Appendix to Demographic Origins of the Startup Deficit

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A Data Appendix

Our analysis uses data on firms and labor markets, both national and local, from several sources. We provide additional details on these sources and the methodology to replicate the estimates in the paper. Throughout the paper, we use data on firms from the restricted-access U.S. Census Bureau Longitudinal Business Database (LBD) and its public-use tabulations, the Business Dynamics Statistics (BDS).[1] We combine these data with measures of labor supply growth from the Census Bureau and Bureau of Labor Statistics. Finally we use tabulations from Census Bureau's County Business Patterns (CBP) for an independent historical estimate of an establishment startup rate.

A.1 Measuring firm dynamics in the LBD and BDS

A.1.1 Firm-level measures

We measure firm-level employment (our measure of firm size), which we then aggregate by state, firm-age, group, and 4-digit NAICS industry. The LBD consists of annual establishment-level data, which are linked longitudinally at the physical establishment level. These linkages span changes in ownership or other reorganizations. For each establishment, the dataset contains employment reported for the week containing March 12 of each calendar year. Since employment is measured at the EIN level via payroll taxes, in the case of multi-unit firms, establishment-level employment is sometimes imputed across establishments within an EIN. Since we will aggregate all employment to the firm level, this imputation has no affect on our measure of firm-level employment. See Jarmin and Miranda (2002) for additional details on the construction and limitations of the LBD.

To measure firm-level employment (our measure of firm size) and exit, we aggregate employment across all establishments within a firm.[2] 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 (or would belong) to an age group in a particular year. An age group's year t employment growth is calculated by first aggregating employment across all firms, E_t^a, currently within the age group cohort $a \in \{y, m\}$ and then calculating the growth relative to the total employment of this cohort in the previous year, E_{t-1}^a, where previous year employment is measured for all firms which, if operating, would be in group a in year t including those who exit.[3] 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. This measure of exit would not count exit through mergers or other reorganizations since establishments at these firms would still report activity in year t.

[1] Specially Sworn researchers with an approved project may request the replication files from CES Project 908 if the corresponding years of the LBD and SSL are within the project scope.

[2] The Census Bureau defines a firm as the highest level of operational control over establishments and this is ascertained during the quinquennial Economic Census or the Annual Company Organization Survey.

[3] The change, $E_t^a - E_{t-1}^a$, between current and previous year employment for an age group cohort a corresponds to the BDS measure of the age group's net job creation. See the discussion below in A.1.4.

We identify startups and distinguish incumbents based on a measure of firm age. To be consistent with the BDS and the prior literature, we calculate firm age as the age of the firm's oldest establishment.[4] An establishment "enters" in the year it first reports employment and ages naturally thereafter (regardless of any ownership changes). Startups are age 0 firms and they are bona fide new firms, since they are composed entirely of age 0 establishments. The startup rate measures the number of startups as a fraction of the total number of employer firms. Incumbents are firms which are age 1 and higher, and we further split these into young (age 1-10) and mature (age 11+) age groups. Our measures of incumbent dynamics by age group start in 1987.[5] Using the LBD or BDS the startup rate can be computed as early as 1977, but it would include true entrants and those firms which may have existed (even with employees) but who did not record any payroll in 1976. Starting in 1979 ensures we look back at least 3 years for any payroll activity before labeling it a startup. This implies that our measure of young firms in 1987-1988 may include some firms mistakenly classified as entrants in 1977 and 1978.

We then tabulate these firm-level measures by age group at the national, state, and state by 4-digit NAICS levels.

A.1.2 Geography

In the case when a firm operates multiple establishments we assign its location (state) as the state with the greatest employment share. For state-level tabulations, following the BDS, our state-level measures count firms separately for every state in which they operate establishments (implying the sum of state firm counts may exceed the total number of U.S. firms). A firm operating in two states will be counted twice, summing only across the respective establishments within each state. Only employment will vary across firm-states for the same firm. Other firm characteristics, such as total size, and industry will be identical.

A.1.3 Industry assignment

We assign firm-level measures of detailed industry using the NAICS 2002 industry classifications. There are two challenges to constructing firm-level measures of industry. The first is that industry classification naturally evolves over time and we need to construct a longitudinally consistent coding of detailed industry. The second is that industry is assigned at the establishment-, rather than firm-level. For example, the headquarters location of a large manufacturing firm may be classified within management of professional enterprises, while the plants may be classified within the manufacturing sector.

To address the periodic reorganization of industry codes over time, we assign a longitudinally consistent measure of industry developed in Fort and Klimek (2016). They use a concordance of

[4] This measure was first popularized by Davis, Haltiwanger, Jarmin, and Miranda (2007) and Haltiwanger, Jarmin, and Miranda (2013).

[5] Because birth year is left censored for any extant firms in the first year of the LBD (1976), we cannot measure the young and mature age groups until 1987 since this is the first year we can identify age 1-10 firms and thus the residual 11+ age group.

SIC to 2002 NAICS coding to "backcast" NAICS codes at the establishment level in years in which only a 6 digit SIC code was assigned. This is straightforward for industries where there is a one to one mapping, however there are many SIC industries that map across multiple NAICS industries and vice versa. In these cases, they assign industry stochastically drawing a NAICS code from the empirical distribution of NAICS codes that map to a specific SIC code (for years in which the standard industry assignment overlapped). They also make some ad-hoc corrections, which are described in the appendix to Fort and Klimek (2016).

Having assigned a Fort-Klimek NAICS code to every establishment year, we then in cases of multi-unit firms assign a firm-level NAICS code. We assign this using an activity (payroll) weighted mode across establishments, but follow a hierarchical procedure to ensure that the NAICS code would be assigned consistently at each level of aggregation. That is, we first assign a 2-digit NAICS code as the modal 2-digit code across establishments within a firm (excluding any management of professional enterprises coding). Then within the firm's 2-digit NAICS industry, we assign a modal 3-digit NAICS industry across those establishments, and so on. This method ultimately assigns a NAICS-2002 6-digit industry to every firmid within every year.

A.1.4 Consistent measures in Business Dynamics Statistics (BDS)

Finally, in order to ensure our main results can be easily replicated, we use the BDS tabulations where possible. This requires some small adjustments in order to ensure consistent measures between LBD and BDS. The BDS report the stock of firms and their employment in each year, but because firms may go temporarily out of scope, measures such as within cohort exit and employment growth cannot be reliably measured only from the change in stocks. Moreover, for multi-age groups the previous year stock is not reported. We follow the procedure from Pugsley and Şahin (2019) to recover lagged cohort employment and number of firms in order to produce more accurate measures of exit and employment growth. We summarize that procedure here.

Stock measures Let EMP_t^a measures within a firm age group a cell the total stock of March 12 employment across all establishments (within the firm age group) in year t, and let $DENOM_t^a$ measure the average of EMP_t^a and the total stock of employment for that same cohort of firms in the previous year, $\widetilde{EMP}_{t-1}^{a-1}$.[6] This imputed previous year employment is computed from the BDS variables $DENOM_t^a$ and EMP_t^a as

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

For firms, let the BDS variable $FIRMS_t^a$ measure within an age group a the total number of firms with positive employment on March 12 of that year, and let variable $DEATHS_t^a$ measure the number of firms in the current age group a cohort that were active in $t-1$, but are now permanently

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

shut down in year t. A shut down requires that all establishments within the firm in the previous year exit by the current year. Then we construct

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

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

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

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

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

Flow Variables Using our above defintions for E_t, F_t, and N_t, we compute the dynamic measure defined in the paper. The **exit rate** is

$$x_t^a \equiv \frac{DEATHS_t^a}{\widetilde{FIRMS}_{t-1}^{a-1}} = 1 - \frac{F_t^a}{F_{t-1}^{a-1}} \ .$$

Note that this is a restrictive definition of exit, since firms that are reorganized are not counted as exits. The growth rate in average size or **conditional growth rate** is [7]

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

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

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

Then also by construction

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

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

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

[7] The conditional growth rate will only equal the growth rate "conditional on survival" when the average size of exiting and surviving firms is identical. Since exiting firms are typically smaller than surviving firms, the conditional growth rate measured in this way would be greater than the growth rate of surviving firms. In general, the growth rate of surviving firms is given by $1 + g_t^{aS} = (1 + n_t^a)(1 - x_t^a(1 - N_{t-1}^{aS}/N_{t-1}^{aX}))$, where $N_{t-1}^{aS}/N_{t-1}^{aX}$ is the ratio of exiting firm to surviving firm size.

The growth rate differs both because of the denominator and because (until the September 2014 release) $JC_t^a - JD_t^a \neq EMP_t^a - \widetilde{EMP}_{t-1}^{a-1}$.[8]

A.2 Measuring labor supply growth rates

Our demographic measures include national- and state-level measures of the working age population and the civilian labor force. We use population data from the Census Bureau's decennial census and annual American Community Survey. We use the Current Population Survey (CPS) to measure the size of the civilian labor force. We define the working age population as the non-institutional population between the ages of 20 and 65 and the civilian labor force as the non-institutional population age 20 or older that are currently employed or actively searching for a job.

A.2.1 Working age population-based estimate

We construct the growth rate of the working-age population using annual Census Bureau intercensal population estimates by age group. These annual data are based on the decennial population census and intercensal estimates formed using data on births, deaths, and migration.[9] We sum the annual estimates by age group to estimate the population ages 20-64 and then take the one year growth rates. This is a benchmark measure of the growth rate of the working age population. This range 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. We have experimented with both narrower and wider definitions of the working-age with little effect on the aggregate patterns or cross-state results.

A.2.2 Civilian labor force-based estimate

At the national level the CLF is estimated monthly by the BLS using the Current Population Survey (CPS), and for states the labor force is estimated as part of the Local Area Unemployment Statistics program, which combines the CPS with information from state-level unemployment insurance programs, the BLS establishment survey, as well as local population estimates from the Census Bureau. We average the monthly estimates of the CLF by year, and then take one year growth rates. Since, even at an annual frequency the CLF is procyclical, see for example Elsby, Hobijn, and Şahin (2015), we also use a version of the CLF growth rates purged of business cycle fluctuations using an HP filter with a smoothing parameter of 6.25 as recommended by Ravn and Uhlig (2002).

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

[9] The Census Bureau annual population estimates and a description of the the estimation methodology are available from https://www.census.gov/programs-surveys/popest.html.

A.3 Cross-state sample construction

A.3.1 Sample description

We measure the startup rate, average startup size, exit rate for firms ages 1-10, and conditional growth rate (growth in average firm size) for firms ages 1-10 for each state and year in the BDS and LBD using the procedure described above in Sections A.1. We do this for years 1979 to 2007 for the startup rate and average startup size variables, and for years 1987 to 2007 for the exit rate and conditional growth rate variables defined for young incumbents. Because birth year is left censored in 1977, the year 1987 is the first year where we can identify all firms ages 1-10. We restrict the sample to states in the contiguous US plus the District of Columbia since Alaska and Hawaii were granted statehood in 1959 and consistent natality and population data are not available before 1960.

To these data defined by state and year, we merge the state-level counterparts for working age population growth and the civilian labor force described above in Section A.2. Then we add the birthrate and migration instruments, which are described in the next section. For the 48 contiguous US states plus DC, Table A.1 reports the sample statistics for the full 1979-2007 (1,421 state-year observations) and shorter 1987-2007 (1,029 state-year observations) samples before and after removing state and year fixed effects from each variable.

Table A.1: Cross-state sample statistics

	Actual values					Residualized			
	mean	sd	p10	p50	p90	sd	p10	p50	p90
Panel A. 1979 to 2007									
Startup rate	10.75	2.09	8.36	10.44	13.62	0.80	−0.87	−0.01	0.78
Startup size	5.96	1.05	4.97	5.84	7.02	0.78	−0.60	−0.06	0.54
WAP growth rate	1.27	1.17	0.16	1.09	2.68	0.72	−0.76	0.00	0.76
CLF growth rate	1.38	1.54	−0.34	1.26	3.23	1.19	−1.34	0.01	1.34
Birthrate (20 yr lag)	18.00	3.69	14.10	17.20	23.60	1.10	−1.25	0.00	1.22
N	1,421								
Panel B. 1987 to 2007									
Startup rate	10.16	1.73	8.11	9.91	12.56	0.59	−0.61	0.01	0.59
Startup size	6.00	1.03	4.95	5.90	7.12	0.71	−0.52	−0.05	0.51
Firm exit 1-10	10.93	1.23	9.48	10.87	12.45	0.67	−0.65	−0.05	0.66
Cdtl. growth 1-10	8.82	3.57	4.92	9.01	12.31	2.78	−2.78	0.01	2.61
WAP growth rate	1.18	1.09	0.17	1.01	2.45	0.64	−0.66	0.00	0.67
CLF growth rate	1.22	1.45	−0.39	1.17	2.89	1.14	−1.31	0.03	1.30
Birthrate (20 yr lag)	16.34	2.40	13.80	16.00	19.10	0.98	−1.11	−0.04	1.17
N	1,029								

Note: Sample used for estimation. Residualized columns report the statistics for each variable after removing state and year fixed effects.

A.3.2 Instrumental variables construction

Measuring state birthrates from Department of Health data We tabulate historical state births from the Natality Data from the National Vital Statistics System of the National Center for Health Statistics. These public-use microdata are available for download from the CDC (https://www.cdc.gov/nchs/data_access/vitalstatsonline.htm) for 1968 through the present. For each state and year we measure the number of births per 1000 adults (measured from the Decennial Census and inter-censal estimates), which is known as a "crude birth rate. We are grateful to Rob Shimer for providing us with his birthrate data constructed from the Statistical Abstracts for the period 1940–91. Data are unavailable for Hawaii and Alaska prior to 1960, and we drop these states entirely from the analysis.

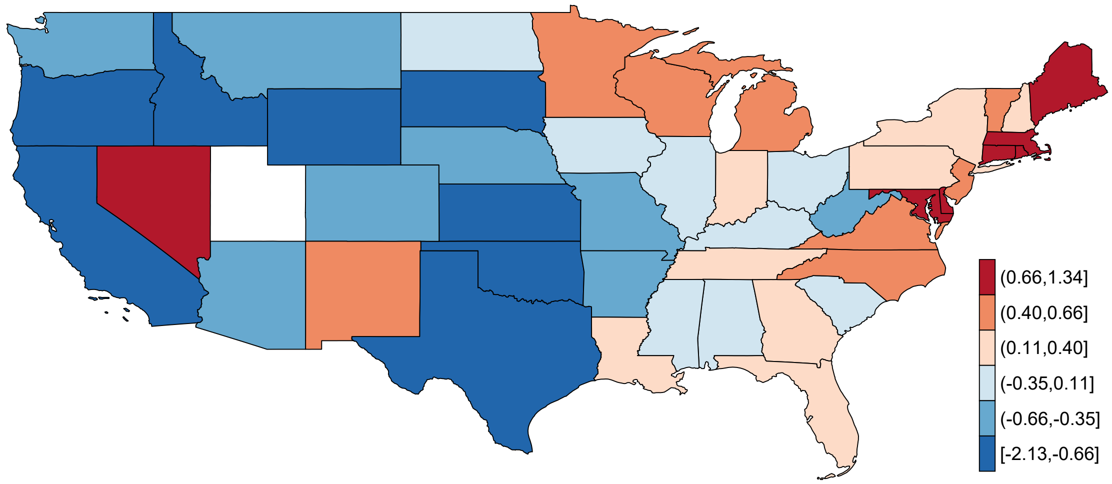
We then use the state-level birthrates lagged 20 years to predict future labor supply growth, measured both by the working age population and the civilian labor force, conditional on state and time fixed effects. Even after removing these fixed effects, there is considerable cross state variation that remains. In Figure A.1 we plot the birthrate residuals having removed state and time fixed effects on a map of the continental United States. For the figure, we average these residuals by decade. The analysis in the paper uses the annual data. Table A.1 reports the descriptive statistics for the annual data. The standard deviation of birth rate across states and years is approximately 3.7 (births per 1000 adults) and falls by roughly 2/3 to 1.1 after conditioning on state and year fixed effects.

Measuring inter-state migration using Census data The long form of the Decennial Census (until replaced by the annual American Community Survey in 2001) asks respondents for the place of birth (U.S. state or country) of each person in the household. We use the 5% microdata samples for 1990 and 1980 Decennial Censuses. In 1970, we use the 1% Form 1 metro sample. These public-use samples are available from IPUMS (Ruggles, Genadek, Goeken, Grover, and Sobeck, 2017). We then aggregate over all native-born persons in that state to estimate the distribution of birth states. For each state k we then condition on all birth states that are not part of the same Census division to form the distribution of intra-division birth states.[10] When constructing the instrument we use the lagged distribution of birth states from at least 1 Census ago, so that there is a minimum of 10 years between current year and the year in which birth states are measured. The questionnaire also reports the state of residence 5 years ago, which can also be used to construct weights. We find similar estimates using these weights to construct the migration instrument, but the first stage regression is weaker.

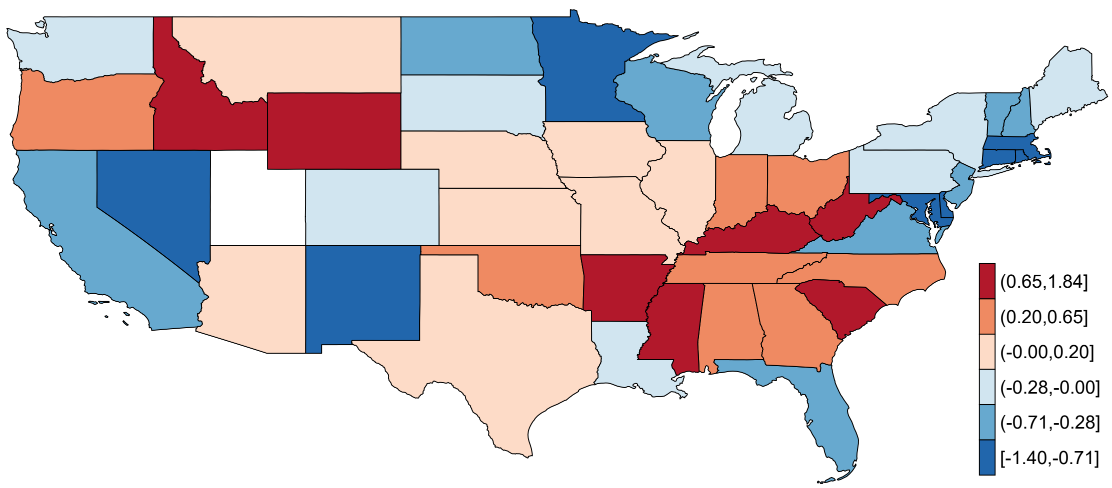
A.4 Census County Business Patterns (CBP) and startup rate imputation

We use data from the County Business Patterns (CBP) and Business Dynamics Statistics (BDS) jointly to impute the establishment entry rate for the pre-1979 period. Below is a detailed descrip-

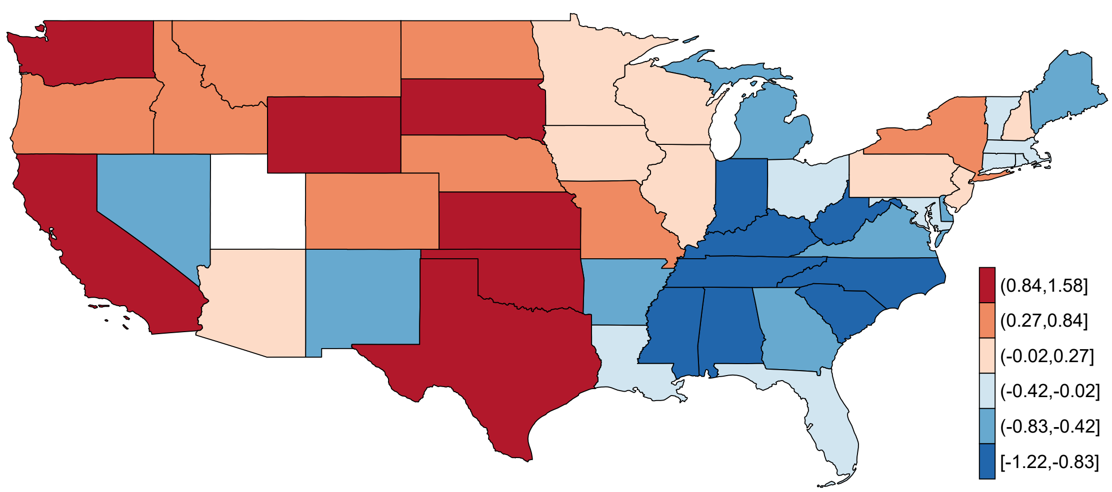
[10]There are 9 Census divisions: New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain and Pacific.



1960s average residual by state (predicts 1980s)



1970s average residual by state (predicts 1990s)



1980s average residual by state (predicts 2000s)

Figure A.1: Across state birthrate residuals averaged by decade (%)

Note: Residuals from regression of birthrate instrument on state and year fixed effects and then averaged within lag decade. Continental U.S. states, excluding UT and DC.

tion of the CBP dataset. See also http://www.census.gov/programs-surveys/cbp.html.

Historical CBP data The Census Bureau's County Business Patterns (CBP) program counts the number of establishments in each U.S. county. It has published tabulations of establishments by geographic area and employment size class annually since 1964.[11] These data are publicly available and downloadable from the Census Bureau (https://www.census.gov/programs-surveys/cbp/data/datasets.html). Years prior to 1986 are available in the National archives as well as digitized versions in ICPSR.[12] Because of slight changes in the CBP design the size categories depend on year:

Years 1964 to 1973 We use state level data binned by year and size category: Number of Employees: 1-3, 4-7, 8-19, 20-49, 50-99, 100-249, 250-499, 500+. For each cell, we measure the establishment count and employment.

Years 1974 to 2014 We use state level data binned by year and slightly different size categories: 1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, 1000+ employees. For each cell, we again measure the establishment count and employment.

These size categories are chosen to correspond as closely as possible to size categories in the publicly available BDS.

Baseline imputation method

1. Iterating over establishment size categories and state geographies, estimate equation 13. Then take predicted values for years 1979-2007 using CBP data from that sample period.

2. For years 1966-1978, assume that for each size category and each state geography, the exit rate was constant at the (fitted) level it was in 1979.[13]

3. Using equation (12) and the predicted annual exit rate, $\hat{x}_t^{sj}$, for each state and size group, compute the establishment startup rate. The aggregate change in establishments Δe_t can be measured directly in the CBP by aggregating the changes by state and size category. Note that size transition flows need not be estimated in order to estimate the aggregate startup rate, as summing across all size categories nets out inflows and outflows.

4. Imputed entry rates for years 1974 and 1983 are dropped because of changes in methodology for tabulating establishments in the CBP. Imputed entry rates for those years are replaced as the midpoints of data from years 1973,1975 and 1982,1984, respectively.

[11]The CBP program provides data as early as 1946 at roughly triennial frequencies. In these early years, multi-unit establishments are often be combined within county and detailed industry. See https://www.census.gov/programs-surveys/cbp/technical-documentation/methodology.html

[12]See https://research.archives.gov/id/613576 and http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/25984

[13]We consider alternative assumptions in Appendix C.4.

B Model appendix

B.1 Global solution method

Here we describe the details of the computational algorithm for solving the balanced growth path equilibrium of the model given a set of parameters.

Discretizing firm behavior We approximate firm decisions over a grid of current firm size n_{t-1}, permanent productivity a and the stochastic component of productivity s_t. For firm size, we use an exponential grid with 80 grid points between 0 and 5000 with shape parameter $\alpha = 0.3$. Here, α controls how many grid points are closer to the lower bound of 0. Specifically, we first create a uniform grid $\tilde{N}$ between 0 and 5000^{α}. Our final grid N is then given by $\tilde{N} = N^{1/\alpha}$.

We use 3 grid points to discretize the distribution of permanent productivity $F(a)$. Given the log normality in the calibration, we choose the middle grid to be the mean log productivity, which is zero, and the lowest and largest points to correspond to log productivities that are 2.5 standard deviations below and above zero. Once the grid points are chosen, the probability of drawing each productivity level is derived from F, which in our case is the CDF of the log normal distribution.

We use 71 grid points to discretize the stochastic productivity s_t. We do so using the Tauchen procedure, which gives us the discrete grid of productivities and the associated matrix of transition probabilities. We also use this grid to approximate the initial productivity distribution $G(s)$.

Solving for a balanced growth path equilibrium The algorithm consists of two steps. In the first step, we find the equilibrium wage by solving the free entry condition, and in the second step we solve for equilibrium entry and the stationary distribution of firms, $\bar{\mu}_t$.

Step 1: Solving for the equilibrium wage. For a given level of wages, we solve firms' optimal size for each grid point. The optimal size decision also gives us the value to the firm of remaining in business, and thus the optimal exit decision. We find the expected value of entry as a function of the wage by integrating the value of a firm with no workers (0 size) over the distribution of permanent and initial stochastic productivities. We use a golden search algorithm to find the value of the wage that satisfies the free entry condition in 6 with sufficient precision.[14] Given the equilibrium wage, we store firms' optimal size and exit decisions.

Step 2: Solving for equilibrium entry. To approximate the equilibrium distribution of firms, we use a finer grid for firm size. Specifically, we use 240 grid points and obtain these using the same approach with an exponential grid with $\alpha = 0.3$. We obtain the optimal firm size and the value of remaining in business for each grid point via linear interpolation over the optimal values on the coarse grid. The interpolated value of staying is used to compute the

[14] We stop when the percentage deviation between the fixed cost of entry and the expected value of entry is less than 10^{-6}.

optimal exit decisions over this extended grid. To compute the equilibrium measure of firm entry and the resulting stationary distribution of firms, we make use of equation (7). Note that given the linearity in this equation, it suffices to solve the stationary distribution once for $\bar{M}_t = 1$. We calculate the stationary distribution of firms that correspond to a mass one of new entrants ($\bar{M}_t = 1$) by iterating on an initial guess $\bar{\mu}^0$ using the updating rule defined by equation (7).[15] We then solve for the equilibrium entry $\bar{M}$ by clearing the goods market. Given the linearity in equation (7), the stationary distribution corresponding to any given measure of new entrants $\bar{M}$ is obtained simply by multiplying this distribution with $\bar{M}$.

B.2 Proof of simple formula in the full model

The formula given by equation (1) from Section 2 also applies in the full model from Section 3. To see this start with the law of motion in equation (7). Along the balanced growth path, the the law of motion is satisfied with a stationary measure of firms per capita, $\bar{\mu}$. Integrating both sides, then:

$$\begin{aligned}
\iiint_{s',a,n} \bar{\mu}\left(ds',da,dn\right) &= \iiint_{s',a,n} \int_s \frac{1-x\left(s,a,n\right)}{1+\eta} F\left(ds'|s\right) \bar{\mu}\left(ds,da,dn\right) + \bar{M} \\
1 &= \iiint_{s',a,n} \int_s \frac{1-x\left(s,a,n\right)}{1+\eta} F\left(ds'|s\right) \frac{\bar{\mu}\left(ds,da,dn\right)}{\iiint_{s',a,n} \bar{\mu}\left(ds',da,dn\right)} + SR \\
1 &= \iiint_{s,a,n} \frac{1-x\left(s,a,n\right)}{1+\eta} \frac{\bar{\mu}\left(da,ds,dn\right)}{\iiint_{s',a,n} \bar{\mu}\left(ds',da,dn\right)} \int_{s'} F\left(ds'|s\right) + SR \\
1 &= \frac{1}{1+\eta} \iiint_{s,a,n} \left(1-x\left(s\right)\right) \frac{\bar{\mu}\left(ds,da,dn\right)}{\iiint_{s',a,n} \bar{\mu}\left(ds',da,dn\right)} + SR \\
&= \frac{1-\iiint_{s,a,n} x\left(s,a,n\right) \frac{\bar{\mu}(ds)}{\int_{s'} \bar{\mu}(ds')}}{1+\eta} + SR \\
SR &= \frac{\eta + \int_s x\left(s\right) \frac{\bar{\mu}(ds)}{\int_{s'} \bar{\mu}(ds')}}{1+\eta} \\
&= \frac{\eta + x}{1+\eta}.
\end{aligned}$$

The 2nd equality comes from dividing through by the total normalized mass of firms so that the $\bar{M}$ term becomes the startup rate (total normalized mass of startups over total normalized mass of firms). The 3rd equality comes from changing the orders of integration. The 4th equality comes from integrating out the conditional density, which is 1 for every s. The 5th equality comes from noting that $\frac{\bar{\mu}(ds)}{\int_{s'} \bar{\mu}(ds')}$ is the firm density and thus integrates for 1, and thus $x = \int_s x\left(s\right) \frac{\bar{\mu}(ds)}{\int_{s'} \bar{\mu}(ds')}$ is the economy's average exit rate.

[15] We stop when the sup norm of the percentage deviation between the guess and the updated distributions is less than 10^{-7}.

C Robustness Appendix

C.1 Trends in firm and labor market dynamics

We supplement the analysis in the main text Section 2 with these additional details on the aggregate trends in firm and labor market dynamics. Together these support our main argument that the declining startup rate and its comovement with measures of labor supply growth are a robust feature of the data. Much of this draws on Pugsley and Şahin (2019) and its robustness appendix.

C.1.1 Aggregate labor supply growth and the startup rate

Figure C.1 plots a smoothed series for the startup rate and our two main proxies of labor supply growth: *working age population* growth surges in the 1960s as early "baby boomers" enter adulthood; *civilian labor force* growth accelerates even faster, because it combines the growth in the working age population with rapidly increasing female participation. The startup rate falls by roughly 3 percentage points exactly over the ensuing period of declining labor supply growth.

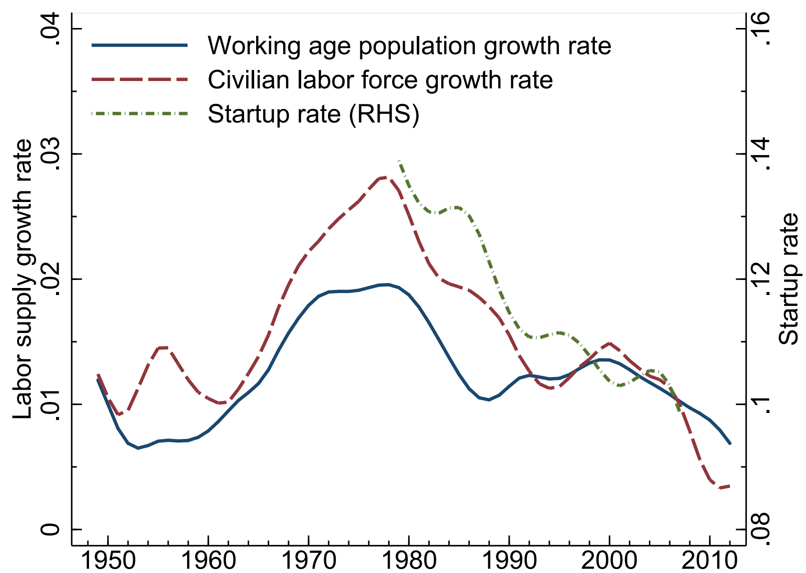


Figure C.1: Trend components of startup rate and labor supply growth rates

Note: Current Population Survey, Census Bureau annual population estimates, Business Dynamics Statistics. Annual data, HP filtered with smoothing parameter 6.25. See appendix Figure C.2 for unfiltered rates. Working age population is ages 20 to 64. Civilian labor force is measured for the adult (16+) civilian non institutional population. Startup rate is number of age 0 (employer) firms as share of the total number of firms within a year.

The unfiltered data, though noisier, show the same patterns. In Figure C.1 we had smoothed the data to remove the high frequency fluctuations primarily in the growth of the civilian labor force, which is both volatile and highly procyclical. However, even in the raw time series, the lower frequency comovement between both measures of labor supply growth and the startup rate is evident. Figure C.2 plots the unfiltered data.

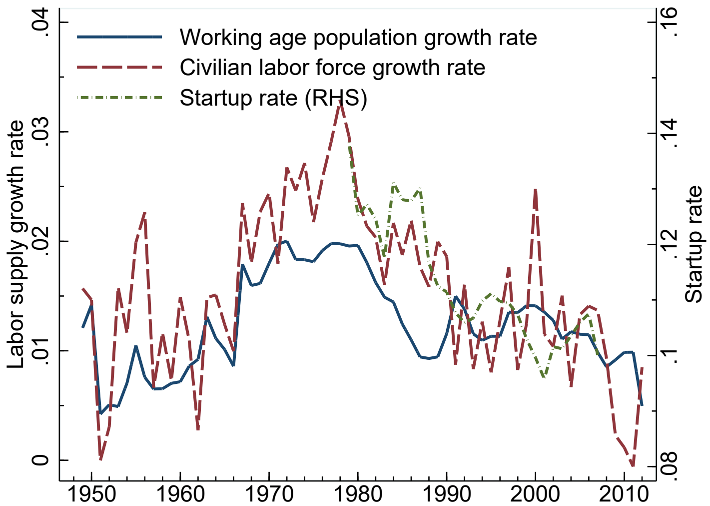


Figure C.2: Unsmoothed aggregate data on startup rate and labor supply growth

Actual and flow balance startup rates Table 1 in the main text reports the actual and flow balance predicted startup rates for the 1979-81 and 2005-07 3-year periods. To be consistent throughout the paper, the actual startup rate is the average within each 3 year period of a smoothed startup rate series estimated using an HP filter with a penalty parameter of 6.25 as suggested by Ravn and Uhlig (2002) for annual data. The economy-wide exit rate for each period is computed the same way. The respective flow balance startup rates are computed using the average labor supply growth rates and average exit rates for each 3-year period. The results are very similar when computed on the unfiltered data. We report below in Table C.1 a version of Table 1 instead computed using 3-year averages of the raw data for the startup rate and exit rate series.

Table C.1: Actual and predicted flow balance startup rates

	Labor Supply Growth (%)		Exit Rate (%)	Startup Rate (%)		
				Actual	Predicted	
	WAP	CLF			η =WAP	η =CLF
1979-1981	1.91	2.49	9.90	13.03	11.59	12.09
2005-2007	1.10	1.37	8.58	10.45	9.57	9.82
Change	−0.81	−1.12	−1.32	−2.58	−2.02	−2.27

Note: Startup rate, exit rate, and labor supply growth rates for working age population (WAP) and civilian labor force (CLF) measured as 3 year averages of raw data. Predicted startup rates use flow balance equation (1) with 3-year averages for η and exit.

Next, we present the entire annual time series for the predicted flow-balance startup rate (Figure C.3). To form the time series, we calculate the flow-balance startup rate using equation (1) with the realized exit rate x_t and labor supply growth rate η_t for each year. That is, the predicted startup rate in each year is the one we would expect if the annual labor supply growth (Figure 1b and

Figure C.2) and the actual average exit rate (Figure 1a) in each year were to prevail indefinitely. The largest declines in both flow-balance predicted startup rates occurs before the actual startup rate. This is to be expected since the flow-balance calculation in each year is based on the long-run effects of the change in labor supply growth and exit. It suggests that the period where the startup rate remains above the flow-balance predictions are part of a transition to the new BGP.

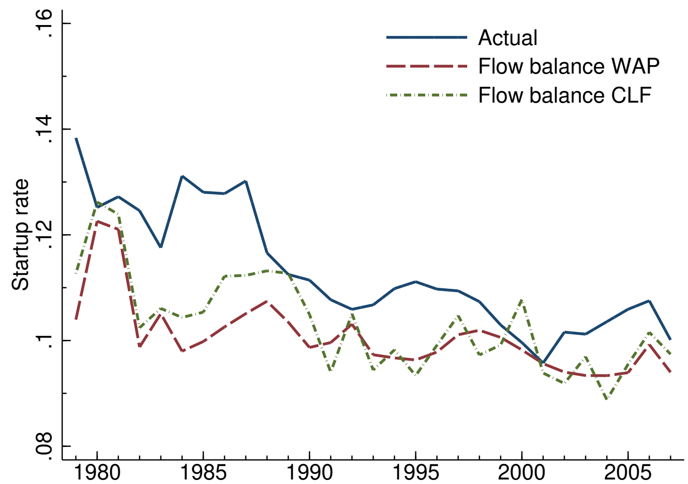


Figure C.3: Actual and flow balance startup rates for 1979 to 2007

C.1.2 Effects of compositional change on the aggregate startup rate

An immediate concern when interpreting the decline in the aggregate startup rate and the ensuing startup deficit, is that the aggregate decline may primarily reflect compositional changes in business sectors.[16] If sectors with lower startup activity are becoming more important because of ongoing structural change, this ongoing reallocation of employment may explain the declines in the aggregate startup rate even if startup rates by industry were unchanged. Here we replicate several exercises from Pugsley and Şahin (2019), who find little support for this hypothesis.

Table C.2: Average sector startup rates by time period

Sectors	1980-1984	2003-2007	2008-2012
A. NAICS Sectors			
Mining (21)	0.182	0.097	0.095
Utilities (22)	0.067	0.053	0.039
Construction (23)	0.140	0.126	0.084
Manufacturing (31-33)	0.102	0.064	0.052
Wholesale Trade (42)	0.110	0.080	0.067
Retail Trade (44-45)	0.122	0.109	0.880
Transportation and warehousing (48-49)	0.146	0.136	0.116
Information (51)	0.160	0.118	0.098
Financial activities (52-53)	0.128	0.115	0.083
Professional and business services (54-56)	0.165	0.118	0.098
Education and healthcare (61-62)	0.101	0.085	0.072
Leisure and hospitality (71-72)	0.165	0.139	0.120
Other services (81)	0.118	0.076	0.064
B. Other Sectors			
High tech industries	0.173	0.120	0.100

Note: U.S. Census Bureau Longitudinal Business Database. Number of age 0 firms as fraction of total firms within each sector. 2-digit NAICS sectors listed in parentheses for each sector in panel A. In panel B. high tech sector is not mutually exclusive and is comprised of 14 NAICS 4-digit industries with highest share of STEM workers: 3341, 3342,3344, 3345, 5112, 5161, 5179, 5181, 5182, 5415, 3254, 3364, 5413, 5417. See Decker, Haltiwanger, Jarmin, and Miranda (2016) for additional details.

Compositional changes from structural transformation have, if anything, slowed the aggregate decline in the startup rate. Table C.2 reports the average startup rate by sector and by time period. Panel A reports the startup rates for each NAICS sector or supersector, and panel B reports a special aggregation of high-tech industries that draws from the manufacturing, information and professional services sectors as in Decker, Haltiwanger, Jarmin, and Miranda (2016). Two features are immediately apparent: First, relative to the early 1980s average, the startup rate has declined in all of these sectors. Even in the high-tech sector, containing firms in the 14 NAICS 4-digit industries with highest share of STEM workers and in which entry rate increases in the late 1990s, the startup rate still declined from 17.3 percent in 1980-84 to 12 percent in 2003-2007 and further to 10 percent in the 2008-2012 period. Second, sectors with declining employment shares such as

[16] The U.S. economy has been undergoing a significant structural transformation—the secular reallocation of employment across sectors—over the past several decades. See for example Duarte and Restuccia (2010) and Dent, Karahan, Pugsley, and Şahin (2016) for additional details.

Table C.3: Decomposition of the startup rate and startup employment share changes into between, between and covariance components.

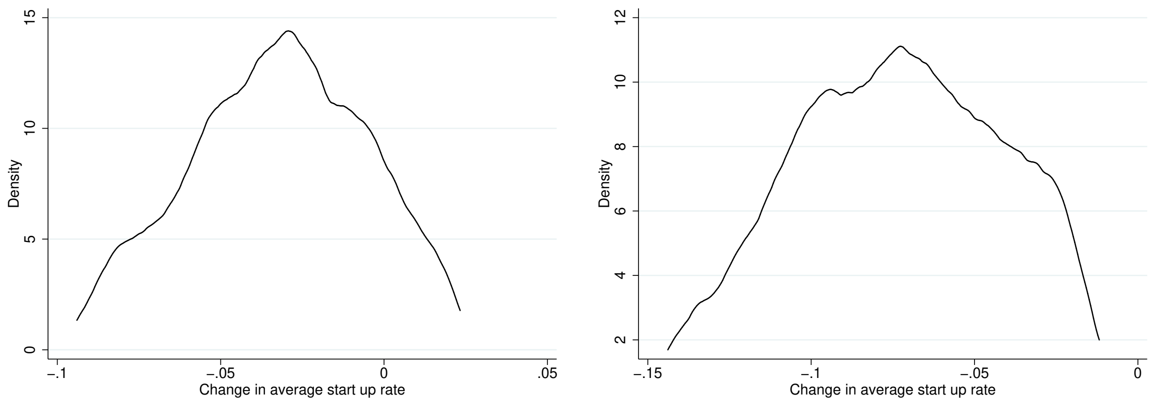
	Startup Firm Share			Startup Employment Share		
	Between	Within	Covariance	Between	Within	Covariance
	A. By Industry (NAICS4)					
1980-84;2003-07	1.19	-2.87	-0.59	1.16	-1.11	-0.82
	(-52.2%)	(126.4%)	(25.8%)	(-149.6%)	(143.4%)	(106.2%)
1980-84;2008-12	1.37	-4.98	-0.76	1.24	-1.80	-0.96
	(-31.4%)	(114.0%)	(17.4%)	(-81.1%)	(118.1%)	(63%)
	B. By County					
1980-84;2003-07	0.68	-2.87	-0.09	0.71	-0.93	-0.57
	(-29.9%)	(126.2%)	(3.73%)	(-90.8%)	(118.5%)	(72.3%)
1980-84;2008-12	0.80	-4.82	-0.32	0.81	-1.62	-0.72
	(-18.3%)	(110.9%)	(7.4%)	(-53.1%)	(105.8%)	(47.3%)
	C. By State × Industry					
1980-84;2003-07	1.44	-3.11	-0.59	1.75	-0.72	-1.80
	(-63.2%)	(137.1%)	(26.1%)	(-225.7%)	(92.9%	(232.8%)
1980-84;2008-12	1.58	-5.20	-0.75	1.83	-1.31	-2.05
	(-36.1%)	(118.9%)	(17.2%)	(-119.9%)	(85.7%)	(134.2%)

Note: U.S. Census Bureau Longitudinal Business Database. Decompose change in average startup firm (employment) share from 1980-1984 period to 2003-2007 or 2008-2012 period. See Pugsley and Şahin (2019) for exact decomposition.

manufacturing already had among the lowest startup rates in the 1980s. Structural transformation, which reallocates employment away from manufacturing and into service providing sectors with higher startup rates, has weighed against the aggregate decline in the startup rate. Even at finer levels of disaggregation, more than 100 percent of the aggregate declines from since the 1980s are within industry.

To evaluate this explanation more formally we decompose the decline in the aggregate startup rate from the 1980-84 period to the 2008-2012 period into three components: within 4-digit NAICS industry changes, between industry changes and a covariance term (Table C.3). Within industry declines account for more than 100 percent of the declines in the aggregate startup rate. This pattern is robust to an alternative period that does not include the financial crisis as well as when computed for startup employment shares. Ultimately, compositional shifts across industries, if anything, moderated the decline in startup formation. Startup deficits are also present even in narrowly defined geographic markets. In the center panel of Table C.3 we present the same decomposition applied to U.S. counties instead of industries to investigate whether changes in geographic allocation of employment can explain the decline in startups. Similar to national industries, more than 100 percent of the aggregate decline is within county.

Allowing simultaneously for both industry and geographic shifts, we find the same pattern even within industry–geography submarkets. We evaluate the decline in the startup rate within 4-digit NAICS industry and state pairs, which yields roughly 13,000 submarkets. Again, the declines are



1980-84 to 2003-07

1980-84 to 2009-11

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

within these narrow submarkets. In all cases, the structural transformation captured by the between terms actually puts upward pressure on the aggregate startup rate. Another way to visualize the widespread nature of the declines in the startup rate is to examine a histogram of the within state and industry long-run changes. For each state and 4-digit NAICS industry, as above in Table C.3 Panel C., we compute the change in the state×industry startup rate since its 1980-84 average. Figure C.4 plots the histogram of the changes from 1980-84 to 2003-07 (left panel) and to 2009-11 (right panel). Over the period that does not include the Great Recession, almost 85 percent of state industry pairs have declines, a share that rises to nearly 100 percent when the change is computed over the longer time period.

C.1.3 Declines in additional measures of entry

In the main text, we focus primarily on the firm startup rate, but the declining entry rate is a robust feature of the data. Here we consider several additional measures of entry activity and show declines in each of the 1979-2007 period.

First, one may worry that defining entry by considering only age 0 firms is too restrictive. To address this concern, we extend our definition of startups to age 0 and age 1 firms and define entry measures accordingly. As a share of all firms and of private payroll employment both broader measures of startups show similar declines (Figure C.5). We can also define an entry measure as the number of new firms per capita, which we plot in figure C.6. This measure also declines over the 30-year period. This also closely tracks the model's prediction that the number of firms per worker should decrease in the labor-supply growth rate / startup rate. A final concern is that the decline the startup rate stems in part from our choice measuring firms rather than establishments. We plot the establishment entry rate and age 0 establishment employer share (Figure C.7). Both measures show a similar decline to our preferred measure of the firm startup rate (Figure 1a).

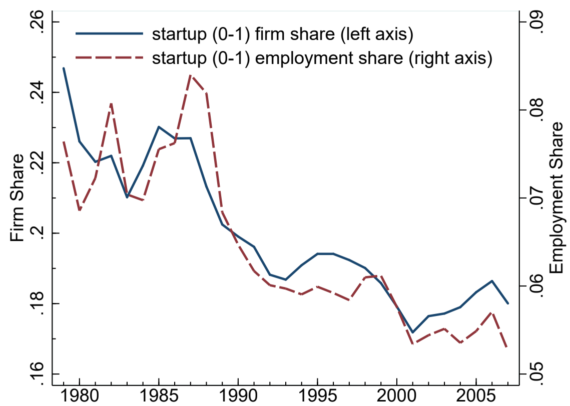


Figure C.5: Startups defined as firms ages 0-1: firm and employment share 1979–2007

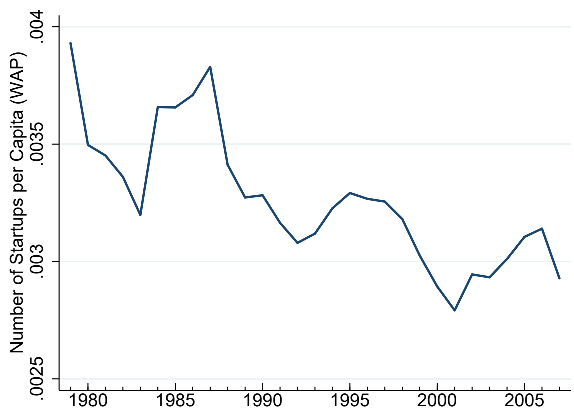


Figure C.6: Number of startups per working age population 1979–2007

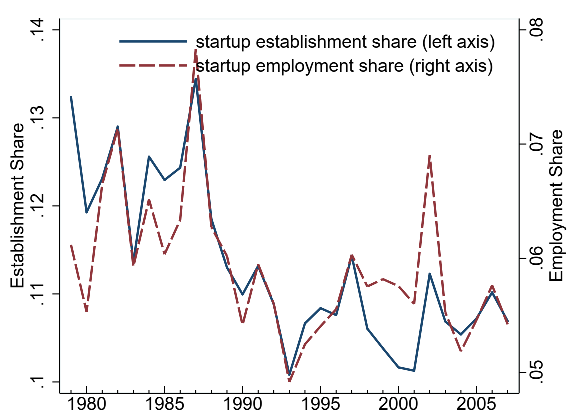


Figure C.7: Startup (age 0) establishment shares 1979–2007

C.1.4 Trends in other margins

Table C.4 confirms the stability of exit and conditional employment growth rates for more detailed age groups. We consider three age groups within the young firm age category: 2-3, 4-5 and 6-10 years old firms and mature firms (11+ years) as well as three size categories: small (1-49 employees), medium (50-249 employees) and large (250+ employees) firms. We filter the exit and employment growth rates by firm age and size with H-P filter using smoothing parameter 6.25 to remove higher frequency fluctuations and report the estimated linear trend of the filtered component. Columns (1) to (8) report the estimated coefficient on the linear trend and show that the stability result still holds. For both young and mature firms—regardless of their sizes—the estimates are quantitatively insignificant. For example, the estimated trend implies that over thirty years, the exit rate of both young and old firms will have changed only by a fraction of 1%.[17] We also plot the raw data, conditional on size and age. We pool ages 1-10 in the young category. Figure C.8 plots exit rates and Figure C.9 plots the conditional growth rates. These correspond to Figure 3 in the paper, except now further conditioned on size.

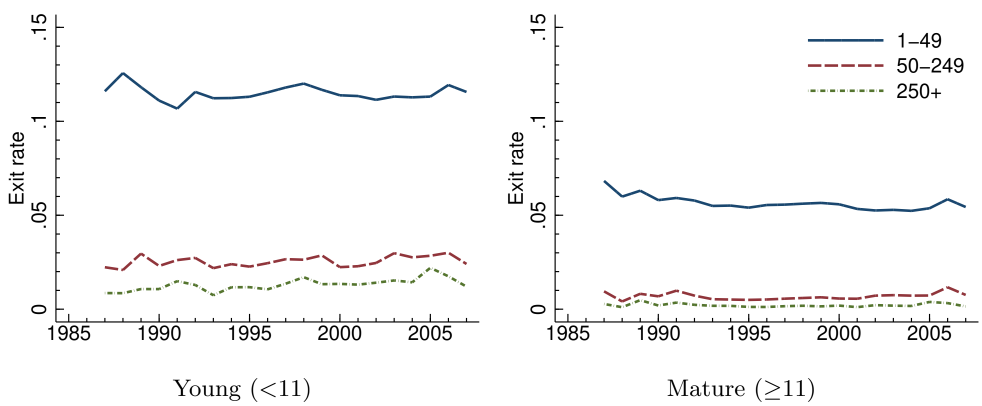


Figure C.8: Incumbent exit rates by firm size for young and mature firms

[17] This finding is robust to controlling for sectors and states. See Pugsley and Şahin (2019).

Table C.4: Average slope of HP trend for exit rate and conditional growth rates, 1987-2007

	Exit Rate x_t				Conditional Employment Growth Rate n_t			
	All Sizes (1)	Small (2)	Medium (3)	Large (4)	All Sizes (5)	Small (6)	Medium (7)	Large (8)
	A. Firm Age 2-3 Years							
Trend	-0.0002*	-0.0002*	-0.0006***	0.0006***	0.0003	0.0002	0.0006	0.001
	(0.0001)	(0.0001)	(0.0002)	(0.00010)	(0.0004)	(0.0003)	(0.0005)	(0.0010)
R^2	0.26	0.25	0.45	0.54	0.03	0.04	0.12	0.08
RMSE	.0024	.0024	.004	.0034	.011	.0075	.011	.025
N	21	21	21	21	21	21	21	21
	B. Firm Age 4-5 Years							
Trend	-0.0002**	-0.0002**	-0.00010	0.0001	-0.00003	-0.00010	0.0002	0.004***
	(0.00008)	(0.00008)	(0.00007)	(0.00008)	(0.0002)	(0.0002)	(0.0002)	(0.0009)
R^2	0.31	0.31	0.12	0.16	0.00	0.01	0.03	0.60
RMSE	.0017	.0017	.0017	.0018	.0047	.0055	.007	.022
N	21	21	21	21	21	21	21	21
	C. Firm Age 6-10 Years							
Trend	0.00007	0.00006	0.0001***	0.0003***	-0.0005**	-0.0003*	-0.0003	-0.0006**
	(0.00008)	(0.00008)	(0.00001)	(0.00003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
R^2	0.06	0.04	0.82	0.86	0.19	0.16	0.11	0.13
RMSE	.0017	.0018	.00043	.00084	.0065	.0046	.0057	.01
N	21	21	21	21	21	21	21	21
	D. Firm Age 11+ Years							
Trend	-0.0004***	-0.0004***	0.00003	-0.00004**	-0.0006***	-0.0005***	-0.0001	-0.0002
	(0.00009)	(0.0001)	(0.00004)	(0.00001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
R^2	0.61	0.63	0.03	0.24	0.40	0.45	0.03	0.05
RMSE	.002	.0021	.001	.00041	.0044	.0037	.0045	.0041
N	21	21	21	21	21	21	21	21

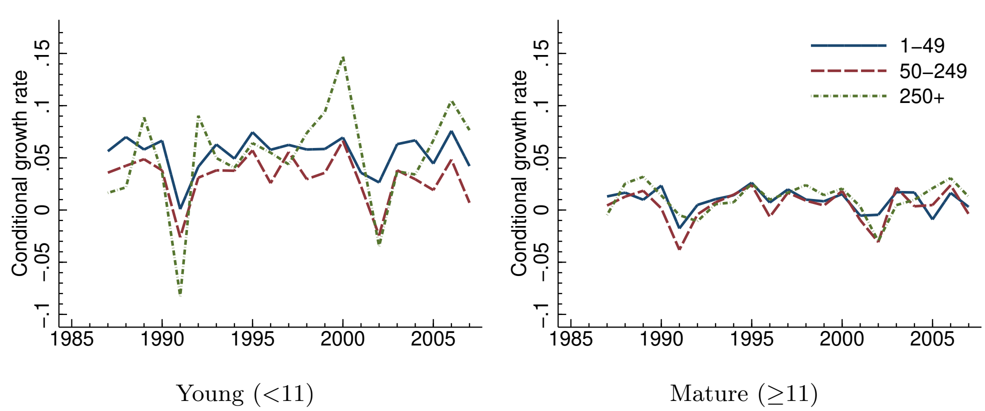


Figure C.9: Incumbent growth rates by firm size for young and mature firms

C.2 Cross-state results

Next, we supplement our analysis in Section 4 of the main text with additional cross state tests of the mechanism.

C.2.1 Civilian labor force results

First, we present the full set of results using Civilian Labor Force (CLF) growth rather than Working Age Population (WAP) growth as the measure of labor supply growth. Figure C.10 replicates Figure 9 from the main text, here predicting CLF growth with the instruments. Scatter plot points are first residualized on state and time fixed effects. Next, Table C.5 replicates Table 6 from the main text using the CLF measure of labor supply growth.

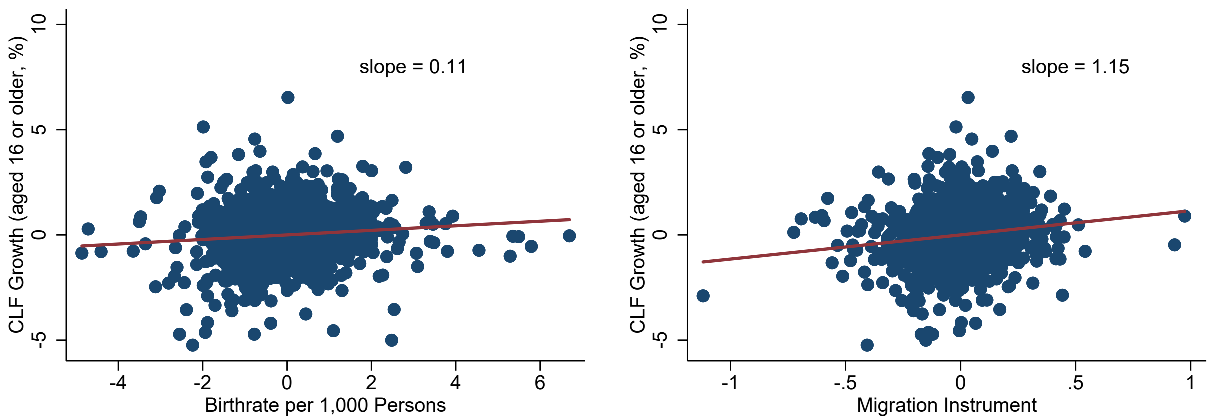


Figure C.10: First-stage regressions of CLF growth rate on fertility and migration instruments.

Table C.5: Start-up rate and civilian labor force growth

	First Stage			OLS	IV_1	IV_2	IV_1&IV_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CLF Growth (%)				0.22	1.38	1.14	1.20
				(0.04)	(0.61)	(0.28)	(0.28)
Birthrate IV	0.11		0.08				
	(0.03)		(0.03)				
Migration IV		1.15	1.03				
		(0.36)	(0.35)				
N	1,421	1,421	1,421	1,421	1,421	1,421	1,421
R^2	0.41	0.42	0.42	0.87	0.44	0.60	0.56
F-test	9.92	10.10	8.45				
p-value of J-test							0.70

Note: Standard errors are clustered on state. State and year fixed effects, years 1979-2007 and lower 48 plus D.C.

In Table C.6, we combine and replicate Tables 7 and 8 from the paper. Panels A and B includes industry controls as well as state-trends, respectively. Panels C, D, and E change the outcome to average startup size, young firm exit rate, and young firm conditional growth, respectively.

Table C.6: Robustness of effect of labor supply shocks on the startup rate.

	(1) OLS	(2) IV_1	(3) IV_2	(4) IV_1 & IV_2
Panel A. Detailed industry controls				
WAP Growth (%)	0.26	0.88	1.09	1.02
	(0.04)	(0.25)	(0.26)	(0.23)
N	300,000	300,000	300,000	300,000
R^2	0.51	0.49	0.48	0.49
J-test p-value				0.25
Panel B. State-specific trends				
WAP Growth (%)	0.20	1.18	1.43	1.32
	(0.04)	(0.32)	(0.36)	(0.29)
N	1,421	1,421	1,421	1,421
R^2	0.90	0.60	0.43	0.51
J-test p-value				0.48
Panel C. Average startup employment				
CLF Growth (%)	−0.01	−0.34	−0.05	−0.12
	(0.03)	(0.22)	(0.13)	(0.14)
N	1,421	1,421	1,421	1,421
R^2	0.45	0.31	0.45	0.43
J-test p-value				0.13
Panel D. Young firm exit rate (%)				
CLF Growth (%)	−0.13	0.13	−0.15	−0.05
	(0.03)	(0.22)	(0.16)	(0.13)
N	1,029	1,029	1,029	1,029
R^2	0.72	0.66	0.72	0.71
J-test p value				0.34
Panel E. Young firm conditional growth rate (%)				
CLF Growth (%)	0.41	−0.88	−0.08	−0.37
	(0.12)	(0.72)	(0.76)	(0.68)
N	1,029	1,029	1,029	1,029
R^2	0.41	0.24	0.39	0.35
J-test p-value				0.26

Note: Standard errors clustered on state. All regressions use specification and sample from Table 6.

C.2.2 Spatial correlation

One concern is firm and labor market activity may be spatially correlated, e.g., across adjacent states. The residual variation in fertility plotted above in Figure A.1 shows some evidence for clusters of similar birth rates. In the results from the main text we compute standard errors clustering on state, which allows for arbitrary serial correlation within a state but assumes that observations across states are uncorrelated. To the extent there is spatial correlation, the standard errors may be biased down.[18]

Table C.7: Adjusting standard errors for spatial correlation

	IV_1			IV_2			$IV_1\&IV_2$		
	CGM (1)	DK (2)	THOM (3)	CGM (4)	DK (5)	THOM (6)	CGM (7)	DK (8)	THOM (9)
Panel A. Working age population growth									
WAP Growth (%)	1.09	1.09	1.09	1.27	1.27	1.27	1.19	1.19	1.19
	(0.33)	(0.22)	(0.32)	(0.26)	(0.27)	(0.29)	(0.25)	(0.22)	(0.26)
N	1,421	1,421	1,421	1,421	1,421	1,421	1,421	1,421	1,421
R^2	0.87	0.87	0.87	0.85	0.85	0.85	0.86	0.86	0.86
p-value of J-test							0.58	0.55	0.61
Panel B. Civilian labor force growth									
CLF Growth (%)	1.38	1.38	1.38	1.14	1.14	1.14	1.20	1.20	1.20
	(0.71)	(0.60)	(0.68)	(0.37)	(0.42)	(0.42)	(0.38)	(0.40)	(0.40)
N	1,421	1,421	1,421	1,421	1,421	1,421	1,421	1,421	1,421
R^2	0.44	0.44	0.44	0.60	0.60	0.60	0.56	0.56	0.56
p-value of J-test							0.69	0.59	0.69

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.

Our cross state results remain significant even allowing for spatial correlation. We consider in Table C.7 three corrections that have been proposed in the literature. In Columns (1), (4) and (7) we estimate the elasticity of the startup rate with birthrate, migration and joint IVs, respectively, where we compute standard errors using the two-way procedure developed by Cameron, Gelbach, and Miller (2011), which allows for arbitrary spatial correlation within a year and arbitrary serial correlation within a state. Panel A. reports the results using the working-age population growth rate proxy for labor supply growth and Panel B. using the civilian labor force growth rate. Next, in Columns (2), (5) and (8) we compute standard errors using the procedure from Driscoll and Kraay (1998), which allows for arbitrary spatial correlation within a year and corrects for aggregate serial correlation using a Newey-West procedure with a bandwidth of 3 years. Finally, for columns (3), (6) and (9) we combine these two approaches using the method recommended by Thompson (2011), which allows for both two way clustering and aggregate serial correlation. Using any of these

[18] See, for example, Foote (2007).

approaches, the results remain significant at reasonable levels. The birthrate IV, particularly when using the CLF growth proxy is the most affected, but still remains significant at the 5 percent level. For all others, to the extent there is spatial correlation present in the data, it enlarges our estimated confidence sets, but those sets still lay far from zero.

C.2.3 Establishment level regressions

While in the cross-state analysis in the paper we focus on the firm startup rate, the cross-state results are robust to an establishment-based measure of the startup rate. Since the vast majority of new establishments are new firms, the establishment results are very similar to the main results (Table C.8).

Table C.8: Labor supply growth elasticity of the establishment entry rate

	(1) OLS	(2) IV_1	(3) IV_2	(4) IV_1 & IV_2
Panel A. Working age population growth				
WAP Growth (%)	0.60	0.94	1.15	1.05
	(0.05)	(0.29)	(0.19)	(0.20)
N	1,421	1,421	1,421	1,421
R^2	0.89	0.88	0.85	0.86
p-value of J-test				0.38
Panel B. Civilian labor force growth				
CLF Growth (%)	0.22	1.18	1.04	1.08
	(0.04)	(0.55)	(0.24)	(0.25)
N	1,421	1,421	1,421	1,421
R^2	0.86	0.50	0.60	0.58
p-value of J-test				0.80

Note: Standard errors are clustered on state. Establishment entry rate is the percentage of age 0 establishments (regardless of firm age) out of the total number of establishments. Regressions contain state and year fixed effects and cover years 1979-2007 and 48 contiguous states plus D.C.

C.2.4 Time period

Conditioning on young incumbents (age 1-10) requires restricting the sample to 1987+, since 1987 is the first year that birth year is not left censored for ages 1 to 10. The main estimates in Table 6 do not depend on including the years 1979 to 1986. Restricting the sample to 1987-2007 as we do in Table C.9 has little effect on the estimates. The first stage using just the migration instrument is considerably weaker, but the predictive power of the birthrate instrument improves. Regardless, point estimates are very similar across the full and restricted sample.

Table C.9: Startup rate elasticity estimated using 1987 to 2007 sample

	First Stage			OLS	IV_1	IV_2	IV_1&IV_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WAP Growth (%)				0.45	1.22	1.12	1.18
				(0.07)	(0.20)	(0.26)	(0.20)
Birthrate IV	0.14		0.13				
	(0.02)		(0.02)				
Migration IV		0.97	0.80				
		(0.43)	(0.39)				
N	1,029	1,029	1,029	1,029	1,029	1,029	1,029
R^2	0.68	0.67	0.69	0.91	0.83	0.85	0.84
F-test	51.06	5.11	25.16				
p-value of J-test							0.68

Note: Standard errors are clustered on state. Regressions contain state and year fixed effects and cover years 1987-2007 and 48 contiguous states plus D.C.

C.3 IV Robustness

We provide additional exercises to support the identifying assumptions in our empirical strategy.

C.3.1 IV effects on age composition

We can directly examine the systematic effects of lagged fertility on share of young people (age 20-34) after removing state and year fixed effects. Table C.10 regresses the share of young people (as share of working age population) on the birth rate and migration instruments individually and together. The partial R^2 reports the incremental increase in fit from adding the instruments to a baseline regression that includes only state and year fixed effects.

Table C.10: Predicting the share of young workers

	(1)	(2)	(3)
	Age 20-34 Share	Age 20-34 Share	Age 20-34 Share
Birthrate IV	−0.000		−0.000
	(0.360)		(0.300)
Migration IV		−0.002	−0.001
		(0.670)	(0.420)
Observations	1,421	1,421	1,421
R^2	0.954	0.954	0.954
Partial R^2	0.005	0.005	0.005

Note: Standard errors clustered on state. Regression of 20-34 year old share of working age population on each instrument and state and year fixed effects. 48 contiguous states plus D.C., and years 1979 to 2007. Partial R^2 is increase in R^2 from adding instrument relative to regression with only fixed effects.

C.3.2 Alternative migration instrument construction

One concern with the migration instrument is that the contemporary push from other-state working age population growth may still be correlated with the own state labor market growth even when the states are geographically far apart. At a very local labor market level this may be common. For example, the Bay area in California may have a similar mix of high tech industries to the Route 128 corridor near Boston, MA. To rule out this possibility we consider an alternative migration instrument that constructs weighted averages of other state lagged birthrates in place of other state working age population growth rates. That is, we construct

$$\hat{m}^*_{st} = \sum_{k \notin C(s)} \omega^k_{st^*} b_{kt-20} \tag{B.1}$$

Here, $\omega^k_{st^*}$ is the share of residents of state s that were born in state k and b_{kt-20} is a 20 year lag of the state k birth rate. 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 $\omega^k_{st^*}$ from 2 censuses ago.[19]

Table C.11: Migration instrument using lagged birthrate push

	First Stage		IV_2	IV_1&IV_2^*
	(1)	(2)	(3)	(4)
Panel A. Working age population growth				
WAP Growth (%)			1.37	1.20
			(0.41)	(0.31)
Birthrate IV		0.10		
		(0.03)		
Migration IV*	0.48	0.29		
	(0.12)	(0.13)		
N	1,421	1,421	1,421	1,421
R^2	0.64	0.64	0.83	0.86
F-test	15.69	21.69		
p-value of J-test				0.39

Note: Standard errors are clustered on state. Regressions contain state and year fixed effects and cover years 1979-2007, 48 contiguous U.S. state plus D.C. Migration IV* constructed using 20 year lags of other state birthrate in place of contemporary working age population growth as pushes in the calculation of the own-state weighted average.

In Table C.11 we show that even when using this alternative migration instrument, the results are quantitatively very similar to Table 6 in the main text and remain statistically significant.

[19]We use the IPUMS microdata, see Ruggles, Genadek, Goeken, Grover, and Sobeck (2017), for the long form responses to the 1970, 1980, 1990 Decennial Censuses. In 1979, the lag is 9 years, i.e., we set $t^* = 1970$ instead of 1960. Appendix A.3.2 provides additional details on the migration instrument construction.

C.4 CBP Startup Rate imputations

Finally, we consider our CBP-based establishment startup rate imputation against some alternatives. First, we show that the trend component of the CBP imputation and the actual establishment startup rate measured in the BDS track each other closely. (See Table C.11, which is the smoothed version of Figure 10 from the main text.)

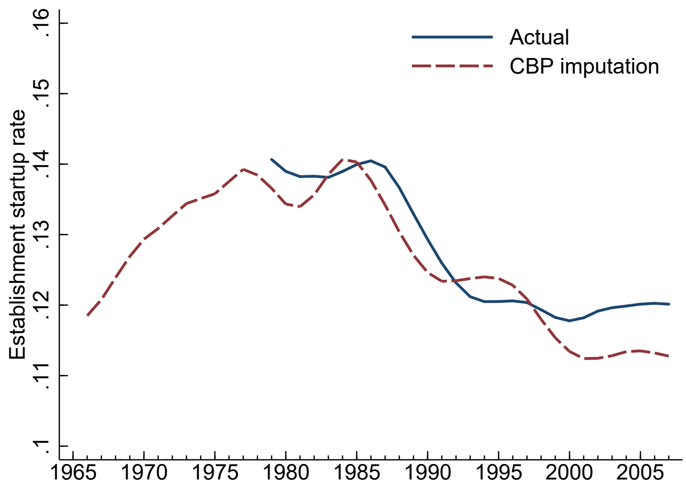


Figure C.11: Comparing trend component of actual and CBP imputed startup rates

Next, we consider the effects of alternative assumptions in the statistical model to predict the aggregate exit rate. In Section 5, we estimate for each state and establishment size category within the BDS the following regression for exit

$$x_t^{sj} = \bar{x}^{sj} + \lambda^{sj} t + \varepsilon_t^{sj}.$$

The linear time trend coefficient λ^{sj} captures the slow movement in exit within size group because of implied changes in the age distribution. We allow this coefficient to differ for each state and size group. When predicting exit rates out of sample, we have to choose whether or not to extrapolate the time trend. In the main text, we keep the trend term fixed at its 1979 level when estimating exit prior to 1979. In Figure C.12, we consider several alternative choices: a symmetric trend, a continuuing trend, or holding exit fixed at its in-sample average. For each, we predict exit by state and size group and year $\hat{\delta}_t^{sj}$, and then compute the imputed CBP startup rate using equation (12).

The solid line plots the actual establishment startup rate measured in the BDS for the years 1979 to 2007. The broken red line plots the imputation used in the paper. As an alternative, the orange and gray lines consider imposing a symmetric trend pre 1979 and continuuing the in-sample time trend, respectively. By construction they are the same for the 1979-2007 period. As a final alternative, we eliminate the time trend entirely and just estimate exit using the average exit rate over the entire period. Regardless of the assumption used to predict exit, the hump shaped pattern in the CBP-based imputed establishment startup rate remains the same.

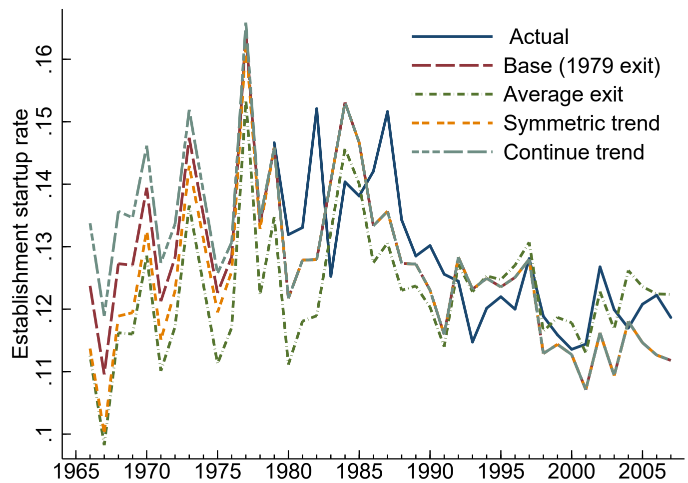


Figure C.12: Imputed startup rate under alternative extrapolation of exit rate by size groups

As a further refinement, we add an aggregate state variable to the exit regression

$$x_t^{sj} = \bar{x}^{sj} + \lambda^{sj} t + \beta^{sj} Z_t + \varepsilon_t^{sj}.$$

Here as a business cycle indicator, we use annual real GDP growth. Figure C.13 plots the same set of alternatives where the exit rate prediction also includes any predicted business cycle fluctuations using state variable Z_t. The results are very similar and also feature the hump shaped pattern.

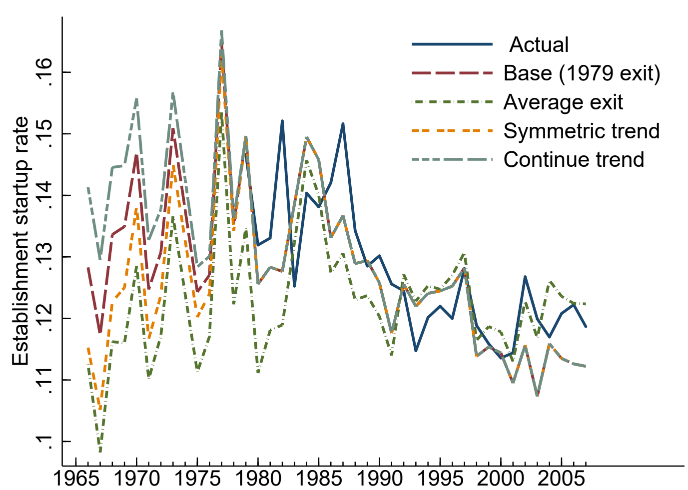


Figure C.13: Imputed startup rate under alternative extrapolation of exit rate with cyclical adjustment

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