +\underbrace{\left(s_{t-1}\beta^s+\left(1-\omega_{t-1}\right)\beta^y+\omega_{t-1}\beta^m\right)Z_t}_{\text{Cyclical component}} \\ & +s_{t-1}\varepsilon_t^s+\left(1-\omega_{t-1}\right)\varepsilon_t^y+\omega_{t-1}\varepsilon_t^m. \end{aligned} \tag{7}$$

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 decompose the effects of the startup deficit on the trend and cyclical components of aggregate employment growth.

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 tabulations, the Business Dynamics Statistics (BDS). This administrative database covers nearly every nonfarm private-sector employer business in the U.S.[9] The data are based on a longitudinally-linked version of the Census Bureau's Business Register and include nearly all private-sector establishments with paid employees. Multiple establishments owned by the same firm are linked through both annual response to a Census Company Organization Survey and results from the quinquennial Economic Census. This is an important detail, since we are interested in true firm startups rather than new locations (new establishments) of an existing firm. By aggregating across one or more establishments within each firm, the data report the total employment of each firm on March 12 of each calendar year from 1976 to 2012 in the LBD and 1977 through 2012 in the BDS tabulations, since age can only be recorded for firms newly formed in 1977 or later. Firms founded prior to 1977 are part of the database, but their age is left censored.[10]

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. We sometimes further distinguish firms by their total employment, which we group into three firm size categories: small (1 to 19 employees), medium (20 to 499 employees) and large (500+) employees. The exact cutoffs are somewhat arbitrary, and the results

[9]Nonemployer firms are not a part of this database. We discuse their role in section 6.4.

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

are robust to alternative definitions of small and large employers. In practice, firms with fewer than 20 employees already constitute almost 90 percent of all firms, and among large firms most employment is concentrated in very large employers so the choice of maximum employment for a small firm and minimum employment for a large firm have little effect on our results.

For our analysis, we use aggregations of employment and net job creation by year, our firm age groups, size groups, industry and state. For each of these cells, we measure the survival rates and conditional growth rates as defined in section 2.1. In almost all cases, the tabulations available in the BDS are sufficient. One exception is aggregating firms by age, location, and industry simultaneously. In this case, we construct a firm level file from the LBD, which we then further aggregate by 2- and 4-digit NAICS industry, state, and firm age.[11] We provide additional details on the variable construction and sample restrictions in appendix A.

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. Mature firms' survival rate is close to 95 percent and conditional on survival mature firms grow roughly 5 percent on average. As we discuss below, the lower survival rate for young firms more than offsets their 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.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 a linearly 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 cyclical unemployment. When possible, we first compute annual measures over a time-shifted year ending in March (Q1) in order to coincide with the week of March 12 employment in the LBD and BDS. The only measure for which this is not possible is gross state product (GSP), which is only released at an annual frequency for calendar years.

Our preferred proxy 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. Al-

[11] We thank Theresa Fort for generously sharing her NAICS industry code assignments for all establishments from 1976 to 2009 on a consistent NAICS 2002 basis. See Fort (2013) for details.

though 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 link between output and employment is in part the object we are investigating. Second, personal income is available at quarterly frequency even at the state level, allowing us to match the timing of employment in the Census Data, which is measured annually at the March 12 levels. 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 (forthcoming). The second is the annual average of the cyclical component of monthly unemployment obtained by first H-P filtering the monthly data with a smoothing parameter of 8.1 million.[12] Moscarini and Postel-Vinay (2012) use this measure to compare the cyclicality of large and small employers. Both unemployment-based proxies also have the advantage of being available at high frequency even at the state-level. Our results for the most part remain similar across all four measures.

In table 2 we summarize the four annual business cycle measures measured at the national and state-level. The personal income based Z_t is highly procyclical, and the change in unemployment is highly countercyclical. It also reports the distribution of time series standard deviations for each measure across all states. State-level measures are more volatile than their national counterpart, which is consistent with a state-level idiosyncratic component to the shocks.

[INSERT TABLE 2 (Z_t SUMMARY) ABOUT HERE]

4 Long Run Behavior of the Margins of Adjustment

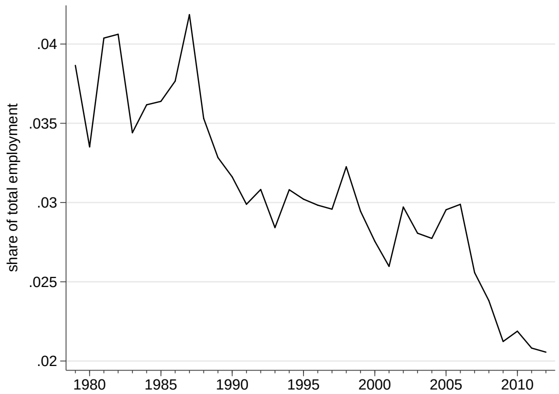
Despite the gradual decline in the startup rate since the 1980s, incumbent firm behavior by age changed little over the same period. Applying the framework from section 2.1 we decompose shifts in the distribution of employment over time into contributions from the sequence of startup employment S_t, and among incumbents the survival rates x_t^a and conditional growth rates n_t^a by age group encoded in P_t.[13] The primary determinant of the expanding mature employment share has been the cumulative effect of the decline in startups since the 1980s.

4.1 The Startup Deficit

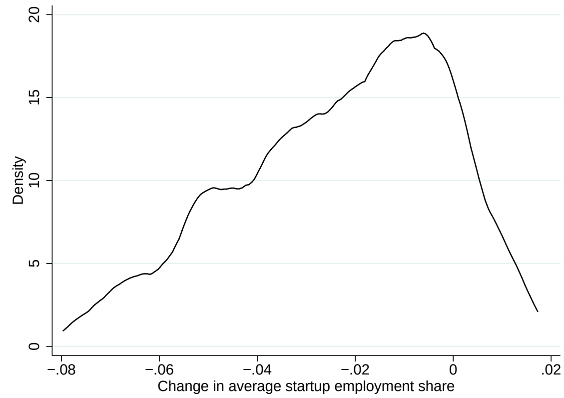
There has been a gradual decline in the firm startup rate starting in early 1980s. Due to this gradual decline in firm entry, startup employment failed to grow at the same rate as aggregate employment growth, causing a gradual decline in their overall employment share. In panel (a) of figure 2 we plot the employment share of startups, s_t, defined as S_t/E_t. As the figure shows, s_t

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

[13] 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. These shifts are relatively minor and nearly zero on average as we discuss further in appendix A.3.



(a) Aggregate share from 1979 to 2012



(b) Distribution of long-run state×industry changes

Figure 2: Declines in the startup employment share

Note: U.S. Census Bureau Business Dynamics Statistics and Longitudinal Business Database. Left panel: employment at age 0 employer firms as fraction of employment at employer firms of all ages. Right panel: Epanechnikov kernel density estimator of distribution of the changes by state×4-digit NAICS industry in startup employment share from its average in 1980-1984 to its average in 2003-2007.

averaged at around 4 percent in the 1980-84 period and has declined to around 2 percent in 2010.[14] With the new entrants bringing less employment than previous cohorts of entrants, the employment share of startups has been on a downward trend. We refer to this growing shortage of entrants as the *startup deficit*.

Startup deficits are pervasive across both industries and locations. The public use tabulations in the BDS only allow us to measure startup employment either by broad sector or by state or metro area. Appendix figures B.7 and B.8 show that startup employment shares have been declining in broadly defined sectors and across U.S. states. To go further and examine business formation within narrower submarkets, we use the LBD, which allows us to analyze the evolution of startup employment jointly in narrowly defined industries and geographic locations. In particular, we focus on 4-digit NAICS industry-state pairs, which results in around 13,000 submarkets. We compute the change in the startup employment share between 2003-2007 and 1980-1984 periods and plot its distribution in panel (b) of figure 2. In 82.8% of these submarkets, the startup rate was lower in the 2003-2007 period relative to its 1980-84 average. If we includes the effects of the Great Recession, the share of industry×state pairs with declines increases to 89.2%.

We focus primarily on startup employment shares rather than the startup rate. 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] However, the results are nearly identical if were were to instead use the changes in the

[14] Because of the measurement concerns we highlight in section 3 we begin our analysis in 1979; including 1977 and 1978 as we do in appendix figure B.3 makes the decline even more striking.

[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

startup rate: 83.5% of state$\times$industry pairs have declining startup rates from the 1980-84 average to the 2003-07 average, and increasing to 95.5% when we include the Great Recession period. For brevity, we present these alternative distributions in appendix B.2.

A final concern is that the decline the startup rate stems primarily from our choice of firms instead of establishments as the unit of observation. Declines in new firm creation fully offset by new production unit (establishment) creation within large incumbent firms would change our interpretation of the startup deficit. However, the startup deficit also extends to establishment entry. In appendix figure B.6, we plot the establishment entry rate and age 0 establishment employer share. Both measures show a similar decline to what we have documented using firms as our unit of observation. While there is evidence in the retail trade sector, see for example Foster, Haltiwanger, and Krizan (2006), of large and technologically sophisticated retail chains crowding out new firms, these effects are not large enough to create a wedge between aggregate establishment and firm entry measures.

4.2 Stability of Incumbent Survival and Growth Margins

The evolution of the distribution of employment across age groups also depends on incumbents' survival and growth prospects. In panel (a) of figure 3 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.[16] 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.[17] The survival rates are also mildly procyclical, showing dips in recession years.

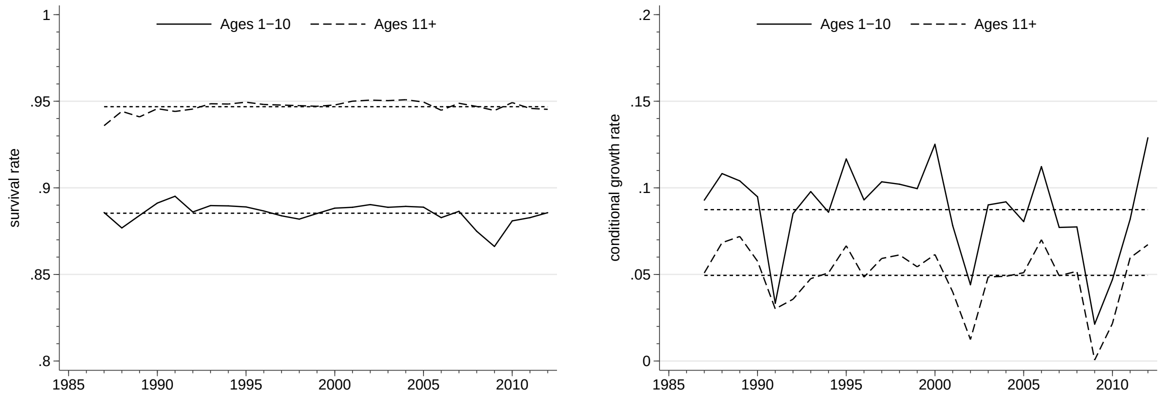
Even with this cyclicality, the within-age group survival rates are remarkably stable over the long-run. We confirm this stability in table 3 where we fit a linear trend to survival rates x_t by age group. Columns (1) and (2) report the estimated coefficient on the linear trend when using just annual aggregates and annual aggregates by state. Using the national data, for both young and mature firms, the estimates are quantitatively insignficant and statistically indistinguishable from zero. For example, the estimated trend implies that over thirty years, the survival rate of both young and old firms will have changed by a fraction of 1%. Using the state-level data provides identical near zero point estimates that are more precisely estimated from the additional variation.[18] Fitting a simple linear trend from the raw time series for survival rates may be sensitive to the pattern of short-run fluctuations during the time period. However, we find the same results even when first

measurement error for this reason.

[16] In the appendix figure B.9 we show that the same pattern holds even within a disaggregated young age group.

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

[18] Throughout the paper when using the state-level data we cluster the standard errors by state to adjust for within state serial correlation in the dependent variable and to be comparable with the related literature (see for example Fort, Haltiwanger, Jarmin, and Miranda (2013), Davis and Haltiwanger (2014) and Foster, Grim, and Haltiwanger (forthcoming)). A significant concern with state-level panel data is spatial correlation (See the discussion in Foote (2007)). When corrected for spatial correlation by clustering by year or spatial and serial correlation using the covariance matrix estimator suggested by Driscoll and Kraay (1998) the results are no longer significant.



(a) Survival rates x_t (b) Conditional growth rates n_t

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

Note: U.S. Census Bureau Business Dynamics Statistics. Survival rate is fraction of young and mature cohorts that survived from previous year. 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.

filtering the data to remove business cycle and higher frequency fluctuations before estimation. The results are similarly unchanged by including controls for sector and firm size and with alternative definition of young firms.[19]

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

The relationship between firm age and conditional employment growth rate is also stable. In panel (b) of 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 (3) and (4) report the estimated coefficient on a linear trend in n_t by age group. For the U.S. overall and within state, the estimated trend coefficients are quantitatively insignificant and for the national data, statistically insignificant. Again, this is robust to alternative methods of removing cyclical fluctuations as well as additional controls for sector and firm size.

Overall, mature firms have both a lower conditional growth rate and as table 1 shows, a 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. Except for the very youngest (age 1) firms, the same patterns hold even when further disaggregating the young age group. There has been a recent shift in both the survival rates and employment growth of startups into their first year. If we extend the definition of startups to include both age 0 and age 1 firms, this recent decline reinforces the startup deficit. Although it is

[19]For brevity, we include these robustness results in appendix tables B.2 and B.3.

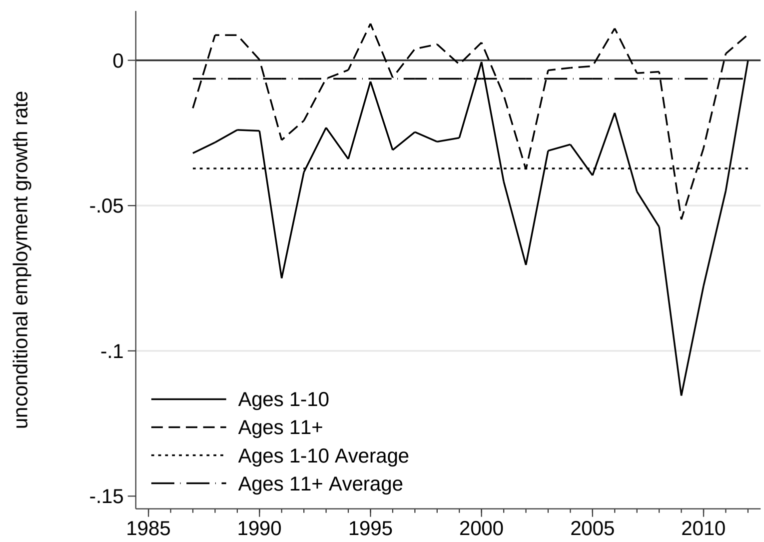


Figure 4: Young and mature unconditional employment growth rates (g_t^y and g_t^m)

Note: U.S. Census Bureau Business Dynamics Statistics. Unconditional growth rate is the growth rate of employment within an age group. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

of independent interest, this recent decline appears isolated to the very youngest firms and has very little effect on our results. Survival and growth rates for other ages appear unchanged as we show in appendix table B.1. 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 on average.[20]

The stability of the survival and conditional growth margins for each age group carries over to the unconditional growth rates. In figure 4 we plot the unconditional growth rates 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. Second, the unconditional growth rate for mature firms exceeds the growth rate for young incumbents. Their higher conditional growth rate is not enough to offset the signficantly lower survival rate of young incumbents. The unconditional growth rate of young firms only exceeds mature firms when the growth contribution from startups is pooled with the growth from young incumbents, as in Haltiwanger, Jarmin, and Miranda (2013). 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, 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 5.1), but they fluctuate around steady averages with no sign of a trend. Interpreted through the decomposition framework

[20]Overall average firm size increases only because of the increasing employment share of mature firms, which are significantly larger.

in section 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.[21]

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 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.

This finding also applies to broad sectors and states. As we showed in section 4.1 and in appendix B.2, startup deficits are common across both. Despite substantial heterogeneity within and across detailed industries in survival and growth, at higher levels of aggregation average measures of survival and growth are stable. To give an example, many industries within both retail trade and manufacturing have changed significantly over this 30 year period, but in both cases the share of older firms is uniformly well predicted by just changes on the entry margin, while holding the incumbent dynamics fixed. In appendix B.3 we provide a more in-depth discussion of these results for states and sectors. Whereas startup deficits are a common factor shared across industries and areas, there is no similar common factor affecting expected firm survival and growth conditional on entry.

[21] The stability of the survival and growth margins might seem at odds with the recent findings of Sedlácek and Sterk (2014). While we find no cohort effects in the net employment growth rate, they find significant and persistent cohort effects in average size conditional on firm age stemming from business cycle fluctuations in the average employment size at age 0. These findings actually reinforce one another: the stability of incumbent growth rates by firm age propagates the fluctuations in employment size of a birth cohort to its average employment *level* in future years.

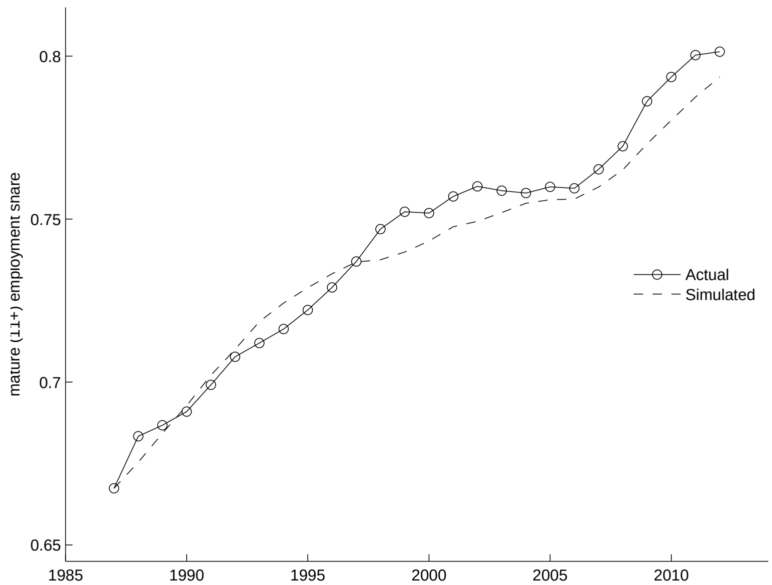


Figure 5: Mature employment share from 1987 to 2012 and its predicted path from constant survival and growth.

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 from equation (3) using actual sequence of startup employment $\{S_t\}$ and constant growth and survival rates $\bar{P}$ in the law of motion. Series begin in 1987 because firms aged 11+ are left censored from 1977 to 1986.

5 Cyclicality of Employment Growth

In this section we estimate each age group's cyclicality using the framework described in section 2.2. We estimate a cyclical elasticity of unconditional employment growth β^y for young firms that is roughly 1.5 to 2 times the magnitude β^m for mature firms. We show that these estimates are robust to a number of concerns. More importantly, anticipating our counterfactual simulation, we find that despite the large changes on the entry margin, these elasticities have not systematically changed over time.

5.1 Estimated Cyclical Elasticities

5.1.1 Incumbent Firms

First we estimate each age group β^a using only the time series variation in unconditional employment growth g_t^a. To do this we estimate equation (4) for each incumbent age group $a = y, m$. Panel A of table 4 reports the estimated β^a for each incumbent age group using four alternative measures for business cycle shock Z_t. We estimate equation (4) over the full sample of 1987 to 2012 for the first three measures of Z_t.[22] Young firms are noticeably more cyclical than mature firms in the annual time series in table 4. For all but the H-P filtered unemployment proxy in column (4)

[22]Results are nearly identical if we estimate the H-P filtered unemployment shock over only 1987 to 2007 to avoid any issue from isolating cyclical frequencies near the endpoint.

young firms are both statistically and quantitatively more cyclical than mature firms, ranging from roughly 40 to 100 percent more. The table also reports an estimated p-value of a test for equality of $\beta^y = \beta^m$, which is rejected at a 5 percent level for all but the H-P-based measure in column (4).

[INSERT TABLE 4 (CYCLICALITY) ABOUT HERE]

The greater cyclicality of young firms is also robust to an alternative source of identification. Estimating an age group β^a from the time series is challenging from only twenty-six annual observations. As an alternative to aggregate time series variation we use cross-state s variation in the business cycle variable Z_{st} and the unconditional growth rates g_{st}. Here we project the age group growth rates on a state-level business cycle variable Z_{st} with both state θ_s and time λ_t fixed effects and estimate

$$g^a_{st} = \theta^a_s + \lambda^a_t + \beta^a Z_{st} + \varepsilon^a_{st}. \tag{8}$$

This specification identifies the parameter β from the within-year and across-state differences in state-level business cycles, averaged over 1987 to 2012 and adjusting for permanent differences in growth rates across-states. Panel B of table 4 reports the estimated β^a for each incumbent age group using four alternative measures for business cycle shock Z_{st}. 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, with a test of equality rejected at a 5 percent level in all cases.

These results are estimated using within-year, cross-state variation of cyclical shocks and growth rates by age group. This specification 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.

Since 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, we calculate firm-level growth rates and aggregate by state, industry (both 2-digit and 4-digit NAICS) and firm size categories, using the LBD, the micro data files underlying the BDS tabulations. The micro data allow us to aggregate firm statastics by state, size groups and industry simultaneously, whereas the BDS only allows for two out of the three and never state and industry at the same time. The estimated cyclical sensitivity of young and mature firms using personal income as the business cycle proxy are reported in table 5. The estimated elasticities are smaller than the ones reported in column (1) of table 4 since some of the variation in cyclicality of employment growth is absorbed by industry controls. Despite the level differences compared to column (1) of table 4, the relative cyclical elasticity of young and mature employment growth rates are remarkably similar, with β^m estimated to be around two thirds of β^y.

In appendix B.4, we also use a publicly available alternative data source, the Quarterly Workforce Indicators (QWI) to control for industry composition. Results are again very similar.

[INSERT TABLE 5 (INDUSTRY VARIATION) ABOUT HERE]

Both when identified off the time series and the cross-section, the greater cyclicality of young firms is a robust result. We show in appendix B.4 that results are robust to (i) using further disaggregated age groups; (ii) controlling for size fixed effects; (iii) control for sectoral changes; and (iv) using establishment age instead of firm age. We also find that the additional cyclicality of young firms extends to both the survival and conditional growth rate margins when estimated separately for each margin. The higher sensitivity of g_t for young firms is both due to their survival and growth rates being more sensitive to business cycles.

Although extremely robust, the greater cyclicality of young firms than mature firms is a reduced form result. We want to be careful when interpreting the magnitudes of β^a for either group. The larger young firm cyclical elasticity β^y captures the stronger comovement of young firms' employment growth with the business cycle than mature firms'. In practice there are likely many underlying structural shocks at any point in time, e.g., a monetary policy or technology shock. We interpret each reduced-form β^a as an average over structural βs to each shock, noting that this average is sensitive to the frequency and magnitudes of the underlying shocks. The key is that both young and old firms are exposed to the same shock, and the difference in β^as captures their relative responses.

5.1.2 Properties of β^s

We next consider the cyclical properties of the growth rate of the startup employment, by projecting startup employment growth g_t^s on Z_t, while allowing its mean to drift, as in equation (5). Estimating the cyclicality of startups requires first detrending the series. For brevity we only report the results of projecting linearly detrended residuals, which we denote $\tilde{g}_t^s$, on a personal-income business cycle measure.[23] Columns (1) and (2) of table 6 show the estimated cyclical elasticity 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 both statistically significant and strongly pro-cyclical. A one standard-deviation increase in state Z_{st} (median standard deviation by state 2.2%) predicts a 2-3% increase in startup employment growth (median standard deviation by state 13%). Similar to incumbents, we also show in appendix B.4 that results are robust to (i) controlling for size fixed effects; (ii) control for sectoral changes; (iii) using a broader measure of startups which includes age 1 firms as startups; and (iv) using establishment age instead of firm age.

Although it appears significantly larger, the startup employment elasticity β^s is not directly comparable to its incumbent counterparts. The main difference is that since $S_t = F_t^0 N_t^0$ the startup

[23] Results using H-P filtered residuals with alternative smoothing parameters and time periods are included in appendix B.4. The procyclicality of startup employment growth is robust to alternative methods of detrending.

β^s captures the combined response new firms F_t^0 and new firm size N_t^0 to the business cycle, whereas the incumbent β^a captures the cyclical response of within-cohort employment growth. Further, since startup employment represents such a small share of overall employment (recently near 2%), the growth rate decomposition in equation (7) reveals that even with $|\beta^s| > |\beta^y| > |\beta^m|$ as comparisons across tables 4 and 6 show, the contribution of the startup β^s to overall cyclical employment fluctuations is trivially small because of its small employment share s_{t-1}. The perhaps surprising very small direct effect of cyclical fluctuations of startups in overall cyclical fluctuations is a point made by Moscarini and Postel-Vinay (forthcoming). Startups still have a critical role in aggregate fluctuations, but their first order effects on the business cycle follow from the effects of their trend μ_t^s and not their cyclical fluctuations.

5.2 Time Variation in Cyclical Sensitivity by Firm Age

It will be important for our description of "grown-up business cycles" in section 6 that the relative cyclicality of employment in across age groups has not shifted over time. One might expect that as firm entry declined and the business age distribution tilted towards mature firms, general-equilibrium effects might systematically shift the cyclical properties *within* age group. Interestingly, this does not appear to be the case.

To test the stability of the cyclical elasticity term, we look for a first order shift over time in either age group's β^a. The idea is to use the same within year and across-state variation in Z_{st} and allow β_t to depend on time through a linear time trend

$$\beta_t^a = \beta_0^a + \beta_1^a t. \tag{9}$$

We re-estimate equation (8) with a trend component to β_t^a as in (9).[24] Table 7 reports the estimated linear trend component β_1^a 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. The slight decrease in cyclicality for mature firms is due partly to compositional changes within the mature category since it has no upper bound for firm age. When examined over a period where we can distinguish 11-15 year old firms from 16+ firms, the downward trend is smaller within the 11-15 age group. To the extent that, if anything, mature firms have become less correlated with the business cycle, we will understate the effects of the startup deficit on aggregate employment in section 6.

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

[24] For a given age group, this strategy is equivalent to estimating a β for each year from the cross-state variation and fitting a line through the βs for each time period.

change in the cyclical sensitivity of startup employment.

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 the 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.[25] The second is the more pronounced cyclicality of young firms (and to a lesser extent startups) 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 in equation (7) (repeated here) is a good starting point to understand the effects of the startup deficit on aggregate employment dynamics:

$$
\begin{aligned}
g_t = & \underbrace{s_{t-1}\left(1+\mu_t^s\right)+\left(1-\omega_{t-1}\right)\bar{g}^y+\omega_{t-1}\bar{g}^m}_{\text{trend component}} \\
& +\underbrace{\left(s_{t-1}\beta^s+\left(1-\omega_{t-1}\right)\beta^y+\omega_{t-1}\beta^m\right)Z_t}_{\text{cyclical component}} \\
& +s_{t-1}\varepsilon_t^s+\left(1-\omega_{t-1}\right)\varepsilon_t^y+\omega_{t-1}\varepsilon_t^m .
\end{aligned} \tag{7}
$$

This equation highlights the dependence of the growth rate of employment on shifts in the age distribution through employment shares s_{t-1} and ω_{t-1} and on the shifts in the trend component μ_t^s of startup employment growth. Recall from section 4.1 we define the startup deficit as the history of μ_t^s relative to a constant value $\bar{\mu}^s$ that would keep the entry rate, either in employment share or firm share, constant over time. We separately consider the effects of this deficit on the trend and cyclical components of employment growth.

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 low levels of μ_t^s clearly reduce the trend contribution to employment growth, but their lagged effect through age distribution is ambiguous. As we showed in section 4.2, $\bar{g}^m > \bar{g}^y$ because of the high exit hazard of young firms. So the increase in ω_{t-1} places more weight on mature firms, resulting in less 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)

[25] This is a point emphasized by Haltiwanger, Jarmin, and Miranda (2013), although they pool startups with other young firms.

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, the negative effect is quantitatively much larger in the U.S. data, implying a declining trend growth rate of employment as we show below.

Cyclical component The cyclical component of aggregate employment growth is reshaped only through changes in the age distribution. As we showed in sections 5.1 and 5.2, startups and young firms have a higher cyclical elasticity than mature firms

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

and that these age group cyclical elasticities have not systematically 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.

6.2 Quantifying the effect of the startup deficit on employment growth

Together these changes to the trend and cyclical components of employment growth resulting from the startup deficit have reshaped aggregate employment dynamics. To quantity the extent of this effect we use the framework we developed in section 2 and compute the evolution of aggregate employment in an identical economy but for the assumption of no startup deficit. We replace the linear declining trend in the startup employment growth rate, μ_t^s, with its 1980-85 average of $\bar{\mu}^s = 0.02$, leaving the exact sequence of cyclical and other shocks in place.[26] 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 where

$$\frac{S_t^c}{S_{t-1}^c} = 1 + \bar{\mu}^s + \beta^s Z_t + \varepsilon_t^s.$$

This imposes for the counterfactual economy a path of aggregate growth rates determined by

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

[26]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.

starting in 1987. As the above formulation shows, 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 *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 in sections 4 and 5.

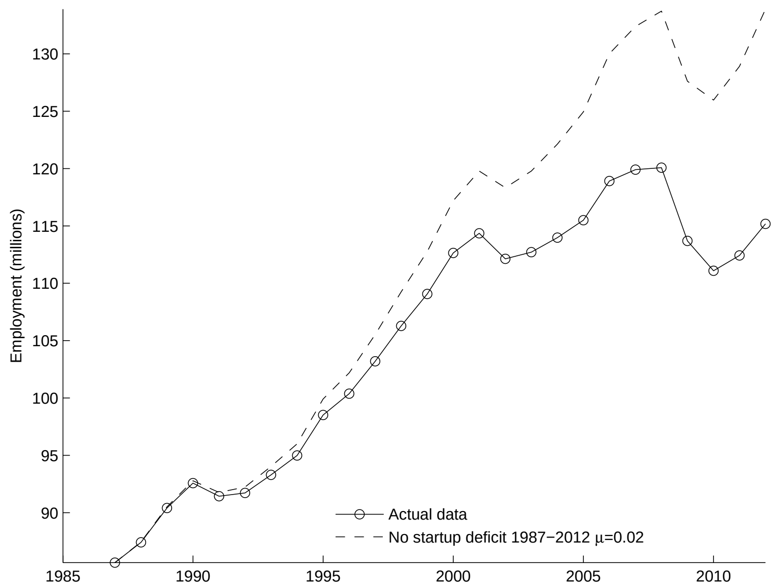


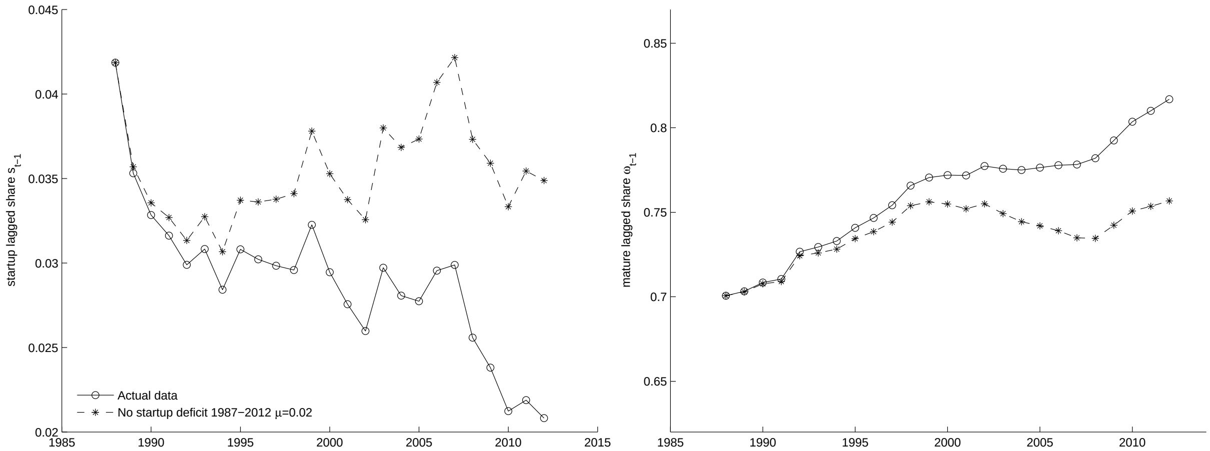
Figure 6: Actual and counterfactual paths for aggregate employment (E_t and E_t^c)

Note: U.S. Census Bureau Business Dynamics Statistics. Actual data represents employment path using exact law of motion in equation (3) from 1987 onward. Counterfactual employment path uses a sequence of startup employment $\{S_t^c\}$ where μ_t^s in g_t^s is replaced with constant $\bar{\mu}^s = 0.02$ for 1987-2012.

Figure 6 shows the paths of actual, E_t, and counterfactual, E_t^c, 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 steadily to quantitatively significant levels by the early 2000s. 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 in figure 6 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. Figures 7a and 7b show the evolution of the lagged startup employment, s_{t-1}, 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 changes the age distribution, undoing almost all the rise in employment share of mature firms in the actual data.

The startup deficit has opposing effects on the startup and the incumbent contributions to aggregate employment growth. Figure 8 plots the difference between actual and counterfactual for



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

Figure 7: Startup and mature incumbent employment weights

Note: U.S. Census Bureau Business Dynamics Statistics. Actual data represents employment shares using law of motion and actual data from 1987 onward. Counterfactual employment shares computed from a sequence of startup employment$\{S_t^c\}$where μ_t^s in g_t^s is replaced with constant $\bar{\mu}^s$= 0.02 for 1987-2012..

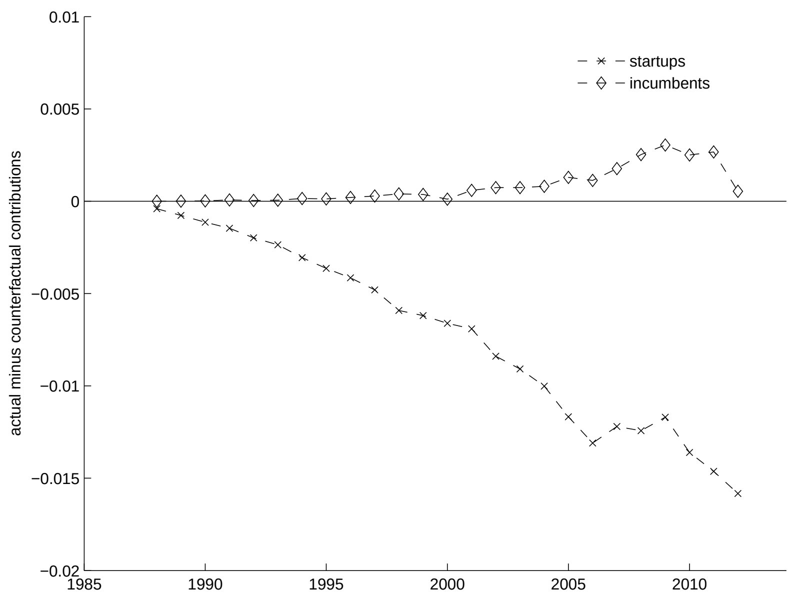


Figure 8: Actual minus counterfactual startup and incumbent growth rate contributions

Note: U.S. Census Bureau Business Dynamics Statistics. Lower line represents the difference between actual and counterfactual startup growth contribution, $[s_{t-1}(1+\mu_t^s)]-[s_{t-1}^c(1+\bar{\mu}^s)]$. Upper line represents difference between actual and counterfactual incumbent growth contributions, $[(1-\omega_{t-1})\,g_t^y+\omega_{t-1}g_t^m]-[(1-\omega_{t-1}^c)\,g_t^y+\omega_{t-1}^c g_t^m]$. Counterfactual employment path uses a sequence of startup employment $\{S_t^c\}$ where μ_t^s in g_t^s is replaced with constant $\bar{\mu}^s$= 0.02 for 1987-2012..

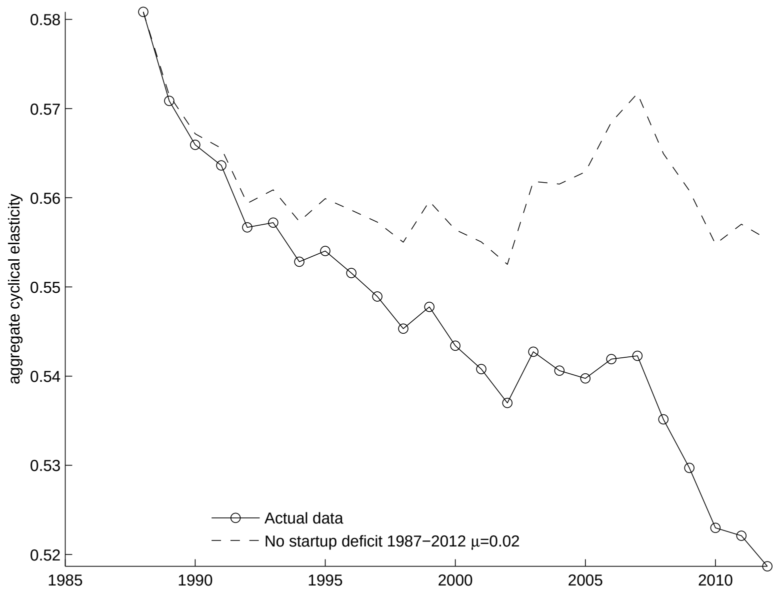


Figure 9: Actual and counterfactual aggregate cyclical elasticity β

Note: U.S. Aggrecate cyclical elasticity computed as $\beta = s_{t-1}\beta^s + (1-\omega_{t-1})\,\beta^y + \omega_{t-1}\beta^m$ using actual and counterfactual employment weights. Counterfactual employment shares computed from a sequence of startup employment $\{S_t^c\}$ where μ_t^s in g_t^s is replaced with constant $\bar{\mu}^s = 0.02$ for 1987-2012.

the startup and incumbent growth contributions. Specifically, the lower line plots $[s_{t-1}(1+\mu_t^s)] - \left[s_{t-1}^c(1+\bar{\mu}^s)\right]$ and the upper line plots $[(1-\omega_{t-1})\,g_t^y + \omega_{t-1}g_t^m] - \left[\left(1-\omega_{t-1}^c\right)g_t^y + \omega_{t-1}^c g_t^m\right]$. The counterfactual economy 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 due to their higher exit rates, their larger share in the counterfactual economy creates a bigger drag on employment growth. However, as the figure shows, the positive effect on employment due to the decreasing weight of young firms is small relative to the negative effect of the declining startups. Put together, our counterfactual experiment shows that the gradual slowdown in trend employment growth over the last 30 years is due primarily to the decreasing employment growth contribution from 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 9 for both the data and the counterfactual economy. The movement towards a more mature firm structure caused a gradual decline in this elasticity from around 0.58 to 0.52, 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.[27] This

[27]This finding resonates with the literature that analyzed the effect of aging of the workforce 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

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.

6.3 Grown-up business cycle dynamics

We consider what the employment dynamics of recessions and recoveries might have looked like absent the startup deficit using our counterfactual economy. In particular, for both the actual and counterfactual time series, we normalize employment to NBER troughs and measure the employment response during contraction and recovery for each business cycle starting with the 1990-91 recession. Figure 10 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 relative to the counterfactual one. The effect of the startup deficits grows over time, creating a bigger wedge between the actual and counterfactual employment. In addition, its qualitative 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 sensitivity 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 than offset 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. This gradual decoupling of employment and business cycle shocks is consistent with the emergence of jobless recoveries in the U.S. economy.

6.3.1 Three Different Great Recessions

The cumulative effects of the startup deficit imply that each business cycle in the last 30 years has impacted a different age distribution of firms. Simply comparing the experiences of employment dynamics across recent business cycles may be misleading, since alternative age distributions would imply a different response of employment even for the same business cycle shock. To isolate the importance of the startup deficit, it is worth considering how the employment effects of the Great Recession (measured by the realizations of Z_t from 2008 to 2012) would have differed were the age distribution closer to the one in the early 1980s, or if the startup deficit continues, how the employment dynamics might look in the distant future. To do this, we apply the same Great Recession shocks to three alternative long-run economies, which differ only in their steady state startup employment growth μ^s.

For any μ^s, using the stationary transition matrix $\bar{P}$ and the law of motion from equation (3), we can compute a long-run distribution of employment shares across age groups. The left panel of figure 11 shows the long-run distribution of employment across age groups for startup growth μ^s

for business cycle volatility.

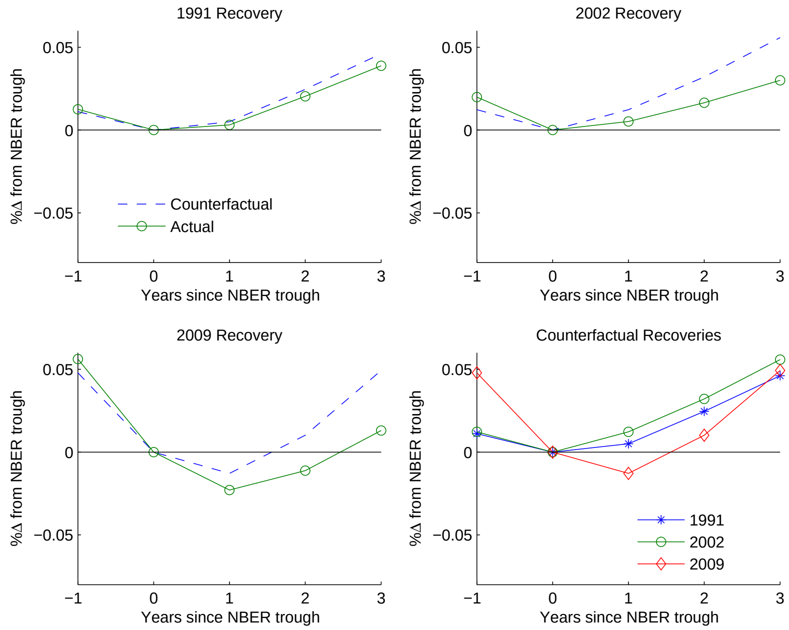


Figure 10: Actual and counterfactual recovery employment dynamics

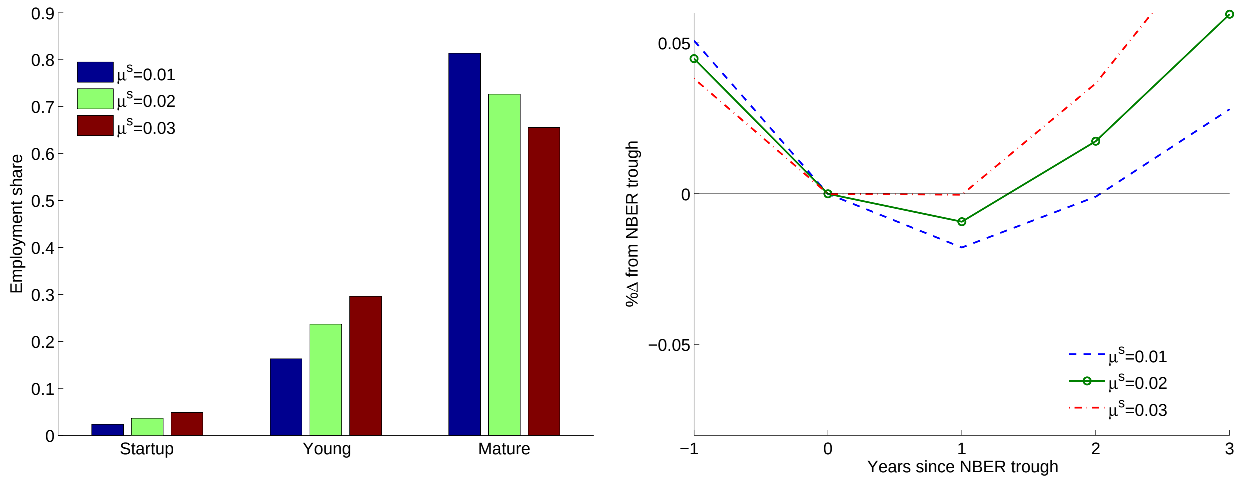
Note: U.S. Census Bureau Business Dynamics Statistics. Actual and counterfactual employment paths normalized to NBER trough years for the 1991, 2002 and 2009 recoveries. Actual data represents employment path using law of motion from 1987 onward. Counterfactual employment path uses a sequence of startup employment$\{S_t^c\}$where μ_t^s in g_t^s is replaced with constant $\bar{\mu}^s$= 0.02.

ranging from 1 to 3 percent. As expected, high entry corresponds to a younger age distribution of employment. In particular, the employment share of mature firms in the economy with low entry (μ^s= 0.01) is around 80 percent while it is around 60 percent in the economy with high entry (μ^s= 0.03). We should emphasize that when the actual age distribution is away from its long-run distribution, the dynamics embedded in a stationary transition matrix $\bar{P}$ imply a very gradual convergence.[28] For example, the actual 1987 age distribution would take roughly 30 years to converge halfway to the long run distribution associated with $\mu^s = 0.01$.

The right panel of figure 11 considers the effect of the Great Recession shocks on three long-run economies with μ^s ranging from 0.01 to 0.03 and their corresponding age distributions. Comparing the responses reveals significant differences in the behavior of aggregate employment. In the economy with high entry, the employment trough coincides with the end of the NBER recession; employment starts increasing one year later and reaches its 2008 level within two years. In both economies with lower entry, the employment troughs lag the end of the recession, a pattern consistent with jobless recoveries Moreover, it takes much longer to recover back to their 2008 levels, (around three years with μ^s= 0.02 and more than three years with μ^s= 0.01).

This experiment shows that the startup deficit and the implied aging of firms are quantitatively important in understanding the decoupling of output and employment during recoveries using the Great Recession as a recent example. In that sense, our analysis in this section is related to

[28]We thank Rob Shimer for this insight when discussing an earlier version of this paper.



(a) Employment share distribution

(b) Great Recession Z_t

Figure 11: Alternative long-run startup employment growth $\mu^s = 0.01, 0.02, 0.03$

Gourio, Messer, and Siemer (2014) and Sedlácek (2014), recent independent contributions which focus specifically on the importance of firm entry and young firms on the recovery dynamics of employment and output after the Great Recession. While our findings are consistent with theirs in recognizing the importance of young firms for recoveries, we emphasize that slow employment recovery after the Great Recession was also expected as a consequence of the 30 year trend decline in firm entry. Our counterfactual exercise also predicts that if the startup deficit continues, we will observe a further decoupling of employment and output in future economic recoveries.

6.4 The offsetting effects of nonemployers

Finally, we show that a recent increase in number of nonemployers does little to attenuate the aggregate effects of the startup deficit. Our analysis has focused only on private sector firms with employees, excluding the far larger universe of nonemployer businesses. The restriction is intentional since the total employment across private sector employers corresponds closely to the aggregate private payroll employment estimated monthly by the Bureau of Labor Statistics from its establishment survey. The nonemployer universe is less well defined and captures business activity reported to the Internal Revenue Service with no associated payroll. However, the number of nonemployers has grown significantly over the past 15 years, from 15.4 million in 1997 to over 22.7 million in 2012 while employers increased by fewer than 300,000. Among these nonemployer businesses are incorporated and unincorporated self-employed who do not have employees as well as independent contractors who receive income reported on a form 1099.[29] Although not counted in measures of payroll employment, these businesses do contribute to broader measures of employment.

[29] To build its nonemployer file, the Census excludes from the IRS data any businesses with less than $1000 in revenue, wholly owned subsidiaries of employer firms, and any discernable pass through entities such as mutual funds. See https://www.census.gov/econ/nonemployer/methodology.htm and the discussion in appendix (B.5) for more details.

If the startup deficit were offset by a rise of nonemployers, the aggregate employment effects could be overstated. This could be the case, for example, if the newly formed nonemployers were small scale businesses that previously would have hired employees for routine tasks, but these tasks can now be automated. Part of or even all of the startup deficit could simply be substitution towards nonemployers. Given the substantial increase in nonemployers over this period, we take seriously this possibility.

To assess the potential offseting effects of nonemployers, we broaden our measure of total employment

$$\tilde{E}_t = N_t + S_t + E_t^y + E_t^m$$

to include the owner-managers of nonemployers N_t. With this measure we consider the following experiment: we suppose the *entire* increase in N_t over this period is due to businesses that would have hired employees (i.e., declines in S_t), and we compare these gains relative to the size of the startup deficit. This is an extreme assumption since it assumes N_t cannot increase for other reasons, but it will deliver an upper bound on the offsetting effect of nonemployers. We start in 1997, which is the first year with the most reliable measures of nonemployer firms. In figure 12 the solid line plots the increase in employment in the counterfactual economy without a startup deficit (computed in section 6.2) relative to the increase in employment in the actual economy. Over the 1997 to 2012 period, the counterfactual economy with no startup deficit creates (on net) 14 million more jobs than the actual economy, ignoring any effects on nonemployers. We can compare this gap with the increase in N_t over this period, which we assume is caused only by substitution away from new employers.

Even under this assumption, it is difficult to know how much employment we should associate with each measured nonemployer, so we consider three possibilities. The blue broken line assumes counts each additional nonemployer as one employee; just below it, the green solid line counts each additional nonemployer as one-half an employee;[30] and just below that we measure the increase in the number of self-employed.[31] The self-employment series is also noteworthy because it moves closely with the increase in nonemployers until the Great Recession when self-employment declines but nonemployer growth is relatively unaffected. Over the 1997 to 2012 period, these increases in N_t account for roughly 45%, 25%, and 0% of the employment loss we attribute to the startup deficit. All are overestimates since they attribute all of the increases in N_t to substitution, but even if employment moved one for one with nonemployers, the substitution could explain less than half of the startup deficit.

There are several reasons why the increase in nonemployers is unlikely to be one for one substitution from S_t into N_t. First, if this were the case, estimates of household employment (which is

[30] This roughly corresponds to the share of nonemployer owners in the 2007 Census Survey of Business Owners that report working 20 or more hours in their business. See https://www.census.gov/econ/sbo/pums.html.

[31] We measure self-employed from the March annual supplement to the Current Population Survey (CPS) as individuals (civilian and 16+), reporting their primary job as self-employed (both incorporated and unincorporated) and working 20+ hours per week. We do not exclude the self-employed that report having employees, which would further reduce the increase in self-employment.

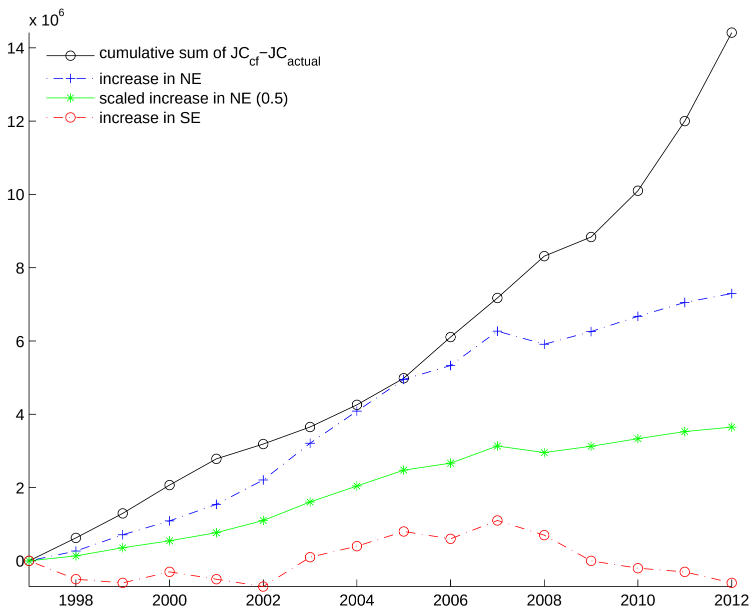


Figure 12: Nonemployer increases relative to the startup deficit

not restricted to payroll employment) should be increasing relative to private payroll employment. Figure 13 shows the annual estimate of household nonfarm private employment from the Current Population Survey (CPS) relative to an annual average of private payroll employment from the Current Employment Statistics (CES).[32] Since 1979, household employment falls instead of rises as a share of payroll employment. This is consistent with the small increases in self-employmentfrom figure 12, which are in proportion to aggregate payroll employment growth. If N_t had increased one for one with the number of nonemployers the Great Recession would have been milder and with a much stronger recovery. Second, substitution towards nonemployers would likely favor industries with smaller scale businesses. Earlier we showed that startup deficits were pervasive across the vast majority of industries. The average size of new employers has also been remarkably stable over this period. Any substitution would have to be balanced across industries and the size distribution of new firms rather than just small scale businesses.

We also can test the substitution channel directly using cross-state evidence and we find the opposite effect. The Census publishes state level tabulations of nonemployers from 1997 to 2012. Using these measures, conditional on year and state fixed effects, we check whether declines in a state's startup rate can predict increases in its nonemployers in the following regression

$$\%\Delta N_{st} = \theta_s + \lambda_t + \beta SR_{st} + \varepsilon_{st}.$$

This test has the additional benefit of controlling for any increases in aggregate nonemployment for

[32]Household employment is estimated by the Bureau of Labor Statistics (BLS) from the CPS and includes all persons who did any work for pay or profit during the survey reference week, including self-employed workers while payroll employment, also measured by the BLS in their establishment survey (CES), measures the total number of persons on establishment payrolls. See http://www.bls.gov/web/empsit/ces_cps_trends.pdf for a detailed comparison.

Figure 13: Ratio of private household employment to private payroll employment (1979-2012)

reasons unrelated to substitution. Using this specification we estimate $\hat{\beta} = 0.66$, with a standard error of 0.14 when clustered at the state-level.[33] Instead of substitution, we see that declines in startup measures actually predict *declines* in nonemployment, suggesting that the increase in the aggregate number of nonemployers is unrelated to the startup deficit despite occurring over the same period. Collectively, the evidence shows that the increases in nonemployers of the period of the startup deficit has only a weak effect on aggregate employment dynamics if at all.

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. Along with two recent independent studies by Decker, Haltiwanger, Jarmin, and Miranda (2014a) and Hathaway and Litan (2014) we documented simultaneous declines in the new firm share and increases in the mature firm share nationally as well as within industry and geography. 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 average 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

[33] This finding is robust to alternative measures of startup behavior. We include additional details in appendix B.5.

decline in entry and the reallocation of employment towards older of firms, these observations imply significant compositional effects on aggregate employment dynamics. The first effect is a decline in trend employment growth and the second is 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 favored by new firms.[34] The second and related trend is the rising real wage of potential business founders. An implication of Lucas's (1978) original span of control model in 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. Evaluating these alternative explanations is the subject of future research.

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[34] Ouimet and Zarutskie (2014) document that new and young firms hire disproportionately younger workers.

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Table 1: Summary statistics from Business Dynamics Statistics (BDS) sample 1980 to 2012

	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	33	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 distribution of these measures across-states 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 for years 1980 to 2012

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

Note: National and state-level monthly unemployment from Bureau of Labor Statistics, and national and state-level output and personal income from Bureau of Economic Analysis. All for the years 1980 to 2012. Quarterly output and personal income are aggregated over year ending in Q1. Annual H-P unemployment measure is annual averages of residuals from H-P filtered monthly unemployment with smoothing parameter 8.1 million over year ending in March. Overall U.S. reports time series correlations and standard deviation of alternative annual measures of Z_t. Within U.S. states reports quantiles of the distribution of time series standard deviation for each measure across-states.

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)
	A. Young Firms (Ages 1-10)			
Trend	-0.0003	-0.0002***	-0.0007	-0.0008***
	(0.0002)	(0.00008)	(0.0008)	(0.0002)
R^2	0.12	0.59	0.04	0.08
N	26	1,326	26	1,326
	B. Mature Firms (Ages 11+)			
Trend	0.0002*	0.0002***	-0.0005	-0.0005***
	(0.0001)	(0.00004)	(0.0005)	(0.00008)
R^2	0.19	0.59	0.05	0.12
N	26	1,326	26	1,326
Years	1987-2012	1987-2012	1987-2012	1987-2012
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***	-0.263
	(0.340)	(0.222)	(0.539)	(0.423)
$\hat{\beta}^m$	0.546**	0.813***	-1.462***	-0.309
	(0.220)	(0.137)	(0.380)	(0.229)
p-value of $\beta^y = \beta^m$	0.014	0.002	0.021	0.877
	B. State Level Measures			
$\hat{\beta}^y$	0.717***	0.436***	-2.058***	-0.921***
	(0.0716)	(0.0598)	(0.210)	(0.168)
$\hat{\beta}^m$	0.438***	0.277***	-1.156***	-0.614***
	(0.0388)	(0.0291)	(0.119)	(0.0634)
p-value of $\beta^y = \beta^m$	0.000	0.000	0.000	0.033
Years	1987-2012	1987-2012	1987-2012	1987-2012

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 H-P 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 state and detailed industry variation

	(1)	(2)
	A. Young Firms (Ages 1 to 10)	
$\hat{\beta}^y$	0.279***	0.258***
	(0.03)	(0.04)
	B. Mature Firms (Ages 11+)	
$\hat{\beta}^y$	0.168***	0.158***
	(0.03)	(0.04)
Size FE	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes
Industry FE	-	Yes
Years	1987-2012	1987-2012

Note: U.S. Census Bureau Longitudinal Business Database, state-level personal income from Bureau of Economic Analysis. Estimated projection by age group of net employment growth rate by state and 4-digit NAICS industry on cumulative log personal income growth over retimed year of April to March to correspond to March 12 employment measure. Data are equally weighted across years and weighted by employment across-states and industries within years. Standard errors 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.

A Data Appendix

A.1 Variable Definitions from Business Dynamics Statistics (BDS)

A.1.1 Stock Variables

The BDS variable EMP_t^a measures within a firm age group a cell the total stock of March 12 employment across all establishments (within the firm age group) in year t. It also provides a variable $DENOM_t^a$ that is the average of EMP_t^a and the total stock of employment for that same cohort of firms in the previous year, which we label $\widetilde{EMP}_{t-1}^{a-1}$.[35] This imputed previous year employment is computed from the BDS variables $DENOM_t^a$ and EMP_t^a as

$$\widetilde{EMP}_{t-1}^{a-1} = 2 \times DENOM_t^a - EMP_t^a \ .$$

For firms, the BDS variable $FIRMS_t^a$ measures within an age group a the total number of firms with positive employment on March 12 of that year. It also provides a variable $DEATHS_t^a$ the measures the number of firms in the current age group a cohort that were active in $t-1$, but are now permanently shut down in year t. A shut down requires that all establishments within the firm in the previous year exit by the current year. An establishment exits when it no longer reports positive employment. The number of firms may fluctuate because of mergers and acquisitions or periods of inactivity that would not be deaths. We use deaths to construct

$$\widetilde{FIRMS}_{t-1}^{a-1} = FIRMS_t^a + DEATHS_t^a \ .$$

We define year t age group a **employment** E_t^a and its lagged value E_{t-1}^{a-1} for the same cohort as

$$E_t^a \equiv EMP_t^a \quad E_{t-1}^{a-1} \equiv \widetilde{EMP}_{t-1}^{a-1} \ .$$

For age 0 firms

$$S_t \equiv EMP_t^0 \ .$$

We define year t age group a **number of firms** F_t^a and its lagged value E_{t-1}^{a-1} for the same cohort as

$$F_t^a \equiv FIRMS_t^a \quad F_{t-1}^{a-1} \equiv \widetilde{FIRMS}_{t-1}^{a-1} \ .$$

Next, we define **average employment size** and its lagged value for the same cohort as

$$N_t^a \equiv \frac{EMP_t^a}{FIRMS_t^a} \quad N_{t-1}^{a-1} \equiv \frac{\widetilde{EMP}_{t-1}^{a-1}}{\widetilde{FIRMS}_{t-1}^{a-1}} \ .$$

[35] For some age groups the previous year's employment may not be directly observable in the BDS. For example, the 6 to 10 age group in year t cannot be observed directly in year $t-1$.

A.1.2 Flow Variables

Using our above defintions for E_t, F_t, and N_t, we compute the dynamic mesaure defined in the paper. The **survival rate** is

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

Note that this is a restrictive definition of exit, since firms that are reorganized are not counted as exits. The growth rate in average size or **conditional growth rate** is

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

The age group **unconditional employment growth rate** is

$$g_t^a \equiv \frac{E_t^a - E_{t-1}^{a-1}}{E_{t-1}^{a-1}} .$$

Then also by construction

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

Unconditional Growth Rate and Net Job Creation Rate The definition of g_t^a will differ slightly from the age group a net job creation rate $NJCR_t^a$ from the BDS where

$$1 + NJCR_t^a = 1 + \frac{JC_t^a - JD_t^a}{\frac{1}{2}\left(EMP_t^a + \widetilde{EMP}_{t-1}^{a-1}\right)} .$$

The growth rate differs both because of the denominator and because (until the September 2014 release) $JC_t^a - JD_t^a \neq EMP_t^a - \widetilde{EMP}_{t-1}^{a-1}$.[36]

A.1.3 Stock-Flow Consistent Measurements in the BDS

For some age group cohorts, we may also be able to directly measure EMP_{t-1}^{a-1}. For example, for age 1 firms, we can measure E_t^1 for the current year and we can measure the age 0 employment E_{t-1}^0 from the previous year. For a variety of reasons, in general

$$\widetilde{EMP}_{t-1}^{a-1} \neq EMP_{t-1}^{a-1}$$

for individual age groups a and overall

$$\sum_{a \geq 1} \widetilde{EMP}_{t-1}^{a-1} \neq EMP_{t-1} ,$$

although the measures are often very close.

[36] Starting in the September 2014 release of the BDS $JC_t^a - JD_t^a = EMP_t^a - \widetilde{EMP}_{t-1}^{a-1}$ nearly exactly.

To ensure the imputed lagged-age group stocks that we use to compute flows are consistent with the aggregate stocks, we define an annual scaling factor κ_t. The scaling factor κ_t satisfies

$$\sum_{a\geq 1} \widetilde{EMP}_{t-1}^{a-1} = \kappa_t EMP_{t-1} \ ,$$

i.e., it rescales lagged aggregate employment so that it is the sum of the lagged age group measures. The purpose of this adjustment factor is to ensure that the implied stocks match the actual stocks, i.e., if g_t^{1+} is the growth rate at incumbent firms $\left(1+g_t^{1+}\right) = \sum_{a\geq 1} EMP_t^a / \sum_{a\geq 1} \widetilde{EMP}_{t-1}^{a-1}$ then

$$EMP_t^{1+} = \left(1+g_t^{1+}\right) \widetilde{EMP}_{t-1} = \left(1+g_t^{1+}\right) \kappa_t EMP_{t-1} \ .$$

Overall employment growth is composed of employment growth at incumbent firms and employment growth from new entrants

$$E_t = S_t + \left(1+g_t^{1+}\right) \widetilde{EMP}_{t-1} = S_t + \left(1+g_t^{1+}\right) \kappa_t EMP_{t-1}$$

On average κ is very close to 1.

Law of motion The results in the paper *do not* apply a stock flow adjustment to any of the growth rates or the law of motion. The reason is that the value of q_{t-1} needed to match the data exactly will also incorporate the necessary stock flow adjustment. The results are nearly identical if we explicitly apply a stock flow correction using κ_t before computing q_{t-1}.

A.2 Measures in Longitudinal Business Database

Using the LBD establishment microdata, we aggregate up from the annual establishment-level files to create firm-level average growth, survival and size measures similar to the BDS. Similarly, although the LBD includes some additional coverage, we limit the scope to establishments within the nonfarm private sector (those tracked by the county business patterns) with positive employment to stay as close as possible to the BDS. We use a concordance generously provided by Theresa Fort to assign industry codes on a consistent NAICS 2002 basis to each establishment. Using these data, we calculate firm-level growth rates and aggregate by state, industry (both 2-digit and 4-digit NAICS) and firm size categories, following the BDS. However, the micro data allow us to aggregate firm statistics by state, size groups and industry simultaneously, whereas the BDS only allows for two out of the three and never state and industry at the same time. Aggregations are employment or firm weighted to correspond to the averages produced from the BDS tabulations. We also exclude the year 2002 from all calculations because of measurement difficulties associated with the 2002 Economic Census.

A.3 Behavior of q_{t-1}

In the decomposition framework, because we pool a range of ages together in the same age group, we use an accounting variable q_{t-1} to capture the fraction of the young age group the previous year, that would remain young in the current year. In a stochastic aging model $1 - q_{t-1}$ would correspond to the probability of aging. With our age group definitions this corresponds to the cohort that is age 10, which will become age 11 in the following year. With additional age groups we would define a q_{t-1}measure for each age group, and with exact age groups q_{t-1} would be zero.

To make the decomposition framework hold exactly, because the data are not stock-flow consistent, we actually need two different measures of q_{t-1}. Both are plotted in figure A.1. The first (solid line) is used in the law of motion for the young age group and the second (broken line) is used in the law of motion for the mature age group. If we first stock-flow adjust the BDS data using the κ measure defined in A.1.3, both q_{t-1} measures (plotted with circles and hashes) are identical. This is the sense in which the two distinct sequences of q_{t-1} naturally provide a stock-flow correction for the data. With these latter two series we can also see that q_{t-1} fluctuates around its average of 0.91, reflecting the small compositional changes within the young age group echoing earlier fluctuations in the startup rate. When we construct the $\bar{P}$ matrix we set both q_{t-1} measures to their long run averages.

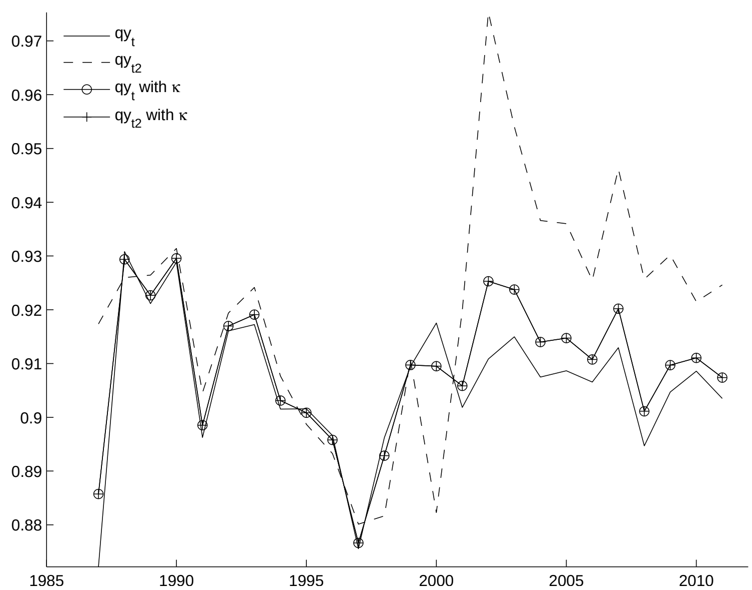


Figure A.1: Measures of q_{t-1} from 1987 to 2012

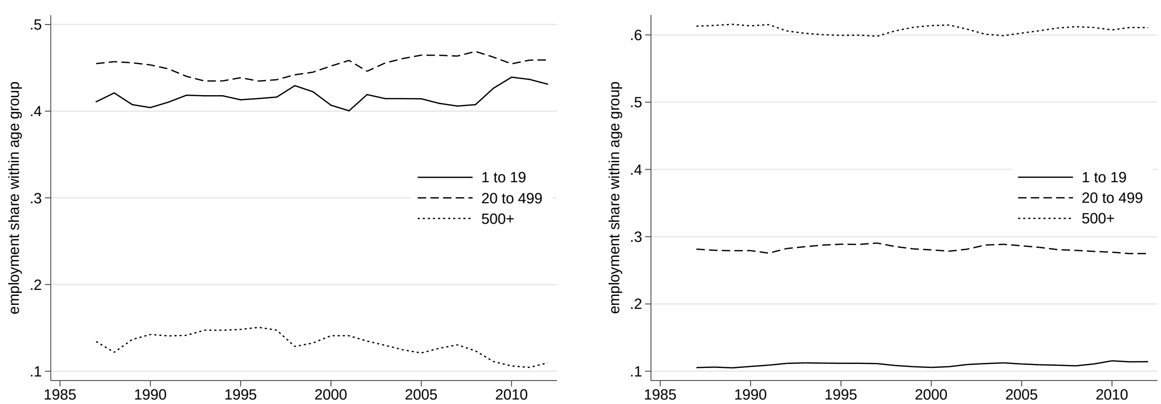
B Robustness Appendix

We summarize a number of robustness exercises that are referenced in the main text. In order to keep this section concise we highlight only the most important robustness results. Any additional results that are not included here are happily provided by the authors upon request.

B.1 Firm Age vs Firm Size

Our paper focuses on firm age instead of firm size for various reasons that we have discussed in the main text. In this subsection, we show that despite the stark change in age distribution of employment, its distribution across firm sizes remained relatively unchanged. Figure B.1 plots the evolution of firm size distribution conditional on age group. The only change in the time series is the decrease in the employment share of young firms that employ more than 500 employers which is likely related to the contraction of large young firms during the Great Recession.

We also compute the average firm size for different age groups. Figure B.2a shows the time series of average firm size for different firm age groups. The average firm size by age group has been stable for new entrants and young firms, and declined among mature firms. The notable *increase* in aggregate firm size is due to the large compositional changes in the age distribution. Interestingly as we have seen in figure B.1, the employment shares by firm size for mature firms appear more stable than the decline in mature firm size would suggest. Since the average firm size statistics is more likely to be contaminated by the difficulty of measurement of the number of firms as pointed out by John Haltiwanger, we put more weight on employment distribution plots.



(a) Young firms

(b) Mature firms

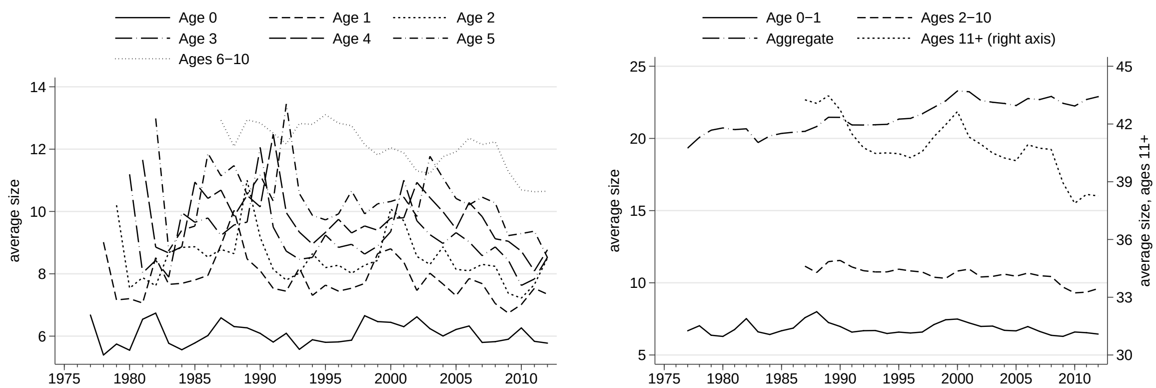
Figure B.1: Changes in firm size distribution conditional on age group

B.2 Startup Deficit

The startup deficit that we characterize in the paper is widespread. We show here that it holds within nearly all industries, geographic areas, and time periods. Finally the declines are also robust to alternative measures of startup activity.

B.2.1 Dropping 1977-1978

We measure startups from 1979 and beyond although we are technically able to identify them starting in 1977. If we include these years the decline in startup rates is even more stark as seen in



(a) Average employment by detailed age groups

(b) Average employment by broad age groups

Figure B.2: Average employment by age groups

figure B.3, although we fear this is a measurement issue. The reason is as we explain that an age 0 firm in 1977 is a firm that wasn't in the database in 1976, whereas an age 0 firm in 1979 is a firm that wasn't in the database in 1976-1978, a point which was made by Rob Shimer in his discussion of our paper.

B.2.2 Startup declines over alternative time periods and measures

The paper presents a smoothed histogram showing the distribution of long run changes in the startup employment share within a state and industry pair that shows that from the 1980–1984 period to 2003–2007 period the startup rate declined in almost 85 percent of all industry $\times$state pairs. Since the number of firms may be less precisely measured than the number of employees in administrative data, our preferred measure of startup activity in the main text is the startup employment share. Here we repeat the same analysis computed for changes in the startup (age 0) rate over the same period. In Figure B.4a we plot the smoothed histogram of the long run changes in the shartup rate in industry $\times$ state pairs along with the employment share changes in Figure B.4b. Both measures show that in more than 85 percent of the pairs, startup activity had declined.

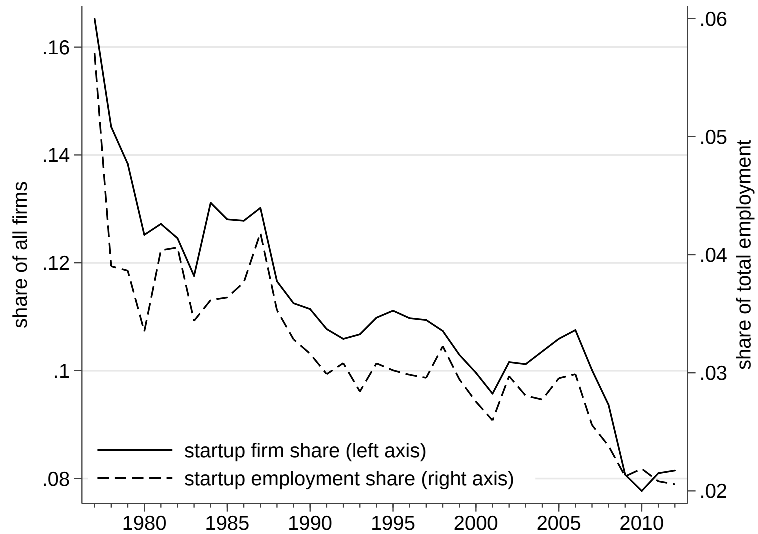
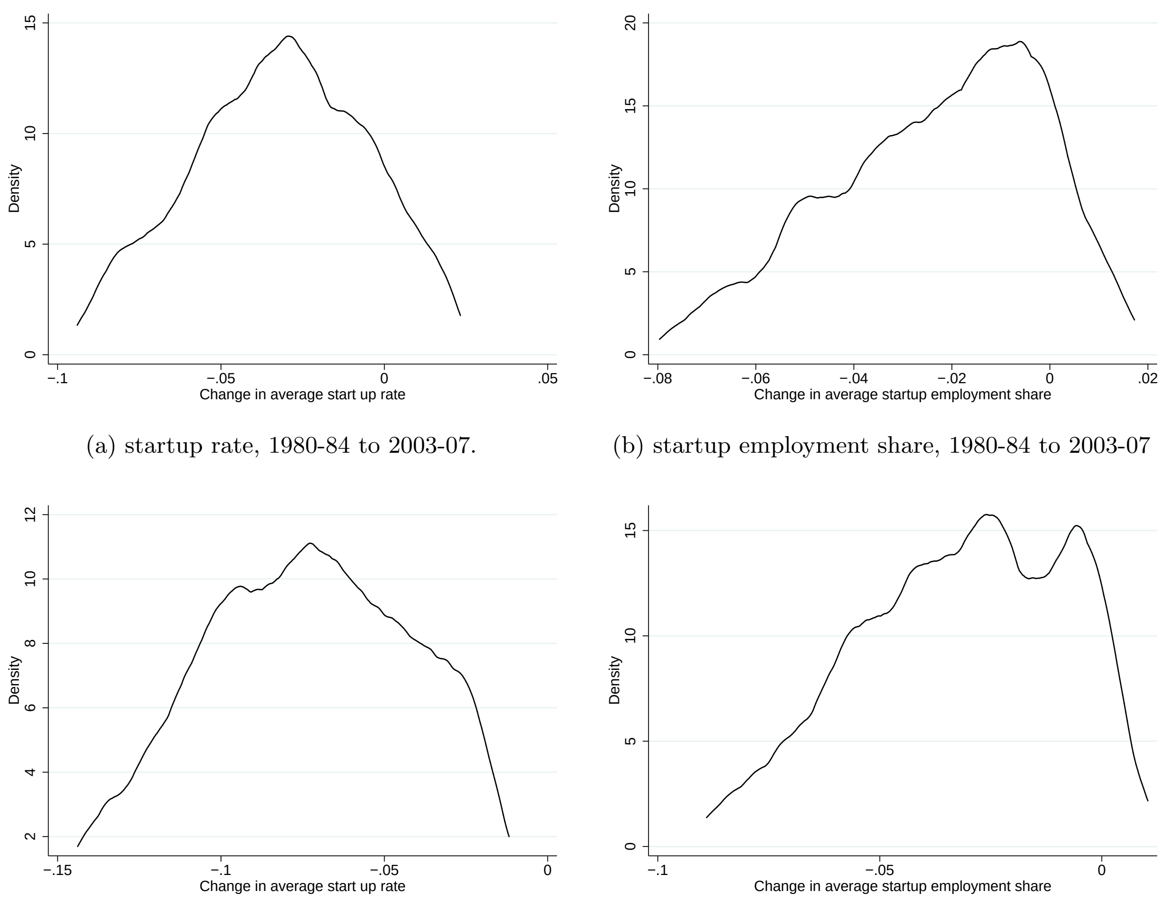


Figure B.3: Firm and employment share of startups for all years 1977-2012



(a) startup rate, 1980-84 to 2003-07.

(b) startup employment share, 1980-84 to 2003-07

(c) startup rate, 1980-84 to 2009-11.

(d) startup employment share, 1980-84 to 2009-11.

Figure B.4: Density estimates of distribution of long run changes in startup rate and employment share over alternative time periods

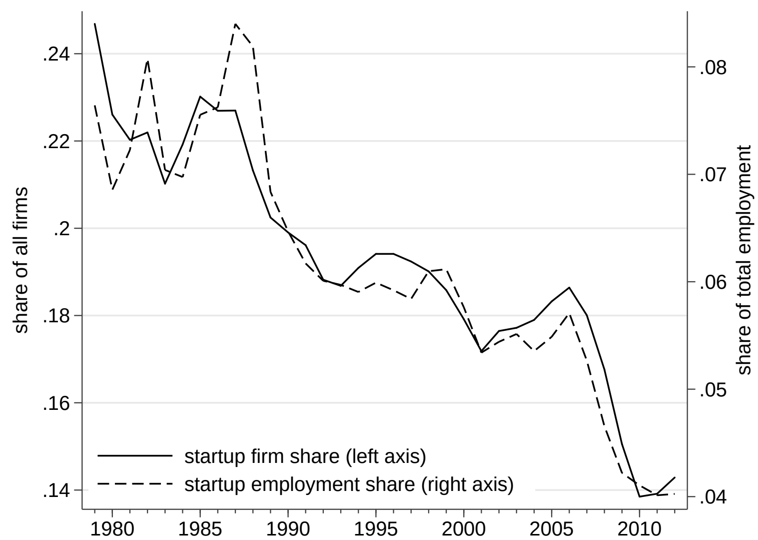


Figure B.5: Startups defined as firms ages 0-1: firm and employment share 1979–2012

In the paper we only measure these long run changes over a time period that ends before the Great Recession. Alternatively, if we compute these changes from 1980–1984 to 2009–2011 using both measures in Figures B.4c and B.4d nearly all industry × state pairs show a decline in the startup rate and the startup employment share.

Another concern is that defining entry by considering only age 0 firms might be too restrictive especially firm forms that are founded close to the deadline for data collection in March. To address this concern, we extend our definition of startups to age 0 and age 1 firms and define entry measures accordingly. Figure B.5 plots the startup rate and startup employment share using this broader measure and shows that the decline is similar.

A final concern is that the decline the startup rate stems in part from our choice measuring firms rather than establishments. In Figure B.6 we plot the establishment rather than firm entry rate and age 0 establishment employer share. Both measures show a similar decline that we have documents using firms as our unit of observation.

B.2.3 Startup rate changes by sector and state

The startup deficit applies to broad sectors and states. Figures B.7a and B.7b show the startup decline across broad sector using two alternative measures of startup activity: the firm startup rate and the startup employment share. Figures B.8a and B.8b plot the same measures for U.S. states. Startup deficits are a common across both sectors and states.

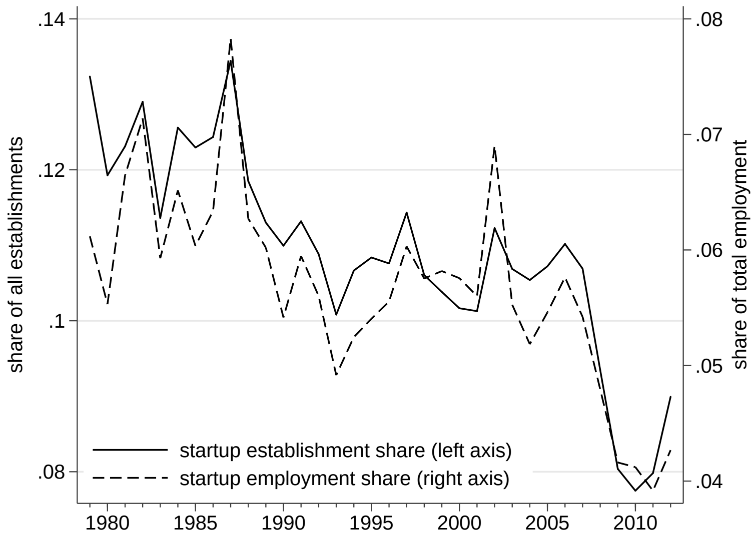
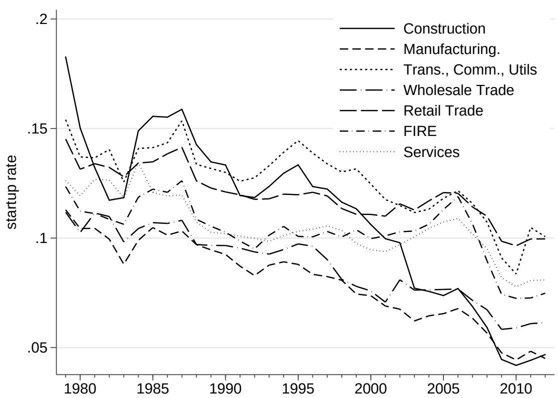
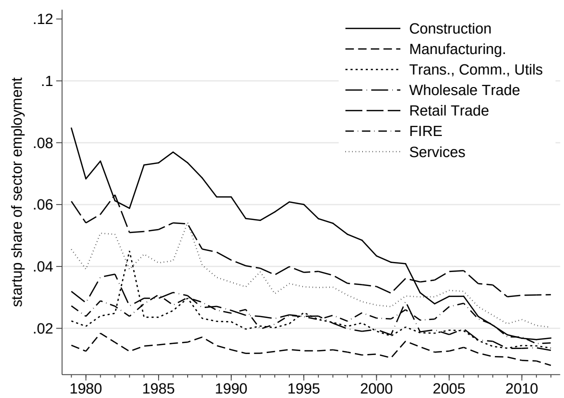


Figure B.6: Establishment entry rate and employment share



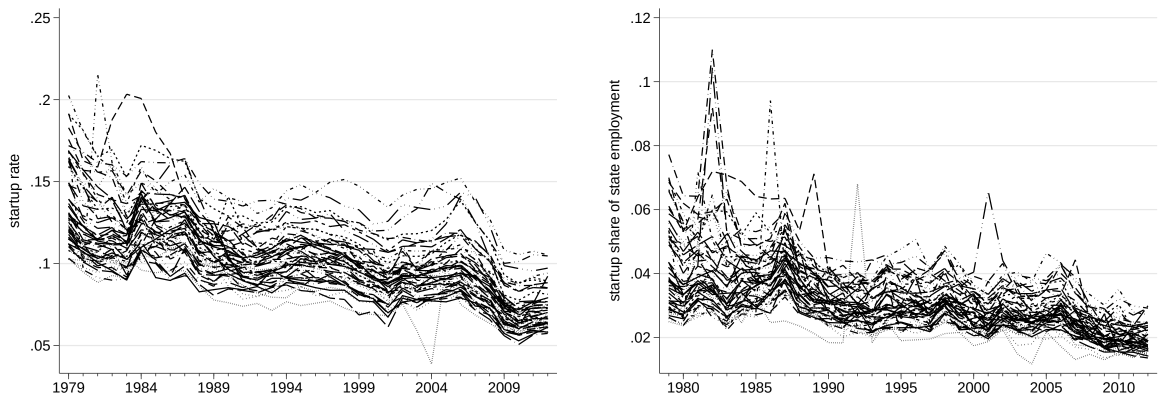
(a) Startup rate within each sector 1977 to 2012



(b) Startup employment share within each sector 1977 to 2012

Figure B.7: Firm and employment 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.



(a) Startup rate within each state 1977 to 2012

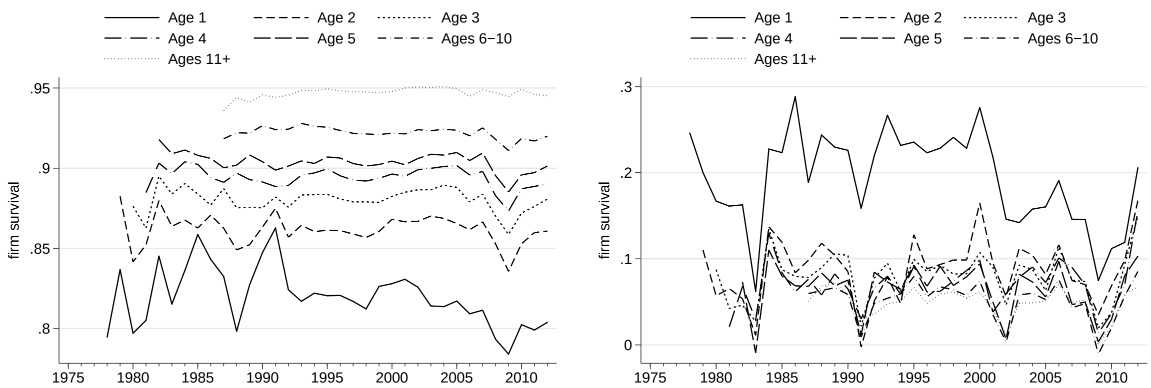
(b) Startup employment share within each state 1977 to 2012

Figure B.8: Firm and employment shares by state

B.3 Stability of Incumbent Survival and Growth Margins

B.3.1 Disaggregated Age Groups

The young age group that we use in our paper 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. Figure B.9 plots the survival x_t and conditional growth n_t rates by detailed age group and table B.1 estimates 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 very early (age 1) survival. This is the survival rate of the previous year's startups into their first year. If we extend the definition of startups to include both age 0 and age 1 as we did in figure B.5, this recent decline reinforces the startup deficit.



(a) Survival x_t by detailed age group (b) Conditional growth n_t by detailed age group

Figure B.9: Stability of survival x_t and conditional growth n_t by detailed age group

Table B.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)
<u>Linear Trend</u>						
Age 1	-0.0014**	-0.00090*	-0.0013***	-0.0043***	-0.0047***	-0.0041***
	(0.00041)	(0.00041)	(0.00013)	(0.0011)	(0.0012)	(0.00031)
Age 2	-0.00011	-0.000022	-0.000070	0.00063	0.00031	0.00044
	(0.00024)	(0.00024)	(0.00010)	(0.0011)	(0.0011)	(0.00036)
Age 3	-0.00016	-0.00016	-0.00014	-0.00011	-0.00031	-0.00032
	(0.00019)	(0.00018)	(0.000095)	(0.00095)	(0.00095)	(0.00029)
Age 4	-0.00017	-0.00019	-0.00016	0.00061	0.00053	0.00057*
	(0.00017)	(0.00016)	(0.000084)	(0.00093)	(0.00096)	(0.00025)
Age 5	-0.00018	-0.00020	-0.00016	-0.00056	-0.00061	-0.00063**
	(0.00015)	(0.00014)	(0.000079)	(0.00077)	(0.00076)	(0.00022)
Ages 6-10	-0.00023*	-0.00027**	-0.00023***	-0.00053	-0.00062	-0.00051**
	(0.00010)	(0.000089)	(0.000058)	(0.00067)	(0.00067)	(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: 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).

B.3.2 Stability of Low Frequency Measures

The main text of the paper reports the estimated coefficients on linear trends in survival rates x_t and conditional employment growth rates n_t by age-group. As an alternative,we filter the time series with H-P filter using smoothing parameter 6.25 to remove higher frequency fluctuations. Table B.2 show the estimated linear trend of the the filtered component and shows that the stability result still holds.

Table B.2: Estimated linear trend in H-P 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)
	A. Young Firms (Ages 1-10)			
Trend	-0.0003**	-0.0002***	-0.0003**	-0.0002***
	(0.00010)	(0.00008)	(0.00010)	(0.00008)
R^2	0.30	0.77	0.30	0.77
N	26	1,326	26	1,326
	B. Mature Firms (Ages 11+)			
Trend	0.0002**	0.0002***	0.0002**	0.0002***
	(0.00008)	(0.00004)	(0.00008)	(0.00004)
R^2	0.26	0.69	0.26	0.69
N	26	1,326	26	1,326
Years	1987-2012	1987-2012	1987-2012	1987-2012
State FE	-	Yes	-	Yes

Note:Business cycle and higher frequency fluctuations removed with H-P 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 state in columns (2) and (4).

B.3.3 Controls for Sector and Size

The stability of the survival rates x_t and conditional employment growth rates n_t by age group is robust to controling for sector and size as we show in Table B.3. While there is a statistically significant decline in the survival and conditional growth rate of young firms, this decline is concentrated in age 1 firms and is economically very small.

Table B.3: Long-run stability with additional controls for sector and size

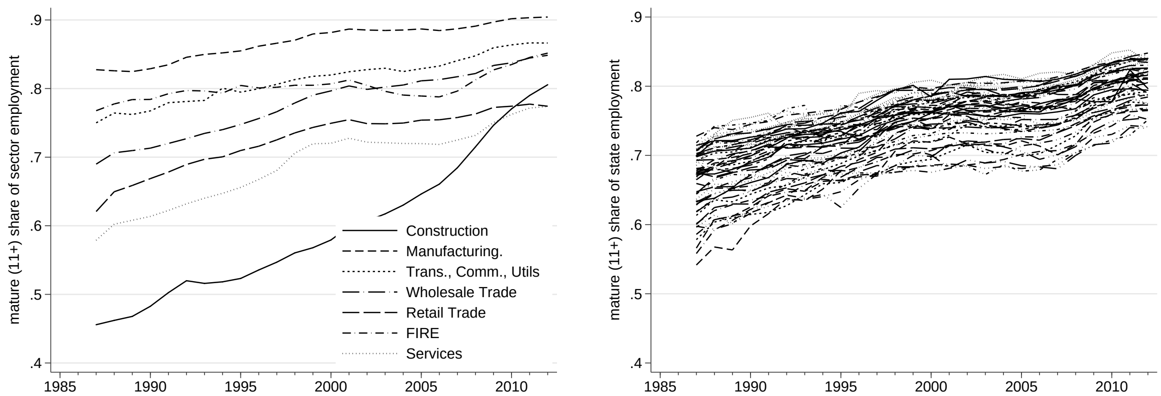
	Survival Rate x_t			Conditional Employment Growth Rate n_t		
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Young Firms (Ages 1-10)					
Trend	-0.0003***	-0.0002**	-0.0002***	-0.00009	-0.0008**	-0.0007***
	(0.0001)	(0.00008)	(0.00005)	(0.0008)	(0.0003)	(0.0002)
R^2	0.99	0.95	0.97	0.03	0.03	0.04
N	78	691	3,946	78	691	3,946
	B. Mature Firms (Ages 11+)					
Trend	0.00003	-0.00004	-0.00001	-0.0003	0.01	-0.0003***
	(0.00007)	(0.00003)	(0.000008)	(0.0003)	(0.02)	(0.0001)
R^2	0.99	0.94	0.98	0.13	0.01	0.07
N	78	702	3,978	78	702	3,978
Years	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012
Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	-	Yes	-	-	Yes	-
State FE	-	-	Yes	-	-	Yes

Note: Data are equally weighted across years and weighted by employment across-states and sizes within years.

B.3.4 Aging Across Sectors and States

Similar to the startup deficit, aging is also a trend common across sectors and states as figures B.10a and B.10b show. 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. There is again considerable variation across states, but there is a striking comovement in employment shares of mature firms. 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.

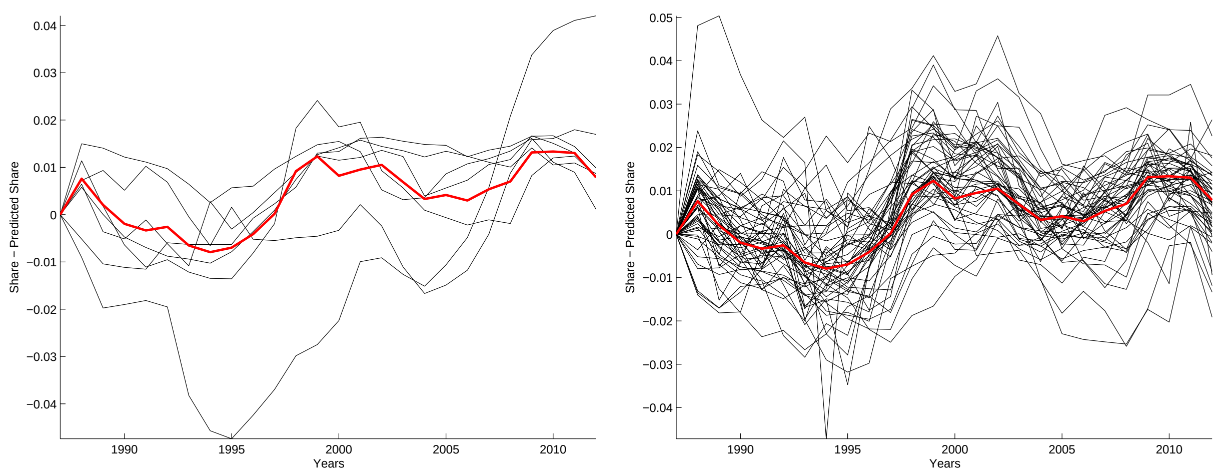
As in the national data, because the survival and growth margins are relatively stable, the accumulation of startup deficits that we have documented in figures B.7b and B.8b, drives the increase in the mature employment share. We separately simulate (3) using $\bar{P}$ and $\{S_t\}$ for each sector and for each state. Figure B.11plots for each sector (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.. 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.



(a) Mature employment share by sector

(b) Mature employment shares by state

Figure B.10: Mature (age 11+) employment shares by sector and state



(a) By sector

(b) By state

Figure B.11: Difference between actual and predicted mature employment shares by sector and state

B.4 Cyclicality of Employment Growth

B.4.1 Incumbents

Controls for Sector and Size

Table B.4 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 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. 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 third column uses data disaggerated into seven broad sectors. Results are very similar.

Columns (4) and (5) in Table B.4 exploit cross-state variation and 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 significantly 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.

Table B.4: 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)	(5)
	A. Young Firms (Ages 1 to 10)				
$\hat{\beta}^y$	0.984***	0.965***	0.873**	0.717***	0.723***
	(0.337)	(0.337)	(0.356)	(0.0716)	(0.0662)
R^2	0.24	0.82	0.69	0.68	0.75
N	26	78	691	1,326	3,946
	B. Mature Firms (Ages 11+)				
$\hat{\beta}^m$	0.546**	0.541**	0.403	0.438***	0.434***
	(0.218)	(0.219)	(0.286)	(0.0388)	(0.0379)
R^2	0.18	0.69	0.05	0.71	0.76
N	26	78	702	1,326	3,978
Sector FE	-	-	Yes	-	-
Size FE	-	Yes	Yes	-	Yes
Year FE	-	-	-	Yes	Yes
State FE	-	-	-	Yes	Yes
Years	1987-2012	1987-2012	1987-2012	1987-2012	1987-2012

Note: 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.

Separating Extensive and Intensive Margin Cyclicality

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.[37] In Table B.5 we separately estimate versions of equation (8) 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 B.4 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

[37]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.

Table B.5: 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)
	A. Young Firms (Ages 1 to 10)			
$\hat{\beta}^y$	0.122	0.241***	0.966***	0.524***
	(0.0928)	(0.0229)	(0.328)	(0.0588)
R^2	0.07	0.82	0.22	0.69
N	26	1,326	26	1,326
	B. Mature Firms (Ages 11+)			
$\hat{\beta}^m$	-0.00533	0.0650***	0.583**	0.392***
	(0.0481)	(0.00672)	(0.238)	(0.0377)
R^2	0.00	0.85	0.18	0.73
N	26	1,326	26	1,326
Year FE	-	Yes	-	Yes
State FE	-	Yes	-	Yes
Years	1987-2012	1987-2012	1987-2012	1987-2012

Note: Data are equally weighted across years and weighted by employment across states and sizes within years. Standard errors are clustered by state.

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 B.4 is not entirely due to the 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.

State x Industry variation

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).[38] These are public-use tabulations of the Census Longitudinal Employer Household Dynamics (LEHD) database. The matched employer-

[38] See http://ledextract.ces.census.gov/

Table B.6: QWI Cyclicality

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Young Firms (Ages 2-10)					
$\hat{\beta}^y$	0.618***	0.586***	0.361***	0.587***	0.540***	0.350***
	(0.134)	(0.174)	(0.0766)	(0.119)	(0.162)	(0.0853)
R^2	0.43	0.50	0.70	0.27	0.29	0.40
N	779	492	343	15,169	9,575	6,685
	B. Mature Firms (Ages 11+)					
$\hat{\beta}^m$	0.378***	0.307***	0.158*	0.382***	0.311***	0.169**
	(0.0709)	(0.0862)	(0.0835)	(0.0669)	(0.0816)	(0.0777)
R^2	0.35	0.44	0.64	0.17	0.22	0.27
N	779	492	343	15,169	9,575	6,685
p-value of $\beta^y = \beta^m$	0.003	0.006	0.002	0.003	0.011	0.007
Sample	Full	BP	BP	Full	BP	BP
Years	1991-2013	2001-2012	2006-2012	1991-2013	2001-2012	2006-2012
States	50	41	50	50	41	50
Industry FE	-	-	-	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

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 close 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 this specification we estimate cyclical elasticities very similar to those in Table B.5. 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.

Alternative Age Group Definitions

To further explore the robustness of our findings in regards to cyclicality, we alter the age group definitions by classifying startups as firms aged 0-1, young now 2-10 and mature the same 11+. Ta-

Table B.7: Estimated cyclical sensitivity β of net employment growth rates by age group using alternative output and employment based business cycle variables (alternate age groupings)

	(1) Personal Inc	(2) GDP/GSP	(3) Change in U	(4) Cyclical U
	A. National Measures			
$\hat{\beta}^y$	0.810**	1.106***	-1.912***	-0.123
	(0.340)	(0.220)	(0.529)	(0.395)
$\hat{\beta}^m$	0.546**	0.813***	-1.462***	-0.309
	(0.220)	(0.137)	(0.380)	(0.229)
p-value of $\beta^y = \beta^m$	0.117	0.020	0.053	0.437
	B. State Level Measures			
$\hat{\beta}^y$	0.694***	0.426***	-2.046***	-0.903***
	(0.0701)	(0.0560)	(0.207)	(0.160)
$\hat{\beta}^m$	0.438***	0.277***	-1.156***	-0.614***
	(0.0388)	(0.0291)	(0.119)	(0.0634)
p-value of $\beta^y = \beta^m$	0.000	0.001	0.000	0.043
Years	1987-2012	1987-2012	1987-2012	1987-2012

ble B.7 includes the results for the alternate definition. Results are quantitatively and qualitatively very similar.

Establishment cyclicality

Our analysis in the main text focuses on firm entry since arguably the age of the main decision making unit is more important than the age of the production unit (establishment age). Recall that in the BDS, a new firm only has age zero establishments. In that sense, the effect of the firm age on the cylical response is a compounded effect of both the firm and the establishment age. It is of interest to examine how establisment age matters for cyclicality of employment growth. Tables B.8 shows the results. Establishment-level employment growth is less cyclical than firm-level employment growth both for young and mature establishments. However, the relative cyclicality of mature and young establishments are similar to relative differences between mature and young firms.

Table B.8: Estimated cyclical sensitivity β of net establishment 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			
$\hat{\beta}^y$	0.574**	0.965***	-1.747***	-0.212
	(0.278)	(0.197)	(0.536)	(0.341)
$\hat{\beta}^m$	0.399*	0.695***	-1.222***	-0.0678
	(0.203)	(0.151)	(0.388)	(0.213)
p-value of $\beta^y = \beta^m$	0.089	0.001	0.004	0.419
	B. State Level Measures			
$\hat{\beta}^y$	0.608***	0.382***	-1.655***	-0.923***
	(0.0507)	(0.0465)	(0.182)	(0.115)
$\hat{\beta}^m$	0.367***	0.228***	-1.113***	-0.658***
	(0.0365)	(0.0287)	(0.116)	(0.0695)
p-value of $\beta^y = \beta^m$	0.000	0.000	0.000	0.001
Years	1987-2012	1987-2012	1987-2012	1987-2007

B.4.2 Startups

Controls for Sector and Size

Table B.9 shows the results for startup cyclicality alternative specifications using personal income, our preferred measure with sector and size fixed effects. Results are very similar.

Table B.9: Estimated cyclical sensitivity β of net employment growth rates for startups using change in personal income as business cycle measure

	(1)	(2)	(3)	(4)	(5)
$\hat{\beta}^s$	0.571	0.647	115.5	1.412**	1.607**
	(1.104)	(1.179)	(131.6)	(0.618)	(0.657)
R^2	0.01	0.11	0.02	0.30	0.13
N	33	97	497	1,683	3,343
Sector FE	-	-	Yes	-	-
Size FE	-	Yes	Yes	-	Yes
Year FE	-	-	-	Yes	Yes
State FE	-	-	-	Yes	Yes
Years	1980-2012	1980-2012	1980-2012	1980-2012	1980-2012
Detrending	Linear	Linear	Linear	Linear	Linear

Alternative Filters

We show that the cyclicality of the startup employment growth residuals is not sensitive to the method used to remove any trend component.

Table B.10: Alternative filters for startup process

	(1) Linear	(2) HP 100	(3) HP 6.25	(4) CF 6-8
		A. National		
$\hat{\beta}^s$	0.571	0.0797	-0.379	-0.771
	(1.104)	(1.099)	(0.981)	(0.959)
R^2	0.01	0.00	0.00	0.02
N	33	33	33	33
Year FE	-	-	-	-
State FE	-	-	-	-
Years	1980-2012	1980-2012	1980-2012	1980-2012
		B. State		
$\hat{\beta}^s$	1.412**	1.184**	0.264*	0.00698
	(0.434)	(0.374)	(0.115)	(0.158)
R^2	0.30	0.30	0.37	0.36
N	1,683	1,428	1,326	1,326
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Years	1980-2012	1980-2012	1980-2012	1980-2012

Alternative Cyclical Indicators

We show that the cyclicality of the startup employment growth is robust across all four measures using state level variation. Similar to personal income, the time series variation is too noisy to detect any cyclicality in startup employment growth. The table shows these results for the linearly detrended startup employment growth residuals.

Table B.11: Alternative cyclical indicators for startups

	(1) Personal Inc	(2) GDP/GSP	(3) Change in U	(4) Cyclical U
	A. National Measures			
$\hat{\beta}^s$	0.571	1.050	-0.0153	1.002
	(1.104)	(0.940)	(0.0193)	(1.648)
	B. State Level Measures			
$\hat{\beta}^s$	1.412***	1.020**	-0.0461**	-1.728**
	(0.434)	(0.477)	(0.0180)	(0.656)
Years	1980-2012	1980-2012	1980-2012	1980-2012

Alternative Startup Definition

To further explore the robustness of our findings in regards to cyclicality, we alter the age group definitions by classifying startups as firms aged 0-1, young now 2-10 and mature the same 11+. Table B.7 includes the results for the alternate definition.

Table B.12: Estimated cyclical sensitivity β of detrended startup employment share (using ages 0-1 as startups)

	(1)	(2)	(3)	(4)
$\hat{\beta}^s$	1.694*	1.160	1.310***	1.157***
	(0.923)	(1.153)	(0.288)	(0.301)
R^2	0.10	0.04	0.43	0.39
N	33	28	1,683	1,428
Year FE	-	-	Yes	Yes
State FE	-	-	Yes	Yes
Detrending	Linear	HP 100	Linear	HP 100
Years	1980-2012	1980-2007	1980-2012	1980-2007

Establishment entry

Our analysis in the main text focuses on firm entry since arguably the age of the main decision making unit is more important than the age of the production unit (establishment age). Table B.13 estimates the cyclical responsiveness of establishment entry ans shows that establishment entry is less cyclical than firm entry. This result is quite intuitive. While most age 0 establishments belog to new firms, some of them belong to mature firms which are less cyclically sensitive.

Table B.13: Estimated cyclical sensitivity β of detrended startup employment share using establishments

	(1)	(2)	(3)	(4)
$\hat{\beta}^s$	0.938	0.129	1.016***	0.787***
	(1.177)	(1.550)	(0.269)	(0.242)
R^2	0.01	0.00	0.54	0.53
N	33	28	1,683	1,428
Year FE	-	-	Yes	Yes
State FE	-	-	Yes	Yes
Detrending	Linear	HP 100	Linear	HP 100
Years	1980-2012	1980-2007	1980-2012	1980-2007

B.4.3 Time Variation in Cyclical Sensitivity by Firm Age

In the main text we have shown that despite the change in the the firm age distribution, the cyclical properties within age-group remained unchanged. This finding is robust to alternative definition of startups and young firms as seen in Table B.14 In particular, we group firms into four categories: 0-1, 2-10, 11-15 and 15 and higher years of age. Similar to the findings in the main text, we find that there is a small decline in cyclical sensitivities of mature firms.

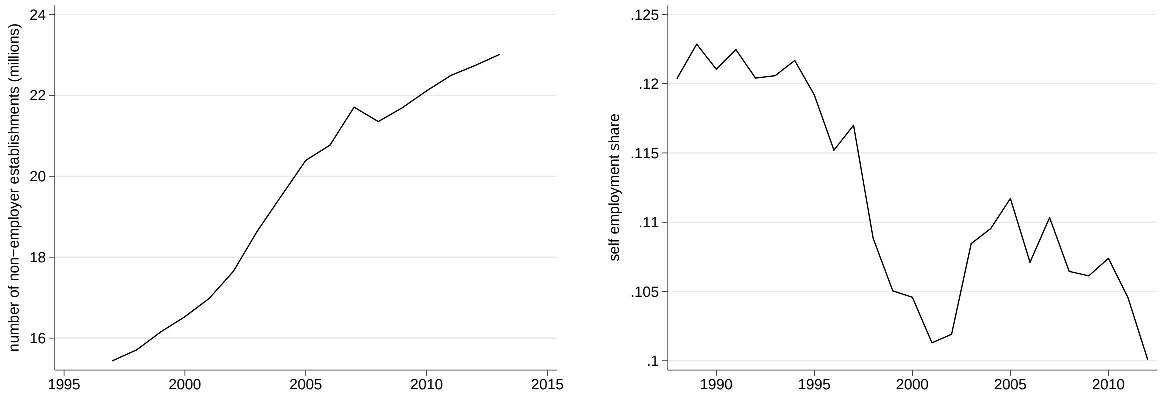
Table B.14: Alternate age groups for trend in β: 0-1, 2-10, 11-15 and 16+

	(1)	(2)	(3)	(4)
	Young Firms (2-10)	Mature Firms (11-15)	Mature Firms (16+)	Startups (0-1)
Trend $\hat{\beta}$	0.0021	-0.014***	-0.018**	-0.041
	(0.0096)	(0.0052)	(0.0067)	(0.028)
R^2	0.67	0.59	0.73	0.44
N	1,326	1,071	1,071	1,683
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Years	1987-2012	1992-2012	1992-2012	1980-2012
Detrending	-	-	-	Linear

B.5 Role of Nonemployer Firms in Aggregate Employment Growth

In the main text, we argue that there are several reasons why the increase in nonemployers, as shown in Figure B.12a, is unlikely to be one for one substitution from employer firms to nonemployers. In this subsection, we present some additional findings to support this view.

In the paper we have shown that since 1979, household employment falls instead of rises as



(a) Nonemployer establishments (1997-2012)

(b) Self-employed as share of private employment (1988-2012)

Figure B.12: Nonemployer establishments and self-employment

a share of payroll employment. This is consistent with the small increases in self-employment. Figure B.12b shows the time series of self employment as share of private payroll employment for 1988-2012. This ratio, if anything, declines suggesting little substitution between the payroll employment and self employment.

We also can test the substitution channel directly using cross-state evidence and we find the opposite effect. Table B.15 shows the results that we discuss in the main text in detail.

Table B.15: Nonemployer establishments and startup measures using cross-state variation

	(1)	(2)
Startup Rate	0.66***	
	(0.14)	
Startup Employment Share		0.56*
		(0.31)
R^2	0.63	0.62
N	765	765
Year FE	Yes	Yes
State FE	Yes	Yes
Years	1998-2012	1998-2012