

Demographic Origins of the Startup Deficit*

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Abstract

We propose a simple explanation for the long-run decline in the startup rate. It was caused by a slowdown in labor supply growth since the late 1970s, largely pre-determined by demographics. This channel explains roughly two-thirds of the decline and why incumbent firm survival and average growth over the lifecycle have been little changed. We show these results in a standard model of firm dynamics and test the mechanism using shocks to labor supply growth across states. Finally, we show that a longer startup rate series imputed using historical establishment tabulations rises over the 1960-70s period of accelerating labor force growth.

Keywords: Firm dynamics, Demographics, Business Dynamism, Macroeconomics

JEL Classification: J11, E24, D22

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1 Introduction

For nearly four decades, the U.S. startup rate has been trending down. In 1979, the startup rate—measured as the share of new employers as a fraction of all employers—was 13 percent. In 2007, *before* the onset of the Great Recession, it was roughly 10 percent, an almost 25 percent decline.¹ This “startup deficit” is also wide-ranging; it is found nearly universally within geographic areas and industries. Remarkably, the declining startup rate and its origins left little apparent effect on the survival or average growth rates of incumbent firms, which have remained steady conditional on firm age. These patterns have significantly shifted the firm age distribution, which is a key determinant of the dynamics of aggregate employment and productivity.²

We propose a simple and novel explanation for these patterns. The startup rate is linked in general equilibrium to the pace of labor supply growth, which for reasons largely pre-determined by demographics, slowed dramatically in the late 1970s. Why should labor supply growth affect the startup rate at all? Ultimately, growing labor supply requires growing labor demand, and this can only happen through a decline in the real wage that allows incumbent firms to expand or through entry of new firms. A lesson from models of firm dynamics, starting with [Hopenhayn \(1992\)](#), is that in the long run, free entry ensures that shifts in labor supply are absorbed entirely at the entry margin. Along the balanced growth path of a standard model of firm dynamics extended to incorporate labor supply growth, slower growth in labor supply requires slower growth in the number of firms and thus a lower startup rate.

This explanation fits the data very well. The slowdown in U.S. labor supply growth since the late 1970s explains roughly two-thirds of the declining startup rate; it explains the widespread declines across markets since the labor force growth slowdown affected them nearly universally; *and* it explains the stability of average incumbent

¹See [Davis, Haltiwanger, Jarmin, and Miranda \(2007\)](#) who first documented declines in measures of business dynamism, and [Haltiwanger, Jarmin, and Miranda \(2011, 2012\)](#) who first noted the decline in the startup rate, in particular. More recently, work by [Decker, Haltiwanger, Jarmin, and Miranda \(2014\)](#), [Hathaway and Litan \(2014a\)](#), and [Pugsley and Şahin \(2019\)](#) have shown the declines are both persistent and pervasive across markets.

²[Bartelsman and Doms \(2000\)](#), for example, find about 25 percent of within-industry gains in TFP occurs from new entrants in the manufacturing sector. [Lentz and Mortensen \(2008\)](#) find a similar share of aggregate TFP growth due to the entry margin in an estimated endogenous growth model. [Haltiwanger, Jarmin, and Miranda \(2013\)](#) and [Decker, Haltiwanger, Jarmin, and Miranda \(2014\)](#) show the importance of young firms, including startups, for aggregate job creation. [Pugsley and Şahin \(2019\)](#) show firm age composition affects aggregate employment dynamics.

dynamics conditional on their age. We show these results quantitatively in an equilibrium model of firm dynamics. Moreover, we validate the model’s implications using demographic variation across states and in the aggregate time series.

We first derive a simple formula that links the equilibrium startup rate to labor supply growth and the aggregate exit rate by equating the inflow and outflow of new firms per worker to keep the number of firms per worker constant. Intuitively, new firms (gross entry) both replace exiting firms and expand the number of firms (net entry) needed to keep pace with labor supply growth. This “flow-balance” link explains between 1.6 to 2.0 percentage points (or 55 to 70 percent) of the decline between 1979-81 and 2005-07, depending on the measure of labor supply growth. Notably, this prediction relies on exogenous declines in both the labor supply growth rate and the economy-wide exit rate in similar proportions. It also imposes a strong assumption of homogeneous firms. Yet, its insights carry over to a more realistic setting with firm heterogeneity and selection, where the aggregate exit rate declines *endogenously* with a decline in labor supply growth.

To show this, we extend the general equilibrium setting of [Hopenhayn and Rogerson \(1993\)](#) to include labor supply growth. While we adopt this well-known setting for its simplicity, the mechanism is present in richer environments that share its key ingredients of firm-level diminishing returns and a linear free entry condition. The first generates downward sloping incumbent labor demand, and the latter allows the entry margin to absorb any pressure on the real wage from shifting labor supply. Shocks to labor supply growth put downward pressure on wages and create incentives for incumbent firms to expand, but the increased profitability also creates opportunities for potential entrants. Any effect on the startup rate depends on how shocks to the labor supply are accommodated by expanding incumbents and new firms. Along the balanced growth path, free entry of new firms make labor demand infinitely elastic.

When the model is calibrated to match U.S. firm dynamics, the observed change in the labor supply growth rate accounts for 40 to 70 percent of the change in the startup rate between 1979-81 and 2005-07, again depending on the labor supply growth measure. These magnitudes are similar to the results from the simple flow-balance calculation, which relied on declines in both labor supply growth and exit for its prediction. The model’s endogenous decline in the aggregate exit rate accounts for 55 to 100 percent of the observed change in the aggregate exit rate used in the flow-balance calculation.

The equilibrium link between labor supply growth and the startup rate has two channels. The first is the direct effect of the change in labor force growth that requires a change in the *net* entry rate to maintain balanced growth. The second is an indirect amplification through its effects on the aggregate exit rate. Since changes in the net entry rate shift the share of new and young firms, which are significantly smaller and more likely to exit, they alter the aggregate exit rate through a compositional effect. These changes in aggregate exit then shift the replacement component of the equilibrium (gross) startup rate. Viewed through the lens of the calibrated model, three decades of declining labor supply growth have reduced the net entry component of the startup rate, which through its compositional effects on the aggregate exit rate, depressed the startup rate even further.³ Taken together, the equilibrium elasticity of the startup rate to the labor supply growth rate is roughly 1.5. If decomposed into the direct and indirect (vis-à-vis exit) effects of demographics, the quantitative model mirrors the proportions of demographics and aggregate exit found using the simple flow-balance model.

Beyond its success in explaining declining firm entry, an appealing feature of this mechanism is that it is also consistent with mostly stable incumbent survival and growth by firm age over the same time period.⁴ Shifts in labor supply growth, unlike, e.g., shifts in costs or frictions, have no direct effect on firms. Labor supply shifts could only affect the dynamics of incumbent firms through changes in the equilibrium real wage, but this is held fixed in the long run by free entry. Thus, changes in labor supply growth should not affect the survival and growth of incumbent firms. Of course, even with unchanged incumbent dynamics *conditional* on firm age, declines in labor supply growth can still generate declines in *aggregate* exit through their effects on firm age composition.

As a further test of the demographic-based explanation, we use two separate IV strategies to generate plausibly exogenous variation in labor supply growth U.S. states and compare the changes in state-level firm dynamics. The first IV predicts labor supply growth by 20-year lags of each state’s birthrate (births per thousand residents) and the second IV exploits persistent historical migration patterns between states. Specifically, the migration IV predicts own-state annual labor supply growth from the historical birthplace distribution across other (non neighboring) states and the size

³This is analogous to the behavior of investment in the neoclassical growth model.

⁴See [Pugsley and Şahin \(2019\)](#).

of each other state’s labor supply growth for that year. We estimate a cross-sectional startup rate elasticity of labor supply growth of roughly 1.2, which is consistent with the model-based elasticity of 1.5. Moreover, elasticities for exit and growth conditional on firm age using the same variation are statistically indistinguishable from zero. These main results, which control for state and time effects, are robust to further controls for industry and state-level trends.

As a final test of the demographic explanation, we test the time-series implication that the 1960s-70s period of rising labor force growth should coincide with an *increasing* startup rate. Although data limitations preclude examining the startup rate prior to the late 1970s, we develop a method to impute an establishment startup rate using the Census Bureau’s static County Business Patterns (CBP) data that extends back to 1965. Given that the establishment startup rate is highly correlated with the firm startup rate over the entire period where we can measure both, the imputed establishment startup rate will be informative about the historical firm startup rate. To do this, we estimate a statistical model for the aggregate exit rate as a function of the distribution of establishment characteristics measurable in the detailed CBP cross sections. We then add the estimated aggregate exit rate to the net entry rate measurable across CBP years to impute a measure of the startup rate. The imputed establishment startup rate co-moves with the labor supply growth rates over their rise and fall, consistent with the demographic hypothesis.

Our paper contributes to an emerging literature on the causes and consequences of declining entrepreneurship, first noted by [Haltiwanger, Jarmin, and Miranda \(2011\)](#) and [Haltiwanger, Jarmin, and Miranda \(2012\)](#). Early descriptive work on the trend decline in the startup rate had explored a myriad of potential explanations and documented cross-sectional correlations of the startup rate with changes in population growth ([Hathaway and Litan, 2014b](#); [Pugsley and Şahin, 2019](#)), business consolidation ([Hathaway and Litan, 2014b](#)), and sectoral import competition ([Pugsley and Şahin, 2019](#)), as well as ruled out other possibilities such as changes in industrial composition ([Decker, Haltiwanger, Jarmin, and Miranda, 2014](#)) and substitution from nonemployers ([Pugsley and Şahin, 2019](#)). We are the first, to our knowledge, to propose demographic changes in the growth rate of the labor supply as a causal explanation for the trend decline in the startup rate as well as the first to quantitatively and empirically evaluate the equilibrium mechanism.

Beyond the labor supply growth channel, several recent papers have examined

other potential causes of the decline in the startup rate using quantitative models. [Salgado \(2017\)](#) and [Kozeniauskas \(2017\)](#) study the effects of skill-biased technical change on entrepreneurship. Demographics can also affect the startup rate through the age composition of the population. [Liang, Wang, and Lazear \(2018\)](#) and [Engbom \(2019\)](#) find that incentives to start new businesses are diminished with an older workforce. [Bornstein \(2018\)](#) shows that population aging depresses firm entry because older consumers are less likely to demand new varieties.

The paper is organized as follows. Section 2 presents the trends in demographics and startups and a simple framework to connect them. Section 3 evaluates the demographic channel in a dynamic general equilibrium model. Section 4 uses cross-state variation, and Section 5 uses an imputation method to further evaluate the demographic channel. Section 6 concludes.

2 Demographic change and the startup deficit

In this section, after first describing our data, we document the decline in the U.S. startup rate and show that it coincides with a significant slowdown in the growth rate of the U.S. labor supply. We then introduce a simple framework to motivate why parallel trends in firm dynamics and labor supply are related economically.

2.1 Trends in U.S. firm dynamics and labor supply

Throughout the paper we use confidential data on employer businesses from the U.S. Census Bureau’s Longitudinal Business Database (LBD). To facilitate replication, whenever possible, we rely on the public-use tabulations available in the Business Dynamics Statistics (BDS). The LBD covers nearly all U.S. nonfarm private-sector establishments with employees starting in 1976.⁵ We construct firm-level measures by aggregating across each firm’s one or more establishments.⁶

We identify startups and distinguish incumbents based on firm age, which, to be consistent with prior literature, we calculate as the age of the firm’s oldest establishment. To measure firm-level employment (our measure of firm size), we aggregate

⁵The LBD is derived from the Census Bureau’s Business Register of all private-sector establishments with paid employees that is then longitudinally-linked at the establishment level. [Jarmin and Miranda \(2002\)](#) provide a detailed description of the linking procedure and LBD construction.

⁶The Census Bureau defines firm boundaries by the highest level of operational control.

employment across all establishments within a firm. Firm-level employment growth, g_{it} , is measured as the employment-weighted average of establishment-level employment growth across all of firm i 's year t establishments. We also consider measures defined at the age group cohort-, rather than firm-, level, where an age group cohort is the set of firms that belong to an age group in a particular year.

We measure firm exit in year t when all of a firm's year $t - 1$ establishments have 0 employment and are reported closed in year t . Similar to an age group's employment growth, we measure an age group's exit rate, x_t^a , as the number of exits in year t for the age group a as a fraction of the year $t - 1$ number of firms. While this measure is defined by age-group, we also compute the economy-wide exit rate, X_t , as the total number of exits as a fraction of the total number of (operating) firms in year $t - 1$. Following [Pugsley and Şahin \(2019\)](#), we refer to the measure of an age group's employment growth $1 + g_t^a = E_t^a/E_{t-1}^a$ as the *unconditional* growth rate, which we decompose as the product of a survival and conditional growth rate: $1 + g_t^a \equiv (1 - x_t^a)(1 + n_t^a)$.⁷

Changes in aggregate entry, exit and labor market growth. We first examine the trends in the startup and exit rates over the 1979-2007 period, which pre-dates any effects from the Great Recession.⁸ The startup rate has fallen almost 25 percent since 1979, from an average of roughly 13 percent to around 10 percent in 2007 (Figure 1a). While not apparent from the aggregate data, the decline in startup activity was widespread across sectors and locations, ruling out compositional shifts as the main cause—a finding that resonates with [Decker, Haltiwanger, Jarmin, and Miranda \(2014\)](#).⁹ The declining startup rate coincides with a decline in the economy-wide exit rate, which declines about 10 percent (1 percentage point) over the same period (Figure 1a). In contrast to the startup rate, lower exit rates are explained almost entirely by compositional change, specifically in *firm age*. As we show below, *within* age groups, the exit rate shows no comparable declines.

Over the same period, there are also declines in measures of labor supply growth

⁷For brevity, we include additional details in the data appendix (Appendix A).

⁸While early work on the changes in the startup rate and job creation from new and young firms, such as [Haltiwanger, Jarmin, and Miranda \(2011\)](#), [Gourio, Messer, and Siemer \(2014\)](#), and [Davis and Haltiwanger \(2016\)](#), focused primarily on the Great Recession and its slow recovery, we focus on the trend and examine the 1979 to 2007 period, *before* any influence from the Great Recession.

⁹We show that within-sector and within-geography changes account for more than 100 percent of the aggregate decline (Appendix C.1.2). We also show that entry declines are not specific to our measure of the startup rate (Appendix C.1.3).

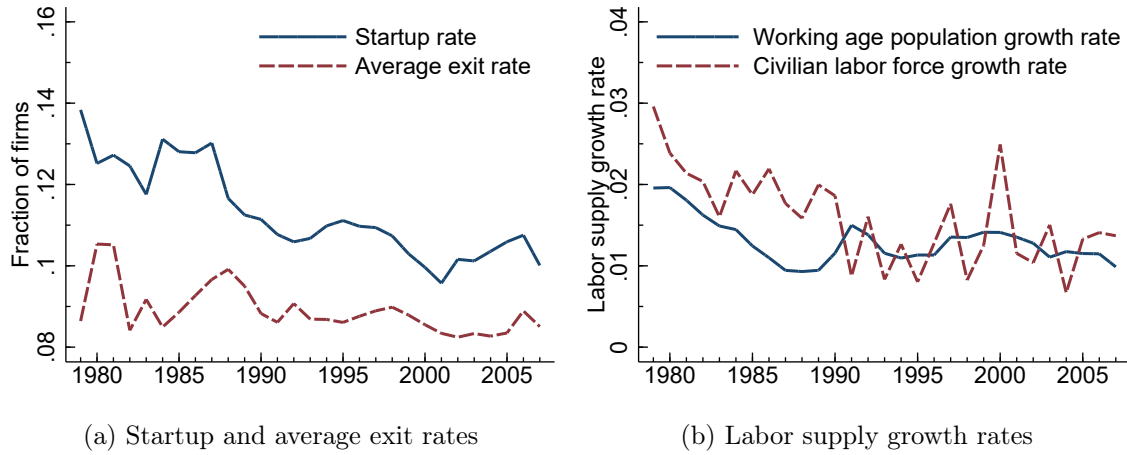


Figure 1: Declines of startup, exit, and labor supply growth rates from 1979 to 2012

(Figure 1b). The growth rate of the working-age population (WAP) surges in the 1960s as the first post-WWII baby boom birth cohorts enter adulthood, and peaks in the late 1970s.¹⁰ It then declines from almost 2 percent in 1979 to just over 1 percent by 2007. Importantly, this trend in labor supply growth was long pre-determined by historical changes in fertility that were plausibly unrelated to the business environment over the 1979-2007 period. Similarly, the growth rate of the civilian labor force (CLF), which includes all individuals age 20 or older currently employed or actively searching for a job, slows from about 3 percent in 1979 to 1 percent by 2007. The peak CLF growth rate is roughly 1 percentage point higher than the WAP growth rate since it adds the effects of rising female participation. After female participation levels off in the late 1990s, both measures grow at roughly 1 percent per year.¹¹

Stability of other margins by firm age. In contrast to the economy-wide entry and exit margins described above, other margins of firm dynamics are little changed once conditioned on firm age. We now examine this stability.

First, among startups, the distribution of employment size has been stable (Figure 2). Average startup size is procyclical but nevertheless remains centered around 6

¹⁰We define working age as 20-64, which is slightly more expansive than the 25-54 “prime-age” range. Participation among ages 20-24 and 55-64 is somewhat lower than prime-age, but it falls off steeply outside of ages 20-64.

¹¹These patterns are a reversal of the rapid labor supply growth in the 1960s and 1970s driven by “baby boomers” and women entering the labor force (Appendix C.1.1).

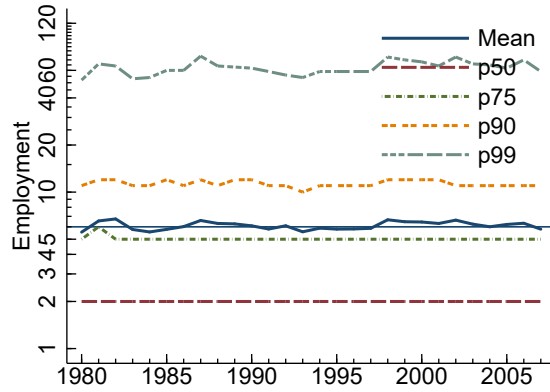


Figure 2: Distribution of startup employment size

Note: Thin reference line plots 1979-2007 average of 6 employees. Log scale; tick marks are placed for each employment size for 1 to 10 employees and in increments of 5 employees thereafter.

employees. This stability appears throughout the distribution. The median new firm had 2 employees from 1979 through 2007, while the 75th percentile has remained 5 employees, except for 1981. Even the 90th and 99th percentiles have remained close to their long-run averages of 11 and roughly 60 employees, respectively.

Next, we examine selection and the average growth of incumbent firms by age. The exit rate for firms age 1-10 (young) and firms 11 or more years old (mature) have been stable (Figure 3a). This may seem puzzling given the decline in the aggregate exit rate, but this decline reflects changes in composition; because mature firms have significantly lower exit hazards, the increasing share of old firms has reduced the economy-wide exit rate.

Finally, we note similar stability in average employment growth (Figure 3b). For both age groups, this conditional growth rate is procyclical, but there is no evidence that it is systematically drifting over time.¹² These patterns in exit and in employment growth rates are robust even when grouping by size and age (Appendix C.1.4).

Taking stock. Over almost three decades, economy-wide entry and exit rates have declined. These changes have been broad-based across sectors and geographic markets. Yet, conditional on firm age, exit and average employment growth have changed

¹²By construction, this measure corresponds to the average growth rate of an age-group cohort. While the average shows little or no change over time, Decker, Haltiwanger, Jarmin, and Miranda (2016) show that for young incumbents, skewness has declined over time. We later show that a decline in skewness, driven for example by increasing adjustment costs, has little effect on the equilibrium startup rate.

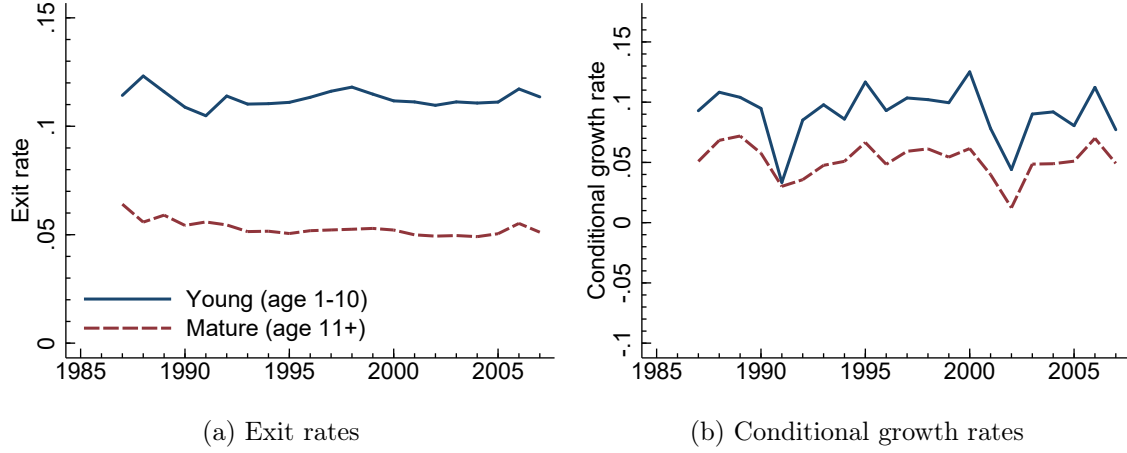


Figure 3: Incumbent exit and conditional growth rates for young and mature firms

little, and the size distribution of startups has been stable. These patterns naturally restrict the set of explanations for the startup deficit. For example, while rising entry costs reduce the startup rate, they also alter the size and profitability of new entrants and by extension their expected growth and survival. In contrast, declines in labor supply growth generate broad-based declines in the equilibrium startup and exit rates without altering other margins, except through changes in firm age composition. We show these effects first in a simple framework with homogeneous firms, which satisfies the stability restrictions by assumption. Later, in Section 3, we show the same effects of changes in labor supply growth in an equilibrium model with heterogeneous firms where the stability emerges endogenously.

2.2 A flow balance framework for the equilibrium startup rate

To see why changes in the growth rate of the labor supply might affect the firm entry rate, it is helpful to start with a simple model. Consider an economy with μ_t identically sized firms in year t and where M_{t+1} firms enter between years t and $t + 1$. The startup rate for this economy is $SR_t \equiv M_t/\mu_t$. Exit is *exogenous* at rate x . Labor supply, N_t , is growing exogenously at constant rate η . At full employment, the number of firms per worker, $\bar{\mu}_t \equiv \mu_t/N_t$, evolves as

$$\bar{\mu}_{t+1} = \frac{1-x}{1+\eta} \bar{\mu}_t + \bar{M}_{t+1}.$$

Here, $\bar{\mu}_{t+1}$ declines with increases in firm exit, x , and faster growth in the number of workers, η . Existence of a balanced growth path with a constant measure of firms per worker $\bar{\mu}$ requires that increases in labor demand equal the increases in labor supply, which is assured here by the constant average firm size. From the law of motion, we can determine that along such a balanced growth path, the startup rate must equal

$$SR = \frac{\eta + x}{1 + \eta}. \quad (1)$$

We refer to this as a “flow balance” startup rate, because it equates the inflow of new firms per worker with the outflows per worker, where outflows are determined both by the exit rate and by the growth in the number of workers.¹³ The faster the labor supply expands ($\uparrow \eta$) the higher the required startup rate, since as labor supply expands, the additional labor demand to clear markets must come from *new* firms. This feature follows immediately because of the assumptions of constant firm size and the exogenous exit rate, but as we will show in Section 3, it extends to a more realistic equilibrium setting where we relax these assumptions on size and exit.

In spite of its simplicity, this stylized framework is useful in assessing the quantitative importance of the demographic channel. We use equation (1) to compute the flow balance startup rates for the 1979-81 and 2005-07 periods using the average exit rate and the average WAP (CLF) measure of labor force growth (Table 1).¹⁴ The actual startup rate declined from its 1979-81 average of 13.0 percent to an average of 10.1 percent for 2005-07, a decline of 2.9 percentage points. For the same period, the flow balance startup rate from equation (1) using WAP (CLF) declined from 11.2 (11.7) percent to 9.7 (same) percent, a decline of 1.6 (2.0) percentage points. Looking across labor supply growth measures, the flow balance calculations explain roughly two-thirds of the decline in the startup rate.

Accounting for the declining startup rate requires exogenous changes in both labor supply growth and the exit rate. Changing only the labor supply growth rate while keeping the exit rate at its 1979-81 average, the startup rate declines 0.7 (1.0)

¹³This calculation is conceptually similar to the flow-balance employment calculation implemented in [Elsby, Michaels, and Ratner \(2017\)](#). They impose balance of inflows and outflows for each employment level in the establishment firm size distribution while we impose balance of the inflow of new firms per worker to the outflow of firms per worker.

¹⁴Average of HP filtered trends ($\lambda = 6.25$). Results are nearly identical if we instead predict annual flow balance startup rates and average over 3-year periods (Table C.1). We plot the entire time series for annual flow balance startup rates against the actual startup rate in Figure C.3.

Table 1: Actual and predicted flow balance startup rates

	Labor Supply Growth (%)		Exit Rate (%)	Startup Rate (%)		
	WAP	CLF		Actual	Predicted	
					η =WAP	η =CLF
1979-1981	1.9	2.5	9.5	13.0	11.2	11.7
2005-2007	1.1	1.1	8.7	10.1	9.7	9.7
Change	-0.8	-1.4	-0.9	-2.9	-1.6	-2.0

Note: Trend component of annual rates using HP filter and smoothing parameter 6.25 averaged over 3-year time periods. Startup rate, exit rate, and labor supply growth rates for working age population (WAP) and civilian labor force (CLF) measured as described in text. Predicted startup rates use flow balance equation (1) with 3-year averages for η and exit.

percentage points—about half of the decline predicted when both labor supply and exit are changed. Generally, the k -period startup rate change can be decomposed as

$$\Delta^k S R_t \approx \frac{\eta_t + x_{t-k}}{1 + \eta_t} - \frac{\eta_{t-k} + x_{t-k}}{1 + \eta_{t-k}} + \frac{\Delta^k x_t}{1 + \eta_{t-k}}. \quad (2)$$

The first two terms account for the difference from changes in labor supply and the last term accounts for the difference from changes in the exit rate.¹⁵ Applied using the averages from Table 1, when the measure of labor supply growth is WAP (CLF) the changes in labor supply alone account for 59% (46%) of the decline in the startup rate, and the change in the exit rate accounts for 40% (53%). Collectively, these calculations show the quantitative importance of changes in both labor supply growth and exit in explaining the majority of the decline in the startup rate.

While our simple framework quantifies the determinants of the declining startup rate, it has some clear limitations. First, exit is exogenous, and empirically, the declines in the exit rate are nearly as important as the declines in labor force growth in the flow balance calculation. While the demographic driven decline in labor force growth is plausibly exogenous, changes in exit are certainly not. Second, the assumption of constant firm size necessarily rules out incumbent employment growth and, by implication, any heterogeneity in age and size—all of which may interact with the changes in labor supply. Motivated by the findings of our simple framework, we extend a standard [Hopenhayn and Rogerson \(1993\)](#) model of equilibrium firm dynamics

¹⁵The residual “covariance” term $\frac{-\Delta^k x_t \Delta^k \eta_t}{(1+\eta_t)(1+\eta_{t-k})} \approx 0$ since both $\Delta^k x_t$ and $\Delta^k \eta_t$ are close to 0.

that relaxes these restrictions by endogenizing the exit and employment growth margins. Ultimately, the conclusions of the flow balance calculation are little changed, but the model reveals that the direct effects of the decline in labor force growth on the startup rate are amplified by a completely *endogenous* decline in the exit rate induced by a compositional shift towards older firms.

3 Firm dynamics with labor supply growth

In this section, we construct an equilibrium model of firm dynamics with endogenous entry, exit and labor supply growth, extending the workhorse [Hopenhayn and Rogerson \(1993\)](#) model, to demonstrate the significant effects of demographic changes in labor supply growth on the equilibrium startup rate.

3.1 Model

Our model economy consists of a continuum of firms that operate in a closed economy owned by a representative household of growing size and who supplies labor inelastically to the firms. Time is discrete, and there is no aggregate uncertainty.

Households. There is a representative household whose size is growing at rate η .¹⁶ Each member has one unit of time and identical preferences over sequences of per-capita consumption c_t , so that household preferences are ordered by

$$U = \sum_{t=0}^{\infty} [(1 + \eta)\beta]^t \log c_t, \quad (3)$$

where β is a time discount factor and $(1 + \eta)^t$ captures the cumulative growth in household size, having normalized its initial size to 1. We use consumption as the numeraire, and let w denote the price of labor. The household has access to a one period bond with risk-free return of r . In anticipation of studying the balanced growth path we have dropped time subscripts on equilibrium prices. Per-capita bond holdings in period t are denoted by b_t . Firms are owned by the households and all profits are distributed immediately as per-capita dividend π_t . The household supplies its full

¹⁶As is customary, we model population growth as a growing representative dynastic household rather than a growing population of fixed-size households. With an appropriately chosen discount rate, this choice makes no difference along a balanced growth path.

time endowment as labor and chooses consumption c_t and savings b_t to maximize (3) subject to the following budget constraint

$$c_t + b_t = (1 + r) \frac{b_{t-1}}{1 + \eta} + w + \pi_t. \quad (4)$$

Incumbent firms. The economy is populated by a continuum of firms that use labor as the only input to produce the consumption good. Each firm has access to a decreasing returns to scale technology, $f(a, s_t, n_t) = e^a s_t n_t^\theta$. Here, a denotes the permanent component of a firm's productivity and s_t denotes the stochastic component, which evolves exogenously according to an AR(1) process, $\log s_t = \rho \log s_{t-1} + \varepsilon_{t+1}$, where ε is normally distributed with mean zero and standard deviation σ_ε .

Firms pay a fixed cost c_f each period that they operate. In addition, adjusting employment from n_{t-1} to $n_t \neq n_{t-1}$ requires an adjustment cost of $\Phi(n_{t-1}, n_t)$. Both costs are denominated in units of output.¹⁷ After production firms may exit, either exogenously with some probability δ or by choice if the value of remaining operational becomes negative. This exit choice is prior to learning next period's productivity s_{t+1} .

Given real wage w and interest rate r , the value V of a firm with productivity $e^a s_t$, and employment n_{t-1} is given by the following Bellman equation

$$V(a, s_t, n_{t-1}) = \max_{n_t} e^a s_t n_t^\theta - c_f - \Phi(n_{t-1}, n_t) - w n_t + \frac{1 - \delta}{1 + r} \max_{X \in \{0,1\}} \{E_{s_t} V(a, s_{t+1}, n_t), 0\}. \quad (5)$$

The inner maximization reflects the end of period exit decision. Let $X(\cdot)$ denote the exit decision, which takes the value 1 if the firm decides to exit and 0 otherwise, and let $h(\cdot)$ be the decision for labor demand, n_t .

Entry. A perfectly elastic supply of potential new firms can enter the economy by paying an entry cost of c_e units of output. Upon paying c_e , firms draw the fixed component of productivity a from the distribution F and the initial stochastic component from the distribution G , and produce in the same period. This implies that potential

¹⁷We assume there is no aggregate trend in productivity growth, so that the choice of costs in terms of output rather than labor makes no difference along the balanced growth path.

entrants will choose to enter only when the following free entry condition holds:

$$c_e \leq \int V(a, s, 0) F(da) G(ds) . \quad (6)$$

This condition must be satisfied at equality in a balanced growth path with $\eta > 0$ since without entry the increases in labor demand needed to clear markets would require a declining real wage.

Entrant and incumbent dynamics. Let $\mu_t(A, S, N)$ be the measure of firms producing in period t with productivity components $a \in A$ (permanent) and $s \in S$ (persistent) and *previous* employment $n \in N$. This measure of firms includes new entrants, M_t , with draws $a \in A$ and $s \in S$, as well as incumbent firms with positive prior employment $n \in N$ that remained in business. We let $\bar{\mu} = \mu/H$ and $\bar{M} = M/H$ denote these objects per-capita (equivalently, per-worker). In per-capita terms, the measure of firms evolves according to

$$\begin{aligned} \bar{\mu}_{t+1}(A, S, N) = (1 - \delta) \int_{a \in A} \int_{s_t} \int_{h(a, s_t, n_{t-1}) \in N} (1 - X(a, s_t, n_{t-1})) P(S|s_t) \frac{\bar{\mu}_t(da, ds_t, dn_{t-1})}{1 + \eta} \\ + \mathbf{1}\{0 \in N\} \bar{M}_{t+1} \iint_{(a, s) \in A \times S} dF(a) dG(s) \end{aligned} \quad (7)$$

$P(s_{t+1} \in S|s_t)$ is the conditional probability implied by the AR(1) process for productivity. Previous period μ_t is scaled by $1/(1 + \eta)$ to express it in terms of this period's population (labor supply).

Closing the model. Using the per-capita measure above, aggregate profits per-capita are given by

$$\pi_t = \iiint (e^a s h(a, s, n)^\theta - w h(a, s, n) - c_f - \Phi(n, h(a, s, n))) \bar{\mu}_t(da, ds, dn) - \bar{M}_t c_e \quad (8)$$

This is the per-capita value of total production net of fixed, adjustment and entry costs. This dividend is paid to the representative household who owns all firms. Implicit in this definition is aggregate labor demand per-capita $\iiint h(a, s, n) \mu_t(da, ds, dn)$, which in equilibrium is equal to 1.

Balanced growth path. Given $\eta > 0$, a balanced growth path equilibrium consists of a constant real wage w , interest rate r , per capita consumption c , per capita savings b and per capita profits π , labor demand and exit policy functions h and X , measure of firms per capita $\bar{\mu}$ and a positive number of entrants $\bar{M} > 0$ such that i) given w , r and π that c and b are optimal given (3) and (4), ii) firm labor demand, $h(\cdot)$, and exit, $X(\cdot)$, maximize firm value in (5), iii) the free-entry condition (6) is satisfied at equality, iv) the per-capita measures of firms, $\bar{\mu}(\cdot)$, and entrants, \bar{M} , satisfy the law of motion (7), and v) per-capita profits satisfy equation (8) (market clearing).

3.2 Calibration

We calibrate the model to match key annual statistics of firm dynamics averaged over the 2005–2007 period. New entrants draw their permanent log-productivity a from a normal distribution with $a \sim N(0, \sigma_a^2)$. The initial condition s_0 for the stochastic component of productivity s is drawn from a lognormal distribution with $\log s_0 \sim N(\mu_0, \sigma_0^2)$ and then evolves according to the AR(1) process. When computing the solution, we discretize the state space for both the permanent and stochastic components of productivity.¹⁸ Adjustment costs are quadratic with $\Phi(n_{t-1}, n_t) = \gamma(n_t/(n_{t-1} + 1) - 1)^2$. Here, $\gamma \geq 0$ controls their magnitude.

Several parameters are set outside the model. We set the time discount rate to 0.96, which corresponds to an interest rate of around $\beta^{-1} - 1 = 4.2\%$. We set the curvature parameter of the production function θ to match the labor’s share of total revenue. This requires setting θ to 0.64. We set $\eta = 0.011$ to match the annual growth rate of the civilian labor force (and of the working age population) over the 2005–07 period. The remaining nine parameters are calibrated within the model. These parameters are: the entry cost c_e , the fixed operating cost c_f , the adjustment cost parameter γ , the exogenous exit rate δ , the productivity parameters σ_a , ρ and σ_ε and the parameters governing the distribution of startups μ_0 and σ_0 (Table 2).

Table 2: Internally calibrated parameters

Parameter values								
c_e	c_f	γ	δ	σ_a	ρ	σ_ε	μ_0	σ_0
6.856	1.898	0.003	0.026	0.163	0.970	0.101	−0.097	0.111

¹⁸For further details, please refer to Appendix B.1.

We estimate their values by minimizing the squared distance between a set of targets in the data and their model counterparts. We target exactly nine moments of firm dynamics in the 2005-07 period: the startup rate, the average size of startups and incumbent firms, and the exit and conditional growth rates of three year old firms in three size categories: 0–49, 50–249, 250+. Consistent with the previous section, to compute these moments in the data, we first HP filter each series with a smoothing parameter of 6.25, and then take the 3-year average for the 2005-07 period of the trend component. Our calibrated model captures the salient features of the U.S. firm dynamics very well in the 2005-07 period (Table 3).

Table 3: Model fit to targeted moments

Moment	Data	Model
Startup rate, %	10.1	9.8
Average startup employment	6.0	5.9
Average incumbent employment	22.5	23.0
Young exit rate by size, %		
1-49 employees	12.1	11.9
50-249 employees	2.5	2.6
250+ employees	2.6	2.6
Young conditional growth by size, %		
1-49 employees	4.3	4.4
50-249 employees	3.0	3.0
250+ employees	−4.9	−4.1

3.3 Equilibrium effects of changing demographics

We now use our calibrated model to provide a quantitative evaluation of the demographic channel.

Effects on the startup rate (and exit rate). Table 4 reports the effects on the startup rate and exit rate in the calibrated model when annual labor supply growth, η , is increased from 1.1%, its average over the 2005-07 period, to 1.9% (2.5%) to match the average WAP (CLF) growth in 1979-81. In response, the startup rate increases from 9.8% to 11.0% (11.9%), accounting for 41% (72%) of the actual change from 10.1% to 13.0%. This calculation is the structural model’s counterpart to the flow-balance calculation in Table 1 using equation (1), except the change in the aggregate

exit rate, x_t , is now endogenous.

Table 4: Effect of labor force growth on startup and exit rates

	Labor Supply Growth (%)		Startup Rate (%)			Economy Exit Rate (%)		
	WAP	CLF	Actual	Model		Actual	Model	
				WAP	CLF		WAP	CLF
1979-1981	1.9	2.5	13.0	11.0	11.9	9.5	9.3	9.7
2005-2007	1.1	1.1	10.1	9.8	9.8	8.7	8.8	8.8
Change	-0.8	-1.4	-2.9	-1.2	-2.1	-0.9	-0.5	-0.9

Note: Actual labor supply growth rates, startup rate and economy exit rate from Table 1. Model startup rates and economy exit rates in the 1979-81 period correspond to the balanced growth paths with only the higher trend labor supply growth (WAP or CLF) and all other parameters unchanged.

The simple framework from Section 2.2 assumed away heterogeneity in firm size and age, and relied on an exogenous decline in exit. In effect, shocks to labor supply growth could *only* be absorbed at the entry margin, since incumbent labor demand was assumed to be fixed. Here, these strong assumptions are relaxed. Decreasing returns generate downward sloping labor demand curves so that shifts in labor supply growth could be absorbed by incumbents, given a decline in the real wage. Nevertheless, free entry ensures that the real wage is fixed along the balanced growth path. Any shift in the real wage also changes the profitability of potential entrants, and entry adjusts to relieve any pressure on the real wage, ensuring the free entry condition (6) is satisfied. Consequently, one can show equation (1) still holds.¹⁹

In the model, unlike the simple framework, the exit rate declines *endogenously* with the reduction in labor supply growth. The decline in the startup rate changes the share of young firms. Since new and young firms are more likely to exit than older firms, this changes the aggregate exit rate through its effects on firm age composition. The model explains 55% (100%) of the observed decline in the exit rate using only the change in WAP (CLF).

Since the startup rate depends on the aggregate exit rate, the induced change in exit amplifies the effect of changes in labor supply growth. To see this, one can use equation (1) to calculate an elasticity in the structural model of the equilibrium

¹⁹This follows from integrating the law of motion in equation (7) for the balanced growth path over all firms. See Appendix B.2.

response of the startup rate to changes in labor supply growth η :

$$\frac{dSR}{d\eta} = \frac{1 - SR}{1 + \eta} + \frac{1}{1 + \eta} \frac{dx}{d\eta}. \quad (9)$$

Here, the first term captures the direct effect of the change in labor supply growth on the (net) growth rate in the number of firms, and the second term captures the indirect effect through the endogenous change in the aggregate exit rate. When calculated for the calibrated model, averaging across the early and late periods and approximating the exit rate elasticity with the changes between periods, the model elasticity is 1.5 (for both WAP and CLF). The direct effect accounts for 58% (59%) with the indirect effect accounting for the other 42% (41%) of the elasticity, closely matching the proportions from the simple framework.

Effects on other margins. Beyond the effects on the startup rate, the model also has implications for the response of other margins to shifts in demographics. Examining these implications and confronting them with the data provide a more complete evaluation of the demographic channel vis-à-vis other hypotheses for declining entry. Figure 4 shows how key margins of firm dynamics are affected by labor supply growth rate changes. The blue circle shows the 2005-07 calibration and the red square indicates the value of each margin when labor supply growth is increased to exactly match the 1979-81 startup rate.

A stark implication of labor supply growth changes is that the size of entrants and the expected growth and exit rates of incumbent firms conditional on age remain intact. That is because a change in labor supply growth has no direct effect on the value of a firm, and thus leaves the equilibrium wage unchanged. Firm employment and exit decisions therefore remain unchanged. The decline in labor supply growth is accommodated by a decline in entry of new firms, as opposed to a contraction of existing firms. This implication of the model is indeed consistent with the stability of these margins empirically (Section 2.1).

Effects on firm age composition. The stationarity of the exit margin may seem at odds with the decline in the economy-wide exit rate that the model predicts. However, this is easily reconciled by recognizing that declining firm entry tilts the firm age distribution towards older ones and that exit rates decline with firm age. Left panel of Figure 5 shows employment shares by firm age for different levels of η .

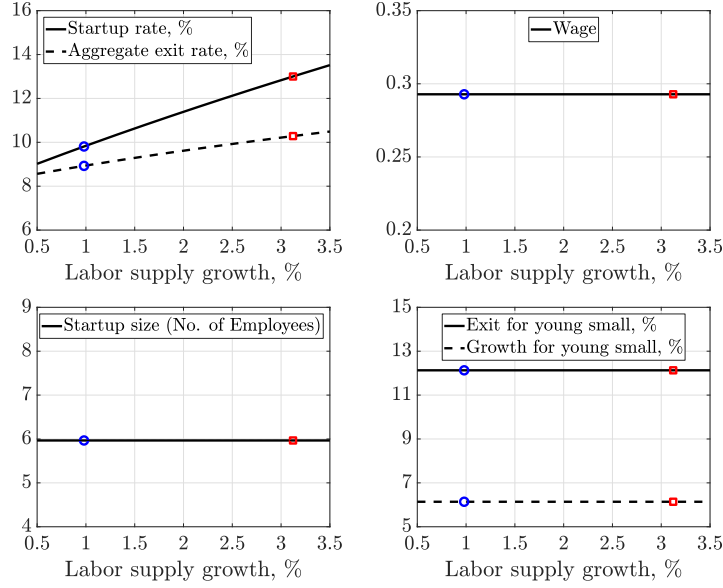


Figure 4: Labor supply growth and firm dynamics

Note: Four panels show how various dimensions of firm dynamics change with labor supply growth, η . Blue circle and red square correspond to values of η needed to exactly match the startup rate for '05-'07 and '79-'81 periods, respectively. Young small refers to age 3 firms with 1-50 employees.

The shift of employment to older firms is evident and consistent with the data.²⁰

A similar result holds for firm size by age. The stationarity of the conditional employment growth rates suggest little change in firm size by firm age. However, the average size of firms in the U.S. economy increased from 20.6 in 1979-91 to 22.6 in 2005-07. The intuition is identical to that of the exit rate. The shift in average firm size is a reflection of the change in age distribution of firms.

To summarize, our quantitative analysis has shown that the demographic channel successfully accounts for 40-70 percent of the decline in the startup rate and 55-100 percent of the decline in the exit rate. In addition, the implications of the demographic channel is remarkably in line with the stability of incumbent margins that have been the feature of U.S. firm dynamics in the last three decades.

²⁰This implication of the model is consistent with [Pugsley and Şahin \(2019\)](#), who using a decomposition framework show that the shift in firm age distribution in the data is the accumulated effect of declining firm entry. The mechanism in the model is precisely the same.

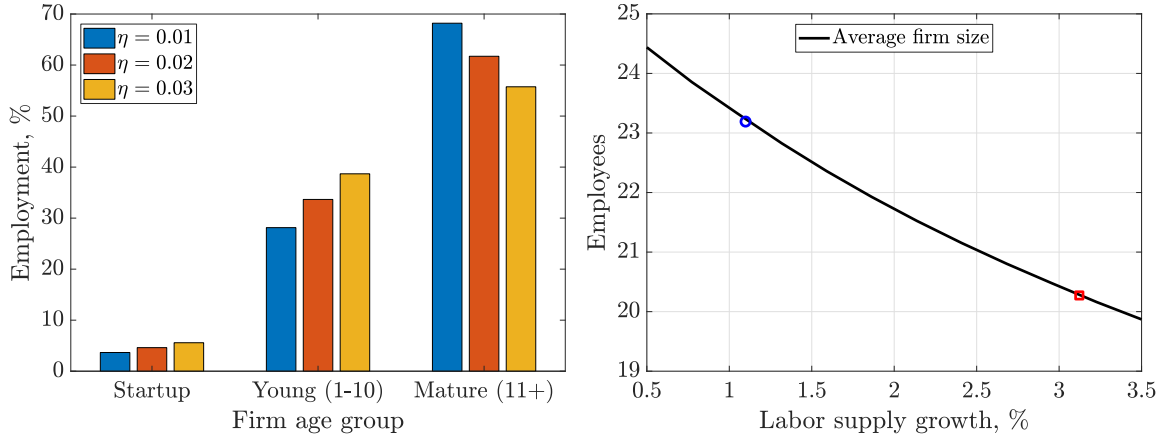


Figure 5: Effects of labor supply growth on firm age composition

Note: Comparative statics of calibrated model varying labor supply growth, η . Blue circle and red square correspond to values of η needed to exactly match the startup rate for '05-'07 and '79-'81 periods, respectively.

3.4 Considering cost-based channels

While the demographic channel accounts for the majority of the decline in the startup rate, changes in the cost structure could also depress the startup rate over time. A key question is how to evaluate the plausibility of potential changes in the economy's cost structure. Unlike the labor supply growth rate, the parameters governing costs do not have obvious empirical counterparts that are independent of the model structure. Since we cannot directly measure the levels and changes of various costs, we adopt the following indirect approach. Within the calibrated model, we ask how much of a change in each cost parameter is required to explain the decline in the startup rate. Then, given this required change, we examine whether the implications for startup size and incumbent exit and growth by firm age are compatible with those observed in the data for the 1979 to 2007 period. We consider changes in entry costs, fixed operating costs, and adjustment costs.

Changes in the entry cost. Stricter regulations and institutional constraints that make it harder for new businesses to enter could be responsible for the decline in the startup rate. The model captures this channel as a rise in the entry costs, c_e , and the effects of its changes can be analyzed by computing the balanced growth path equilibrium for a range of values around its calibrated value.

In Figure 6 we plot the comparative statics of each margin to changes in c_e ,

analogous to Figure 4 for labor supply growth. As before, the blue circle indicates the entry cost of the 2005-07 calibration and the red square indicates the entry cost necessary to generate the higher 1979-81 startup rate. It is apparent that changes in entry costs can match qualitatively the changes in the startup and aggregate exit rate observed in the data, although quantitatively the change in the predicted exit rate is significantly larger than observed in the data. This is a general feature: along the balanced growth path with positive labor supply growth, any induced changes in the startup rate increase the aggregate exit rate more than one for one.²¹

Figure 6 also shows that the effects of changes in entry costs on other margins are at odds qualitatively with the data. Unlike changes in labor supply growth, changes in entry costs affect the choices of startup and incumbent firms in equilibrium. Rising entry costs imply a declining real wage. While quantitatively the effects on firm growth are small, a declining real wage would significantly increase the expected size of new firms and decrease the expected exit rate of incumbent firms. Both of these implications are inconsistent with the stability we documented in Section 2.1.

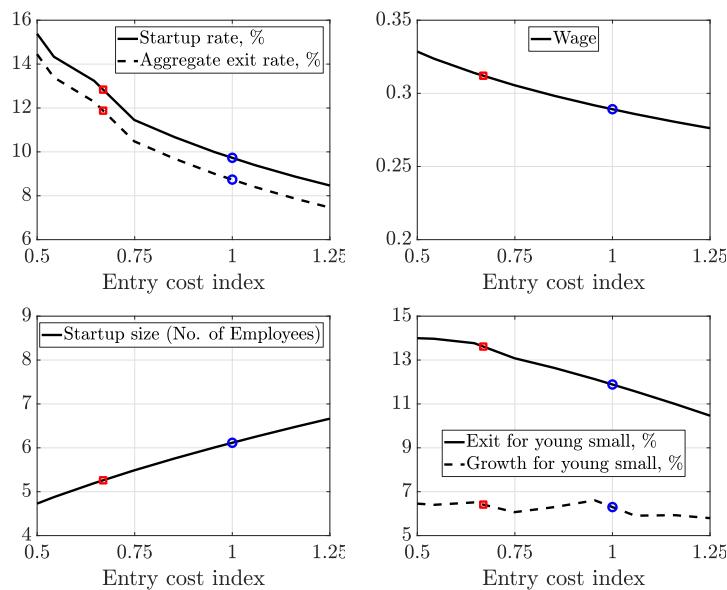


Figure 6: Entry costs and firm dynamics

Note: Four panels show how various dimensions of firm dynamics change with entry costs. Blue circle and red square correspond to values of entry cost needed to exactly match the startup rate for '05-'07 and '79-'81 periods, respectively. Young small refers to age 3 firms with 1-50 employees.

²¹An implication of equation 1 is that $\frac{dx}{dSR} = 1 + \eta$, which holds in equilibrium even with both SR and x are determined endogenously. Appendix B.2.

Calculating the *required change* in the entry cost to explain the decline in the startup rate is also useful in assessing the plausibility of this channel. This calculation corresponds to the horizontal gap between the red square and blue circle. For entry costs to explain the decline in entry, they should have been almost 33% lower in early 1980s (Table 5). This would also imply that the size of startups in 1979-81 would have been 14% lower, and exit and growth rates of young and small incumbent firms would have been 1.7 ppts and 0.1 ppts higher, respectively. Therefore, we conclude that the rise in entry cost is unlikely to be the major driver of the decline in firm entry since it has counterfactual implications for entrant size and incumbent exit rates. Moreover, there is little empirical evidence of such a big rise in entry costs.²²

Table 5: Implications of cost driven factors for firm dynamics

	Entry cost	Operating cost	Adjustment cost
Required change in parameter, %	−33.2	55.7	NA
Change in average startup size, %	−14.0	36.2	NA
Change in exit rate, ppts	1.7	2.2	NA
Change in conditional growth, ppts	0.1	0.9	NA

Note: Required change in each parameter (relative to 2005-07 calibration) to explain the 1979-81 startup rate of 13%, keeping all other parameters fixed.

Changes in the operating costs. Figure 7 conducts a similar exercise for fixed operating costs, c_f . For operating costs to explain declining entry, they should have *declined* over time. An increase in operating costs would have pushed up the productivity for remaining in business thereby increasing the exit and startup rates. The equilibrium effect is key for the result: without changes in labor supply growth, only changes in the aggregate exit rate can alter the startup rate.

As shown on Table 5, for operating costs to explain all of the decline in entry, they should have been 56% *higher* in the early 1980s. If operating costs were indeed that much higher, we also would have observed an average startup size that is 36% higher, and exit and growth rates of young and small incumbent firms that are 2.2 ppts and 0.9 ppts higher, respectively. These implications are clearly inconsistent with the stability of these margins. Furthermore, the required decline in operating

²²See Liang, Wang, and Lazear (2018).

costs over time stands in contrast to evidence of increasing regulatory costs of running a business in the U.S. (Davis and Haltiwanger, 2014).

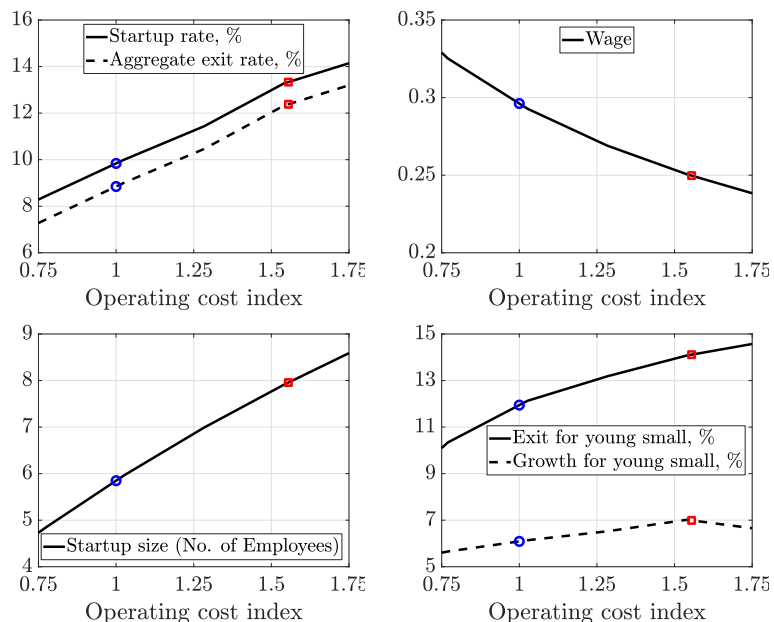


Figure 7: Operating costs and firm dynamics

Note: Four panels show how various dimensions of firm dynamics change with operating costs. Blue circle and red square correspond to values of operating cost needed to exactly match the startup rate for '05-'07 and '79-'81 periods, respectively. Young small refers to age 3 firms with 1-50 employees.

Changes in adjustment costs. In Figure 8, we study the effect of adjustment costs. While higher adjustment costs have a small effect on the size of new entrants, quantitatively even 50 percent deviations in adjustment costs do not have a measurable effect on the average firm value and thus no effect on the equilibrium real wage. They also have little if any effects on the exit or growth rates of incumbent firms. Without any effect on firm exit, conditional on firm age and size, they cannot change the startup rate vis-a-vis the aggregate exit rate. Even if empirically adjustment costs have increased, as found by Decker, Haltiwanger, Jarmin, and Miranda (2018), this should have had little effect, if any, on the startup rate.

To sum up, our quantitative analysis has shown that changes in the entry and operating costs can generate the observed change in the startup rate in the long run. However, such explanations of declining entry also have sizable effects on the behavior of incumbent firms. This is in contrast to the data where these margins are relatively

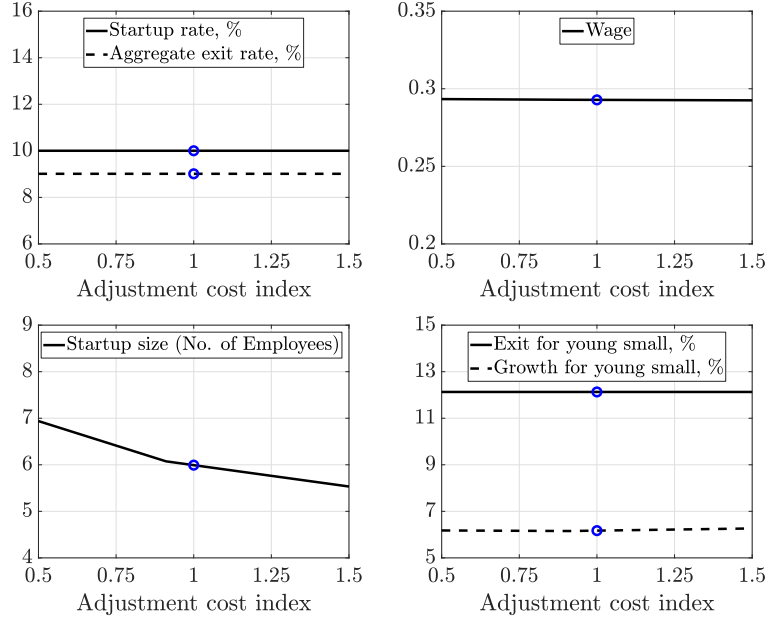


Figure 8: Adjustment costs and firm dynamics

Note: Four panels show how various dimensions of firm dynamics change with adjustment costs. Blue circle corresponds to values of adjustment cost needed to exactly match the startup rate for '05-'07. While a higher adjustment cost places a downward pressure on the startup rate, changes in the adjustment cost alone cannot account for declining entry since the '79-'81 period. Young small refers to age 3 firms with 1-50 employees.

stable over time. Moreover, the required changes in these cost parameters are quite large, for which no empirical evidence exists in the literature. Our analysis thus concludes that cost-based explanations have counterfactual predictions for various margins of firm dynamics. Demographic changes, however, keep those margins intact and therefore provide a credible explanation for the declining startup rate.

4 Evaluating the mechanism in the cross section

In this section, we evaluate the central predictions of the model using geographic variation in firm dynamics and demographics. Namely, we test whether (i) exogenous declines in the growth rate of labor supply reduce the firm entry rate and (ii) the change in entry rate absorbs the entire effect of the shift in labor supply growth, i.e., conditional on firm age, exit rates and employment growth are unaffected.

4.1 Empirical strategy

To evaluate the model’s testable implications, our empirical analysis compares the responses of startup rates and other key margins of firm dynamics to shifts in labor supply growth across states.²³ We estimate the following regression for margin y_{st} in state s in year t :

$$y_{st} = \alpha_s + \gamma_t + \beta_y g_{st} + \varepsilon_{st}. \quad (10)$$

The margins are identical to those in Section 2, i.e., the startup rate, startup size, and the survival and growth rates of young firms, except now measured at the state rather than national level.²⁴ The terms α_s and γ_t capture state s and year t fixed effects, respectively, and ε_{st} other unobserved determinants of the state-level firm dynamics margin y_{st} . The coefficient β_y is the (semi-) elasticity of margin y to changes in labor supply growth g_{st} . With the time-effect absorbing national changes in all variables, the coefficient captures only the relative responses across states within a year, and we refer to it as a cross-sectional elasticity.²⁵ We estimate these elasticities for each margin using the same proxies for labor supply growth, i.e. the growth rate of the entire population ages 20-64 and the growth rate of the civilian labor force as estimated by the BLS, also now measured at the state rather than national level.

The challenge with estimating these cross-sectional elasticities via OLS is that, even within a state, changes in the growth rate of labor supply are likely endogenous: the same unobserved time-varying features of the business environment within ε_{st} that affect firm dynamics may also influence labor supply. For example, states that become more profitable for incumbent firms may both attract new firms and new workers. A successful empirical strategy to measure the causal effects of labor supply growth on each margin must rely on plausibly exogenous shifts in labor supply growth. To generate variation in labor supply growth that is unrelated to other labor demand

²³Our choice of states as the unit of analysis requires mobility costs to be large enough to prevent geographic mobility from completely equating differences across these segmented labor markets. Drawing on Kennan and Walker (2011), who estimate an average moving cost of \$312,000 (in 2010 dollars), we argue this is likely the case. This cost encompasses psychic as well as monetary costs and suggests that labor market differences across-states are unlikely to be offset by geographical mobility. However, to the extent this is not true and mobility attenuates the local effects of labor supply shocks, our cross-state estimates will likely understate the effects of demographics on startups and incumbent dynamics.

²⁴See Appendix A.3 for additional detail on the state-level variable construction.

²⁵See the discussion of cross-sectional elasticities in Nakamura and Steinsson (2018) and references therein.

related factors, we use two distinct instrumental variables identification strategies.

Fertility instrument. Our first IV identification strategy uses within-state variation in labor supply growth rates predicted by past fertility. Specifically, similar to [Shimer \(2001\)](#) and [Karahan and Rhee \(2014\)](#), we instrument each state’s current labor supply growth rate with 20-year lags of its birthrate. To the extent that young adults enter the labor force in their state of birth, the state’s lagged birthrate will affect future labor supply growth.²⁶ We compute these annual state-level birth rates for the years 1959-1987, which we use to instrument labor supply growth for the years 1979-2007, a 20-year lag. We show below that lagged birthrates are a strong predictor of future labor supply growth, even after conditioning on state and year fixed effects.

This strategy relies on the exclusion restriction that conditional on state and year fixed effects, higher fertility or its determinants have no effect on future firms except indirectly through their effect on labor supply growth. This requires that any lagged economic conditions that had generated variation in past fertility rates are uncorrelated with current business conditions. The assumption would be violated, for example, if people in a given state had a higher fertility rate 20 years ago in anticipation of persistently (but not permanently) stronger labor market conditions relative to other states.²⁷

While we believe this to be a reasonable assumption, one potential caveat is that changes in birthrates may also shift the age composition of the future workforce together with the workforce growth rate, as the primary effect of increases in fertility is an increase in the future inflow of young workers.²⁸ This feature makes disentangling the effect of labor supply growth versus an effect from worker age composition difficult. To address this concern, we adopt a second strategy.

Migration instrument. We use an [Altonji and Card \(1991\)](#)-style instrument which utilizes differences across states in the historical patterns of inter-state migration. We

²⁶These birthrates are measured in births per thousand residents and are available in the various Statistical Abstracts of the United States. We are grateful to Rob Shimer for providing us with his digitized data from the Statistical Abstracts for the period 1940–91. For additional details on the fertility instrument construction, please refer to our data appendix, section [A.3.2](#)

²⁷We believe this is a reasonable assumption for business conditions far in the future although it may be violated over a shorter horizon. At the national level [Buckles, Hungerman, and Lugauer \(2018\)](#) find fertility to be a leading indicator of the business cycle for the 1990, 2001 and 2007 recessions and recoveries.

²⁸Fertility may also affect future labor supply composition through changes in female labor supply. See, for example, [Bloom, Canning, Fink, and Finlay \(2009\)](#).

rely on the lagged distribution of individuals’ birthplaces within each state, which can be measured using historical Decennial Census data. These lagged shares then serve as weights for adding up “pushes” from other states’ labor supply growth. Changes in the population growth of a state k will predict changes in the population growth of state $s \neq k$ if, historically, migrants out of state k tend to move to state s . We implement this idea as follows:

$$\hat{m}_{st} = \sum_{k \notin C(s)} \omega_{st^*}^k g_{kt}, \quad (11)$$

Here, $\omega_{st^*}^k$ is the share of residents of state s in time t^* that were born in state k and g_{kt} is the growth rate of the working age population in k at time t . In computing \hat{m}_{st} , we exclude states in the same Census Bureau division $C(s)$ since the labor supply growth in neighboring states, g_{kt} , may be related to state s business conditions. To isolate the historical component of migration patterns, we use the birthplace shares $\omega_{st^*}^k$ from 2 censuses ago, t^* ²⁹ Thus, if t is a census year (those ending in 0) then $t^* = t - 10$, and if t is an inter-censal year then t^* is the census year from the previous decade, e.g. for $t = 2005$, then $t^* = 1990$.

The identifying assumptions implicit in the exclusion restriction are two-fold. First, as with the fertility instrument, we assume that any changes in the lagged distribution of birth states, conditioned also on future time effects, are unrelated to differences across states in future business conditions and have no effect on firms except through their effects on labor supply. Second, we must assume that the “push” from source state k labor supply growth, g_{kt} , is also unrelated to the current business conditions in destination state s .³⁰ That is, labor supply growth rates in states outside of the same Census division are not driven in part by state s economic conditions.

First-stage regressions. We first examine the first-stage regressions for both instruments. The left panel of Figure 9 plots the variation in the working age population growth rate against the fertility instrument, where each variable has already been

²⁹We use the IPUMS microdata for the long form responses to the 1970, 1980, 1990 Decennial Censuses; see [Ruggles, Genadek, Goeken, Grover, and Sobeck \(2017\)](#). In 1979, the lag is 9 years ($t^* = 1970$ instead of 1960). See Appendix A.3.2 for additional details.

³⁰In appendix C.3.2, we consider alternative constructions of this instrument that relaxes this assumption. For example, given that lagged birthrates are a predictor of future labor supply, we can use state k lagged birthrates as an alternative “push” to state s . These alternative instruments are weaker, but give very similar results in the second stage estimation of equation (10) (Table C.11).

purged of state and time fixed effects. The horizontal axis plots, for each year and state, the state’s lagged fertility relative to its within-state average and the year’s between-state average. Notably, even conditional on permanent differences across states, there is considerable variation in residual birthrates.³¹ The vertical axis plots the corresponding residual working age population growth rate for each state and year. The positive correlation between these two measures confirms the relevance of the instrument. The slope is equal by construction to the coefficient on the instrument in the first-stage regression; a 10 percentage point increase in the lagged birthrate predicts a 1.4 percentage point increase in the growth rate of the working age population (Column (1) of Table 6). The birthrate instrument is also strong, with an F statistic of roughly 33.

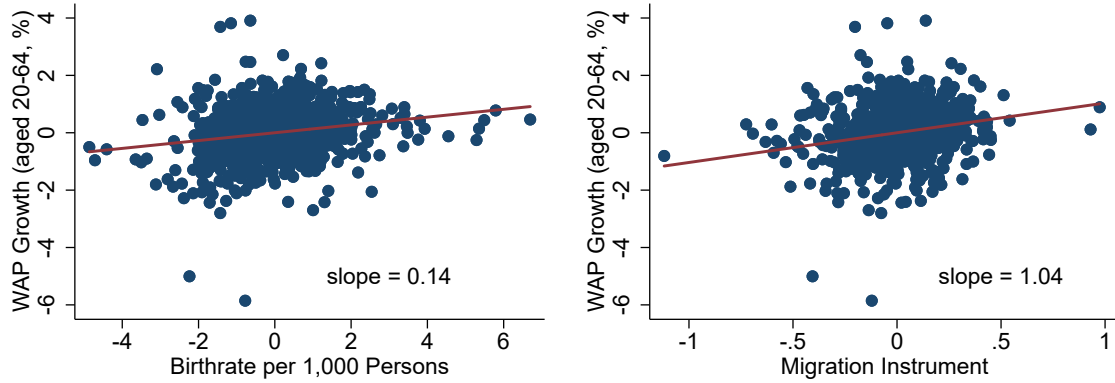


Figure 9: First-stage regressions of WAP growth rate on each instrument

Turning to the second instrument, the right panel of Figure 9 plots the variation in the working age population growth rate against the migration instrument, both residualized in a similar fashion by regressing on state and year dummies. The migration instrument, even after removing state and year fixed effects, varies significantly and predicts differences in states’ working age population growth rates. A one percentage point increase in the migration “push” instrument (a weighted average of other-state working-age population growth) predicts a 1.04 percentage point increase in own-state working-age population growth (Column (2) of Table 6). Although, not as strong as the birthrate instrument, the migration instrument is still a good predictor of working-age population growth.

³¹In appendix Figure A.1 we plot this residual variation in birthrates (averaged across decades) on a map of U.S. states.

Table 6: Regression of startup rate on working-age population growth

	First Stage			OLS	IV ₁	IV ₂	IV ₁ &IV ₂
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WAP Growth (%)				0.61 (0.05)	1.09 (0.32)	1.27 (0.22)	1.19 (0.22)
Birthrate IV	0.14 (0.02)		0.11 (0.02)				
Migration IV		1.04 (0.30)	0.87 (0.28)				
<i>N</i>	1,421	1,421	1,421	1,421	1,421	1,421	1,421
<i>R</i> ²	0.64	0.64	0.65	0.90	0.87	0.85	0.86
<i>F</i> -test	32.65	11.83	17.48				
<i>p</i> -value of <i>J</i> -test							0.55

Note: Standard errors are clustered on state. Regressions contain state and year fixed effects and cover years 1979-2007 and 48 contiguous states plus D.C.

The migration instrument also contains independent information for the growth rate of working age population. Column (3) of Table 6 shows that each instrument has predictive power conditional on the other. Further, the migration instrument does not have any systematic effect on the age composition. The partial R^2 of including the migration instrument in a regression of the 20-34 year old share of the working age population on state and year fixed effects is only 0.005.³² Both instruments perform equally well in predicting growth of the civilian labor force (Appendix Table C.5).

4.2 Labor supply growth and the startup rate

We now turn to our main results evaluating the role of shifting labor supply growth in declining startup rates. To this end, we estimate equation (10) on pooled state-level data for the period of 1979-2007. Our benchmark estimates use the growth rate of the working age population as a proxy for labor supply growth, but they are robust to the alternative civilian labor force growth measure.³³ All specifications include state and year fixed effects. Where possible, we utilize the publicly-available data from the BDS

³²See Appendix Table C.10 for the regression of the share of young workers on each instrument and their combination.

³³For brevity, we present the full set of results using the civilian labor force growth as our proxy for labor supply growth in Appendix C.2.1

so that others can easily replicate the results; we turn to the confidential micro data from the LBD when necessary to include detailed industry controls.³⁴ Throughout, standard errors are clustered by state.

We start by presenting the OLS estimate. Column (4) of Table 6 shows that a one percentage point increase in labor supply growth is associated with a 0.61 percentage point increase in the startup rate. This is a nonnegligible effect. Over our sample period, the startup rate declined by 2.9 percentage points. If the elasticity is applied to the aggregate changes, the OLS estimate implies that the 0.8 percentage point decline in working-age population growth explains 16.8 percent of the decline in the startup rate. As we discussed, a major concern with a causal interpretation of the OLS estimate is that the realized labor supply growth rates may be correlated with state-level demand shocks. To identify the causal effect of declining labor supply shifts, we turn to our instrumental variables estimates.

Column (5) of Table 6 presents the results using the lagged birthrate instrument. According to this estimate, a one percentage point reduction in the working age population growth rate leads to a 1.09 percentage point decline in the startup rate. In terms of the aggregate changes over the period, the estimate implies that the 0.8 percentage point decline in the working age population growth rate can explain 30.1 percent of the decline in the startup rate.

One concern is that this estimate may reflect both the effects of a labor supply growth shift and the effects of any follow-on changes in the worker age composition. Because changes in fertility will predict future labor supply growth primarily through changes in the inflow of young workers, it may also change the age composition of the labor supply. Although we see little evidence of this (Appendix Table C.10), to the extent that it is the case, then our estimates could also reflect any effect of the aging population on business formation and may either under- or over-state the effects of shifts in labor supply growth.

To avoid contaminating our estimates of labor supply growth effects with any effects from an aging workforce, we utilize the migration instrument discussed in Section 4.1. We re-estimate equation (10) now instrumenting labor supply growth rates with the migration instrument, which we report in column (6) of Table 6, and

³⁴Special sworn researchers may request the replication files to be transferred from Census project 908 if the analysis as well as LBD and SSL databases are within the scope of their Census project. See Appendix A.1 for additional details.

with both the migration and lagged birthrate instrument in column (7). The point estimates for both specifications point to somewhat larger effects, although they are statistically close to those using just the birthrate IV. Using the migration IV alone, the elasticity is 1.27 (explains 35.0 percent of the aggregate startup rate decline) and when combined with the birthrate IV, the elasticity is 1.19 (explains 32.8 percent of the aggregate startup rate decline). Incorporating two instruments also permits a J test of over-identifying restrictions, which we would fail to reject at any level below 0.55. Given the similarity of the estimates, going forward, we take the results using both IVs, Column (7), as our benchmark.³⁵ This benchmark estimate of roughly 1.2 is smaller but consistent with the elasticity of 1.5 in the quantitative model.

The statistical significance of the estimates and their quantitative stability across alternative sources of variation are a robust feature of the data. We consistently find an elasticity slightly larger than 1, which when multiplied by the roughly 0.8 percentage point decline in the aggregate working age population growth rate explains about one-third of the aggregate decline in the startup rate. We explore here the robustness of this result to several choices and report three main robustness checks: allowing for detailed industry controls, using the civilian labor force growth as the labor supply growth measure, and allowing for state-specific trends.³⁶

Industry controls. Our benchmark results are based on cross-state variation pooled over time to measure the responsiveness of the startup rate to demographic shocks. Demographic shocks, in theory, could also affect the industry composition of production in a state and change the state’s startup rate purely through an industry compositional shift. Instead of supporting evidence for the equilibrium entry mechanism, it is possible that our results might only reflect demographic shocks shifting economic activity towards high-entry industries, such as those common in the service sector. In contrast, our mechanism would predict an across the board decline in entry

³⁵ It may seem puzzling that the estimated effects on the startup rate by OLS are roughly half as large as those estimated using the two instruments individually or in conjunction. However, this finding is consistent with the predictions of the model. If uninstrumented growth in the labor force within a state is driven both by labor supply shocks and labor demand shocks, then the startup rate elasticity should be smaller, since labor demand shocks will also affect the survival and growth of incumbents and reduce the required change in the equilibrium startup rate.

³⁶We present additional analyses in a robustness appendix including: the full set of results using CLF (Appendix C.2.1), allowing for spatial correlation (Appendix C.2.2), establishment level startup rates (Appendix C.2.3), alternative time periods (Appendix C.2.4), and alternative IV construction (Appendix C.3.2).

in response to a demographic shock, i.e., an effect within industry.

To address this concern, we use data from the confidential Census Bureau Longitudinal Business Database (LBD), which provides detailed industry information at the firm level. We aggregate these data to form startup rates by year, state, and 4-digit NAICS industry.³⁷ Now using these detailed data, Panel A of Table 7 reports the estimated response of the startup rate to demographic shocks when including 4-digit industry dummies in addition to the state and year fixed effects. The first column reports the OLS estimate, and the next three columns report the estimates using the fertility, migration, and combined instruments, respectively. In all cases, the estimates are very similar to the ones without detailed industry controls, which is in line with the implications of our theoretical framework. Since the effects are present even within detailed industry, our estimates do not reflect changes in industrial composition that may have coincided with shifts in labor supply growth.

Different measure of labor supply. Our main proxy for labor supply, working-age population, counts people regardless of labor force status. While demographic change is one important factor in driving long-run changes in labor supply, another important margin is change in labor force participation, especially among women. Since the 1960s, female participation has increased, at first sharply and then more gradually, eventually leveling off by the late 1990s. Our state-level analysis might yield biased results if changes in female labor force participation across states are correlated with the changes in working age population growth predicted by the instruments. To evaluate this possibility, Panel B of Table 7 reproduces the same analysis using the growth rate of the civilian labor force as the main dependent variable. The estimates using the IV strategy are similar to those in Table 6 and in the case of the benchmark estimate using both instruments, nearly identical. For brevity, we provide the full set of results across all margins using civilian labor force as the labor supply proxy in Appendix C.2.1.

State-specific trends. Another concern is that the elasticity we estimate may actually reflect state-level secular trends in business dynamics unrelated to demographics affecting both the startup rate and the instruments. For example, a state could have persistent long-run declines in both the startup rate and fertility. State

³⁷We use the Fort-Klimek measure of NAICS industry (Fort and Klimek, 2016). For additional details on industry assignment, please refer to Appendix A.1.2.

Table 7: Robustness of effect of labor supply shocks on the startup rate.

	(1)	(2)	(3)	(4)
	OLS	IV ₁	IV ₂	IV ₁ & IV ₂
<i>Panel A. Detailed industry controls</i>				
WAP Growth (%)	0.62 (0.06)	0.89 (0.25)	1.14 (0.20)	1.06 (0.20)
<i>N</i>	300,000	300,000	300,000	300,000
<i>R</i> ²	0.51	0.51	0.50	0.51
<i>J</i> -test <i>p</i> -value				0.25
<i>Panel B. Alternative labor supply measure</i>				
CLF Growth (%)	0.23 (0.04)	1.38 (0.61)	1.14 (0.28)	1.21 (0.28)
<i>N</i>	1,421	1,421	1,421	1,421
<i>R</i> ²	0.87	0.44	0.60	0.56
<i>J</i> -test <i>p</i> value				0.70
<i>Panel C. State-specific trends</i>				
WAP Growth (%)	0.58 (0.05)	1.11 (0.21)	1.57 (0.29)	1.32 (0.19)
<i>N</i>	1,421	1,421	1,421	1,421
<i>R</i> ²	0.92	0.89	0.82	0.86
<i>J</i> -test <i>p</i> -value				0.10

Note: Standard errors clustered on state. All regressions use specification and sample from Table 6 with the following change: Panel A is industry by state by year startup rate and includes industry (NAICS4) fixed effects (and only years 1980-2007); Panel B uses the civilian labor force growth rate in place of working age population growth rate; Panel C includes state-level linear trends.

fixed effects would control for the permanently low startup rates and fertility, but not for continued declines in both. Our empirical strategy would interpret the within state parallel declines as evidence of a positive elasticity. To examine whether our results may be affected by state-level secular trends, we consider an additional specification where we allow the state effect to have a linear trend, i.e. we replace the state fixed effect α_s in equation (10) with time varying $\alpha_{st} = \alpha_{0s} + \alpha_{1s}t$. To the extent that $\alpha_{1s} \neq 0$ for any state, we now estimate the elasticity β by comparing each state's changes relative to their linear trends of the startup rate and the (instrumented) labor supply growth rate. The time effects already remove any aggregate trends in the variables.

We re-estimate (10) allowing for state fixed effects and state-specific linear trends and report the estimates in Panel C of Table 7. The OLS estimate is nearly identical to the benchmark in Table 6. When estimated using the instrumented labor supply growth, the elasticities are slightly larger than the corresponding benchmarks.

Collectively, these robustness analyses paint a consistent picture of the effects of changes in labor supply growth on the startup rate. Across all specifications, when interpreted in terms of the aggregate changes, labor supply growth explains between 10 and 60 percent of the decline in the startup rate. Looking just at the range of instrumented estimates, this range narrows considerably to between 35 and 60 percent. As we show below, the cross-sectional evidence also supports the model’s predictions for additional margins of firm dynamics.

4.3 Effects on incumbent exit and growth

The model implies that changes in labor supply growth rates should *not* affect the growth and survival rates of incumbent firms. These predictions are the flip side of the strong effect on the startup rate; the free entry condition implies all adjustment to a labor supply growth rate shift is on the entry margin and thus relieves any pressure on real wages that would otherwise shift incumbent dynamics or the labor demand of new firms.

We test these predictions for incumbent selection and growth by estimating equation (10) using several additional margins of firm dynamics as outcomes. We find that shifts in labor supply growth have no statistically significant effect on startup size or on survival and employment growth rates, conditional on firm age. We present these results in Table 8. It is helpful to start with Column (2), which estimates labor supply growth elasticity for each margin using differences across states in labor supply growth rates predicted only by past fertility. For average startup size (Panel A), the exit rate of young firms (Panel B) and their conditional growth rate (Panel C) the estimates are statistically indistinguishable from zero.³⁸

Even economically the point estimates are small. The average startup size in a state with 1 percentage point faster labor supply growth would fall by about 0.3 employees, which is about 5% below the average of about 6 employees across all states and years. The same 1 percentage point faster labor supply growth would increase

³⁸The conditional growth rate refers to the within cohort growth in average firm size (Section 2.1).

Table 8: Effects of labor supply shocks on additional firm margins

	(1)	(2)	(3)	(4)
	OLS	IV ₁	IV ₂	IV ₁ & IV ₂
<i>Panel A. Average startup employment</i>				
WAP Growth (%)	0.03 (0.04)	-0.27 (0.18)	-0.05 (0.15)	-0.15 (0.14)
<i>N</i>	1,421	1,421	1,421	1,421
<i>R</i> ²	0.45	0.41	0.45	0.43
<i>J</i> -test <i>p</i> -value				0.20
<i>Panel B. Young firm exit rate (%)</i>				
WAP Growth (%)	-0.37 (0.04)	0.12 (0.21)	-0.21 (0.21)	-0.01 (0.15)
<i>N</i>	1,029	1,029	1,029	1,029
<i>R</i> ²	0.74	0.68	0.73	0.71
<i>J</i> -test <i>p</i> value				0.34
<i>Panel C. Young firm conditional growth rate (%)</i>				
WAP Growth (%)	0.75 (0.19)	-0.84 (0.65)	-0.11 (1.07)	-0.54 (0.75)
<i>N</i>	1,029	1,029	1,029	1,029
<i>R</i> ²	0.41	0.33	0.39	0.36
<i>J</i> -test <i>p</i> -value				0.45

Note: Standard errors clustered on state. Young firms (ages 1-10) do not include startups. All regressions use RHS specification and sample from Table 6 with the following additional LHS margins: Panel A is average employment size of startup firms; Panel B is the survival rate in percent of young firms; Panel C is the young firm within-cohort percent growth in average firm size. Panels B and C of young incumbents use years 1987 to 2007, because of birth year censoring.

the exit rate of firms ages 1 to 10 in the state by about 0.1 percentage points (less than 1 percent of the average exit rate of 11 percent), and reduce their conditional growth rate by 0.8 percentage points (a little less than 10 percent below the average of 8.9 percent). We condition on firm age since in the presence of the long-run declines in entry, the overall age composition is slowly shifting towards older firms. The incumbent regressions use data starting in 1987, which is the first year where we can identify firms ages 1 to 10 because of birth year censoring.³⁹

³⁹The shorter 1987 to 2007 time span has no effect on the main results. See the discussion in our robustness appendix, Section C.2.4.

When estimated using differences in labor supply growth predicted only by the migration instrument (Column (3)) or both the fertility and migration instrument (Column (4)), the results are even closer to zero. The point estimates for average startup size and the conditional growth rate remain positive; the estimated elasticity for the exit rate actually changes sign. For startup size, exit, and growth, the results are quantitatively and statistically insignificant for a test of any reasonable size.⁴⁰ For the benchmark results in Column (4) the p-values of a zero elasticity null are 0.29, 0.94 and 0.47, respectively. The insignificant cross-state responses to exogenous shifts in labor supply growth are consistent with the aggregate response predicted by the model in Section 3.

The small, or non-existent, effects we find using exogenous shifts in labor supply growth, however, stand in contrast to those estimated using all variation across states (Column 1). While the effect on startup size is still zero, the exit rate for young firms declines and the conditional growth rate increases. Since OLS uses variation in labor market growth that may also be determined by local economic conditions, these results are unsurprising. If labor markets are growing due to increases in local profitability, which increase labor demand, incumbent firms would be less likely to exit and more likely to expand. These patterns also help explain the consistently smaller elasticity of the startup rate estimated via OLS found throughout Tables 6 and 7; the additional increases in incumbent labor demand from less exit and more growth require a smaller response along the entry margin. Incumbents respond in this case because of the direct effects of the boost in profitability, whereas shifts in labor supply growth affect incumbents indirectly through short-run changes in the real wage.

Overall, the cross-state evidence supports the labor supply growth mechanism in the model both qualitatively and quantitatively. When using plausibly exogenous shifts in labor supply growth identified via historical fertility or inter-state migration patterns we estimate an elasticity for the startup rate that accounts for one-third to one-half of the aggregate decline. Admittedly, while the product of the estimated cross-sectional elasticity of the startup rate and the aggregate decline in labor supply growth is a helpful reference point, and it provides one estimate for the aggregate effects of the demographic change, there are important caveats. First, our identification by construction suppresses general equilibrium effects by looking at variation

⁴⁰These patterns are identical for the Civilian Labor Force proxy of labor supply growth.

across states within each year. Second our estimation may not necessarily identify the long-run effects as it uses year-to-year variation.

Finally, as implied by the model, the same shocks have no significant effect on the size of new entrants, nor the average survival and growth patterns of incumbent firms, conditional on firm age. Beyond a test of the benchmark model in Section 3, these cross-state regressions also provide empirical restrictions to evaluate more intricate models of firm dynamics. Next, we consider the aggregate time-series predictions of the benchmark model.

5 Evaluating the mechanism in the time-series

As a final test of our hypothesis, we assess the principal time-series implication of the mechanism. Namely, the startup rate should co-move with the labor supply growth rate, including the roughly two decades since 1960 marked by *increases* in both measures of labor supply growth. The difficulty with examining this implication directly is the absence of longitudinal firm-level data over this entire period.

To address this challenge, we provide a novel method to impute an aggregate startup rate over the longer time span. Although we lack comprehensive longitudinal data prior to 1977, the Census Bureau has collected annual tabulations of establishments by county and size since 1964 as part of its County Business Patterns program.⁴¹ These static data do not contain any measures of entry, but we propose a methodology to impute a historical aggregate entry rate series from these detailed cross sections. Essentially, we recover the number of startup establishments or “gross entry” by summing the net change in the stock of establishments with the number of exiting establishments. Since the latter cannot be observed, we predict exits using a simple statistical model based on the establishment size distribution.

Imputing the startup rate. Our imputation methodology begins with a simple law of motion for the total number of establishments e_t

$$e_t = (1 - x_t)e_{t-1} + s_t,$$

⁴¹For further details on the CBP data, see Appendix A.4

where x_t is the average establishment exit rate and s_t is the number of startup establishments. Given annual establishment counts and an average establishment exit rate, we could trivially recover the number of startup establishments using the law of motion. While the establishment counts are readily available in the CBP, to our knowledge, there are no measures of U.S. establishment exit rates prior to the LBD.

Instead, we propose to predict exit using the annual state-level employment size distributions observable in the CBP. The aggregate exit rate can also be written as an establishment-share weighted average across states s and size groups j

$$x_t = \sum_s \sum_j x_t^{sj} \frac{e_{t-1}^{sj}}{e_{t-1}}.$$

We condition on both size group and state, since both characteristics are also easily measured in the LBD and BDS data. We estimate a model for each x_t^{sj} “in sample” using the longitudinal data and then predict \hat{x}_t^{sj} “out of sample” in the CBP. With these predicted values in hand, we plug the predicted exit rate into the law of motion. When normalized by e_{t-1} to express in terms of rates, this procedure imputes the establishment startup rate as

$$\frac{\hat{s}_t}{e_{t-1}} = \frac{\Delta e_t}{e_{t-1}} + \sum_s \sum_j \hat{x}_t^{sj} \frac{e_{t-1}^{sj}}{e_{t-1}}. \quad (12)$$

That is, we recover a “gross” entry rate or startup rate from summing the “net” entry rate (the growth rate of the number of establishments) with our predicted aggregate exit rate.

To implement the imputation from equation (12) we use six size categories {1-19, 20-49, 50-99, 100-249, 250-499, 500+} and all 50 states plus the District of Columbia.⁴² In the absence of observed exit rates by state and size category for the CBP, we estimate exit rates by size group and state in the BDS for the years 1980 to 2007 using a simple linear time trend

$$x_t^{sj} = \bar{x}^{sj} + \lambda^{sj}t + \varepsilon_t^{sj}. \quad (13)$$

We then predict \hat{x}_t^{sj} for the CBP using the fitted values from 1980 to 2007 and holding

⁴²Our choice of 500+ as the largest category is not restrictive since average exit rates vary little among large firms.

exit rates constant at their predicted 1980 values, \hat{x}_{1980}^{sj} , for 1965 to 1979.⁴³ We discuss some alternative assumptions below, and our results are qualitatively unchanged.

Historical startup rate. The imputed establishment startup rate confirms the central prediction of our mechanism. To see this we start with Figure 10, which plots the imputed establishment startup rate for 1965-2007 and the actual establishment startup rate for 1979 to 2007 measured from the BDS. The imputed establishment entry rate increases throughout the period of increasing labor supply growth. Although the annual data are noisy, a linear trend estimated from 1965 to 1979 shows a significant upward trend in the entry rate over the exact period of increases in our two measures of labor supply growth. This is exactly the time-series prediction of our mechanism where shifts in the growth rate of labor supply are accommodated primarily along the firm entry margin.

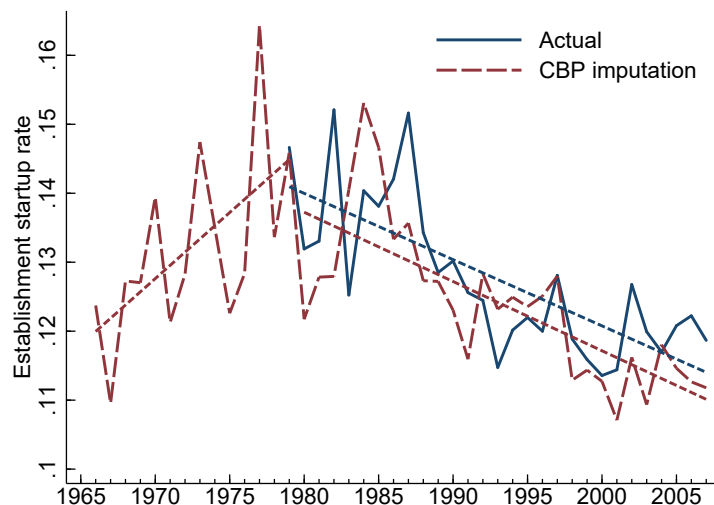


Figure 10: Imputed historical establishment entry rates and the BDS entry rate.

Note: Actual establishment startup rate measured in the BDS. CBP establishment startup rate imputed using equation (12) and interpolated across dropped years 1974 and 1983.

There are two additional features to note. First, the establishment startup rate declines significantly over the 1979-2007 period. One limitation of the CBP is that we can only impute an establishment entry rate. However, since the vast majority of new establishments are also new firms, the declines in establishment and firm startup rates

⁴³We drop years 1964, 1974, and 1983 from the imputation because of significant data quality problems.

are very similar.⁴⁴ Second, for the period in which they overlap, the imputed startup rate tracks on average the path of the BDS establishment startup rate relatively well. Linear trends estimated over the 1979-2007 period for both series are very close, confirming that the method for predicting exit rates performs reasonably well.

The hump shaped pattern in the imputed establishment entry rate is robust to alternative assumptions on the path of establishment exit. Our baseline imputation holds the exit rate by size and state constant before 1979. The hump shape persists whether we use a constant average exit rate by size or even extrapolate the downward trend to the pre-1980 period (Appendix C.4). The trend controls for the gradual declines in exit rate within size-group from changes in age composition induced by changes the declines in entry. If anything, a higher establishment entry rate over the earlier period would increase average exit from the same age composition channel. If we were instead to extrapolate exit over the earlier period by reversing the sign on the trend term, the hump shaped pattern would be even more pronounced.

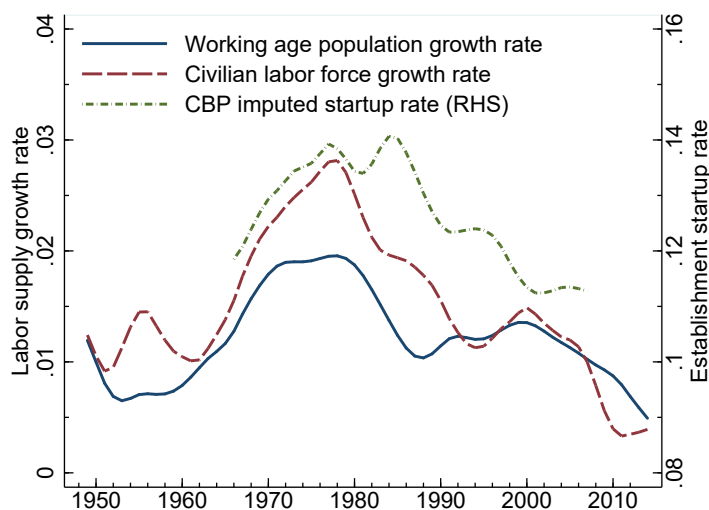


Figure 11: Imputed historical startup rate and measures of labor supply growth

Note: WAP is ages 20 to 64. CLF is measured for the adult (20+) civilian non institutional population. Establishment startup rate is imputed from the CBP using equation (12). Growth rates and startup rate are HP filtered with a smoothing parameter of 6.25, consistent with [Ravn and Uhlig \(2002\)](#) for annual data, to estimate the trend component.

Collectively, the time series evidence strongly supports the labor supply growth

⁴⁴Over the 1979-2007 period, the firm startup rate declines from roughly 13 to 10 percent, whereas the establishment startup rate declines from roughly 14 percent to 12 percent.

mechanism. To see this most clearly, in Figure 11 we apply an HP filter to the annual data for both measures of labor supply growth and the imputed establishment startup rate and plot the trend components. Here, the comovement of startup rate with the measures of labor supply growth is clear. The decline in the startup rate is a reversal of its earlier increases, mirroring the hump-shaped patterns for labor supply growth.⁴⁵

6 Conclusion

The startup rate has been trending down since the series begins in the late 1970s, raising some alarm over the decline in U.S. entrepreneurship. In this paper, we identify declines in the growth rate of the labor supply—long preordained by demographics—as the leading cause the startup rate’s decline, explaining 50 to 70 percent of the decline, depending on the measure of labor supply growth. In fact, the underlying equilibrium link between labor supply growth and the startup rate, although previously unexamined, is an inherent feature of standard models of firm dynamics. The explanation fits the data remarkably well, as we show in three independent ways: (i) quantitatively, in an equilibrium model of firm dynamics calibrated to match the U.S. economy, (ii) across U.S. states, using plausibly exogenous variation in labor supply growth, and (iii) in the aggregate time series, using a startup rate series extended to include the period of increasing labor supply growth. Moreover, this labor supply growth-based account of the startup deficit explains both the widespread nature of the declines in entry and the relative stability of incumbent survival and growth conditional on firm age.

The demographic origins of the decline in the startup rate should not diminish its macroeconomic significance. If anything, the decline in the startup rate and the implied shift in the age distribution of firms have far-reaching macroeconomic effects. An emerging literature has already started to explore these consequences. Glover and Short (2018) and Hopenhayn, Neira, and Singhania (2018) link the demographic channel to the decline in the labor share; Pugsley and Şahin (2019) show that the emergence of jobless recoveries can be traced back to the decline in firm entry and subsequent aging of firms; Alon, Berger, Dent, and Pugsley (2018), Atkeson, Burstein, and Chatzikonstantinou (2018) and Peters and Walsh (2019) link the de-

⁴⁵Using the firm startup rate, we can only observe the same comovement over the period of declining labor supply growth (Figure C.1).

demographic driven declines in entry to the slowdown of aggregate productivity growth; and Crump, Eusepi, Giannoni, and Şahin (2019) argue that the demographic channel is an important driver of the secular downward trend in unemployment. If present trends in fertility and immigration continue, the startup rate will remain near its current levels, and understanding the equilibrium implications of slowing labor force growth will be especially relevant.

References

- ALON, T., D. BERGER, R. C. DENT, AND B. PUGSLEY (2018): “Older and Slower: The Startup Deficit’s Lasting Impact on Productivity Growth,” *Journal of Monetary Economics*, 93, 68–85.
- ALTONJI, J. G., AND D. CARD (1991): *The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives* pp. 201–234. University of Chicago Press.
- ATKESON, A., A. BURSTEIN, AND M. CHATZIKONSTANTINO (2018): “Transitional Dynamics in Aggregate Models of Innovative Investment,” Discussion paper, National Bureau of Economic Research.
- BARTELSMAN, E. J., AND M. DOMS (2000): “Understanding Productivity: Lessons from Longitudinal Microdata,” *Journal of Economic Literature*, 38(3), 569–594.
- BLOOM, D. E., D. CANNING, G. FINK, AND J. E. FINLAY (2009): “Fertility, Female Labor Force Participation, and the Demographic Dividend,” *Journal of Economic Growth*, 14(2), 79–101.
- BORNSTEIN, G. (2018): “Entry and Profits in an Aging Economy: The Role of Consumer Inertia,” mimeo.
- BUCKLES, K., D. HUNGERMAN, AND S. LUGAUER (2018): “Is Fertility a Leading Economic Indicator,” Discussion paper, National Bureau of Economic Research.
- CRUMP, R., S. EUSEPI, M. GIANNONI, AND A. ŞAHIN (2019): “A Unified Approach to Measuring u^* ,” *Brookings Papers on Economic Activity*.
- DAVIS, S., AND J. HALTIWANGER (2016): “Dynamism Diminished: The Role of Housing Markets and Credit Conditions,” mimeo.
- DAVIS, S. J., AND J. HALTIWANGER (2014): “Labor Market Fluidity and Economic Performance,” Discussion paper, National Bureau of Economic Research.
- DAVIS, S. J., J. HALTIWANGER, R. JARMIN, AND J. MIRANDA (2007): “Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms,” *NBER Macroeconomics Annual 2006*, 21, 107–156.
- DECKER, R., J. HALTIWANGER, R. S. JARMIN, AND J. MIRANDA (2014): “The Role of Entrepreneurship in US Job Creation and Economic Dynamism,” *The Journal of Economic Perspectives*, 28(3), 3–24.
- (2018): “Changing Business Dynamism and Productivity: Shocks vs. Responsiveness,” Working Paper No. 24236, National Bureau of Economic Research.
- DECKER, R. A., J. HALTIWANGER, R. S. JARMIN, AND J. MIRANDA (2016): “Where has all the skewness gone? The decline in high-growth (young) firms in the US,” *European Economic Review*, 86, 4–23.

- ELSBY, M. W., R. MICHAELS, AND D. RATNER (2017): “The Aggregate Effects of Labor Market Frictions,” mimeo.
- ENGBOM, N. (2019): “Firm and Worker Dynamics in an Aging Labor Market,” mimeo.
- FORT, T. C., AND S. D. KLIMEK (2016): “The Effects of Industry Classification Changes on US Employment Composition,” mimeo, Dartmouth University.
- GLOVER, A., AND J. SHORT (2018): “Demographic Origins of the Decline in Labor’s Share,” mimeo.
- GOURIO, F., T. MESSER, AND M. SIEMER (2014): “A Missing Generation of Firms? Aggregate Effects of the Decline in New Business Formation,” mimeo.
- HALTIWANGER, J., R. JARMIN, AND J. MIRANDA (2011): “Historically, Large Decline in Job Creation from Startup and Existing Firms in the 2008-2009 Recession,” Business Dynamics Statistics Briefing 5, Kauffman Foundation.
- (2012): “Where Have All the Young Firms Gone?,” Business Dynamics Statistics Briefing 6, Kauffman Foundation.
- HALTIWANGER, J., R. S. JARMIN, AND J. MIRANDA (2013): “Who creates jobs? Small versus large versus young,” *Review of Economics and Statistics*, 95(2), 347–361.
- HATHAWAY, I., AND R. E. LITAN (2014a): “Declining Business Dynamism in the United States: A Look at States and Metros,” mimeo, Brookings Institution.
- HATHAWAY, I., AND R. E. LITAN (2014b): “What’s Driving the Decline in the Firm Formation Rate? A Partial Explanation,” Discussion paper, Brookings Institution.
- HOPENHAYN, H., J. NEIRA, AND R. SINGHANIA (2018): “From Population Growth to Firm Demographics: Implications for Concentration, Entrepreneurship and the Labor Share,” Discussion paper, National Bureau of Economic Research.
- HOPENHAYN, H., AND R. ROGERSON (1993): “Job turnover and policy evaluation: A general equilibrium analysis,” *Journal of Political Economy*, pp. 915–938.
- HOPENHAYN, H. A. (1992): “Entry, exit, and firm dynamics in long run equilibrium,” *Econometrica: Journal of the Econometric Society*, pp. 1127–1150.
- JARMIN, R. S., AND J. MIRANDA (2002): “The Longitudinal Business Database,” Working Paper CES-02-17, US Census Bureau Center for Economic Studies.
- KARAHAN, F., AND S. RHEE (2014): “Population Aging, Migration Spillovers and the Decline in Interstate Migration,” *FRB of New York Staff Report*.
- KENNAN, J., AND J. R. WALKER (2011): “The Effect of Expected Income on Individual Migration Decisions,” *Econometrica*, 79(1), 211–251.
- KOZENIAUSKAS, N. (2017): “What’s Driving the Decline in Entrepreneurship,” mimeo, New York University.
- LENTZ, R., AND D. T. MORTENSEN (2008): “An Empirical Model of Growth Through Product Innovation,” *Econometrica*, 76(6), 1317–1373.
- LIANG, J., H. WANG, AND E. P. LAZEAR (2018): “Demographics and Entrepreneurship,” *Journal of Political Economy*, 126(S1), S140–S196.
- NAKAMURA, E., AND J. STEINSSON (2018): “Identification in macroeconomics,” *Journal of Economic Perspectives*, 32(3), 59–86.
- PETERS, M., AND C. WALSH (2019): “Declining Dynamism, Increasing Markups and Missing Growth: The Role of The Labor Force,” mimeo.
- PUGSLEY, B. W., AND A. ŞAHİN (2019): “Grown-up Business Cycles,” *The Review of Financial Studies*, 32(3), 1102–1147.

- RAVN, M. O., AND H. UHLIG (2002): “On adjusting the Hodrick-Prescott filter for the frequency of observations,” *Review of economics and statistics*, 84(2), 371–376.
- RUGGLES, S., K. GENADEK, R. GOEKEN, J. GROVER, AND M. SOBECK (2017): “Integrated Public Use Microdata Series: Version 7.0 [dataset],” Minneapolis: University of Minnesota.
- SALGADO, S. (2017): “Technical Change and Entrepreneurship,” mimeo, University of Minnesota.
- SHIMER, R. (2001): “The Impact of Young Workers on the Aggregate Labor Market,” *Quarterly Journal of Economics*, Vol. 116, No: 3 (Aug., 2001), 969–1007.