Grown-up Business Cycles

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The entry rate of U.S. employer businesses has declined for more than 30 years. We use a novel dynamic decomposition framework to show that regardless of its causes, the direct effects of the continued decline in the entry rate and its delayed effects on firm age distribution together play a major role in the slowing of trend employment growth and the emergence of jobless recoveries. We identify changing demographic structure of the population and increased import competition as leading factors behind the decline in startup activity. (*JEL* L26, M13, E24, D22)

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There have been two significant changes in U.S. entrepreneurship in the past 30 years. The first is a dramatic decline in the share of new employer businesses, or startup rate, which has fallen from 13% in the early 1980s to about 8% in 2012. The second is a large increase in the share of mature employer businesses: their share has increased from one-third in 1987 to almost 50% by 2012. Employment shares have exhibited similar patterns.

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In this paper we show that these shifts in entrepreneurship have had real macroeconomic consequences by reshaping aggregate employment dynamics. Starting with the recovery from the 1990-91 recession, U.S. employment has recovered more slowly than output, a pattern referred to as *jobless recoveries*. We find the emergence of jobless recoveries to be tightly linked with declines in the startup rate. This effect on aggregate employment has two channels. First, declines in the entry rate have an immediate effect on aggregate employment because of the direct contribution of new businesses to net employment growth. Second, by shifting the composition of employment toward older businesses that respond less to business cycles, the declines in entry rate have a delayed but growing effect on the aggregate cyclical elasticity of employment. Together, these ongoing changes slow the cyclical employment recovery from a recession, a permanent shift in employment dynamics we refer to as "grown-up business cycles."

To establish this link, we develop a dynamic decomposition framework where employment shares by firm age are determined both by the history of firm entry and of incumbent firm survival and employment growth. To measure the effects of changes in firm entry on aggregate employment, it is crucial to account for the entry margin's dynamic effects through subsequent changes in the firm age distribution. An added benefit of our approach is that the empirical counterparts of our measures are readily available in the U.S. Census Bureau's Business Dynamics Statistics (BDS) database. Using this data source, we show that declines along the entry margin are widespread and not explained by compositional changes across sectors or geography. Instead, we find changing worker demographics and secular increases in import competition to be the most promising explanations for the declines in entry *within* both sectors and geography.

After showing that the decline in the startup rate is driven by within market economic forces rather than shifts in sectoral or geographic activity, we decompose the changes in age structure of firms into changes in the entry margin and incumbent dynamics. Remarkably, when applying our decomposition we find the shifts in employment shares and the shifts in aggregate employment dynamics have been entirely determined by the cumulative effects of the shifts in the entry margin. Expected survival and growth margins by firm age have held steady. In other words, despite the notable decline in the startup rate, conditional on age, the expected dynamics of incumbent firms remain approximately stationary.[1] Consequently, as we show explicitly by applying our decomposition framework, the shifts in the age distribution

[1] This is a surprising fact, because, for example, the trend decline in firm entry could have coincided with a shift toward higher quality entrants with higher survival probabilities or higher expected employment growth keeping young firms' employment share constant.

have been driven only by the declines in the startup rate and not by a change in the dynamics of new and extant businesses. We refer to this shortage of entrants that induces a decline in the startup employment share and shift in the firm age distribution as a "startup deficit."

To examine the effects of these startup deficits on the dynamics of employment over the business cycle, we further decompose each margin by firm age into a stable long-run average and a cyclical component, where the latter is identified by projecting the age group's employment growth onto a mean zero business-cycle shock. We proxy for business-cycle conditions using a variety of measures, and we find in the aggregate time series that the growth rate of both startups and young incumbents are significantly more cyclical than the growth rate of mature firms. To address concerns about examining cyclicality with comparatively short annual time series, we also estimate these cyclical elasticities using pooled cross-state variation in local business conditions and find very similar results. The pooled cross-state variation also allows us to test whether these cyclical elasticities have changed over time in light of the persistent declines in entry. Here, we find no evidence of a shift in the cyclical elasticity of young firms and, if anything, a slight weakening of the cyclical elasticity of mature firms.[2]

These findings together with the shift toward older firms change the aggregate cyclical elasticity of employment to business-cycle shocks. To see this 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%, we compute a counterfactual employment path that is subject to the same sequence of shocks, for both incumbents and startups, as the actual data but purged of the total effects of trend declines in entry. While the measurement exercise does not require a structural interpretation of this counterfactual, our findings on the stability of incumbent firms support one. In the face of an unmistakable decline in entry, survival and growth by firm age as well as their covariance with the business cycle are remarkably steady. If the root causes of the decline in entry had no effects on these incumbent margins, we can interpret the counterfactual as the economy we would have expected in the absence of these forces.

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

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Alternatively, a decline in entry could have coincided with increased survival of incumbent firms.

[2] The latter is in part explained by the age composition changes even within the mature age group.

during expansions; second, the gradual shift in the age distribution toward 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, with 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 without the declines in the startup rate and its implied reallocation of employment to older firms, we would have expected an employment recovery (at least to the pre-recession peak) a full 2 years ahead of the actual recovery.

Collectively our findings suggest that in light of the persistent declines in the startup rate since the 1980s, simply comparing the experiences of employment dynamics across recent business cycles may be misleading. Each business cycle in the last 30 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! Looking forward, absent any recovery in the startup rate, we expect grown-up business cycles to be a permanent change in employment dynamics rather than an anomaly. An exciting area for future research will be to examine whether these effects extend to other aggregate phenomena, such as wage or productivity dynamics.

Our paper is closely related to an emerging literature on declining business 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 over the same period. Building on this discovery, our paper along with work by Decker et al. (2014a) and Hathaway and Litan (2014b) documents declines in the share of new firms also within sectors and markets as well as a growing share of older firms. While these patterns are suggestive, by developing and applying the dynamic decomposition framework, our paper is the first to uncover the stability in average firm survival and growth by firm age, which transmits the shifts in entry directly into shifts in the firm age distribution. The stationarity of incumbents' survival and employment growth margins in the long run and over the business cycle despite an unmistakable decline in the startup rate is a surprising but important finding. It also motivates our counterfactual to quantify the effects of the decline in entry on aggregate employment dynamics. Using our dynamic decomposition framework, we apply the actual incumbent dynamics by firm age to an economy that lacks the trend decline in entry, but is otherwise identical.

Our work also builds on a literature that considers the varying impact of business cycles on different types of firms to study the propagation and impact of business-cycle shocks. Our analysis adds to this literature by showing that sensitivity to business-cycle shocks depends importantly on firm age *and* highlighting the stability of these differences over time. Although most of the earlier literature focused on firm size (see, e.g., Gertler and Gilchrist 1994; more recently, Moscarini and Postel-Vinay 2012), we focus on firm age.[3] 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.[4] For example, Fort et al. (2013) consider employment cyclicality across both firm age and size groups and show that considering differences across size groups alone can be misleading.[5] Adelino et al. (2017) also show that firm age is an important determinant of the employment response to investment opportunities from local demand shocks. Interestingly, unlike the shocks driving the decline in entry, local demand shocks have effects on both entrants and incumbents. Our paper, in addition to confirming the greater cyclicality of young firms (regardless of their size) in another setting, shows that this heterogeneity in business-cycle elasticities by firm age has been little changed despite the declines in the entry rate.

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 in 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) and that on reorganization and adjustment costs-based explanations (Bachmann 2012; Berger 2012; Koenders and Rogerson 2005). It is also consistent with Faberman (2017), who shows

[3] 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 the 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 mainly apply to younger firms.

[4] See Haltiwanger et al. (2013) for an in-depth discussion of the competing roles of firm size and firm age in firm and employment dynamics.

[5] Although almost all new and young firms are small, many older firms are still small. As shown by Hurst and Pugsley (2011), the vast majority of young small firms that survive become old small firms. As a result, Fort et al. (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.

in a structural VAR model a significant shift during the period we study in the estimated impulse response of job creation to an aggregate shock. Both Jaimovich and Siu (2009) and Lugauer (2012) have shown that shifts in the age distribution of the labor force yield effects on aggregate output and employment over the business cycle. We show the presence of similar compositional effects in aggregate labor *demand* stemming from shifts in the firm age distribution.

Finally, we contribute to a nascent literature examining potential explanations for the longstanding declines in entry using confidential firm-level microdata. We find declines in the growth rate of the working age population. A significant role for demographic changes in understanding the decline in entry is consistent with evidence from Hathaway and Litan (2014a), who show a significant correlation between the declines in entry and decline in population growth (as well with increases in business consolidation). It is also consistent with Liang et al. (2014), who show across countries that declines in entrepreneurship are predicted by aging populations, arguing older populations may provide fewer opportunities for younger potential entrepreneurs to acquire sufficient business skills. Karahan et al. (2016) also show, in an equilibrium with entry and exit, that changes in demographics are accommodated primarily through shifts in entry. We also uncover a link between the aggregate decline in entry and changes in import exposure. Despite a large literature on the effects of the openness to trade on the labor market, this channel has not yet been explored for the decline in the startup rate.

1. Long-run Startup Deficit

We document a significant and persistent decline of U.S. firm entry beginning in the early 1980s. Throughout this period, as the growth of startup employment failed to keep pace with aggregate employment growth, the startup share of employment has declined, a shortage of entrants we term the "startup deficit." In this section, we show that startup deficits are pervasive across industries and regions: compositional changes have, if anything, restrained further declines. The many secular changes since the 1980s complicate inferring a simple explanation from the aggregate time series. We instead turn to differences in the extent of the declines in entry across industries and regions to better understand the origins of the startup deficit. Using pooled cross-industry and cross-region variation, we identify changes in worker demographics and import competition as leading explanations of the startup deficit. While the national increase in nonemployers (businesses with no paid employees) is a promising explanation for the decline in the startup rate, we find little evidence for substitution away from few-employee startups toward nonemployers across states, and the overall increase in nonemployers is too small to explain the decline in entry.

1.1 Measuring firm startups

To measure firm startups, 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). The LBD covers all nonfarm private-sector employer businesses in the United States starting in 1976.[6] The establishment-level microdata are derived from the Census Bureau's annual Business Register, covering all businesses with paid employees, which are then longitudinally linked at the establishment level by administrative identifiers and auxiliary information.[7] An establishment is a physical location of business activity, and when multiple establishments belong to the same firm, they may be grouped by a shared firm identifier.[8] This is an important detail, since we are interested in the decline of true firm startups rather than new locations (new establishments) of an existing firm.

Aggregating across the one or more establishments within each firm, we measure total firm employment for the week containing March 12 of each calendar year. We then group firms by firm age. To be consistent with the BDS, we assign firm age as the age of each firm's oldest establishment, where an establishment "enters" in the year it first reports employment and ages naturally thereafter (regardless of any ownership changes). New firms or "startups" are age 0 firms. This measure of firm entry is robust to mergers and other reorganizations: any age 0 firm is a bona fide new entrant since the firm entirely comprises one or more age 0 establishments. One drawback of this measure of firm age is that birth year is left censored for any firms founded prior to 1977, when new establishments may first be observed. These firms are part of the database but their age can only be bounded below. For example, we can infer starting in 1981 that the group of left censored establishments is at least 5 years old.

For each year, starting in 1979, we construct several common measures of entry.[9] The *startup rate* measures the number of age 0 firms as a

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[6] Nonemployer firms are not a part of this database. We discuss their role in Section 1.3 and in further detail in Online Appendix B.5.

[7] Jarmin and Miranda (2002) provide a detailed description of the linking procedure and the construction of the LBD.

[8] The Census Bureau identifies the boundaries of firms through the annual Company Organization Survey and quinquennial Economic Census as the highest level of operational control of an establishment.

[9] Although we can, in principle, measure age 0 firms as early as 1977, for robustness, we begin our analysis in 1979 to ensure that every age 0 establishment did not report any prior

fraction of the total private sector firms in that year, and the *startup employment share* measures the employment at these firms as a fraction of total private payroll employment. Finally, we will also measure the *growth rate of startup employment*, that is, the year-to-year growth in the number of employees at age 0 firms. These national measures are also readily available in the BDS. At finer levels of disaggregation such as state and industry, we rely on measures computed from the underlying microdata within the LBD.

1.2 Examining the aggregate U.S. startup deficit

Looking first at the aggregate data, there have been two notable changes in U.S. entrepreneurship. The first is a significant decline in the firm startup rate starting in early 1980s. The solid line in the left panel of Figure 1 shows the startup rate declines from approximately 13% in the early 1980s to about 8% by 2012. On this decline in entry and without any offsetting increase in average startup size, startup employment growth did not keep pace with aggregate employment growth, causing a decline in the startup employment share. The dashed line in the left panel of Figure 1 plots the downward trend in the startup employment share, which was roughly 4% in the 1980–1984 period and by 2012 has declined by around half to almost 2%. Relative to the startup employment growth needed to maintain a steady employment share, we refer to this growing shortage of entrants as a *startup deficit*.

Second, as we will show formally, these startup deficits are also driving an increase in the share of older businesses. The right panel of Figure 1 shows the analogous measures for mature firms, which we define as 11 or more years old. The share of mature firms plotted as the solid line has increased from one-third in 1987 to almost one-half of all firms by 2012, while their employment share plotted as the dashed line increased from around 65% to almost 80%. To the extent that employment dynamics vary by firm age, as we will show that they do, this large shift in the firm age distribution provides scope for effects on aggregate employment dynamics.

An immediate concern when interpreting the decline in the aggregate startup rate and the ensuing startup deficit, is that the aggregate decline may primarily reflect compositional changes in business sectors.[10] If sectors with lower startup activity are becoming more important because of ongoing structural change, this ongoing reallocation of employment

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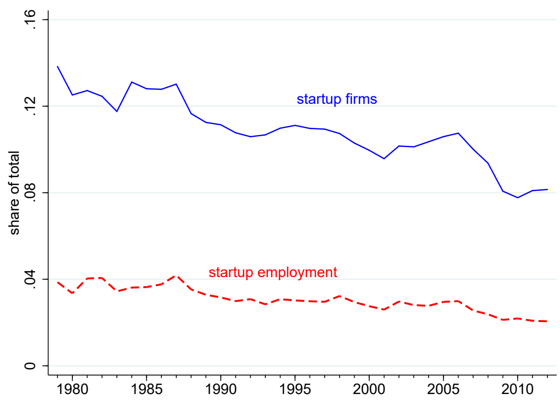
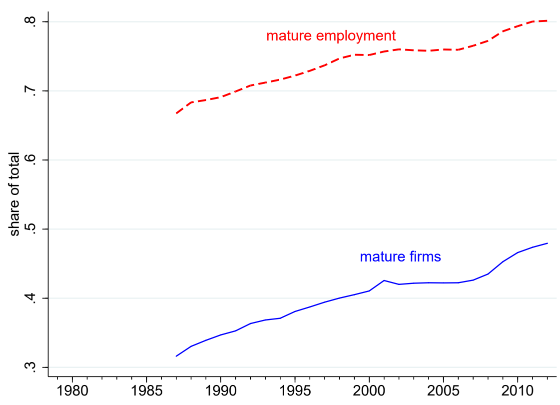
employment for at least 3 consecutive years. We thank Rob Shimer for this suggestion. Including 1977 and 1978 as we do in Online Appendix Figure B.3 makes declines in the startup rate and employment share even more striking.

[10] The U.S. economy has been undergoing a significant structural transformation—the secular reallocation of employment across sectors—over the past several decades. (See, e.g., Duarte and Restuccia (2010) and Dent et al. (2016) for additional details.)



(a) Startups (age 0)



(b) Mature (age 11+)

Figure 1
Firm and employment share of startups and mature firms

may explain the declines in the aggregate startup rate even if startup rates by industry were unchanged.

We find little support for this hypothesis. In fact, compositional changes from structural transformation have, if anything, slowed the aggregate decline in the startup rate. The sector level tabulations in the BDS are too broad to examine this hypothesis thoroughly. For example, the BDS pools a wide variety of service industries under a general service sector. For more detail, we turn to the LBD and compute an average

Table 1
Average sector startup rates by time period

Sectors	1980-1984	2003-2007	2008-2012
A. NAICS sectors			
Mining (21)	.182	.097	.095
Utilities (22)	.067	.053	.039
Construction (23)	.140	.126	.084
Manufacturing (31-33)	.102	.064	.052
Wholesale Trade (42)	.110	.080	.067
Retail Trade (44-45)	.122	.109	.880
Transportation and warehousing (48-49)	.146	.136	.116
Information (51)	.160	.118	.098
Financial activities (52-53)	.128	.115	.083
Professional and business services (54-56)	.165	.118	.098
Education and health care (61-62)	.101	.085	.072
Leisure and hospitality (71-72)	.165	.139	.120
Other services (81)	.118	.076	.064
B. Other sectors			
High-tech industries	.173	.120	.100

Source: U.S. Census Bureau Longitudinal Business Database. Number of age 0 firms as fraction of total firms within each sector. Two-digit NAICS sectors are listed in parentheses for each sector in panel A. In panel B, the high-tech sector is not mutually exclusive and comprises 14 NAICS 4-digit industries the with highest share of STEM workers: 3341, 3342, 3344, 3345, 5112, 5161, 5179, 5181, 5182, 5415, 3254, 3364, 5413, and 5417. See Decker et al. (2016) for additional details.

startup rate of all two-digit sector or supersector for each of the 1980–1984, 2003–2007, and 2008–2012 5-year time periods.[11] Table 1 reports the average startup rate by sector and by time period. Panel A reports the startup rates for each NAICS sector or supersector, and panel B reports a special aggregation of high-tech industries that draws from the manufacturing, information and professional services sectors like in Decker et al. (2016). Two features are immediately apparent: first, relative to the early 1980s average, the startup rate has declined in all of these sectors. Even in the high-tech sector, containing firms in the 14 NAICS 4-digit industries with highest share of STEM workers and in which entry rate increases in the late 1990s, the startup rate still declined from 17.3% in 1980–1984 to 12% in 2003–2007 and further to 10% in the 2008–2012 period.[12] Second, sectors with declining employment shares such as manufacturing already had among the lowest startup rates in the 1980s. Structural transformation, which reallocates employment away from manufacturing and into service providing sectors with higher startup rates, has weighed against the aggregate decline in the startup rate. Even at finer levels of disaggregation, more than 100% of the aggregate declines from since the 1980s are within industry.

Startup deficits are also pervasive across geography and even within industry across geography. The public use tabulations in the BDS only

[11] Online Appendix Figure B.8 plots the startup rate and employment share by BDS sector.

[12] The startup rate in the high-tech sector does surge in the late 1990s before declining again after 2000. See Haltiwanger et al. (2014) for more details.

allow us to measure startup employment either by broad sector or by state and metro area. We go further and examine business formation within narrower submarkets using the LBD.[13] Applying a within and between decomposition now by county to the change in aggregate startup rate from its 1980–1984 average to its 2003–2007 average reveals more than 100% of the decline is captured by within county changes.[14] We find significant declines even within industry across geography. In particular, we focus on 4-digit NAICS industry-state pairs, which results in around 13,000 submarkets. Again, within industry $\times$ state changes account for more than 100% of the aggregate decline between the 1980s and 2000s. This does not imply that 100% of the industry x state pairs had declines, but in fact we find declines in entry for the vast majority of state $\times$ industry pairs. In Figure 2, we plot a smoothed histogram of the actual changes in the startup employment share between the 1980–1984 and 2003–2007 periods for every state x industry pair. For 82.8% of these submarkets, the startup employment share was lower in the 2003–2007 period relative to its 1980–1984 average. If we includes the effects of the Great Recession, the share of industry $\times$ state pairs with declines increases to 89.2%.[15]

Evidently, understanding the decline in the startup rate requires an investigation of *within* industry and region changes in the startup activity. Importantly, although the declines are pervasive, we observed from the distribution of long-run declines in startup employment shares in Figure 2 that the *extent* of the declines in entry substantially varies across industries and markets. We leverage these differences to examine next the effects of alternative channels for which exposure also varies across industries and markets.

[13] See Online Appendix Figures B.8 and B.9, which show that startup employment shares have been declining using the broadly defined sectors and across U.S. states using the BDS data.

[14] See Online Appendix B.2.3 for a full description of the decomposition and Table B.1 for the results of applying the decomposition across county, industry, and state $\times$ industry pairs.

[15] In our decomposition framework, we primarily focus 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 by establishments and by firms. Establishments may be over- or undermeasured as very small establishments hire or fire a single employee and go out of scope. We thank John Haltiwanger for pointing out the susceptibility of establishment and firm counts to measurement error for this reason. However, the results are nearly identical if we were to instead use the changes in the startup rate: 83.5% of state $\times$ industry pairs have declining startup rates from the 1980–1984 average to the 2003–2007 average, and increasing to 95.5% when we include the Great Recession period. For brevity, we present these alternative distributions in Online Appendix B.2. In Online Appendix Table B.1, we also provide the exact within and between decomposition of the aggregate declines at the detailed industry, county and industry $\times$ state levels.

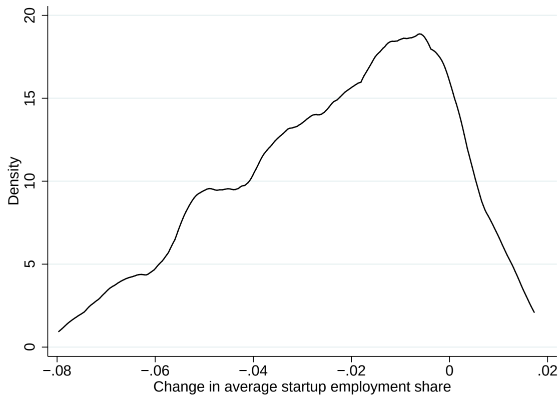


Figure 2
Declines in the startup employment share

Source: U.S. Census Bureau Business Dynamics Statistics and Longitudinal Business Database. Epanechnikov kernel density estimator of distribution of the changes by state x 4-digit NAICS industry in startup employment share from its average from 1980 to 1984 to its average from 2003 to 2007.

1.3 Why is the startup rate declining?

There have been numerous changes in the U.S. economy coinciding with the decline in the business startup rate. Since many of the changes in the U.S. economy are slow moving and overlapping, it is challenging to extract simple explanations from time-series variation alone. To make progress, we enlist cross-industry and cross-region variation in entry rates.

Declines in entry coincide with significant changes in the age structure of the U.S. population: the baby boom cohorts, the first of which reached working age in the 1960s and are now reaching retirement. With fewer inflows and increased retirement, the growth rate of the working-age population declined substantially; the population share of prime-age workers (aged 25–55), peaked at around 58% in 1997 and has declined to around 50% in 2015. We use state-level variation in the growth rate of population and examine whether states with the largest declines in their population growth rates also had larger declines in the startup rate.

Declines in working age population growth are tightly linked with declines in entry. Table 2, panel A, reports the projection of state level changes in the startup rate on changes in working age population growth, and the estimated effects are quantitatively and economically significant. Since the 1980s, average state-level working-age population growth declined by 0.6 percentage points. Abstracting from general equilibrium effects and mindful that without an instrument for demographic shifts

Table 2
Predicted effects of alternative explanations for the declining startup rate

	A. Demographics
Working age population growth across states	0.941*** (0.135)
	B. Import competition
Change in import exposure across industries	−0.176** (0.083)
	C. Automation and nonemployers
Nonemployer growth across state	0.053 (0.051)

Note: This table summarizes three regressions of the long-run change in startup rate rate measured in the Census Bureau Longitudinal Business Database within industry or area on the corresponding long-run change in the specified variable. Regressions are weighted by the average number of firms in each industry or area. In all regressions except for nonemployers, to minimize the influence of business-cycle conditions near the beginning and end of the sample, we use the difference between 5-year time averages in the startup rate: from 1980–1984 to 2003–2007. Panel A uses the change from 1980–1982 to 2005–2007 in the average growth rate of the age 20–64 population by state. Panel B uses the percentage-point change from 1993 to 2010 in the EHS measure of import exposure (see Elsby et al. (2013) for additional details) by EHS NAICS3 industry. The estimated coefficient -0.130 and standard error (0.061) are rescaled by 23/17 to account for the difference in time spans. For panel C, we regress the percentage-point change in the startup rate on the percentage point change in the net growth rate (log difference) in the number of nonemployers by state. Because nonemployer data is not available by state prior to 1998, for the nonemployer regression we use the difference in 3-year averages over a shorter period from 1998–2000 to 2005–2007.

we want to be cautious about interpreting this elasticity causally, the estimate in panel A of 0.941 implies that around one third of the decline across states can be explained purely by the demographic channel. Karahan et al. (2016) investigate the general equilibrium effects of demographic changes on entry using a calibrated equilibrium model and find similar effects.

There also has been a substantial increase in trade volume in the United States over the last few decades. Increases in competition from lower priced imports may discourage potential entrants. To explore this hypothesis we use the industry-specific import exposure measure developed by Elsby et al. (2013). Constructed from the annual input-output matrices from the Bureau of Economic Analysis, this import exposure measure estimates how much additional value added each industry would have produced if the United States were to produce domestically all the goods that it imports. This measure takes into account both imports of final goods and intermediate goods, either of which also might be provided by startups.

Using this measure, we do find a link between changes in import exposure and business entry. We regress the long-run industry-level changes in the startup rate on the long-run changes in import exposure, and we find statistically significant declines in startup rates in industries whose exposure to import competition increased the most. From 1993 to 2010, import exposure increased on average by 7.2 percentage points across sectors. Using the estimate of -0.176 in panel B of Table 2 and with the caveat that the changes in industry import exposure are likely not entirely exogenous, we find that the overall 7.2-percentage-point increase implies a 1.27-percentage-point decline in the startup rate, which is also roughly one-third of the actual aggregate decline.

Another possibility is that our focus on "employer" startups may overlook an offsetting increase in "nonemployer" businesses. We only measure a startup in the year when it hires its first employee. However, the business may have already existed as a "nonemployer" in prior years. Technological improvements could have changed the optimal size of entrants and allow the business to delay, even indefinitely, hiring its first employees. For example, the introduction of easy to use bookkeeping software reduced the need to hire an employee to manage the books. David et al. (2003) show that similar type of innovations in information, communications and technology more broadly have reduced the need to hire employees for many occupations intensive in routine tasks. There is also some support for this hypothesis in our aggregate data: the decline in the aggregate startup rate did coincide with an increase in the total number of nonemployer firms. If startup deficits were offset by a sufficient rise of nonemployers, the aggregate employment effects could be overstated.

We test the substitution channel directly using cross-state differences in the growth of nonemployers and find the opposite effect. The Census Bureau publishes state-level tabulations of nonemployers from 1997 to 2012. Using these measures, we check whether states with increases in the growth rate of nonemployers experience larger declines in the startup rate. We regress the long-run difference from 1998 to 2012 in a state's annual startup rate on the long-run change in the average annual growth rate of its nonemployers and see no evidence of substitution. The results are both statistically and quantitatively insignificant, and if anything, indicate employers and nonemployers are complements rather than substitutes. A 1-percentage-point increase in the growth rate of nonemployers predicts a 0.05-percentage-point (standard error 0.05) *increase* in startup rates. While this test relies on cross-state patterns, in Online Appendix B.5 we also show that the aggregate increase in nonemployers is too small to explain the aggregate declines in the startup rate over the same periods.

1.3.1 Interpreting the demographic and import competition channels. Having examined a number of promising explanations, our findings suggest two channels whose cross-sectional implications are consistent with the patterns we uncover in the LBD: changes in the demographic structure of the U.S. population and an increase in import competition.[16] If changes in worker demographics or increases in import competition are responsible for the aggregate decline in entry, it is not clear why they should affect entrants so much more than incumbents. Nevertheless, we see evidence of this pattern in other settings with shrinking and expanding sectors. In structural transformation, for example, Dent et al. (2016) show that the reallocation of employment from manufacturing to services (driven by changes in technology and trade) is accomplished primarily through changes in the entry margin rather than adjustments to the survival and growth of incumbent firms.

There is also a theoretical basis for a more elastic entry margin in the case of demographic change. The workhorse Hopenhayn (1992) equilibrium model of entry and exit implies infinitely elastic long-run labor demand through the free entry of new firms rather than changes in incumbent size or survival. If individual firms have downward sloping labor demand curves, additional incumbent labor demand, for example, requires a decline in the real wage, but this would also increases the profitability of profitability of potential entrants. Karahan et al. (2016) show that this property implies in the long run, any demographic shock to labor supply is entirely "absorbed" by the entry margin, leaving wages and thus incumbent dynamics unaffected.

The stability of incumbent dynamics is not universal. Although there are reasons to expect a more muted response of incumbent survival and growth in the face of demographic and import competition changes, their stability is not required in general to other types of shocks. An interesting example of this is Adelino et al. (2017), who identify product demand shocks in the cross section using plausibly exogenous shifts in household income and find significant employment growth responses of both entrants *and* incumbents.

Finally, if one thinks of demographic factors as mostly a labor supply factor and increased import exposure as a demand shift, our analysis suggests that both demand and supply factors are at play. However, there is an important caveat to interpreting these significant reduced-form correlations since we lack plausibly exogenous variation in either of these channels. Without a compelling argument for an exclusion restriction, we cannot be confident in assessing the relative importance of labor supply versus labor demand factors. In the next section, we develop a framework that remains agnostic on the ultimate sources of the decline in entry and yet still quantifies the effect of the decline of

[16] In Online Appendix B.6 we consider other potential Explanations, such as changes in unionization and regulations, that do not explain declines in entry across states and industries.

entry on aggregate employment dynamics. The key to developing such a framework is to examine firm dynamics by age and decompose the changes in firm demographics into entry, survival and growth margins.

2. Decomposing Firm Dynamics by Age

In this section, we develop a dynamic decomposition framework for the firm age distribution that preserves heterogeneity in survival and growth by firm age to understand the key margins driving the reallocation of employment toward older firms. Although our framework is only a statistical model of firm dynamics, it also could be interpreted as the reduced-form of an equilibrium model. Formulated this way, it will also pose a set of restrictions that any 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 et al. (1988) has identified the key role of firm age in firm survival and growth in the manufacturing sector.[17] Recently, Haltiwanger et al. (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.[18]

2.1 The basic framework

We distinguish three key margins that determine the dynamics of firms and the distribution of employment E_t^a in year t across firms of varying ages a. The first is the entry margin, which we measure by employment

[17] Dunne et al. (1988) focus on plant-level rather than firm-level behavior.

[18] Changes in the unconditional firm size distribution over this period primarily reflect the compositional changes in firm age. We include a more detailed discussion of firm age and size in Online Appendix B.1.

E_t^0 at age 0 firms or "startups" and label it as

$$S_t \equiv E_t^0.$$

Total startup employment is the product of the number of startups F_t^0 and their average employment size N_t^0. Fluctuations in S_t reflect changes along both the entry (extensive) and average entrant size (intensive) margins, but because the average entrant size has remained stable, this distinction is not important for the current analysis.[19] 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. Since by construction $E_t^a = x_t^a(1+n_t^a)E_{t-1}^{a-1}$, 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

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

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

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[19] 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 is equivalent to the product of the *startup rate* F_t^0/F_t, which is plotted in the upper-left panel of Figure 1 (also as the solid line in Online Appendix Figure B.3), 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 toward older firms), whereas the average size of entrants has remained relatively steady, so the startup employment share has declined even faster than the startup rate. Another possible measure of entry is the number of new firms per capita, which we plot in Online Appendix Figure B.6 and also declines over this period.

We can write the law of motion for the distribution of employment across age groups as an exact decomposition by firm age. For simplicity we use only three age groups: 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 life cycle documented in Haltiwanger et al. (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 is a reasonable simplification for our analysis. As we will discuss in Section 3.2, we have repeated the decomposition exercises with more disaggregated age groups for young firms with little change 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

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

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.[20,21] Then

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

and for young firms we can write

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

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

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

[20] 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 life-cycle component, where $1-q_{t-1}^y$ is the probability a young firm in $t-1$ becoming a mature firm.

[21] In Online 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.

Letting $\mathbf{E}_t = (S_t, E_t^y, E_t^m)'$ be the vector of employment across firm age groups we can define a transition matrix P_t for each year t

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

and write the law of motion for the employment distribution

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

Writing (3) as a moving average

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

emphasizes how the employment age distribution in any year exclusively depends 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 as the workhorse Hopenhayn (1992) model, have a statistical representation analogous to Equation (3). Our framework emphasizes the importance of heterogeneity in firm age as opposed to heterogeneity in firm-level productivity (see, e.g., Hopenhayn 1992). As formulated by Equation (3), the empirical behavior of P_t places important restrictions on age dependence in models of firm dynamics. We will argue in Section 3.2 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 by allowing 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 use all information and instead project each age group's annual 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, that is, 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 overall startup employment, 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 employment share of startups $s_t = S_t / E_t$ must decline. For the period we study, not only is μ_t^s not high enough to keep startups' employment share constant, but it also may be slowly declining. The aggregate time series is too noisy to estimate the magnitude of a decline with a reasonable level of confidence.

2.3 Dynamics of aggregate employment

The dynamics of aggregate employment follow immediately from aggregating over the dynamics by age group. The level of aggregate employment is $E_t = S_t + E_t^y + E_t^m$ and when formulated in growth rates, aggregate employment growth is

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

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*, which is an employment weighted average of the growth rates of young and mature incumbents, respectively. Note that weight ω_{t-1} measures the employment share of the current year t mature cohort in the previous year $t-1$:

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

Because the current young group includes last year's startups the incumbent lagged employment weights sum to exactly 1. This weight evolves in accordance with 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}.

Substituting in Equations (4) and (5), we can write (6) in terms of its trend and cyclical components:

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

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. Startup Deficits' Effects on the Age Composition of Firms

Our theoretical framework allows us to link the decline in entry with its dynamic effects on the age composition of firms. A key input to this framework is the behavior of incumbent firms. We first describe how we measure incumbent firm dynamics in the data and then examine the evolution their survival and employment growth rates over time. We find that despite the decline in the startup rate since the 1980s, incumbent firm behavior by age changed little over the same period. Applying the dynamic decomposition from Section 2.1, we show that the expanding mature employment share is almost entirely the cumulative effect of the startup deficit.

3.1 Measuring incumbent dynamics

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+). The method for assigning firm age necessarily limits us to starting in 1987 when conditioning on firm age, since 1977 is the first year a new establishment could have been observed. 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 are robust to alternative definitions of small and large employers. In practice, firms with fewer than 20 employees already constitute almost 90% 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 3.1. Where possible, we use the tabulations available from the BDS, so that our results are easily replicable without access to the confidential microdata. In almost all cases, the BDS tabulations 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.[22] We provide additional details on the variable construction and sample restrictions in Online Appendix A.

In Table 3 we summarize the data on incumbent firms 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% and conditional on survival, young firms grow on average at almost 9%. Mature firms' survival rate is close to 95% and conditional on survival, mature firms grow roughly 5% 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. If young firms survive to 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 3 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

[22] 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 and Klimek (2016) for details.

Table 3
Summary statistics from Business Dynamics Statistics 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 United States						
Mean	0	-0.037	0.885	0.087	-0.006	0.947	0.049
SD	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
SD							
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	1,836	1,326	1,326	1,326	1,326	1,326	1,326

Note: U.S. Census Bureau Business Dynamics Statistics (BDS). 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.

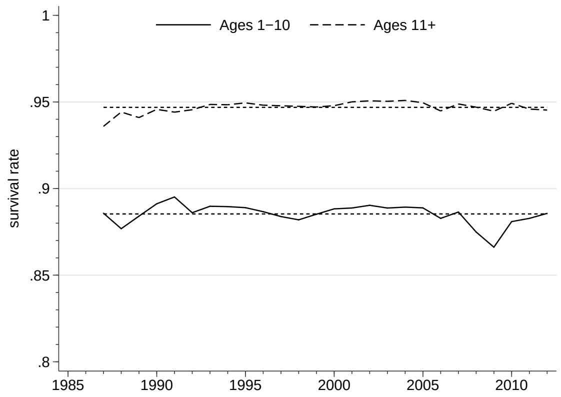
national counterparts. In the top panel, we report the standard deviation of a linearly detrended startup growth rate.

3.2 Incumbent survival and growth by firm age

Linking the startup deficits with the evolution of the distribution of employment across age groups also crucially depends on incumbents' survival and growth prospects. In Figure 3A we plot the 1-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 et al. (1988) for the manufacturing sector, the exit hazard for U.S. firms overall declines predictably with age.[23] 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 4 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

[23] In the Online Appendix Figure B.10, we show that the same pattern holds even within a disaggregated young age group.



(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

Source: 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 1-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. The series began in 1987, because firms aged 11+ are left censored from 1977 to 1986.

insignificant and statistically indistinguishable from zero. For example, the estimated trend implies that over 30 years, the survival rate of both young and old firms will have changed by a fraction of 1%. The state-level data provide identical near-zero point estimates that are more

Table 4
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	.12	.59	.04	.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	.19	.59	.05	.12
N	26	1,326	26	1,326
Years	1987-2012	1987-2012	1987-2012	1987-2012
State FEs	-	Yes	-	Yes

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

precisely estimated from the additional variation.[24] 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 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 definitions of young firms.[25]

The relationship between firm age and conditional employment growth rate is also stable. In Figure 3B, we plot the 1-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%. Mature firms similarly fluctuate around their average conditional growth rate of 4.9%. Similar to survival rates, Table 4 Columns 3 and 4 report

[24] Throughout the paper when using the state-level data, we cluster the standard errors by state to allow for within-state serial correlation in the dependent variable and to be comparable with the related literature (see, e.g., Fort et al. 2013; Davis and Haltiwanger 2014; Foster et al. 2016). 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.

[25] For brevity, we include these robustness results in Online Appendix Tables B.3 and B.4.

the estimated coefficient on a linear trend in n_t by age group. Both for the U.S. overall and within-state, estimated trend coefficients are quantitatively insignificant, and, in the case of the U.S. overall, statistically insignificant. Again, this is robust to alternative methods of removing cyclical fluctuations and additional controls for sector and firm size.

Overall, mature firms have both a lower conditional growth rate and as Table 3 shows, a volatility roughly half of their younger counterparts. The first observation is consistent with Haltiwanger et al. (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 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 Online Appendix Table B.2. Even more remarkable is that over a 30-year period, startups and young firms (conditional on survival) tend to have roughly the same number of employees on average.[26]

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 significantly 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 et al. (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, life-cycle dynamics are remarkably stable over

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

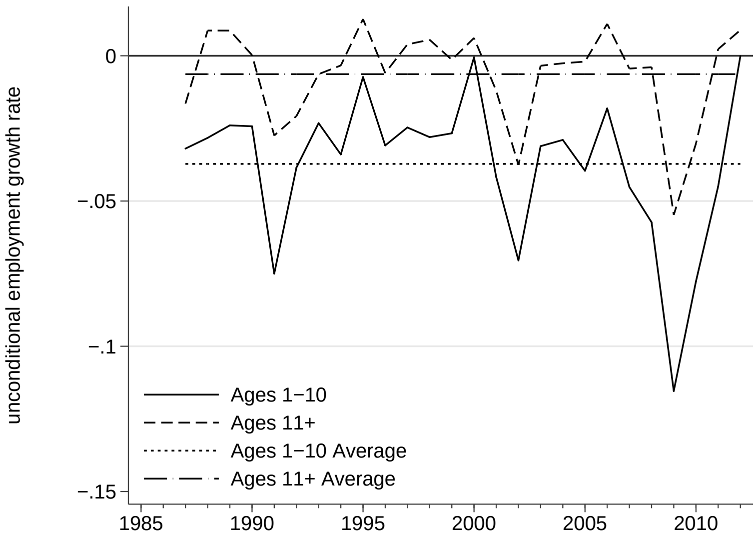


Figure 4
Young and mature unconditional employment growth rates (g_t^y and g_t^m)

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

time. Growth and survival rates fluctuate as one would expect over the business cycle (a point we will take up in detail in Section 4.2), but they fluctuate around steady averages with no sign of a trend. Interpreted through the decomposition framework 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.[27]

3.3 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 accumulation of the startup deficit since the early 1980s. Each successive year brings a relatively smaller share

[27] The stability of the survival and growth margins might seem at odds with the recent findings of Sedlácek and Sterk (2017). Whereas 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.

of entrants, but they behave exactly as the cohorts that preceded them. The shortage of entrants gradually tilts the composition toward 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 toward 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 decline along the entry margin drives the shifts in the age distribution of employment.

This finding also applies to broad sectors and states. As we showed in Section 2.2 and in Online 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 Online 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.

4. 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.

4.1 Measuring business-cycle shocks

As a proxy for business-cycle shock Z_t we consider mean deviations of four measures: (1) log differences in annual personal income, (2)

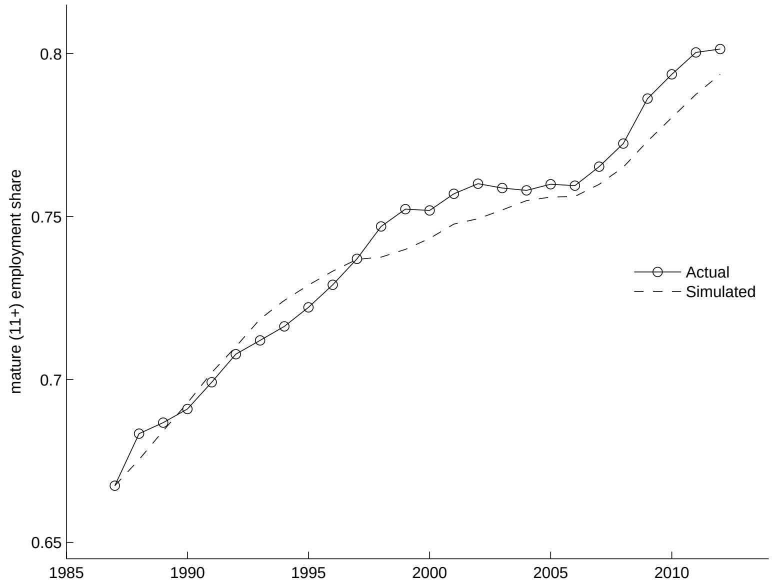


Figure 5
Mature employment share from 1987 to 2012 and its predicted path from constant survival and growth

Source: 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 the actual sequence of startup employment $\{S_t\}$ and constant growth and survival rates $\bar{P}$ in the law of motion. The series began in 1987, because firms aged 11+ are left censored from 1977 to 1986.

log differences in annual gross domestic or state output, (3) changes in annual average of monthly unemployment, and (4) 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. Although we cannot observe the true business-cycle shock Z_t, what we have in mind are shocks to output. Employment-based measures, while also correlated with real GDP growth are less ideal since the 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

Table 5
Alternative measures of business-cycle shock Z_t for years 1980 to 2012

	Overall United States			Within U.S. states			
	Corr(Z_t,Y_t)	N	SD	N	SD		
					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
HP 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 the year ending in Q1. Annual H-P unemployment measure is annual averages of residuals from HP-filtered monthly unemployment with smoothing parameter 8.1 million over year ending in March. Overall U.S. reports the 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.

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 et al. (2013) and Foster et al. (2016). 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.[28] 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 5, we summarize the four annual business-cycle measures measured at the national and state levels. 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.

4.2 Cyclical elasticity by incumbent firm age

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 6 reports the estimated β^a for each incumbent age group using four alternative measures for business-cycle shock Z_t. We estimate Equation

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

Table 6
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 $\beta^y = \beta^m$	.014	.002	.021	.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 $\beta^y = \beta^m$	.000	.000	.000	.033
Years	1987-2012	1987-2012	1987-2012	1987-2012

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

(4) over the full sample of 1987 to 2012 for the first three measures of Z_t.[29] Young firms are noticeably more cyclical than mature firms in the annual time series in Table 6. For all but the HP-filtered unemployment proxy in Column 4 young firms are both statistically and quantitatively more cyclical than mature firms, ranging from roughly 40% to 100% 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% level for all but the HP-based measure in Column 4.

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

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

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

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 6 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% 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, industry compositional changes within states also may be driving the results. Second, a reverse causality concern is 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 preferable 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.

Using the LBD we find similar patterns for the elasticities when controlling for industry. The public-use BDS data do not allow us to condition on both state and sector, and even if it were possible, the sector measures are very broad. Instead, we turn to the LBD to calculate firm-level growth rates, which we then aggregate by state, industry (both 2-digit and 4-digit NAICS) and firm size categories. The estimated cyclical sensitivities of young and mature firms using personal income as the business-cycle proxy are reported in Table 7. The estimated elasticities are smaller than the ones reported in Column 1 of Table 6 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 6, 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 Online Appendix B.4, we also use the publicly available Quarterly Workforce Indicators (QWIs) to control for industry composition, and again the results are again very similar.

Both when identified off the time series and the cross-section, the greater cyclicality of young firms is a robust result. We show in Online Appendix B.4 that results are robust to (1) using further disaggregated age groups; (2) controlling for size fixed effects; (3) controlling for sectoral changes; and (4) using establishment age instead of firm age.

Table 7
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+)	
$\hat{\beta}^m$	0.168***	0.158***
	(0.03)	(0.04)
Size FEs	Yes	Yes
Year FEs	Yes	Yes
State FEs	Yes	Yes
Industry FEs	-	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.

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.

4.3 Cyclicality of startup employment

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, like 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.[30] Columns 1 and 2 of Table 8 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 procyclical. A 1-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 Online Appendix B.4 that results are robust to (1) controlling for size fixed effects; (2) control for sectoral changes; (3) using a broader measure of startups which includes age 1 firms as startups; and (4) 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 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 6 and 8 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 (2015). 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.

4.4 Time variation in cyclical sensitivity by firm age

The relative stability of the cyclicality across age groups will be relevant for our description of grown-up business cycles in Section 5. One might expect that as firm entry declined and the business age distribution tilted toward mature firms, general-equilibrium effects might systematically shift the cyclical properties *within* age group. Interestingly, this does not appear to be the case.

[30] Online Appendix B.4 provides results using HP-filtered residuals with alternative smoothing parameters and time periods.
The procyclicality of startup employment growth is robust to alternative methods of detrending.

Table 8
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.

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 reestimate Equation (8) with a trend component to β_t^a like in (9).[31] Table 9 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 in which we can distinguish 11- to 15-year-old firms from +16-year-old 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 5.

We also reestimate 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 9 reports the estimated

[31] 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.

Table 9
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	.68	.75	.71	.76	.30	.30
N	1,326	3,946	1,326	3,978	1,683	1,683
Size FEs	-	Yes	-	Yes	-	-
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	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.

linear trend component β_1 for startups and shows that there is no statistically significant change in the cyclical sensitivity of startup employment.

5. 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.[32] The second is the more pronounced cyclicality of young firms and startups that we have shown in Table 6.

5.1 The 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:

[32] This is a point emphasized by Haltiwanger et al. (2013), although they pool startups with other young firms.

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

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. We characterize the startup deficit as the declines of μ_t^s from a level $\bar{\mu}^s$ that would keep the startup employment share stable over time. He we separately consider the effects of this deficit on the trend and cyclical components of employment growth.

5.1.1 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 the age distribution is ambiguous. As we showed in Section 3, $\bar{g}^m > \bar{g}^y$ 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) 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.

5.1.2 Cyclical component. The cyclical component of aggregate employment growth is reshaped only through changes in the age distribution. As we showed in Sections 4.2 and 4.4, 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.

5.2 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 quantify 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. This counterfactual exercise isolates the role of the startup deficit on aggregate employment if the startup deficit did not also affect the average incumbent margins or their covariance with business-cycle shocks. For this interpretation, we are reassured by the evidence in Sections 3.2 (long-run) and 4.4 (cycle) documenting the stability of these margins throughout this period despite the trend decline in the entry rate.

To proceed, we replace the linear declining trend in the startup employment growth rate, μ_t^s, with its 1980–1985 average of $\bar{\mu}^s = 0.02$, leaving the exact sequence of cyclical and other shocks in place.[33] 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 the 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

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

starting in 1987. As the above formulation shows, 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

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

counterfactual exercise. As we describe, this choice is motivated by the stability of the average growth rates and the cyclical responsiveness of employment growth evident in Sections 3.2 and 4.4.

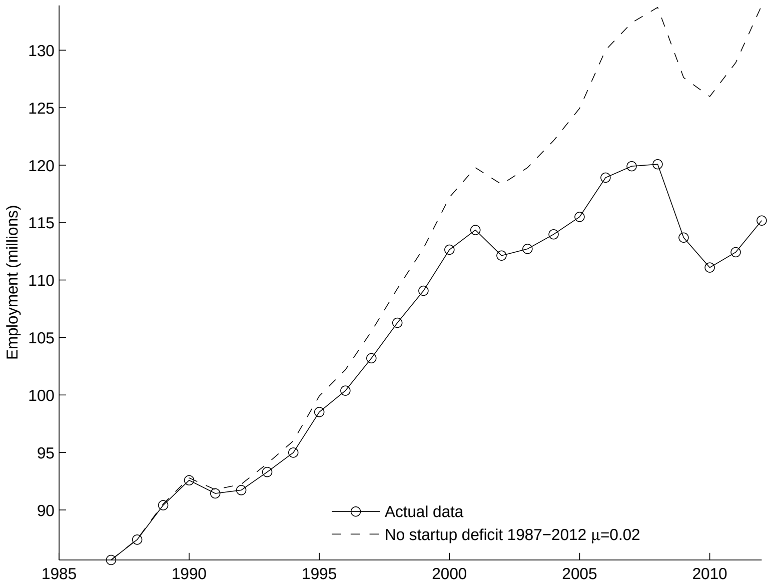
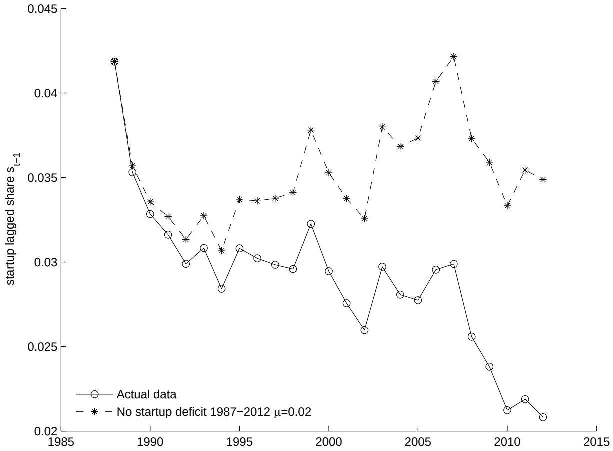


Figure 6
Actual and counterfactual paths for aggregate employment (E_t and E_t^c)

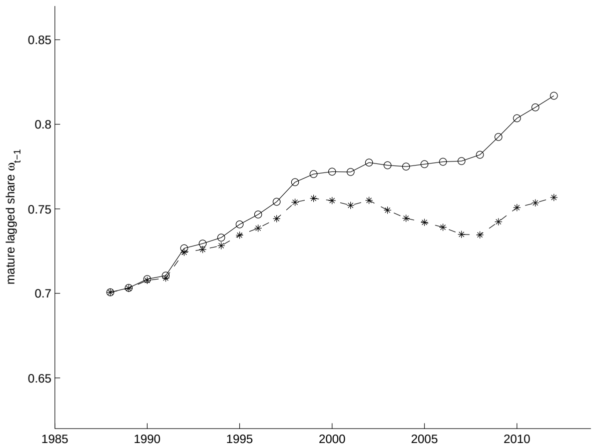
Source: U.S. Census Bureau Business Dynamics Statistics. Actual data represent the employment path using the exact law of motion in Equation (3) from 1987 onward. The counterfactual employment path uses a sequence of startup employment $\{S_t^c\}$, where μ_t^s in g_t^s is replaced with constant $\bar{\mu}^s$= 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 divergence between two paths. The effects of the startup deficit start small in the early 1990s and increase 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% higher than the actual employment levels in 1990, 2001, and 2008, respectively.

Aggregate employment growth in figure 6 is a weighted average of growth rates of startup employment and incumbent young, and mature



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



(b) Actual and counterfactual ω_{t-1}

Figure 7
Startup and mature incumbent employment weights

Source: U.S. Census Bureau Business Dynamics Statistics. Actual data represent the employment shares using the law of motion and actual data from 1987 onward. The counterfactual employment shares are 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.

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 shares, ω_{t-1}, in the data and our counterfactual economy. The counterfactual startup employment share fluctuates around 3% instead of declining from around 4% in 1987 to roughly 2% in 2012. Eliminating the startup deficit changes the age

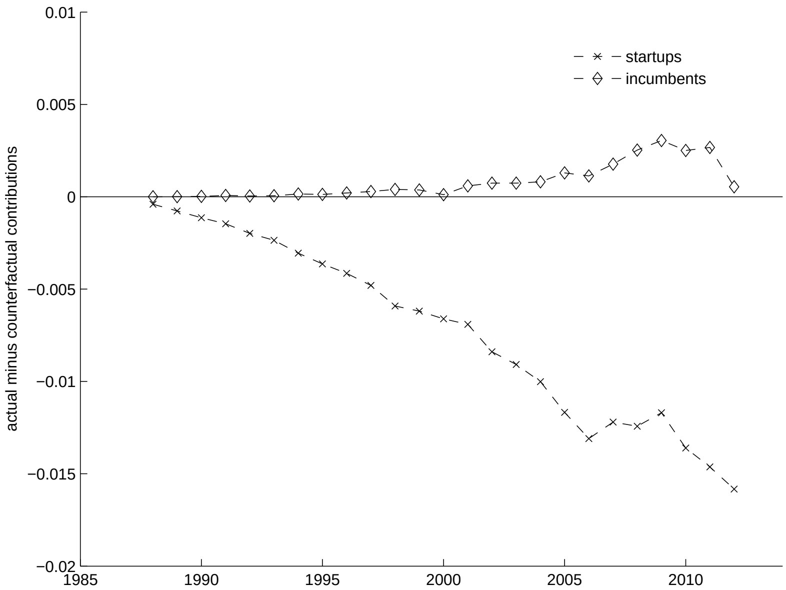


Figure 8
Actual minus counterfactual startup and incumbent growth rate contributions

Source: U.S. Census Bureau Business Dynamics Statistics. The lower line represents the difference between actual and counterfactual startup growth contribution: $[s_{t-1}(1+\mu_t^s)]-\left[s_{t-1}^c(1+\bar{\mu}^s)\right]$. The upper line represents difference between actual and counterfactual incumbent growth contributions: $[(1-\omega_{t-1})g_t^y+\omega_{t-1}g_t^m]-\left[\left(1-\omega_{t-1}^c\right)g_t^y+\omega_{t-1}^c g_t^m\right]$. The counterfactual 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.

distribution, undoing almost all of the rise in the 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 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

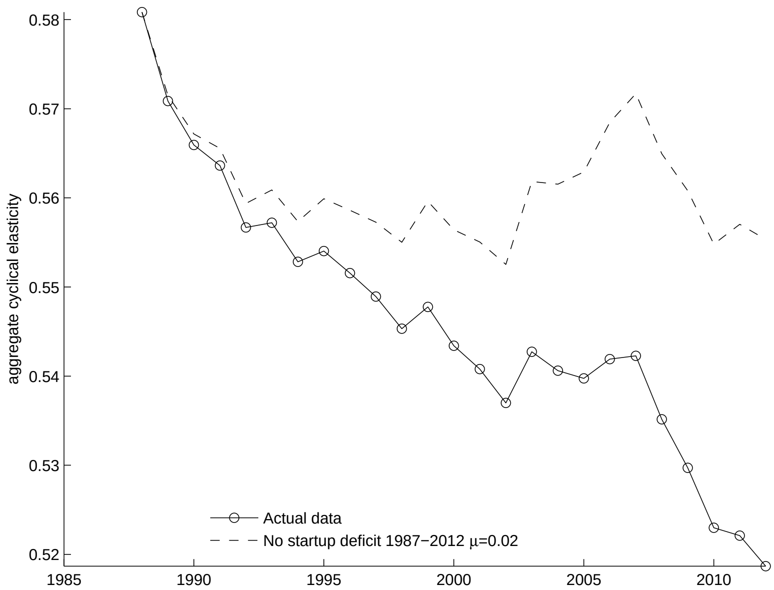


Figure 9
Actual and counterfactual aggregate cyclical elasticity β

U.S. aggregate cyclical elasticity is 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. The counterfactual employment shares are 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.

weight of young firms is small relative to the negative effect of the declining startups. Put together, our counterfactual experiment shows that the 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 toward a more mature firm structure caused a gradual decline in this elasticity from around 0.58 to 0.52, roughly a 10% decline. Put differently, employment response in the current economy to a business-cycle shock of the same magnitude is now 10% lower in the incumbent firms than in 1987.[34] This decline in cyclical responsiveness of employment is much smaller in the counterfactual economy since the

[34] This finding resonates with the literature that analyzes the effect of aging of the workforce on business-cycle volatility. In particular, Gomme et al. (2005), Clark and Summers (1981),

elimination of the startup deficit undoes most of the shift of employment toward less cyclical mature firms.

5.3 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 1990–1991 recession.[35] 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 deficit also grows over time, creating a larger 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 decoupling of employment and business-cycle shocks is consistent with the emergence of jobless recoveries in the U.S. economy.

5.3.1 Three different great recessions. The cumulative effects of the startup deficit imply that each business cycle in the last 30 years has affected 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

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Ríos-Rull (1996), Jaimovich and Siu (2009), and Lugauer (2012) examined how the aging of the labor force acts as a stabilizing force for business cycle volatility.

[35] We focus on aggregate employment dynamics over the business cycle rather than unemployment, primarily because of the tight link with our analysis of firms. Since the main driver of unemployment fluctuations is employment, our analysis could be extended to the effects on unemployment fluctuations. However, this also requires an account of the determinants of the participation margin, which has been shifting.

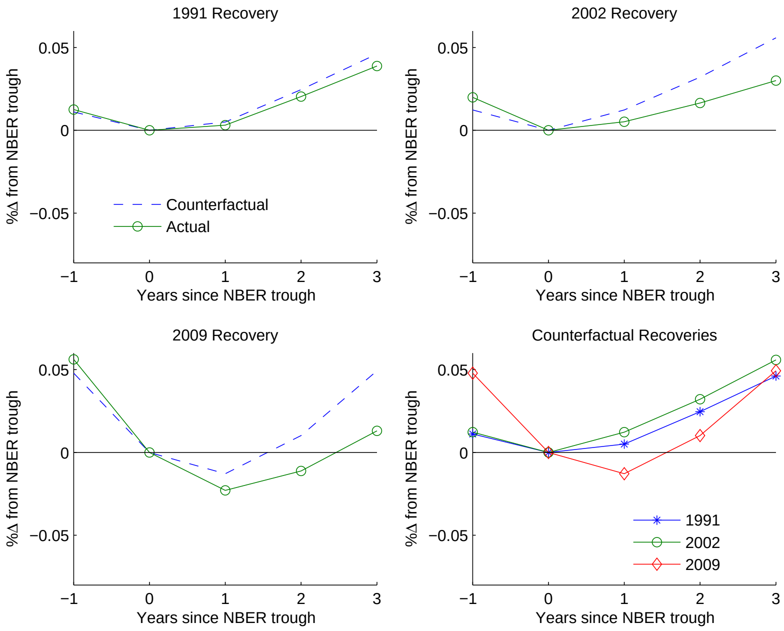
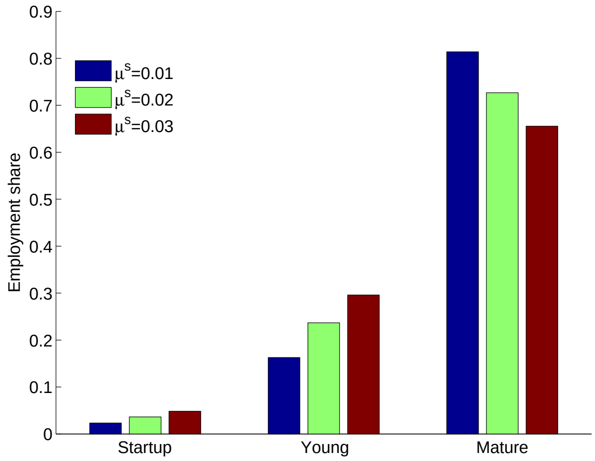


Figure 10
Actual and counterfactual recovery employment dynamics

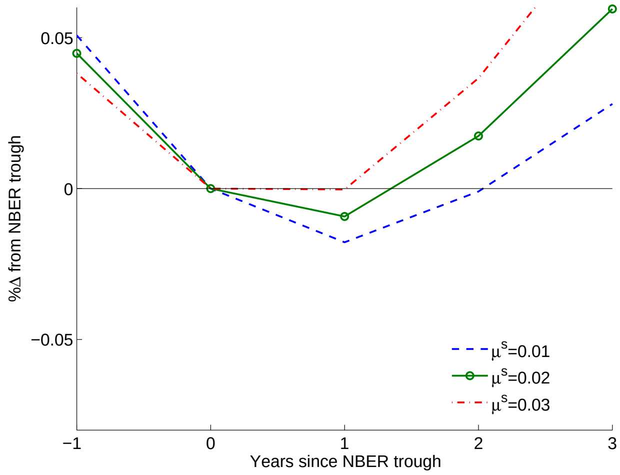
Source: U.S. Census Bureau Business Dynamics Statistics. Actual and counterfactual employment paths are normalized to NBER 1991, 2002, and 2009 recoveries. Actual data represent the employment path using law of motion from 1987 onward. The counterfactual employment path uses a sequence of startup employment$\{S_t^c\}$,where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

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. Figure 11a shows the long-run distribution of employment across age groups for startup growth μ^s ranging from 1% to 3%. 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%, whereas it is around 60% 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



(a) Employment share distribution



(b) Great Recession Z_t

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

stationary transition matrix $\bar{P}$ imply a very slow convergence.[36] For example, the actual 1987 age distribution would take roughly 30 years to converge halfway to the long-run distribution associated with $\mu^s = 0.01$.

Figure 11b 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

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

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 1 year later and reaches its 2008 level within 2 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 3 years with $\mu^s = 0.02$ and more than 3 years with $\mu^s = 0.01$).

This experiment shows that the startup deficit and its implied aging of firms are quantitatively important to understanding the decoupling of output and employment during economic recoveries. Recent work by Sedlácek (2014), Siemer (2014), and Gourio et al. (2014) focuses on the role of firm entry in the slow recovery from the Great Recession. In addition to supporting their conclusions, our analysis shows that the slow employment recoveries even *before* the Great Recession are a consequence of the 30-year trend decline in firm entry. Our counterfactual exercise also predicts that as long as the startup deficit continues, we expect further decoupling of employment and output over the business cycle.

6. Conclusions

The aggregate consequences of entrepreneurship are often overlooked. New employer businesses now account for less than 2% of private sector employment, and even at their peak, accounted for only 4%. Yet, as we show, the aggregate consequences of this 2-percentage-point decline are profound. Startups are the most important margin of aggregate employment growth. They are also, necessarily, the only source of young businesses.

Persistent shortages of new businesses have allowed the stock of incumbent firms to age substantially. And this shift in employer age composition has brought with it the introduction of *grown-up business cycles*, with lower trend employment growth, jobless recoveries, and, generally, a reduction in the elasticity of employment to the business cycle. Continuing low levels of entrepreneurship will induce a permanent shift in employment dynamics.

To establish this argument, we developed a novel dynamic decomposition framework to quantify the full effects on employment dynamics of shifts in the entry margin. Applying this framework, we simulate a counterfactual economy using the exact sequence of shocks observed in the actual economy, but for a shift in the trend growth of startup employment to eliminate startup deficits. We then measure the differences in employment dynamics. Relative to this counterfactual, we observed that the shift in entry explains the emergence of grown-up business cycles.

While one can view this purely as a measurement exercise, our findings for incumbent dynamics makes the exercise especially informative. Over a period with an unmistakable decline in entry, we find little if any shift in incumbent survival and growth and no systematic change in their covariance with the business cycle. We take these surprising findings as evidence that the underlying determinants of the decline in the startup rate have had few effects on incumbent firms. While an intervention specifically to increase entry would likely have effects on all firms—something our thought experiment cannot capture—the stability of these incumbent margins for this period brings credence an economic interpretation of our counterfactual: it represents the economy we would have expected to observe in the absence of the underlying causes of the decline in the startup rate. A virtue of our approach is that it does not rely on a specific cause of the decline in entry, but rather quantifies the effects, vis-a-vis the firm creation margin on aggregate employment.

Whether or not startup deficits will continue, or even whether they are cause for concern and any scope for corrective policy, depend critically on the underlying causes of the declining entry rate. We identify shifts in worker demographics and increases in import competition as promising channels to understand the decline in entry. While our framework does not offer any specific policy prescriptions, we can draw some important lessons. First, absent any intervention the startup deficit is likely to continue given ongoing trends in demographics and trade. Working age population growth rate in the United States remains near 1% and the Census Bureau projects that the number of individuals aged 65 or older as a share of the adult population will continue to rise. Import penetration continues to increase across many U.S. sectors as imported goods and services play a more prominent role in the global value chain of U.S. production. Second, the inevitability of continued low levels of entry does not make these changes to labor market dynamics innocuous. Jobless recoveries imply longer spells of nonemployment following recessions. These long spells of joblessness leave lasting effects on the separated workers as well as those who enter the labor market during a jobless recovery period.[37] To the extent that increases in import competition have depressed the startup rate for some industries, these effects may be particularly pronounced for workers in these industries.[38] Third, corrective policy may take a surprising form. If the declines in

[37] See Davis and von Wachter (2011) for recent evidence on these effects and the references therein.

[38] A large literature on trade, for example Autor et al. (2013), studies the effects of increased import competition on the U.S. labor market typically finding adverse effects on labor market outcomes (such as wages) in import-competing industries. Our analysis identified

entry primarily result from shifting demographics, specifically a decline in the growth rate of the working age population, it may appear there is little room for corrective policy. However, one exception may be policies that promote labor supply growth such as immigration policy and paid parental leave. While these policy changes might not provide a quick remedy for demographic shifts, they might alleviate labor supply constraints in the medium run. Further study of the welfare implications of the startup deficit and of the proposed remedies is an exciting area for future research.

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