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The Role of Startups for Local Labor Markets

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Abstract

We investigate the dynamic response of local U.S. labor markets to increased job creation by new firms and compare the effects to overall labor demand shocks. To account for both dynamic and spatial dependence we develop a spatial panel VAR that builds on recent advances in the VAR literature to identify structural shocks using external instruments. We find that startup shocks have a small but persistent effect on local employment through population growth. Population growth, in turn, is largely driven by immigration. We also investigate how the responses differ by local characteristics such as population density. Finally, we show that startups are not closely linked to innovation.

Keywords: Startups; entrepreneurship; local labor markets; proxy VAR; spatial panel VAR.

JEL classification: C33, C36, E24, L26, R11.

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1 Introduction

A growing literature has documented the importance of startups for the U.S. labor market: Haltiwanger et al. (2013) may have been the first to document the significant role of new firms in creating jobs in the U.S. economy. New firms created an average of 3.6 million jobs between 1977 and 2013, adjusted for changes in the working-age population relative to 2013. At the same time, the economy as a whole created 2.1 million jobs, on net. Of course, gross job creation ran higher, at 19.6 million – but Haltiwanger et al. (2013) also show that surviving new firms grow faster than incumbents. This picture of the secular importance of startups is complemented by Decker et al. (2014) and Pugsley and Sahin (2015), who document a trend decline in startup formation. In addition, Siemer (2014), Gourio et al. (2015), and Sedlacek and Sterk (2014) document a drop in startup activity in the Great Recession.

In this paper we examine two questions: First, to what extent is startup activity driven by shocks to startups? Second, what effects do startups have on the local economy? We develop a spatial panel VAR that uses external instruments to separately identify shocks to overall labor demand and to startup labor demand. Identifying both shocks matters, because more firms enter when overall labor demand is high. Half of local startup job creation is due to startup shocks. These startup shocks have small but persistent effects on local employment through gradual increases in population.

There is a small but growing literature looking at either the causes or the economic effects associated with the slowdown in new firm entry. A number of recent papers consider the importance of demographic shifts for explaining the decline in startups. Karahan et al. (2015) show that a decline in the working-age population accounts for an important share of the decline in firm entry. Hathaway and Litan (2014) also find a correlation between the startup deficit and slowing population growth as well as an increased rate of business consolidations. Lazear et al. (2014) document that countries with older workers have lower rates of entrepreneurship and new business formation. Ouimet and Zarutskie (2014) show the proportion of a state's young workers is a good predictor of its startup rate, especially for high-tech firms. Dent et al. (2016) look at the role of startups in the evolution of employment across firm age for three sectors: manufacturing, retail trade, and services. They find that since the late 1980s, the entry margin accounted for one-half of employment reallocation across sectors. Decker et al. (2016) note that since 2000 there has a rapid decline in skewness in the growth rates of employment with differential patterns across sectors. They report that the decline reflects a notable decline in the 90th percentile of the employment growth rate distribution "accounted for by the declining share of young firms and the declining propensity for young firms to be high-growth firms."[1]

[1]See Karahan et al. (2015) for a broader discussion of the causes of the startup deficit, such as financial constraints or changes in regulation.

There has been considerably less research concerning the economic consequences of the startup deficit, which is what we study. In a paper closely related to ours, Gourio et al. (2016) use a panel of U.S. states for the period 1982–2014 and find that shocks to the number of startups has long-lasting effects on employment, productivity, and to a lesser extent on population. We similarly find small but persistent effects of startup shocks on population and employment. But our strategy for estimating the regional consequences of the startup decline differs from Gourio et al. (2016) because we jointly identify shocks to startups and to overall labor demand. This is important because both Adelino et al. (2014) and we find that positive shocks to overall labor demand also increase firm entry. As both the labor demand shocks in Adelino et al. (2014) and the entry shocks in Gourio et al. (2016) are identified using instruments based on local industry structure and national industry outcomes, the identified entry shocks in Gourio et al. (2016) plausibly also reflect overall labor demand shocks. Our strategy is to first identify overall labor demand shocks with the same interpretation as in Bartik (1991) and Blanchard and Katz (1992) and then identify startup shocks using the residual variation in the exposure of local labor markets to sectoral job creation rates.[2] In contrast to Blanchard and Katz (1992), where migration is a residual, we provide direct evidence on the response of migration to labor demand shocks. We find that startup shocks are more important for population growth and migration than overall labor demand shocks.

Specifically, we construct two instruments: one proxy for local startup shocks and another for overall labor demand shocks in the tradition of Bartik (1991). The idea of Bartik (1991) was to instrument for local labor demand using predictors based on the past industry structure of a location and the national evolution of its different industries. Here, we use the standard Bartik (1991) instrument alongside a second instrument that predicts local job creation through startups by the national evolution of startups and the local industry structure.

We use a structural VAR for our analysis that allows us to flexibly capture the equilibrium effects of startup activity. Our setup uses the Bartik (1991)-type shocks as an external instrument to identify the shock, building on the recent proxy-VAR literature initiated by Stock and Watson (2012) and Mertens and Ravn (2013, 2014). The advantage of the proxy-VAR approach is that it allows not only for dynamic but also for contemporaneous feedback between startups and incumbents, unlike the traditional Choleski identification. In our context, this can be important, because Hombert et al. (2014) show that entry by startups leads to significant crowding out of incumbents that we do not want to limit using zero restrictions.

In the analysis, we combine the spatial error panel VAR in Mutl (2009) with the identification strategy in Mertens and Ravn (2013). Mutl (2009) models error terms as spatial-

[2]We also differ from Gourio et al. (2015) because we look at MSAs, which are local labor markets. In addition, we model and estimate the degree of spillovers among MSAs directly by allowing for the errors to be spatially correlated.

autoregressive (SAR) processes, with a spillover parameter that is common for all variables in the VAR.[3] A SAR process for the VAR errors implies in our context that the local markets are small open economies, but that these economies influence each other through trade or migration linkages. We document that this SAR structure is important in the data. However, we allow the degree of spillovers to differ across variables. This generalization is also supported by the data: For example, we estimate smaller spillovers for job creation than for population growth. We also show how to factor several shocks that are jointly identified by proxies differently from Mertens and Ravn (2013) so that one of the shocks is identified exactly by one of the instruments. This is natural in our application because it allows us to identify an overall labor demand shock as in the literature. Our framework is useful beyond the specific question we analyze here, because as Beaudry et al. (2014) illustrate, it is straightforward to use regional variation to identify both demand and supply shocks using historical predictors.[4]

Jentsch and Lunsford (2016) have shown that a block bootstrap in a time series setup is asymptotically valid for proxy VARs as in Mertens and Ravn (2013). Here, we use a block bootstrap on the spatially filtered data. To account for potential bias in the estimates of autocorrelation over time and space, we use a bootstrap after bootstrap procedure following Kilian (1998).

Estimates of the causal effects of startups also matter from a substantive point of view: Policy makers have often pinned hopes for improving the economy on promoting entrepreneurship. A recent example is in the city of Detroit, where an initiative to promote startups is reported to have been put in place to help reverse the decline in population.[5] Within the VAR, a typical, i.e., a one-standard deviation, shock to startup labor demand increases startup employment initially by 0.6% of overall employment. On impact, the effect of overall employment is ambiguous, but employment gradually increases and after five years stabilizes 1% higher. We show that this response is driven by population growth. We also construct historical counterfactuals of population growth in specific MSAs with and without the identified shocks. For example, population growth in the San Francisco MSA would have been about 0.25pp. lower per year from 2008 to 2013 without startup shocks.

To shed light on the driving forces behind our results, we also estimate variants of our model that allow for heterogeneity across ex ante different MSAs. In the main text, we focus on initial

[3] Yang and Lee (2015) consider a wide range of spatial interactions in dynamic models. Spatial lags in outcomes, rather than just spatial errors, are challenging, however, since they can lead to explosive dynamics across time and space.

[4] For example, a Card (2001)-type instrument could identify population supply shocks.

[5] *The Economist* writes that "people continue to leave a city that has shrunk from 1.8m inhabitants in 1950 to 680,000 today. To reverse this trend, Detroit and the state of Michigan are pinning their hopes on entrepreneurs. In his address the mayor announced the creation of 'Motor City Match', a new programme funded by foundations and the federal government that will provide $500,000 every quarter for the next five years as seed money for people wanting to start a business." ("After the bankruptcy. Green shoots. Can entrepreneurs revive Motor City?", US edition, 03/21/2015, p. 22)

density. Density matters because it captures both congestion or agglomeration forces. We find that our results are mostly driven by stronger responses of low-density MSAs to startup shocks. We also extend the analysis to patenting activity as a measure of innovation. We find that patenting shocks do not lead to much startup activity, nor do startup shocks lead to greater patenting activity.[6]

We proceed as follows: In Section 2 we introduce the data and summarize national trends and regional variation. In Section 3 presents the spatial panel VAR and discusses shock identification. Section 4 discusses our findings: First, we present standard impulse-responses, the variance decomposition, and historical counterfactuals for specific MSAs in our baseline model. Second, we summarize various robustness checks. Third, we allow for heterogeneity by initial density. Fourth, we analyze patenting activity and startups. Section 5 concludes.

2 Regional Data on Startups

2.1 Data description

We collect data on local labor markets for 354 MSAs from 1978 to 2014, although some series are available only for a shorter period. The main challenge in assembling the data from various sources is consistency across space and time: Various sources sample at different points of the calendar year. Similarly, the composition of metropolitan areas has changed over time. When combining different data sources we also carefully align the timing as closely as possible with the startup and employment data. Appendix A provides more detailed descriptions of the data and how we construct the variables.

Startup data. We use the administrative data from the U.S. Census Bureau's Business Dynamics Statistics (BDS), described in Haltiwanger et al. (2013), for sector-level and metropolitan area-level employment by firm age, and firm exit and entry rates.[7] Following Haltiwanger et al. (2013), we define rates relative to a denominator that averages employment or the number of firms in the current and the previous year.

Metropolitan area definitions. For consistency with the BDS, we aggregate counties to MSAs using the 2009 MSA definitions. In rare cases, the definitions of counties themselves have

[6] This exercise is similar in spirit to the model with group specific coefficients and fixed effects in Bonhomme and Manresa (2015), except that our cluster is deterministic and based on a single measure. Introducing a clustering step based on one or multiple measures should be a straightforward extension of our work.

[7] The sectors are: Agricultural services, mining, construction, manufacturing, utilities, wholesale, retail, FIRE (finance, insurance, and real estate), and services.

changed over time. We found only one MSA that was affected by this change.[8] Table A.1 lists all MSAs in our sample.

Metropolitan employment. We use the administrative data from the Census' County Business Patterns for average wage rates and industry-level employment at the MSA level. Average wage rates are simply first quarter payroll per employee, both summed across all counties within an MSA. To compute industry-level employment, we need to impute some county-industry-level employment data. We build on the code from Autor et al. (2013) for the imputation. See Appendix A for details.

Migration data. Migration data for the United States are obtained from the Internal Revenue Service's (IRS) Statistics on Income Division. The migration data are based on year-to-year address changes reported on individual income tax returns filed with the IRS. We use county-to-county flows for the period 1990–2013 and convert the county flows to MSA flows using the 2009 MSA definitions. For the period from 1984 to 1989, we use archived IRS data from the National Archives.[9] As most households file tax returns by mid-April of each year, the migration data lines up with our snapshot of employment and startup data.

Population and density data. Population data were obtained at the county level from the Census Bureau. Counties are aggregated to MSAs using the 2009 MSA definitions. We calculate population density as population per square km per MSA, using data from the Census' American Fact Finder.[10] Population is measured for the middle of the calendar year.

MSA proximity matrix. We construct the proximity matrix based on the Census Bureau's MAF/TIGER shape files. The proximity is the (inverse) squared Euclidean distance between the centroids of any pair of MSAs.[11] In the appendix, we also consider alternative measures.

House prices. Metropolitan area housing prices are from the CoreLogic Solutions monthly repeat-sales Housing Price Index. We use March values of the index. MSA level data were used. However, MSA data where not available for eleven MSAs (Boston, Chicago, Dallas, Detroit,

[8] The newly created Broomfield county was split out of the Boulder, CO, MSA and as a new county became part of the neighboring Denver, CO, MSA. We therefore combine the data on the Denver and Boulder MSAs. In 1997, Dade county, FL, was renamed to Miami-Dade county. This change does not affect our analysis.

[9] See https://www.irs.gov/uac/soi-tax-stats-migration-data for data from 1990 onward and https://catalog.archives.gov/id/646447 for the archived data.

[10] The population data is from https://www.census.gov/programs-surveys/popest/data/data-sets.All.html and the area data from https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_09_5YR_G001&prodType=table.

[11] https://www.census.gov/geo/maps-data/data/tiger-line.html.

Los Angeles, Miami, NYC, Philadelphia, San Francisco, Seattle, Washington DC). For these MSAs, we used data at the NECTA metropolitan division level.[12]

Patent data. Patents data are often used as an indicator of innovation and we use them as a robustness check on our finding for startup activity. We use data on patent applications obtained from the NBER Patent Data Project. The data span the years 1976–2006.[13] We identify the inventors on a patent using data on inventor codes found in the Patent Network Dataverse (Lai et al., 2013). Patents are assigned to locations based on the zip code associated with the residential address of the first inventor on the patent. When there are multiple inventors named on a patent, we assigned the patent to MSAs in proportion to the number of inventors in each MSA.[14]

2.2 National trends and regional variation

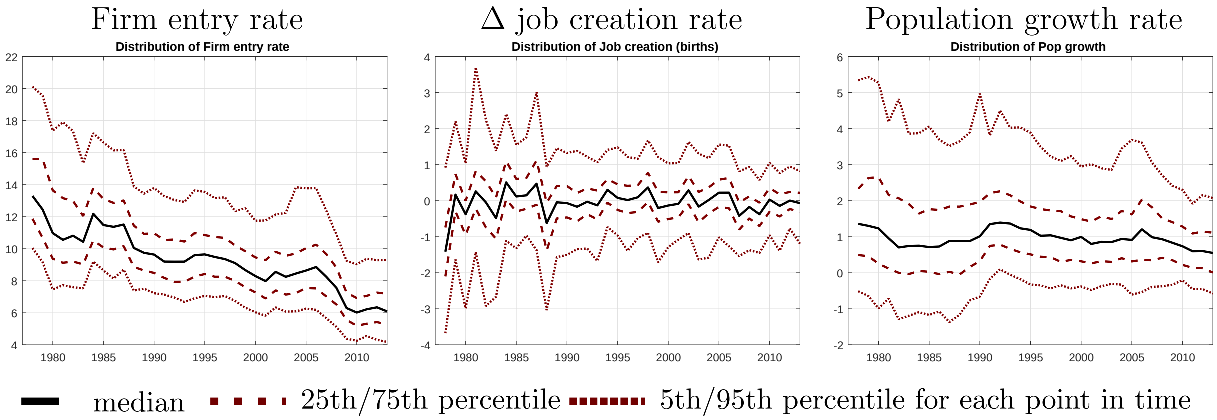
The national context of our analysis of the local effects and determinants of startup activity is a trend decline in firm entry, as Figure 1 shows. The median entry rate, measured relative to the stock of firms, has declined from about 13% in 1978 to 6% in 2014. At the same time, job creation rates by startups have remained relative stable: The median change in startup job creation, relative to MSA employment, declined substantially in 1978, but has been averaged around zero since. The median MSA grew its population around 1% in our sample. There is, however, substantial variation around these national trends: The median change in the job creation rate was about 1.25pp. in 1978, and 5% of MSAs experienced a decline of more than 3.5pp. At the same time, however, 5% of MSAs also saw an increase of 1pp. or more. The range of outcomes in the firm entry rate is also large: in 1978, the bottom 5% of MSAs had entry rates below 10%, while the top 5% saw entry above 20%. Along with this disparity, population growth also varied widely.

In our analysis, we study this regional variation. We ask to what extent labor demand shocks to startups and established firms can explain the different outcomes. Our focus are regional outcomes relative to time fixed effects. As in Blanchard and Katz (1992), these have

[12]We use CoreLogic Solutions' Single Family Combined Index (HPI 4.0 Data) that excludes distress sales. There are 11 MSAs deemed large enough to be subdivided into their component metropolitan divisions. For example, the Dallas-Fort Worth-Arlington, Texas MSA is composed of the Dallas-Plano-Irving, Texas Metropolitan Division and the Fort Worth-Arlington, Texas Metropolitan Division. We aggregate both metropolitan divisions in this case, and proceed similarly in the other ten cases. We use house prices for the first quarter of each calendar year to line up approximately with the BDS and CBP data. In rare cases, the first quarter is missing so we use the last quarter of the preceding year.

[13]We use only applications up to 2001 to ensure they were processed by 2006. http://www.nber.org/patents/

[14]We use application dates for which we only have the calendar year. For grant dates we observe both year and month, but but the grant date is typically several years in the future.



Firm entry shows a trend decline in the average MSA, while the change in the job creation rate by startups and population growth have remained relatively stable. The regional variation around these median outcomes is large. Our paper studies regional variation and uses predictors based on local industry structure to identify shocks.

Figure 1: National trends and cross-sectional distribution of VAR variables: 1978 – 2014.

the interpretation of national averages in our baseline analysis. To identify the labor demand shocks, we also use regional variation. Bartik (1991) proposes to identify shocks using past local industry composition and industry-specific growth.

Following Bartik (1991), we define our instruments $Z^x_{m,t}$ for some target variable x as:

$$Z^x_{m,t} = \sum_i \omega_{m,i,t-\tau} \times x_{i,t}, \tag{2.1}$$

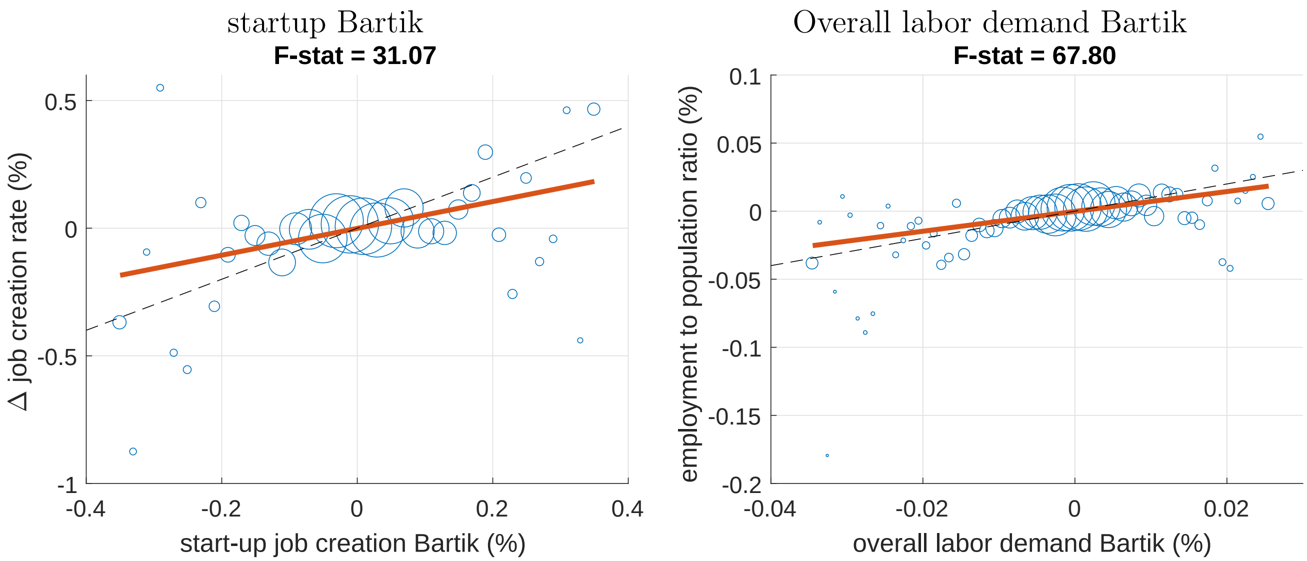
where $\omega_{m,i,t-\tau}$ is the industry ith share in region m at time $t-\tau, \tau > 0$. $x_{i,t}$ is the national value of x in industry i at time t, for example, the growth rate of employment in an industry or the change in the startup job creation rate. In the special case of constant industry shares, subtracting year and MSA fixed effects, as we do in our analysis, highlights the residual variation we use to identify shocks:

$$Z^x_{m,t} - \hat{\mu}_m - \hat{\gamma}_t = \sum_i (\omega_{m,i} - \bar{\omega}_{m,i}) \times (x_{i,t} - \bar{x}_i) = \widehat{\text{Cov}}[\omega_{\circ,m}, x_{\circ,t}]. \tag{2.2}$$

The residual variation predicts higher x in area m at time t, say employment growth, when m is historically relatively stronger in industries that have grown faster than average in time t. As Blanchard and Katz (1992, p. 49) discuss, this instrument is valid for labor demand if national x_t is uncorrelated with supply shocks in areas m.[15]

Figure 2 shows that the standard Bartik (1991) instrument for overall labor demand is a good

[15]Data permitting, we compute $x_{i,t}$ excluding the MSA whose outcome we want to predict to further vouch against a mechanical relationship between national $x_{i,t}$ and $x_{m,t}$. Data limitations prevent us from doing so for startup labor demand. However, we use data at the sector level that is less concentrated in few areas.



In the raw data, Bartik (1991)-type instruments for startup activity and overall labor demand are good predictors. To visualize the data, we winsorize the variables at the 0.5% and 99.5% levels. All four variables are in deviations from time and MSA fixed effects. We bin the observations for clarity with the radius of the circles indicating the number of observations.

Figure 2: Static reduced form first stage relationship

predictor. Its deviation from year and time fixed effects predicts changes in MSAs employment-to-population ratio well, with an F-statistic of 67.8. We also construct an analogous instrument to predict changes in startup job creation. For this instrument, we have to rely on a coarser industry classification, but we also find it to predict the local change in startup job creation well with an F-statistic of 31.1. These statistics are, of course, only suggestive: They do not account for spatial correlation or predictable variation in the outcomes. To do this, we now turn to a spatial panel VAR. In this VAR, the Bartik (1991)-type predictors serve as external instruments to identify orthogonal shocks.

3 Empirical Methodology

Our empirical approach is built on a reduced form spatial panel VAR. We use spatially filtered instruments to identify two shocks in the VAR and use a bootstrap algorithm for inference.

3.1 Reduced form VAR

Our VAR is meant to model local labor markets and ultimately identify shocks based on how well national industry-specific trends predict outcomes in these local markets. To rule out that the estimation and identification is biased by common aggregate factors or excluded MSA specific characteristics, we allow for both location fixed effects μ_i and year fixed effects η_t. In addition, we suspect potential spatial dependence in the shocks affecting the different locations and therefore allow for a spatial error structure via the distance weights $D = [d_{ij}]_{i,j=1}^{N}$. Here, d_{ij} is a measure of the spatial proximity between locations i and j.[16] The resulting model for location i at time t is given by:

$$Y_{i,t} = \sum_{\ell=1}^{k} A_\ell Y_{i,t-\ell} + \mu_i + \eta_t + \underbrace{u_{i,t}}_{q\times 1} \tag{3.1}$$

$$u_{it} = \sum_{j=1}^{N} d_{ij} R u_{jt} + B\epsilon_{it}, \qquad \epsilon_{it} \overset{iid}{\sim} \mathcal{N}(\mathbf{0}, I_q), \tag{3.2}$$

where $R = \text{diag}([\rho_1, \ldots, \rho_q])$ with $-1 < \rho_1, \ldots, \rho_q < 1$ parametrizes the degree of spatial dependence. D is row-standardized such that non-zero rows sum to one and the matrix has a maximal eigenvalue of unity.

As it stands, equation (3.2) is part of a system of simultaneous equations and as such untractable. To simplify, it is useful to bring it into vector notation. As a first step, rewrite equation (3.2):

$$u_{it} = R \begin{bmatrix} u_{1t} & \ldots & u_{Nt} \end{bmatrix} D' e_{i,N} + B\epsilon_{it} \equiv R u_t D' e_{i,N} + B\epsilon_{it},$$

where $e_{i,N}$ is an $N \times 1$ selection vector of zeros except for a one in its Nth position. When obvious from the context, we drop the second subscript of the selection vector in what follows.

Stacking the model horizontally for each period across all MSAs:

$$Y_t \equiv \begin{bmatrix} Y'_{1t} \\ \vdots \\ Y'_{Nt} \end{bmatrix}' = AX_{t-1} + \mu + \eta_t \mathbf{1}'_N + u_t, \qquad A \equiv \begin{bmatrix} A_1 & \ldots & A_k \end{bmatrix}, X_{t-1} \equiv \begin{bmatrix} Y_{t-1} \\ \vdots \\ Y_{t-k-1} \end{bmatrix} \tag{3.3}$$

$$u_t \equiv \begin{bmatrix} u'_{1,t} \\ \vdots \\ u'_{N,t} \end{bmatrix}' = R u_t D' + B\epsilon_t. \tag{3.4}$$

Using the vec operator rule that $\text{vec}(ABC) = (C' \otimes A)\,\text{vec}(B)$ and that $\text{vec}(BC) = (C' \otimes I)\,\text{vec}(B)$, this can in turn be rewritten as:

$$\text{vec}(Y_t) \equiv (I_N \otimes A)\,\text{vec}(X_{t-1}) + \text{vec}(u_t), \tag{3.5}$$

$$\begin{aligned} \text{vec}(u_t) &= (D \otimes R)\,\text{vec}(u_t) + (I_N \otimes B)\,\text{vec}(\epsilon_t) \\ &= (I_{Nq} - (D \otimes R))^{-1} \left((I_N \otimes B)\,\text{vec}(\epsilon_t)\right), \end{aligned} \tag{3.6}$$

[16] We discuss the specific proximity measures below.

where $\text{vec}(\epsilon_t) \sim \mathcal{N}(\mathbf{0}, I_{Nq})$. This form of the spatial VAR is tractable as it expresses the forecast error in terms of the *iid* standard normal residuals $\text{vec}(\epsilon_t)$ and therefore allows us to write down the likelihood function or to derive the form of the impulse-responses. To gain intuition, however, it is instructive to consider two special cases:

Special case 1: Common spatial autocorrelation.

Let $R = I_q\rho$. Then:

$$\begin{aligned}(I_{Nq} - (D \otimes R))^{-1} &= (I_N \otimes I_q - (D \otimes I_q\rho))^{-1} \\ &= (I_N \otimes I_q - (D\rho \otimes I_q))^{-1} \\ &= ((I_N - D\rho) \otimes I_q)^{-1} \\ &= (I_N - D\rho)^{-1} \otimes I_q\end{aligned}$$

Using $\text{vec}(AB) = (B' \otimes I)\,\text{vec}(A)$ in reverse:

$$\begin{aligned}\text{vec}(u_t) &= (I_{Nq} - (D \otimes R))^{-1}(I_N \otimes B)\,\text{vec}(\epsilon_t) \\ &= \text{vec}\left(B\epsilon_t(I_N - D'\rho)^{-1}\right) \\ \Leftrightarrow u_t &= B\epsilon_t(I_N - D'\rho)^{-1}\end{aligned}$$

The term $(I_N - D\rho)^{-1} = \sum_{s=0}^{\infty}(\rho D)^s$ captures that shocks are multiplied across neighboring regions. The condition that $-1 < \rho < 1$ guarantees convergence given that D is row-standardized. This corresponds to the case in the literature, e.g. Mutl (2009).

Special case 2: Univariate process.

Let $q = 1$. Then:

$$(I_{Nq} - (D \otimes R))^{-1} = (I_N - D\rho)^{-1}$$

and $\text{vec}(u_t) = u_t'$ and similarly for μ. Therefore:

$$u_t = \text{vec}(u_t)' = (I_N\epsilon_t'B')'\,(I_N - D'\rho)^{-1},$$

in line with the results for a common spatial autocorrelation before.

3.2 Identification

We propose to use instruments external to our spatial panel VAR model for identification, as in Stock and Watson (2012) and Mertens and Ravn (2013). Denote these instruments by z_t.

Stack the $q_z \times N$ instrument matrix z_t below the $q \times N$ forecast error u_t matrix to yield:[17]

$$\text{vec}\begin{bmatrix} u_t \\ z_t - \mu_z - \eta_t^z \mathbf{1}_N' \end{bmatrix} = (I_{N(q+q_z)} - (D \otimes \tilde{R}))^{-1}(I_N \otimes \tilde{B})\,\text{vec}(\tilde{\epsilon}_t), \tag{3.7}$$

where $\tilde{\epsilon}_{i,t} = [\epsilon_{i,t}', (\epsilon_{i,t}^z)']'$ stacks the shocks to the instruments and the endogenous variables.

Ordering the shocks of interest first, we assume that

$$\tilde{B} = \begin{bmatrix} B & \mathbf{0}_{q,q_z} \\ [G, \mathbf{0}_{q_z,p-q_z}]B & C \end{bmatrix}$$

for full rank matrices B, C, and G. The zero restriction on the upper right corner simply states that the VAR is not subject to the measurement or prediction error that the instruments are subject to and that is implicit in the standard VAR formulation. The zero restriction on the lower left corner $[G, \mathbf{0}_{q_z,q-q_z}]B$ corresponds to the standard exclusion restriction in the literature on instrumental variables: The instruments are uncorrelated with the other structural shocks. The assumption that G is of full rank corresponds to the standard assumption of instrument relevance. Together these assumption imply that the q_z external instruments identify the q_z structural shocks that are ordered first.

If we have $q_z > 1$ instruments to identify q_z shocks, impulse-responses are only set-identified.[18] Formally, Mertens and Ravn (2013) show that the instruments reduce the identification problem from imposing the standard $\frac{q(q-1)}{2}$ identifying restrictions in the VAR to the lower dimensional problem of imposing the $\frac{q_z(q_z-1)}{2}$ restrictions to factor S_1S_1' in the following equation:

$$\beta_{[1]} = \begin{bmatrix} (I - \eta\kappa)^{-1} \\ (I - \kappa\eta)^{-1}\kappa \end{bmatrix} (S_1S_1')^{1/2}. \tag{3.8}$$

See Drautzburg (2016, Appendix A.4) for closed-form expressions of η, κ, and S_1S_1' in terms of the reduced-form VAR covariance matrix $V = \tilde{B}\tilde{B}'$.

Since there are infinitely many square-root matrices when $q_z > 1$, the identified sets for the impulse-responses are wide. Mertens and Ravn (2013) consider two particular decompositions: lower and upper triangular factorizations of S_1S_1'. While Drautzburg (2016) shows that certain policy rules justify these factorizations in the case of policy shocks, our analysis is concerned with a different type of shock.[19] Instead, we pursue a different type of identification. Importantly, neither of the schemes we consider imposes zero restrictions on impulse-responses.

[17] More precisely, we extract year and MSA fixed effects from the instruments first.

[18] See Moon et al. (2011) for a frequentist analysis of identified sets in VARs.

[19] Both Mertens and Ravn (2013) and Drautzburg (2016) analyze fiscal and monetary shocks that may well be described by policy rules for which the theory in Drautzburg (2016) applies. Here, the upper and lower triangular factorizations have different implications.

We identify shocks by attributing the variation in the well-understood Bartik instrument for overall labor demand entirely to the labor demand shock. This makes sure the overall labor demand shock inherits the standard interpretation in the literature, starting with Bartik (1991) and with Blanchard and Katz (1992) for VAR models. The startup shock identifies a startup shock based on the residual variation.

Formally, our identification works by identifying the first shock as proportional to the covariance between the first instrument, here the Bartik (1991) instrument, and the within-MSA forecast errors. We then choose the other shocks to be the orthogonal shock that explains the residual variation that is jointly explained by all instruments. In our case, there are only $q_z = 2$ instruments and this pins down both shocks exactly.

Proposition 1 (Identifying shocks.). *Let $V = \tilde{B}\tilde{B}'$ and $\Gamma = V'_{q+1:q+q_z,1:q}$. Partition $\Gamma = [\Gamma_1', \Gamma_2]'$, where Γ_1 is $q_z \times q_z$. Assume Γ_1 is invertible, so that $\kappa = \Gamma_2\Gamma_1^{-1}$ is well defined.*

(a) If we only use the first instrument for identification of the first shock, we have $\beta_{[1]} = [1, (\Gamma_2 e_1)' \frac{1}{\Gamma_1 e_1}]' \times \bar{c} \propto \Gamma e_1$ for $\bar{c} > 0$ defined below.

(b) Let $q_1 = \bar{c}_1(I - \eta\kappa)\Gamma_1 e_1$. Let $q_2 = F chol(\Lambda)$, where F are the $q_z - 1$ eigenvectors and Λ the diagonal matrix of strictly positive eigenvalues of $S_1 S_1' - q_1 q_1'$. Then the first identified shock equals the shock identified using only the first instrument, i.e., $\beta_{[1]} e_1 \propto \Gamma e_1$.

See Appendix B for the proof.

While we find shocks identified according to Proposition 1, we also report shocks based on the conditional Cholesky factorization. We find that a lower Cholesky factorization of $S_1 S_1'$ yields results similar to attributing the entire variation in the first instrument to the first shock.

3.3 Inferring additional responses

Using data rather than zero-restrictions to identify shocks makes shock identification more uncertain. This is particularly true in higher dimensions, when the covariance matrix that drives the identification grows in size. We therefore find it useful to proceed in a block-recursive manner, following Zha (1999) and Uhlig (2003): (1) We identify shocks in a relatively small-scale VAR that contains q core variables, as specified in (3.1); and (2) we estimate the dynamics of a second block of q_p variables. These peripheral variables respond to all shocks and variables in the system, but do not influence the core variables themselves.[20]

This approach allows us to infer the response of a number of additional variables without impeding inference. Of course, if the information set of the smaller VAR were insufficient,

[20] If we wanted to consider more variables, we could also consider a dynamic factor model or factor-augmented VAR (Bernanke et al., 2005) estimated at the MSA level in which the external instruments identify structural shocks to the factors. For the small number of variables we consider, we prefer our simpler approach.

this approach would be invalid. We show, however, that in practice our findings in the core-periphery VAR are consistent with estimates of a larger VAR. The larger VAR has qualitative similar implications but wider confidence intervals for some responses.

Formally, we add two additional sets of equations to the model, analogous to (3.1) and (3.2):

$$Y_{i,t}^{p} = \sum_{\ell=0}^{k} A_{\ell}^{p,c} Y_{i,t-\ell} + \sum_{\ell=1}^{k} A_{\ell}^{p,p} Y_{i,t-\ell}^{p} + \mu_i^p + \eta_t^p + \underbrace{u_{i,t}^{p}}_{p\times 1} \tag{3.9}$$

$$u_{it}^{p} = \sum_{j=1}^{N} d_{ij} R^p u_{jt}^{p} + B^{pp}\epsilon_{it}, \qquad \epsilon_{it} \overset{iid}{\sim} \mathcal{N}(\mathbf{0}, I_{q_p}). \tag{3.10}$$

We only use the own lags for the peripheral variables, so that $A_{\ell}^{p,p}$ is diagonal. But importantly, we include all the contemporaneous core variables $Y_{i,t-\ell}$ in the peripheral VAR. This allows us to infer responses of the peripheral variables as $A_{\ell}^{p,c}\beta_{[1]}$. More generally, the responses of $Y_{i,t}^{p}$ at longer horizons depend on the interplay of the core and the peripheral variables. The combined system has a VAR(k) representation with zero restrictions; see Uhlig (2003).[21] We can estimate the error structure, however, without any complications. Below we define $\tilde{R} = \text{diag}([\rho_1, \ldots, \rho_q, \rho_1^p, \ldots, \rho_{q_p}^p])$. Also define $A^p = [A_0^{p,c}, \ldots, A_k^{p,c}, A_1^{p,p}, \ldots, A_k^{p,p}]$.

3.4 Estimation

We follow the two-step procedure proposed in Mutl (2009) and adapted for our setup with varying degrees of spatial autocorrelation. First, we difference the data and use an IV procedure with model-internal instruments to identify the dynamic relationship between the variables of interest, i.e. A and A^p. Second, we compute the concentrated likelihood for given D and conditional on $\hat{A}, \hat{A}^p$ and choose $\rho_1, \ldots, \rho_q, \rho_{q+1}, \ldots \rho_{q+q_z}$ to maximize the concentrated likelihood of $\{u_t, z_t\}_t$.[22]

The concentrated log likelihood is given by:

$$\log L^c = -\frac{1}{2}\left(NT\log(2\pi) + 2T\log(|I_{N(q+q_p+q_z)} - D\otimes\tilde{R}|) - NT\log(|\hat{V}|)\right) + c, \tag{3.11}$$

where $\hat{V}$ is the sample covariance matrix of $\{\tilde{\epsilon}_{i,t}\}_{i,t}$, that is of the residuals $[\hat{u}_{it}', z_{it}', u_{it}^p]'$ after spatial filtering, and c is a constant independent of parameters. The concentrated likelihood thus depends directly on $\{\rho_i\}$ through the determinant $|I_{Nq} - D\otimes\tilde{R}|$ and indirectly through the determinant of $\hat{V}$. Intuitively, more spatial autocorrelation tends to lower the remaining

[21] To trace out the dynamic effects, we can write the VAR without constants and spillovers as $[Y_{i,t}; Y_{i,t}^p] = \sum_{\ell=1}^{k}[I, 0; A_0^{p,c}, I][A_\ell, 0; A_\ell^{p,c}, A_\ell^{p,p}][Y_{i,t-\ell}; Y_{i,t-\ell}^p] + [B, 0; A_0^{p,c}B, B^{pp}]\epsilon_{i,t}$.

[22] For numerical purposes we impose bounds on each ρ_i to lie within $(-0.999, 0.999)$, but these bounds do not appear to bind in practice.

variance of the spatially filtered residuals $\{\tilde{\epsilon}_{i,t}\}_{i,t}$ and thereby increases the likelihood, but simultaneously lowers the likelihood by lowering the determinant of the Jacobian of the spatial transform, i.e. $|I_{N(q+q_z+q_p)} - D \otimes \tilde{R}|$.

For future reference, it is useful to rewrite the quasi-likelihood function by commuting rows and columns of the spatial transform. This corresponds to re-ordering the vector of VAR-residuals. It simplifies performing the computations and extending the model below. Since $|I_{N(q+q_z+q_p)} - \tilde{R} \otimes D| = \prod_{s=1}^{q+q_z+q_p} |I_N - \tilde{\rho}_s D|$, it follows that:[23]

$$\log L^c = -\frac{1}{2}\left(NT\log(2\pi) + 2T\sum_{s=1}^{q+q_z+q_p}\log(|I_N - \tilde{\rho}_s D|) - NT\log(|\hat{V}|)\right) + c, \qquad (3.12)$$

3.5 Inference

Since the distribution of the implied estimator is non-standard given our two-step estimation procedure, we use a bootstrap procedure.[24] In designing the bootstrap procedure, we exploit that the residuals are spatially uncorrelated once run through an appropriate spatial filter. We therefore draw *iid* with replacement from the spatially filtered residuals vectors, pooled across MSAs and blocks of time of length τ.[25] See Algorithm 1 for details. In practice, we set $B = 500$ and $\tau = 3$. $\tau = 3$ equals $T^{1/3}$ up to rounding in our different specifications.

Blocking of residuals over time accounts for potential residual correlation in the instrument equations and VAR residuals. We find that it matters little in practice. This is intuitive for the VAR, because its lags should capture the autocorrelation. And because we use growth rates to construct the instruments, these should be close to uncorrelated over time absent strong mean reversion.

When applying this procedure we notice small biases in the estimated autocorrelation: an upward bias in the estimated degree of spatial autocorrelation and a slight downward bias in the degree of temporal autocorrelation. We therefore adapt the "bootstrap-after-bootstrap" procedure from Kilian (1998)[26] and run the bootstrap twice. First, with half the number of

[23]To derive the equality, first define a square $N(q+q_z+q_p) \times N(p+p_z v)$ commutation matrix $P_{N(q+q_z+q_p)}$. $|P_{N(q+q_z+q_p)}| = |P_{(q+q_z+q_p)N}| = \pm 1$, depending on whether N and $q+q_z+q_p$ are even or odd, see Lütkepohl (2005, p. 664) for this and the following results. Then $P_{N(q+q_z+q_p)} D \otimes \tilde{R} P_{(q+q_z+q_p)N} = P_{N(q+q_z+q_p)} D \otimes \tilde{R} P^{-1}_{N(q+q_z+q_p)} = \tilde{R} \otimes D$. Putting these results together $|I_{N(q+q_z+q_p)} - D \otimes R| = |P_{N(q+q_z+q_p)}||I_{N(q+q_z+q_p)} - D \otimes R||P^{-1}_{N(q+q_z+q_p)}| = |I_{N(q+q_z+q_p)} - P_{N(q+q_z+q_p)} D \otimes \tilde{R} P^{-1}_{N(q+q_z+q_p)}| = |I_{N(q+q_z+q_p)} - \tilde{R} \otimes D|$. Because R is diagonal, the matrix inside the determinant is block-diagonal. Using the rule for the determinant of partitioned matrices (Lütkepohl, 2005, p. 660) repeatedly gives us that $|I_{N(pq+q_z+q_p)} - \tilde{R} \otimes D| = \prod_{s=1}^{q+q_z+q_p} |I_N - \tilde{\rho}_s D|$.

[24]Note that the wild bootstrap in Mertens and Ravn (2013) typically does not take uncertainty about the covariance between instruments and forecast errors into account. Jentsch and Lunsford (2016) show that, in a pure time-series setup, a moving block bootstrap provides asymptotically valid inference.

[25]For the terminal period, the terminal block has length $\tau + \mod(T, \tau)$. We sample $\lceil T/\tau \rceil$ blocks with replacement and use only the first T observations.

[26]To be precise, Kilian (1998) proposes a bias correction that shrinks the bias correction term towards zero

Algorithm 1 Bootstrap

For $b = 1, \ldots, B$:

1. Set the initial observations $Y_{i,0}^{(b)}, \ldots, Y_{i,-(k-1)}^{(b)}$ equal to the actual values.

2. For $r = 1, \ldots, \lceil T/\tau \rceil$ and $n = 1, \ldots, N$:

   (a) Draw $j(b, n, r)$ and $s(b, n, r)$ *iid* (with replacement) from $\{1, \ldots, N\}$ and blocks $\{1, \ldots, \lfloor T/\tau \rfloor\}$, respectively.

   (b) For each n, retain the first T observations to account for the (weakly) longer length of the terminal block.

3. For $t = 1, \ldots, T$ and $n = 1, \ldots, N$:

   (a) Generate spatially correlated error terms from spatially filtered residuals: $\text{vec}(res_t^{(b)}) = (I_{Nq} \otimes (D \otimes \widehat{\tilde{R}}))^{-1} \text{vec}([\hat{\epsilon}_{(j(b,n,r(t))),\tilde{s})}]_n)$ for $\tilde{s} \in s(b, n, r(t))$.

   (b) Generate variables of interest:

      - $Y_{i,t}^{(b)} = c_i^y + \eta_t^y + \sum_{\ell=1}^{k} A_\ell Y_{i,t-\ell}^{(b)} + res_{i,t,1:p}^{(b)}$, where $res_{i,t,1:p}^{(b)}$ denotes elements $1, \ldots, p$ of $res_{i,t}^{(b)}$.
      - $Y_{i,t}^{p(b)} = c_i^{y,p} + \eta_t^{y,p} + \sum_{\ell=0}^{k} A_\ell Y_{i,t-\ell}^{(b)} + \sum_{\ell=1}^{k} A_\ell^p Y_{i,t-\ell}^{p(b)} + res_{i,t,q+q_z+1:q+q_z+q_p}^{(b)}$, where $res_{i,t,q+q_z+1:q+q_z+q_p}^{(b)}$ denotes the last q_p elements of of $res_{i,t}^{(b)}$.

   (c) Generate instruments: $Z_{i,t}^{(b)} = \hat{c}_i^z + \eta_t^z + res_{i,t,p+(1:q_z)}^{(b)}$.

4. Re-estimate the VAR: $\hat{A}_{IV}^{(b)}, \widehat{A_{IV}^{p,(b)}}, \{\widehat{\tilde{\rho}}_i^{(b)}\}_i, \hat{V}^{(b)}$. Compute and save the statistics of interest.

repetitions we estimate the average bias in the VAR coefficients and the spatial autocorrelation. Second, we re-run the algorithm with the bias-corrected coefficients. See Algorithm 2.

Algorithm 2 Bootstrap with bias-correction

1. Run algorithm 1 with $B/2$ repetitions.
2. For $X \in \{[A_1, \ldots, A_\ell], [\rho_1, \ldots, \rho_{q+q_z}]\}$:
   (a) Compute the average bias: $\Psi_X = \mathbb{E}[\widehat{\hat{X} - X}] = \frac{1}{B/2} \sum_{b=1}^{B/2} \hat{X}^{(b)} - \hat{X}$.
   (b) Compute the bias-corrected coefficient: $\tilde{X} = \hat{X} - \Psi_X$.
3. Re-run Algorithm 1 with B repetitions and $\{[\tilde{A}_1, \ldots, \tilde{A}_\ell], [\tilde{A}_1^p, \ldots, \tilde{A}_\ell^p], [\tilde{\rho}_1, \ldots, \tilde{\rho}_{q+q_z+q_p}]\}$ in step (3).

3.6 Heterogeneous coefficients

We also examine whether the dynamics differ depending on MSA characteristics. To do so, we split the sample based on MSA characteristics. When possible, we choose characteristics before the start of our estimation sample, such as the population density in 1976 or the startup entry rate in 1978. We then estimate VAR-coefficients, within-MSA VAR-covariances, and spatial correlations with neighboring MSAs separately for each group. However, we do take account of the fact that the errors are dependent across groups.[27]

Specifically, a simple transformation still purges the overall MSA-specific error term of their spatial dependence. Take the ith component of the overall error term in (3.6). Let $G(m)$ map MSA m to group g. Define $v_t^i = e_i'[B_{G(m)}\epsilon_{m,t}]_{m=1}^N$ to be the vector of within-MSA forecast errors. With heterogeneous spatial correlations, the overall error term becomes:

$$\begin{aligned} u_t^i &= \left[\sum_n d_{mn} \rho_{G(m)}^i u_{n,t}^i + v_{m,t}^i \right]_{m=1}^N \\ &= u_t^i D \operatorname{diag}([\rho_{G(m)}^i]_m) + v_t^i \\ &= v_t^i (I - D \operatorname{diag}([\rho_{G(m)}^i]_m))^{-1} \end{aligned} \tag{3.13}$$

Post-multiplying the spatial errors by $I - D\operatorname{diag}([\rho_{G(m)}^i]_m)$ therefore rids the error terms of

to ensure that the largest root of the companion matrix of A_{IV}, i.e. K_{IV} in our notation, lies inside the unit circle. While this correction is irrelevant in our baseline specification, we include it for robustness exercises for both A_{IV} and $\{\rho_j\}$.

[27] This is similar in spirit to Bonhomme and Manresa (2015) with group fixed effects and heterogeneous coefficients, but with known group assignments.

their spatial dependence. We can estimate $\Sigma_g = B_g B_g'$ from the transformed error terms of all MSAs m that belong to group g.

Thus we conduct our inference separately across groups of MSAs, except for estimating the spatial correlation coefficients. The group-specific spatial correlation coefficients still maximize the joint quasi-likelihood across MSAs of all groups. Of course, the bootstrap re-samples from v_t^i, either using an *iid* or a block bootstrap, ant then re-introduces the estimated spatial correlation by post-multiplying with $(I - D\,\text{diag}([\rho^i_{G(m)}]_m))^{-1}$. This, of course, affects the quasi-likelihood.

Specifically, in (3.12) the common spatial transform now becomes group-specific:

$$\log L^c = -\frac{1}{2}\left(NT\log(2\pi) + 2T\sum_{s=1}^{q+q_z} \log(I - D\,\text{diag}([\rho^s_{G(m)}]_m)) - NT\log(|\hat{V}|)\right) + c. \quad (3.14)$$

4 Results

Here we present our estimates of the local labor market effects of shocks to startups and overall labor demand. First, we present our baseline specification in detail. Second, we discuss that the findings carry over to several variations of the baseline specification. Third, we analyze how the results differ by MSA characteristics. Fourth, we argue, based on our analysis of patenting and trademark filings, that the average startup boom differs from increases in innovation.

Our specification varies slightly with the available data. Unless we analyze innovation, we consider 354 MSAs. We allow two lags in our annual VAR. Most samples cover 1986 to 2013, the era for which we have migration data with $k = 2$ lags. Discarding the late 1970s and early 1980s has the advantage of excluding observations of rapid decline in startup activity that may be due to inaccurate measurement in the early part of the sample. However, we show that similar results hold for the longer sample.

We design our main VAR to capture local labor demand and supply factors. It includes the change in the job creation rate by startups, the (log) of the employment-to-population ratio, population growth, and the growth of average wages. We back out the response of the employment level by accumulating the (log) population response and adding this cumulative change to the response of the (log) employment-to-population ratio for each bootstrap realization. The periphery includes the firm entry rate, the firm exit rate of firms aged one, the net migration rate, and house price growth. While wage growth and house price growth are nominal variables, we control for national inflation rates and MSA-specific trend inflation by subtracting year and MSA fixed effects. We thus interpret these variables as real.

4.1 Baseline results

Impulse-responses. Figure 3 shows the impulse-response functions of our baseline specification.[28] The top panel in parts (a) and (b) shows the response of the variables in the main VAR, the bottom panel the response of additional variables. We show the 68% and 90% point-wise confidence intervals in shades of gray, with the median as the center of the confidence interval as the black line. We normalize shocks so that both the shock to labor demand by startups and the overall labor demand shock increase the job creation rate and the employment-to-population ratio, respectively.

We find that startup shocks have small but persistent effects on local labor demand. In response to a one standard deviation shock to startup labor demand, the job creation rate by startups rises by 0.6pp. This means that startups increased employment by about 0.6% of initial employment. The response of the employment level is, however, initially centered around zero and becomes significantly positive only after one year. In response to the increased startup activity, employment rises by about 1% after four years and stays persistently high, driven by population growth. Population growth, however, leaves the average wage rate unchanged. As net migration mirrors population growth, this is consistent with low-wage migration in response to the job creation. We also find a small but persistent increase in house prices following a startup shock, consistent with population growth causing congestion. Qualitatively, our findings are in line with the effects of a state-wide entry rate shock identified in Gourio et al. (2016). They also find persistent increases in population and employment, and higher house prices.

A startup shock also increase firm entry and, with a delay, exit. The firm entry rate increases by about 0.15pp. on impact and slowly declines back to zero after seven years. The exit rate of firms one year of age is initially centered at zero and then rises by about 0.01–0.02pp. and also slowly declines to zero. The higher exit rate following entry likely reflects a selection effect as unproductive firms exit. However, the entry effect is much stronger – both rates are measured relative to the stock of firms of all ages.

Overall labor demand shocks largely resemble persistent business cycle shocks: a one standard deviation overall labor demand shock has a large effect on MSA employment, increasing employment by about 2.5% and the average wage rate by 1.0% to 1.5%. Population growth and net migration rise temporarily, but the population level reverts to its mean after about ten years. Since the employment-to-population ratio is also stationary, employment reverts to zero after about ten years. Both entry and, with a one year lag, exit rates rise. The effect on entry is only slightly weaker than the effect of a shock to startup labor demand.

Surprisingly, house prices increase only initially, then start falling two years after the ini-

[28] We compute IRFs for a counterfactual isolated MSA without spatial spillovers. With spatial autocorrelation in the errors, the spatial spillovers change the IRFs in each MSA by a constant factor of proportionality that depends only on the MSA and the variable of interest, but not on the horizon of the IRF.

tial shock. While this could reflect either construction booms or endogenous changes in land regulation, we show below that only the pattern, not the relative magnitudes, are robust to different specifications. The robust pattern of initial appreciation and subsequent reversal is intuitive for a temporary shock.

Startups also respond to the overall labor demand shock by entering in greater numbers and increasing their job-creation rate. Subsequently, this leads to higher exit rates of startups. On impact, however, we find that the exit of young and old firms drops (not reported). This points to a selection effect concentrated among firms that enter opportunistically as demand for an MSAs product, or local productivity, increases profits.

We interpret the difference between the responses of the net migration rate and population growth as reflecting measurement error. Note that the migration response is roughly 0.6 times that of population growth and shares the same shape in response to both shocks. Figure 4(a) shows that if we just regress the net migration rate on the population growth rate, after purging it of MSA fixed effects, we find a coefficient of 0.55. This is about the factor of proportionality of the VAR responses. Figure 4(b) compares the demeaned time series within the median-sized Lake Charles, LA, MSA. Except for the late 1980s, the series track each other almost perfectly. Figure A.1 shows similar patterns for ten more MSAs. Because the series track each other most of the time, we interpret the discrepancy as measurement error. The alternative would be an influx of migrants who do not file tax returns or a sudden increase in fertility.

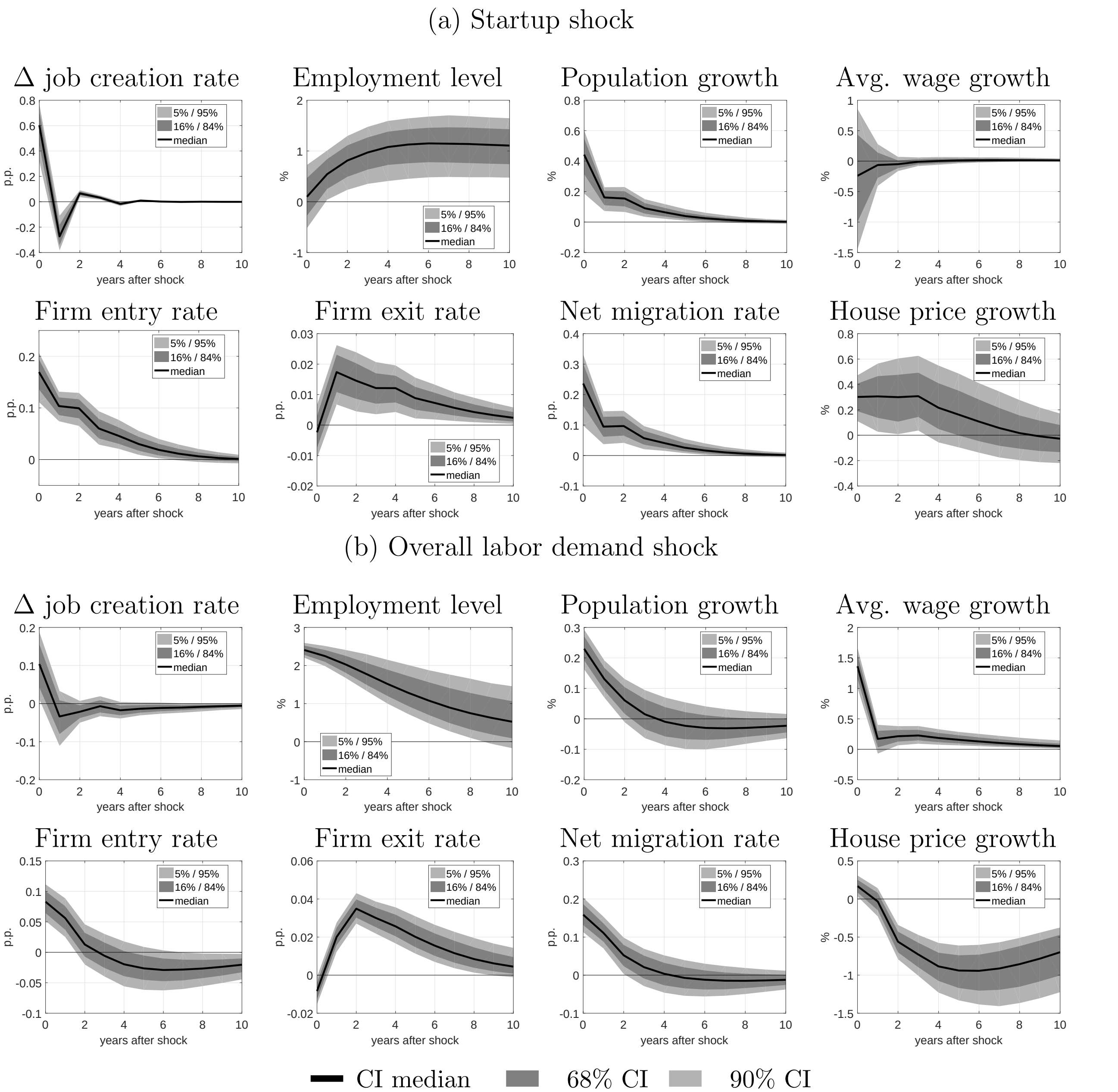
Quality of instruments. Our instruments are good predictors of the shocks. After stripping out the predictable VAR-variation and disentangling shocks we find F-statistics of 16.2 and 84.3 for the two identified shocks, see Table 1. The 68% confidence interval lies significantly above 10.0. These F-statistics test for each of the two identified shocks whether the instruments are a good predictor of these shocks.

Table 1: First-stage F-statistics

Variable	Point estimate	Confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	16.2	7.0	10.0	14.8	20.7	26.0
Employment/Pop (log, BDS)	84.3	34.3	47.3	72.6	92.9	104.7

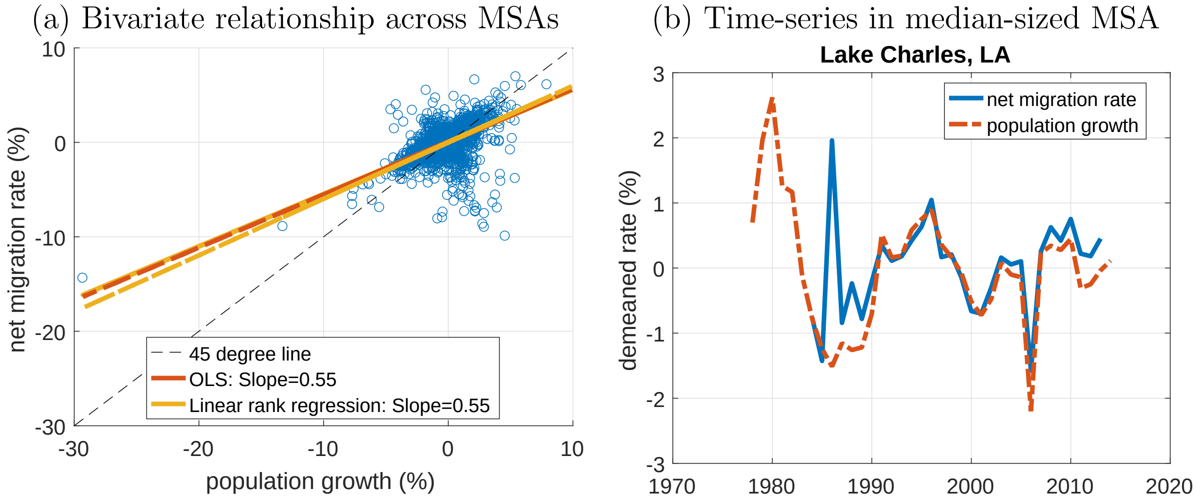
We find that the instruments in our baseline specification are strong: The F-statistics of the first stage regression of the identified structural shocks on the (spatially filtered) instruments are above 10 with a bootstrapped 90% confidence interval of (7.0, 26.0) and (34.3, 104.7), respectively.

Spatial correlation. We find that the spatial autocorrelation ranges from small to large across variables. Table 2 lists the estimated correlation coefficients for each variable: the



Startup shocks have small but persistent effects on local employment, driven by population growth. Average wages do not rise, possibly due to migration. Overall labor demand shocks have only small effects on startup employment, but large initial effects on employment that die out after about 10 years. Both shocks lead to more entry and exit. House price data are from CoreLogic Solutions.

Figure 3: Impulse-responses to startup shocks and overall labor demand shocks in our baseline VAR.



We argue that the migration impulse-responses are a scaled-down version of population growth. The lower scale likely reflects attenuation bias due to measurement error in net migration rates. The scaling factor corresponds virtually to the slope coefficient in regressions of net migration rates on population growth; see panel (a). As our example for the MSA with median population size in 1986 in panel (b) shows, the net migration rate often tracks the population growth rate closely, but can, at times, differ erratically, indicating measurement error in migration rates.

Figure 4: Relationship between net migration rates and population growth rates

point estimates range from 0.08 for the change in the gross job creation rate to 0.76 for net migration rates and 0.79 for house price growth. Our bootstrap finds that these estimates are biased upward. The bias is absolutely larger for the larger coefficients, but always small. The autocorrelation is significantly positive for all variables at the 95% level, even for the small autocorrelation for the change in the gross job creation rate.

Table 3 compares our baseline specification with variable-specific spatial auto-correlation to two restricted specifications: First, a version with common spatial autocorrelation. Second, a version without spatial correlation. Given that Table 2 documents a high but variable-specific degree of spatial correlation, it is unsurprising that we can reject the more restrictive hypotheses: We compare the increase in the (log) quasi-likelihood of our unrestricted model relative to the restricted models to the bootstrapped differences in the quasi-likelihood under the more restrictive hypotheses. In both cases we find that the actual increase in the log-likelihood far exceeds the 99% bootstrapped critical value.

Variance decomposition. Our variance decomposition shows that much of the variation in labor demand by startups and incumbents is driven by the identified labor demand shocks for a hypothetical MSA with no neighbors. However, Table 4 also shows that one-fifth to two-thirds of the variation in the startup job creation rate could be explained by non-identified shocks, both on impact and at the ten-year horizon. The overall labor demand shock is more

Table 2: Spatial autocorrelation: Coefficients estimates by variable.

Variable	Point estimate	Avg. bias	Bias-corrected confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	0.08	-0.01	0.03	0.05	0.08	0.12	0.16
Employment/Pop (log, BDS)	0.41	-0.02	0.36	0.37	0.40	0.43	0.45
Pop growth	0.55	-0.02	0.49	0.50	0.53	0.56	0.57
Wage growth	0.25	-0.01	0.20	0.21	0.24	0.27	0.30
Firm entry rate	0.58	-0.03	0.52	0.53	0.55	0.57	0.58
House price growth	0.79	-0.03	0.73	0.75	0.76	0.77	0.78
Firm exit rate	0.38	-0.02	0.33	0.34	0.36	0.38	0.40
Net migration rate	0.76	-0.03	0.70	0.71	0.73	0.75	0.76
Firm exit rate (all)	0.54	-0.02	0.49	0.50	0.52	0.53	0.54
Bartik: Entrant's job creation	0.74	-0.03	0.68	0.70	0.71	0.73	0.74
Bartik: Employment	0.55	-0.03	0.50	0.51	0.53	0.55	0.57

The estimated spatial correlation varies significantly across variables as shown in panel. Prior to bias-correction, the estimated spatial correlation shows a small upward bias across all variables. House price data are from CoreLogic Solutions.

Table 3: Spatial autocorrelation: Bootstrapped likelihood ratio test for differential spatial autocorrelation.

Comparison	Point estimate	Confidence interval 1%	5%	Median	95%	99%
H0: Constant spatial correlation						
Same ρ vs. varying ρs	4.384	0.009	0.015	0.035	0.074	0.115
H0: No spatial correlation						
No spatial correlation vs. varying ρs	32.786	0.012	0.018	0.042	0.077	0.108

The table shows likelihood ratio test statistic $-2\ln(L_{restricted}/L_{varying})$, divided by N for legibility with bootstrapped confidence intervals. The hypotheses of a common spatial correlation or no spatial correlation are rejected at the 1% level according to the simulated distribution of the test statistic in panel. Underlying house price data are from CoreLogic Solutions.

tightly estimated, and we find that other shocks account for only one-third to one-quarter of the variation in the employment-to-population ratio. The identified shocks account for 29% to 72% of the variation in population growth and less than 36% of the variation in wage growth. This is consistent with a potentially important role for labor supply shocks.

Despite the estimation uncertainty, we find that startup shocks are an important driver of population growth at both horizons. Because in this model population growth is the only source of long-run employment growth, this highlights that both startup shocks and the non-identified shocks are important sources of employment fluctuations. In contrast, the shock to startup labor demand only has a modest effect on the firm entry rate. This indicates that increases in startup employment largely operate through the intensive margin of a small number of entrants.[29]

Counterfactual histories. A concrete way of understanding the impulse-responses and the variance decomposition is to look at the historical implications for specific MSAs. We focus on three large MSAs: Boston, MA (Boston-Cambridge-Quincy, MA-NH), Chicago, IL (Chicago-Joliet-Naperville, IL-IN-WI), San Francisco, CA (San Francisco-Oakland-Fremont, CA). Figure 5 shows for each of these MSAs the change in the job creation rate and the rate of population growth, net of the MSA and year fixed effect. For each series and MSA, we also show estimates of the counterfactual evolution without either the startup shock (gray area plot) or the overall labor demand shock (dashed red lines) with 68% confidence intervals.

One conclusion is that the startup job creation rate reflects startup shocks and other shocks, but overall labor demand shocks hardly matter: In all three MSAs, the path of overall labor demand shocks are hard to distinguish from the actual data. While the counterfactual without startup shocks differs significantly from the data, the variation without it is far from zero, leaving a role to other, unidentified shocks. This confirms the variance decomposition.

The specific contribution of startup shocks varies across MSAs – as it should, given that we strip out national factors. In Boston, the job creation rate would have been significantly higher in the absence of startup shocks around 1990 and 2004, but would have been lower in the mid-1990s and since 2007. In Chicago, we find that the increase in the job creation rate in 1992 was largely driven by startup shocks, but not the one in 1988. Startup shocks subtracted from job creation for much of 2000 to 2006. In San Francisco, a large startup shock lowered job creation in the early 2000s. But startup shocks largely contributed to the 1988 boom and to job creation since 2007.

Both labor demand shocks have significant effects on population growth: In Boston, population growth would have been lower without either shock. In particular, startup shocks contributed to its population growth in the late 1980s and 2010s, but subtracted from it in

[29] We verify that this finding also holds when we include the firm entry rate in the core VAR; see Table C.4.

Table 4: Variance decomposition in our baseline VAR. 68% confidence interval.

(a) Impact effect

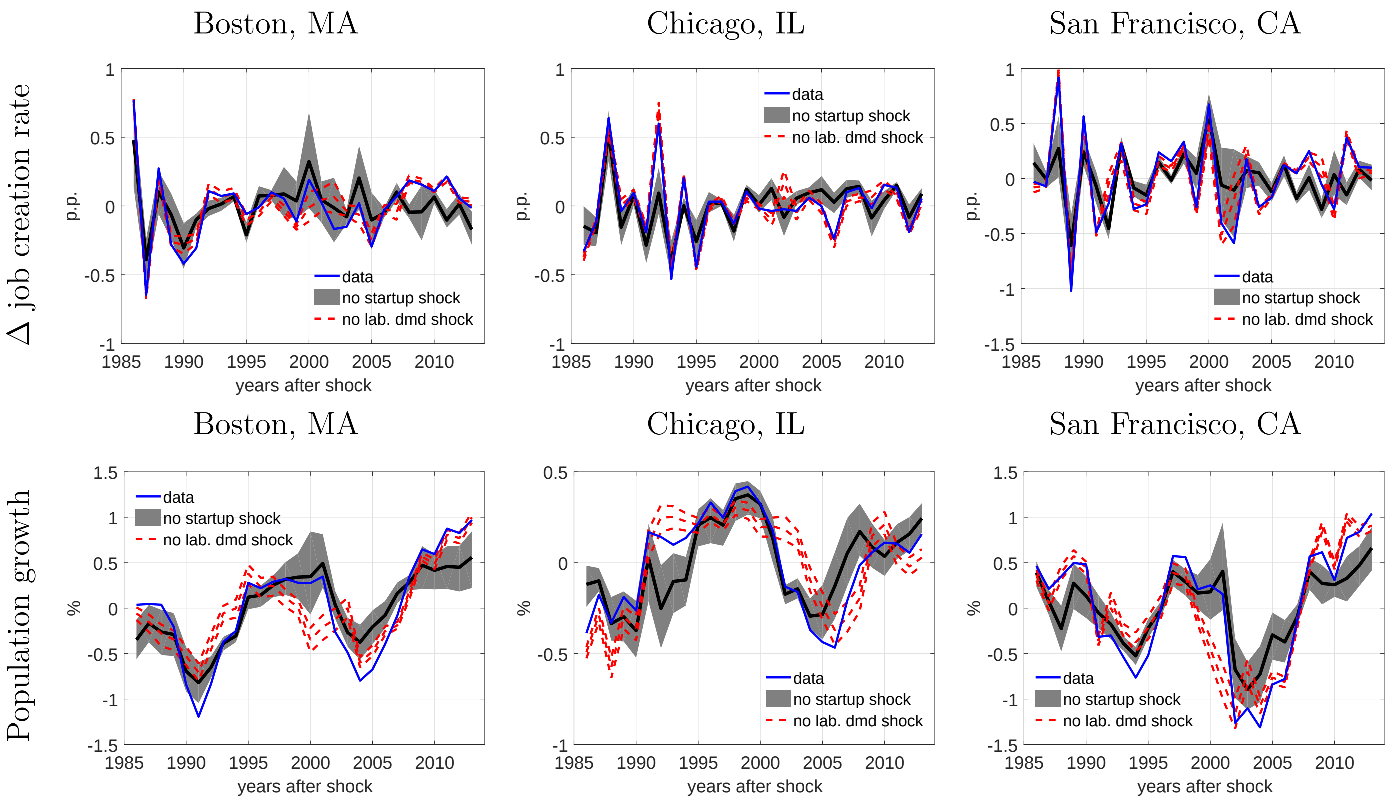
	Startup shock		Overall labor demand		Other VAR shocks		Idiosyncratic shock	
Gross job creation (births)	53.0	(28.8, 76.2)	1.9	(0.3 , 3.5)	45.0	(22.2, 68.8)	0.0	(0.0 , 0.0)
Employment/Pop (log, BDS)	3.8	(0.2 , 7.9)	70.4	(64.0, 77.4)	25.8	(18.1, 33.3)	0.0	(0.0 , 0.0)
Pop growth	39.5	(18.1, 61.3)	10.8	(6.9, 14.6)	49.8	(27.6, 71.0)	0.0	(0.0 , 0.0)
Wage growth	6.2	(0.2, 12.7)	20.4	(14.7, 26.1)	73.4	(64.5, 82.5)	0.0	(0.0 , 0.0)
Firm entry rate	6.8	(4.4 , 9.0)	1.7	(1.0 , 2.4)	2.4	(0.7 , 4.0)	89.2	(87.7, 90.7)
House price growth	0.7	(0.2 , 1.1)	0.2	(0.0 , 0.4)	0.7	(0.3 , 1.1)	98.4	(97.9, 98.9)
Firm exit rate	0.1	(0.0 , 0.1)	0.1	(0.0 , 0.3)	0.3	(0.1 , 0.4)	99.5	(99.3, 99.7)
Net migration rate	13.9	(6.3, 21.8)	6.2	(4.2 , 8.2)	18.5	(10.1, 27.5)	61.3	(56.6, 66.2)
Firm exit rate (all)	0.8	(0.1 , 1.5)	1.9	(1.4 , 2.5)	1.9	(0.9 , 3.0)	95.3	(93.9, 96.8)

(b) 10 year horizon

	Startup shock		Overall labor demand		Other VAR shocks		Idiosyncratic shock	
Gross job creation (births)	50.9	(26.8, 74.0)	1.8	(0.4 , 3.3)	47.2	(24.4, 70.8)	0.0	(0.0 , 0.0)
Employment/Pop (log, BDS)	2.9	(1.1 , 5.1)	76.5	(70.8, 82.6)	20.6	(14.6, 26.6)	0.0	(0.0 , 0.0)
Pop growth	39.1	(18.0, 60.5)	11.6	(7.8, 15.3)	49.3	(27.6, 70.2)	0.0	(0.0 , 0.0)
Wage growth	6.2	(0.6, 12.3)	20.7	(15.7, 25.8)	73.1	(64.7, 81.4)	0.0	(0.0 , 0.0)
Firm entry rate	9.9	(8.0, 11.9)	2.3	(1.5 , 3.1)	3.9	(2.4 , 5.3)	83.9	(82.3, 85.6)
House price growth	1.1	(0.4 , 2.0)	11.0	(9.9, 12.2)	3.9	(2.8 , 5.0)	83.9	(83.0, 84.9)
Firm exit rate	0.8	(0.4 , 1.2)	3.5	(3.1 , 3.8)	1.1	(0.7 , 1.5)	94.6	(94.1, 95.0)
Net migration rate	15.7	(7.3, 24.4)	7.4	(5.3 , 9.5)	20.7	(11.3, 30.6)	56.2	(51.5, 61.0)
Firm exit rate (all)	1.0	(0.3 , 1.7)	4.1	(3.6 , 4.7)	2.7	(1.7 , 3.8)	92.2	(90.9, 93.7)

The variance decomposition shows that startup shocks explain about half of the variation in the job creation rate by startups and about 40% of population growth. Overall labor demand shocks contribute little to the variation in the job creation rate by startups, but explain most of the variation in the employment-to-population ratio. The variance decomposition differs little at the 10-year horizon. The estimates are more precise for the overall labor demand shock. Except for migration, the VAR shocks explain relatively little of the peripheral variables. But Table C.4 shows that the results are similar when we include more variables in the core VAR. House price data are from CoreLogic Solutions.

the early 1990s and 2000s. Overall labor demand shocks are significant at times, but removing them leaves a counterfactual closer to the actual data. In Chicago, population growth would have been lower without startup shocks during the early 1990s, but higher from 2004 to 2008. Overall labor demand pulled Chicago's population growth down in the early 1990s and 2000s, after being expansionary in the late 1980s. San Francisco mirrors Boston's population growth, with a more pronounced contribution from startups to population growth in since 2007 and before 1990.[30]



Startup shocks, but not overall labor demand shocks, are important determinants of the change in the job creation rate. For example, job creation would have been significantly lower in Boston at the end of our sample without positive startup shocks. These shocks also matter for population growth, which would also have been lower in Boston at the end of our sample absent positive startup shocks. All variables in deviations net of MSA and year fixed effects. We show 68% confidence intervals.

Figure 5: Historical contributions to the change in the job creation rate and population growth: Comparison of three large MSAs, 1986–2013.

[30]Note that here, unlike the variance decomposition, we take spatial autocorrelation into account. Setting the spatial autocorrelation to zero when constructing the counterfactual data diminishes the role of both shocks, but particularly of overall labor demand shocks. Figure C.1 illustrates that turning off the spatial autocorrelation in counterfactuals shrinks the counterfactuals toward zero. See, for example, San Francisco's population growth in the early 2000s.

4.2 Alternative specifications

We consider variations of our baseline specification in Appendix C.2. To assess the role of the identification scheme, we consider alternative a conditional Cholesky factorization to distinguish the overall labor demand shock from the startup labor demand shock. Figure C.2 shows the results. For most responses, it is hard to tell the difference between the two schemes. The difference is most pronounced in the response of the change in the job creation rate to overall labor demand shocks. With the conditional Cholesky factorization the startup-response has slightly tighter confidence intervals. Similarly, our block bootstrap produces results that are very similar to an *iid* bootstrap. In Figure C.3, the most noticeable difference is the upper error bands of the population and employment level response to the overall labor demand shock. The similarity is intuitive because we choose a long enough lag length for the VAR to capture the autocorrelation of residuals. We also construct instruments out of growth rates that have little or no persistence.

Using a different distance measure changes the analysis little. In Figure C.4 we classify MSAs as neighbors when they share a common state, rather than using the inverse Euclidean distance. The resultant responses are hard to distinguish from the baseline. The same figure also shows results using the correlation of HP-filtered (log) employment as a proximity measure. This measure is in the spirit of Crone (2005), who uses it to cluster regions. The results are again very similar. But Table C.1 shows that the data strongly favors our baseline measure and both geographic measures beat the measure based on business cycle correlations. This indicates that the spatial correlation is related to trade costs or commuting costs.

Our results are largely comparable when we extend the lag length. First, the larger number of regressors does not change the quality of our first stage, see Table C.5. Second, when we examine impulse-response functions in Figure C.5, we find that the main results carry through to a VAR estimated with three lags: A startup shock leads to a small but persistent increase in the employment level that is driven by population growth, the firm entry rate rises, and house prices increase. An overall labor demand shock causes only a transient increase in the employment level, has few effects on employment by startups, and raises the entry rate temporarily. House prices follow the same qualitative pattern of initial appreciation and subsequent reversal. But the reversal of house price growth is much shorter and simply undoes the initial increase when employment returns to its initial level. In contrast, a VAR with a single lag appears misspecified: Figure C.5 indicates that with a single lag, the VAR appears non-stationary. This suggests that the VAR does not approximate labor market dynamics well.[31]

[31] Note that if the underlying data were generated from a DSGE model, our $VAR(k)$ would have to be fundamental and to approximate the underlying state-space system well. Being fundamental requires a large enough number of variables in the VAR. Approximating the state-space system requires adding more lags to the VAR. We therefore trust the results with $k \geq 2$ lags that give qualitatively comparable results.

Moving variables from the periphery to the core VAR has few effects on the impulse-responses. In particular, it leaves the responses of the core variables largely unchanged, see Figure C.6.[32] The responses of the peripheral variables show some differences, but still convey the same message: The firm entry rate still rises significantly in response to a startup shock, but the impact-response is no longer significant in the larger VAR. House price growth exhibits the same pattern, but the impact response has a much larger confidence interval in response to the startup shock. This pattern is intuitive, because the larger VAR and its larger covariance matrix make it harder to identify the shock with external instruments. We find that the first-stage F-statistics fall by about half compared to our baseline model (Table C.3).

We also consider a longer estimation sample in Figure C.7. Dropping the migration rate, we begin the estimation in 1980. We find qualitatively similar results, but the effects of the startup shock on employment and population growth are noisier. At the beginning of the sample measured startup activity was high but quickly declining. This may reflect a different type of dynamic than during the remainder of the sample.

4.3 Metro characteristics

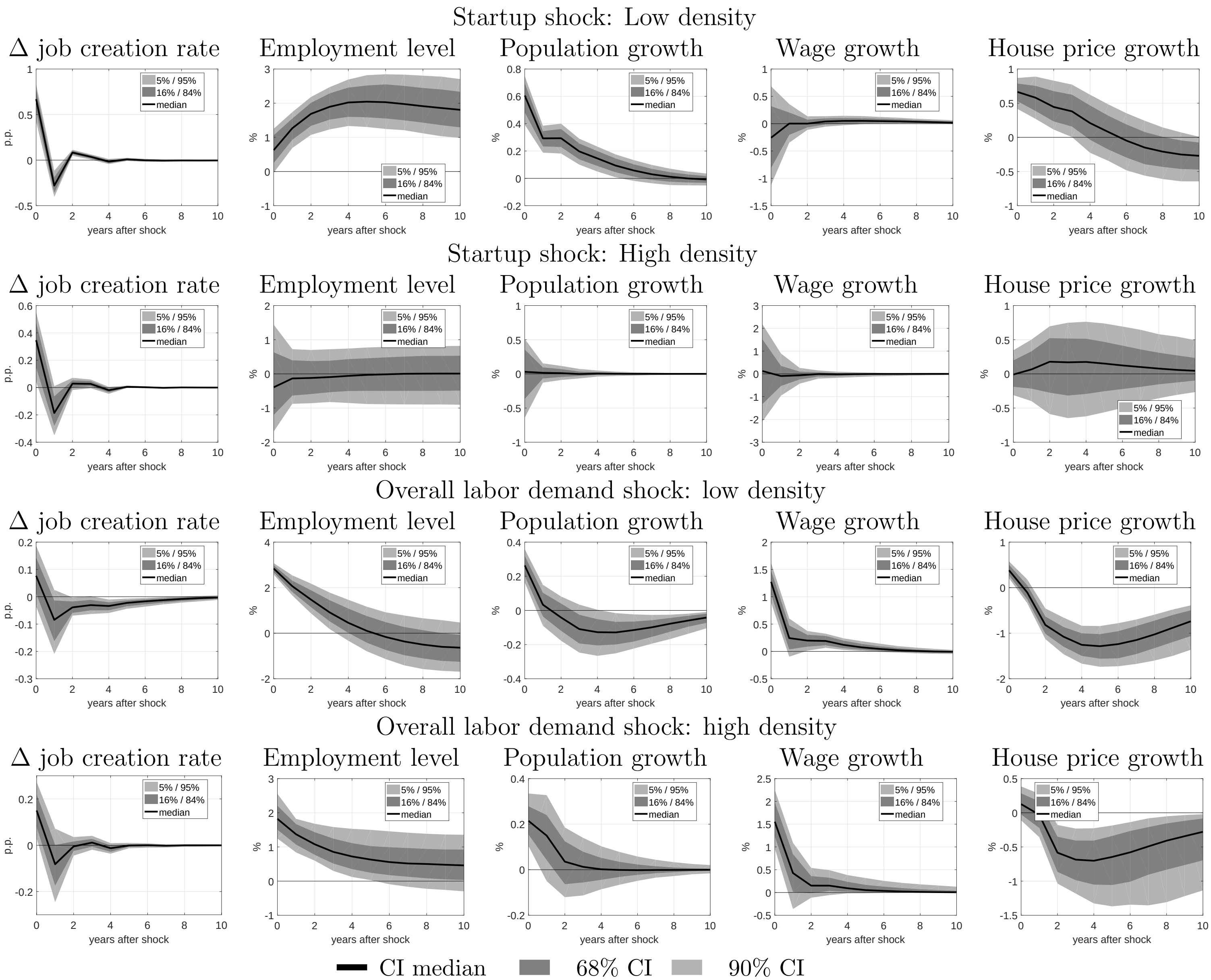
Here we analyze whether labor market dynamics differ as a function of an MSA's characteristics. In the main text, we focus on the initial density of an MSA. Density is related to spillovers, which could be positive externalities from innovation, or negative congestion. In Appendices C.4 and C.5 we show that when we split the sample by the initial firm entry rate or Wharton Regulation Index (Gyourko et al., 2008) the estimates are similar.

Figure 6 shows the main impulse-responses when we allow the 25% densest MSAs in 1978 to differ from the sparser 75% of MSAs. For overall labor demand shocks we find few differences across sparser and denser MSAs. However, a one standard deviation shock to overall labor demand is smaller in denser MSAs and the effect on population growth is slightly smaller, whereas the effects on wages are slightly larger. By and large, however, the effects mirror our baseline results in Figure 3.

For startup shocks we find that the response in sparser MSAs is a stronger version of our baseline estimates, whereas the response in denser MSAs is insignificant. This difference may reflect weaker spillovers from entry in the denser MSAs or weaker identification. Indeed, we cannot rule out that our instruments are weak predictors of startup shocks in the denser MSAs (Table 5). Table C.6 also shows that the spatial correlation is much stronger among denser MSAs, reducing the independent variation we use for identification. We conclude that the

[32] Table C.4 compares the variance decompositions. We find that for the firm entry rate, the identified shocks in the larger VAR that includes the entry rate in the core VAR explain just as much as the shocks in the baseline VAR. For house prices, the explanatory power is higher in the larger VAR, but still 13% of the variance are explained by the identified shocks.

sparser MSAs drive our main results, although it remains unclear whether this is for economic or statistical reasons.



We find that MSAs with low initial density have a stronger response to startup shocks than our baseline estimates, while we cannot identify a significant response in high density MSAs. Overall labor demand shocks, which are identified well in both groups, have smaller effects in denser MSAs. House price data are from CoreLogic Solutions.

Figure 6: Impulse-responses to startup and overall labor demand shocks for MSAs grouped by their initial population density.

Table 5: First-stage F-statistics for MSAs grouped by their initial population density.

(a) Low density MSAs

Variable	Point estimate	Confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	27.7	14.3	18.3	25.1	34.0	40.4
Employment/Pop (log, BDS)	81.5	42.3	59.7	77.8	96.0	108.0

(b) High density MSAs

Variable	Point estimate	Confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	1.5	0.4	0.8	2.3	4.7	6.4
Employment/Pop (log, BDS)	21.5	5.2	9.1	17.1	27.6	34.8

Our instruments are strong predictors of the structural shocks in the low-density MSAs. However, the startup shock is not well identified in high-density MSAs.

4.4 Innovation

Startups are sometimes conceived as innovators, even though Hurst and Pugsley (2011) caution that many firms are started for motives other than growing a large business. Here we compare the response of startups to shocks to patenting in an MSA, one measure of innovation. We also consider the response of patenting as well as trademark filings to the startup shock we previously defined. Below we show that the response of innovation to startup shocks and startups to innovation are insignificant. This finding is in line with Hurst and Pugsley (2011) that not all startups are innovative – and innovation can be independent of startups.

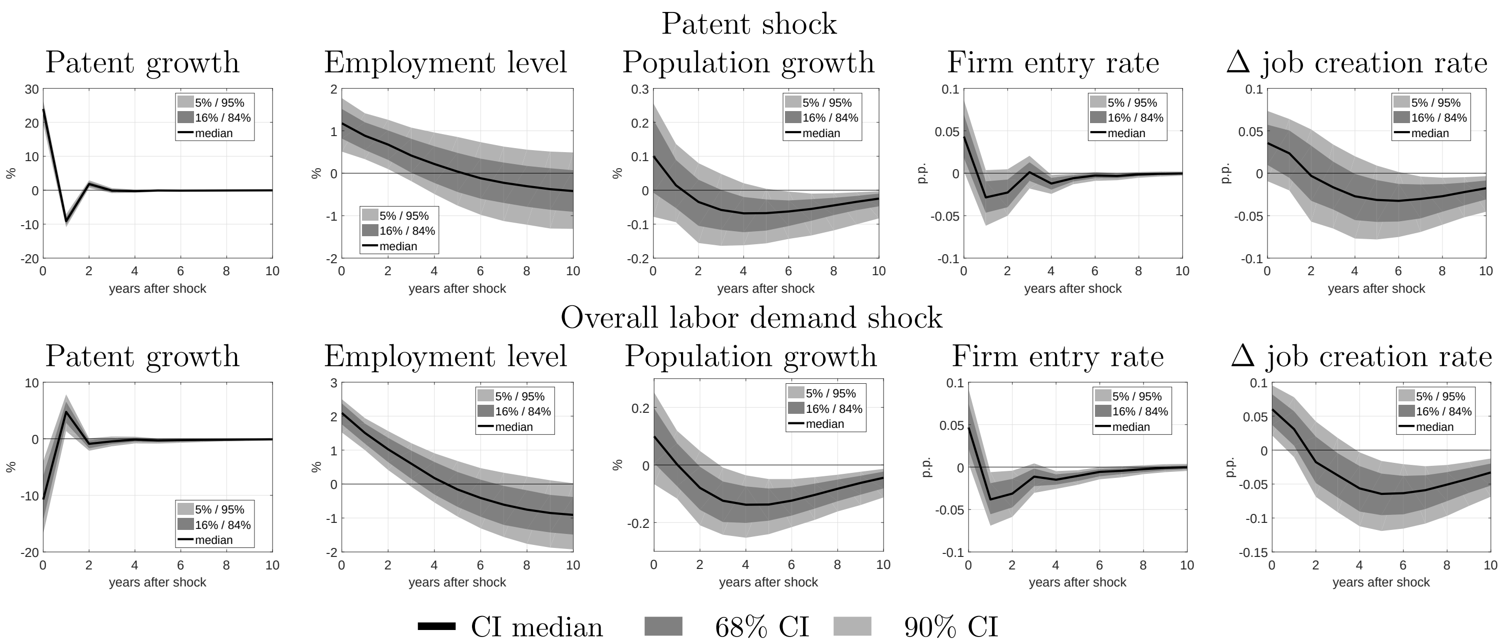
We identify patenting shocks using historic patenting patterns and nationwide growth in the technological category of patents. The first stage is similar for both factorizations. The instruments are weaker than in our baseline specification, but the point estimates of the F-statistics are above 10 for both shocks (Table C.2).[33] To allow for the possibility that innovation drives (part of) industry-level employment, we treat the variation in the patent-Bartik as independent, now assigning the overall labor demand shock the remainder.[34]

While we find some evidence that the patenting shock stimulates economic activity, the effects are short-lived: The employment level reverts to zero after three years. Job creation by startups increases only by about one-tenth of the increase of the startup shock we identified previously. The increase in firm entry is statistically significant, but reversed within one period.

[33] We found that historic trademark filing patterns were only a weak predictor of local trademark filings.

[34] In Figure C.10, we show the analogous results when we identify the overall labor demand shock as in our baseline. We find less significant effects on startups, but also on economic activity overall. This is intuitive, because patenting shocks are likely to also benefit certain industries more than others and the identified shocks in Figure 7 look very similar. Our baseline identification that treats overall industry variation would thus attribute most variation to the labor demand shock, even if some is coming from industry shocks to innovation.

Overall, the responses to patenting resemble those of the overall labor demand shock that is now identified as the residual. See Figure 7.

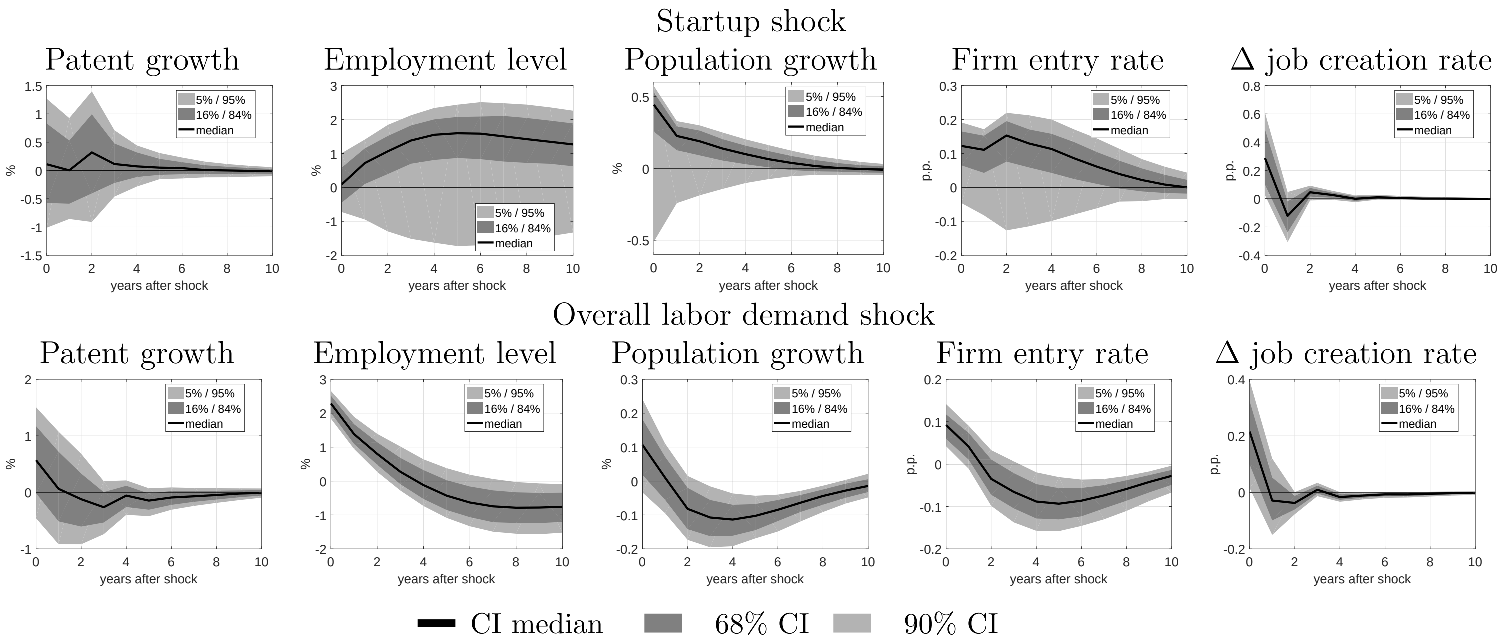


Treating variation in predicted patenting as independent, we find that the identified innovation shock resembles a shock to overall labor demand, but with smaller effects on employment. The effects of these innovation shocks on entry and job creation by startups are small.

Figure 7: Impulse-responses to patenting and overall labor demand shocks: 1986–2001.

The response of patenting to startup shocks is centered around zero, but positive in response to overall labor demand shocks; see Figure 8. Both shocks are identified as before, but estimated on the smaller sample of MSAs with data on patents.[35] This may imply that the overall labor demand shock picks up industry-specific innovation, but the same is not true for startup shocks. Figure C.12 shows that for trademarks, the connection between startup shocks and innovation is weaker still: Trademark filings drop when labor demand increases after a startup shock, but rises slightly two years after an overall labor demand increase.

[35] The responses are very close to our baseline response, but noisier given the smaller sample. Extending the sample to the years for which we do not have migration data confirms the results with tighter confidence intervals; see Figure C.11.



Patenting activity reacts little to startup shocks, identified as in our baseline VAR but estimated in the smaller sample with patent data. Other responses are affected little and the estimates are similar but more precise when we extend the sample to 1980 (Figure C.11).

Figure 8: Impulse-responses to startup and overall labor demand shocks in MSAs with patent data: 1986–2001.

Table 6: First-stage F-statistics in VAR with patent shock

Variable	Point estimate	5%	16%	Median	84%	95%
		Confidence interval				
Patent growth	10.3	5.9	7.8	11.1	14.6	17.4
Employment/Pop (log, BDS)	23.5	13.1	16.2	23.4	31.3	37.3

Our Bartik (1991)-type predictor of patenting activity has a reasonably strong first-stage F-statistic and the overall labor demand shock is well-identified in the smaller sample with patenting data.

5 Conclusion

Startup activity has declined in the U.S. over the last 35 years. Our main contribution is to analyze to what extent startup activity is driven by startup shocks and what the consequence of startup shocks are for local labor markets. Our second contribution is to develop a spatial panel VAR to do so.

For our analysis, we adapt the recent VAR-identification via external instruments (Stock and Watson, 2012; Mertens and Ravn, 2013) for spatial panel data models. We base inference on a simple bootstrap algorithm that allows for residual autocorrelation within MSAs. This spatial panel VAR model with external instruments allows us to generate external instruments using historical predictors based on local characteristics. Here, we follow the approach by Bartik (1991) to generate these instruments for labor demand, but one can derive supply-side instruments analogously following Card (2001). In our context, multiple instruments jointly identify the shocks of interest. We show how to factor the identified shocks to preserve the interpretation of a well-studied first shock, here labor demand shocks as in Blanchard and Katz (1992).

Our analysis focuses on identifying startup shocks and their dynamic effects on local U.S. labor markets. We differentiate shocks to labor demand by startups from overall labor demand shocks. Both types of shocks increase firm entry, so it is important to allow for both channels. Startup shocks account for roughly half of the variation in labor demand by startups. They have small but persistent effects on local labor markets. An average startup shock increases population by roughly 1% after ten years and with it overall employment. The initial employment effects are small. The population increase is driven by migration, which may explain why we find that wages are flat after a startup shock. In contrast, overall labor demand shocks have larger initial effects on employment, but these effects die out after a few years. Our findings on startup shocks are largely driven by less densely populated and regulated areas. We also find that startup activity does not relate closely to innovation, in line with research showing that many firm owners have non-pecuniary motives.

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Online Appendix

Contents

A Data

County-industry employment imputation. We build on Autor et al. (2013) for our imputation. Their code uses the county of establishments within industry-size brackets as well as employment totals at higher levels to impute county-level employment at the four digit SIC and six digit NAICS level. Intuitively, the algorithm computes a year-industry specific mapping of the binned size distribution of establishments to total year-industry employment. The algorithm runs repeatedly until estimates on the pooled disclosed and imputed data converge. We then aggregate the county-industry-level employment to the metropolitan level. Following Autor et al. (2013), we begin with OLS imputation, imposing lower and upper bounds for average employment by size bracket after the estimation. This procedure always converges for the decadal data analyzed in Autor et al. (2013), but not in all years. When the OLS analysis with ex-post bounds does not converge, we switch to non-linear least squares that imposes the bounds during the estimation. After imputing employment according to the prevailing classification scheme in each year, we use cross-walks from the 1977 SIC classification to the 1987 SIC classification and from future NAICS classifications to the 1997 six-digit NAICS classification, which we then, in turn, transform to the 1987 four-digit SIC classification and aggregate up to the three-digit level.[36] We also use this data to compute sectoral weights to predict startup activity.

Trademark data. We believe the concept of innovation has two parts: the generation of ideas and the conversion of these ideas into useful commercial applications. A patent refers to the first stage of innovation. Many inventions are patented, but most patents never reach the point of commercialization. Those that do often require a long gestation period. A trademark is a brand name used to identify and distinguish a firm's goods and services from those of other firms. We believe trademarks are more closely linked to commercialization of a product than are patents. Trademarks often do not require a corresponding patent. For these reason we use trademarks as an additional robustness check.[37]

Main variable definitions.

- Net migration rate: We define the net migration rate as the difference between inflows

[36]For the NAICS to SIC crosswalk, we use the crosswalk from Autor et al. (2013). We could not find a comprehensive crosswalk for the minor within-SIC and within-NAICS changes. To that end, we first use correspondence tables to identify the mapping between sectors. For some industries, this identifies the mapping uniquely, i.e., 100% of one or more industries map into a single industry. If one industry maps into more than one industry, we compute the weights in the crosswalk by regression: We regress the share in the originating industry in the last year of the old classification on the shares of the receiving industries in the new classification at the county-industry level. In our baseline specification, we use OLS and set negative coefficients to zero before normalizing weights to add up to unity. A non-linear LS procedure that respects these constraints yields similar results, but can become unwieldy in the rare cases when a large number of industries are the receiving industries, e.g. in the case for some wholesale sectors.

[37]U.S. Patent and Trademark Office. Overview of the U.S. Patent Classification System (USPC). Washington, D.C. (2012), http://www.uspto.gov/patents/resources/classification/overview.pdf.

and outflows of IRS exemptions, divided by the population level in the prior period. The number of exemptions on tax returns is, typically, the number of household members.

$$\text{net migration rate}_{m,t} = \frac{\text{No. exemptions (inflow)}_{m,t} - \text{No. exemptions (outflow)}_{m,t}}{\text{Population}_{t-1}} \tag{A.1}$$

- Job creation rate: We define the job creation rate as the change in job creation by firms aged 0, divided by the average of overall private employment in the current and prior year.

$$\Delta\text{job creation rate}_{m,t} = \frac{\Delta\text{job creation by firms aged 0 in MSA}_{m,t}}{\frac{1}{2}(\text{MSA employment}_{m,t-1} + \text{MSA employment}_{m,t})} \tag{A.2}$$

The numerator follows Haltiwanger et al. (2013).

- Firm entry rate: We define the firm entry rate as the number of firms aged 0, divided by the average of the number of firms of any age in the current and prior year.

$$\text{firm entry rate}_{m,t} = \frac{\text{Firms aged 0 in MSA}_{m,t}}{\frac{1}{2}(\text{All firms}_{m,t-1} + \text{All firms}_{m,t})} \tag{A.3}$$

- Firm exit rate: We define the firm exit rate as the number of firms aged 1 that exit, divided by the average of the number of firms of any age in the current and prior year.

$$\text{firm exit rate}_{m,t} = \frac{\text{Firm deaths of firms aged 1 in MSA}_{m,t}}{\frac{1}{2}(\text{All firms}_{m,t-1} + \text{All firms}_{m,t})} \tag{A.4}$$

- Overall firm exit rate: We define the overall firm exit rate as the number of firms of any age that exit, divided by the average of the number of firms of any age in the current and prior year.

$$\text{overall firm exit rate}_{m,t} = \frac{\text{Firm deaths of any firm in MSA}_{m,t}}{\frac{1}{2}(\text{All firms}_{m,t-1} + \text{All firms}_{m,t})} \tag{A.5}$$

- Employment-to-population ratio: We use overall employment from the County Business Patterns to compute the log growth rate. This measure agrees closely with BDS employment; see Figure A.2. It enters the analysis in logs.

- Population growth: We compute the log growth rate. The log growth rate has the advantage of being additive to compute level changes, from which we can back out the change in the employment level.

- Growth of average wages: We compute the log growth rate of the average wage rate in the County Business Patterns.

- House price growth: We compute the log growth rate of first quarter house prices.

- Patent growth: We compute the log growth rate of one plus the inventor-weighted number of patents in an MSA. We add one to account for the sometimes small number of patents.
- Trademark growth: We compute the log growth rate of one plus the number of trademark filings in an MSA. We add one to account for the sometimes small number of trademarks.

Definition of instruments.

- Overall labor demand shock proxy:

$$Z_{m,t}^{\text{overall}} = \sum_i \omega_{m,i,t-5}^{SIC3} \Delta(\log(emp_{i,t} - emp_{m,i,t}) \tag{A.6}$$

- Startup labor demand shock proxy:

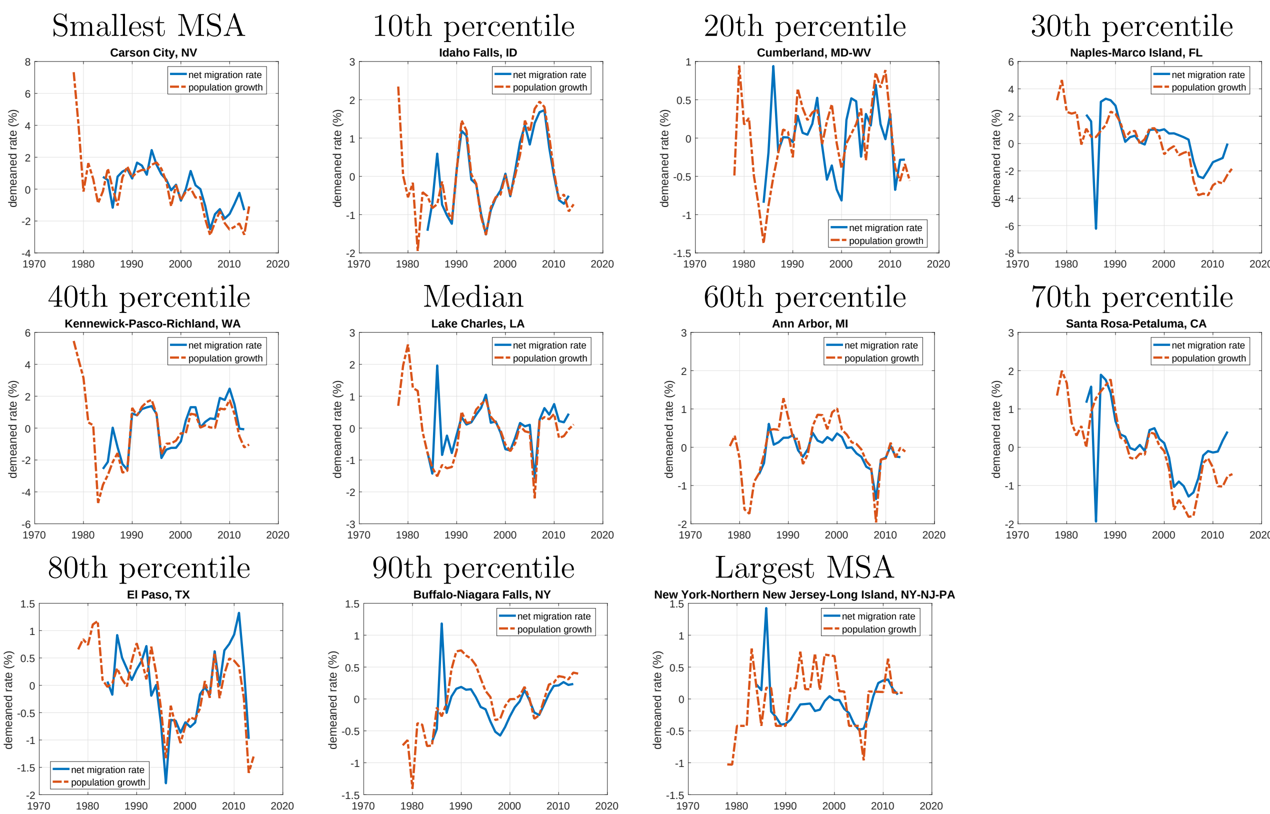
$$Z_{m,t}^{\text{startup}} = \sum_i \omega_{m,i,t-5}^{sector} \Delta \text{job creation rate}_{i,t} \tag{A.7}$$

- Patenting and trademark shock proxy:

$$Z_{m,t}^{\text{patent}} = \sum_i \omega_{m,i,t-5}^{technologicalcategory} \Delta(\log(\#patents_{i,t} - \#patents_{m,i,t}) \tag{A.8}$$

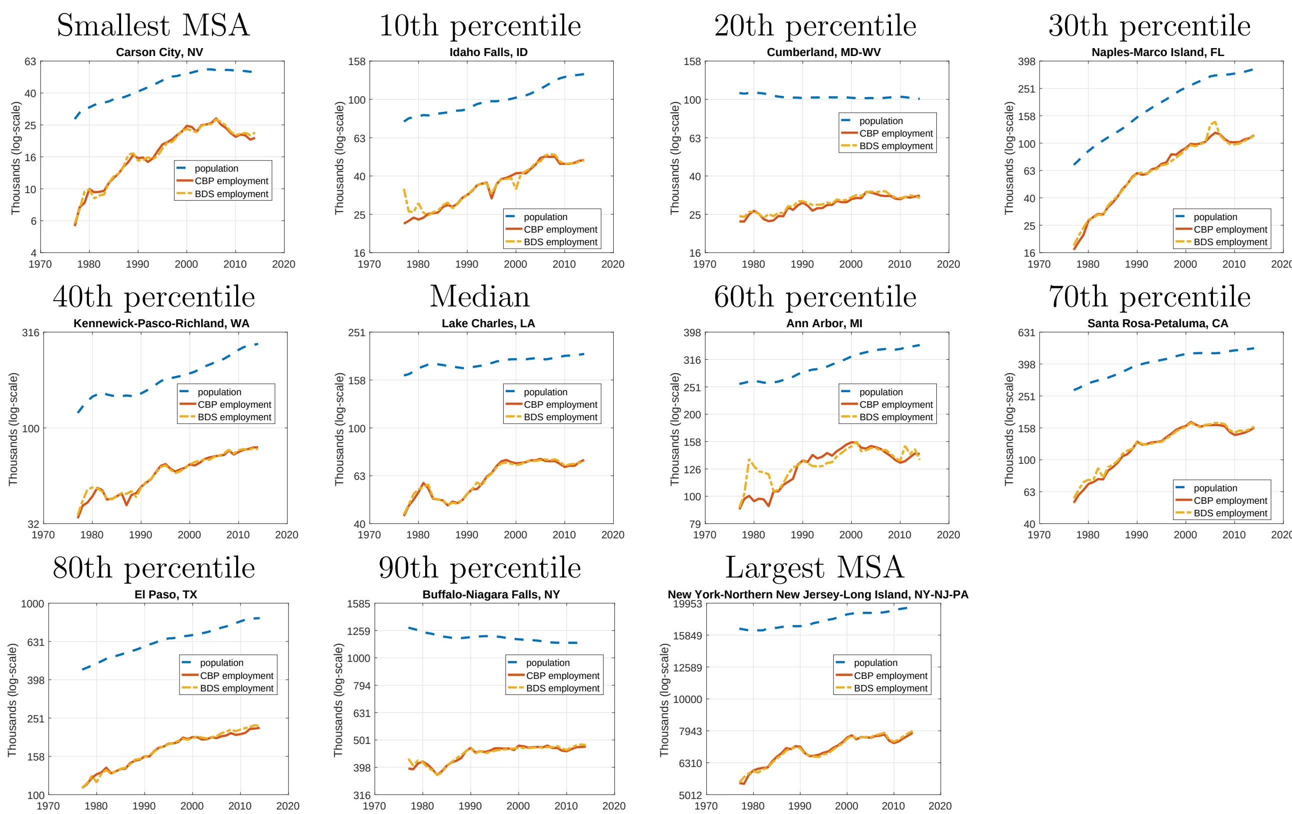
- Trademark shock proxy:

$$Z_{m,t}^{\text{trademark}} = \sum_i \omega_{m,i,t-5}^{USPTOclass} \Delta(\log(\#trademarks_{i,t} - \#trademarks_{m,i,t}) \tag{A.9}$$



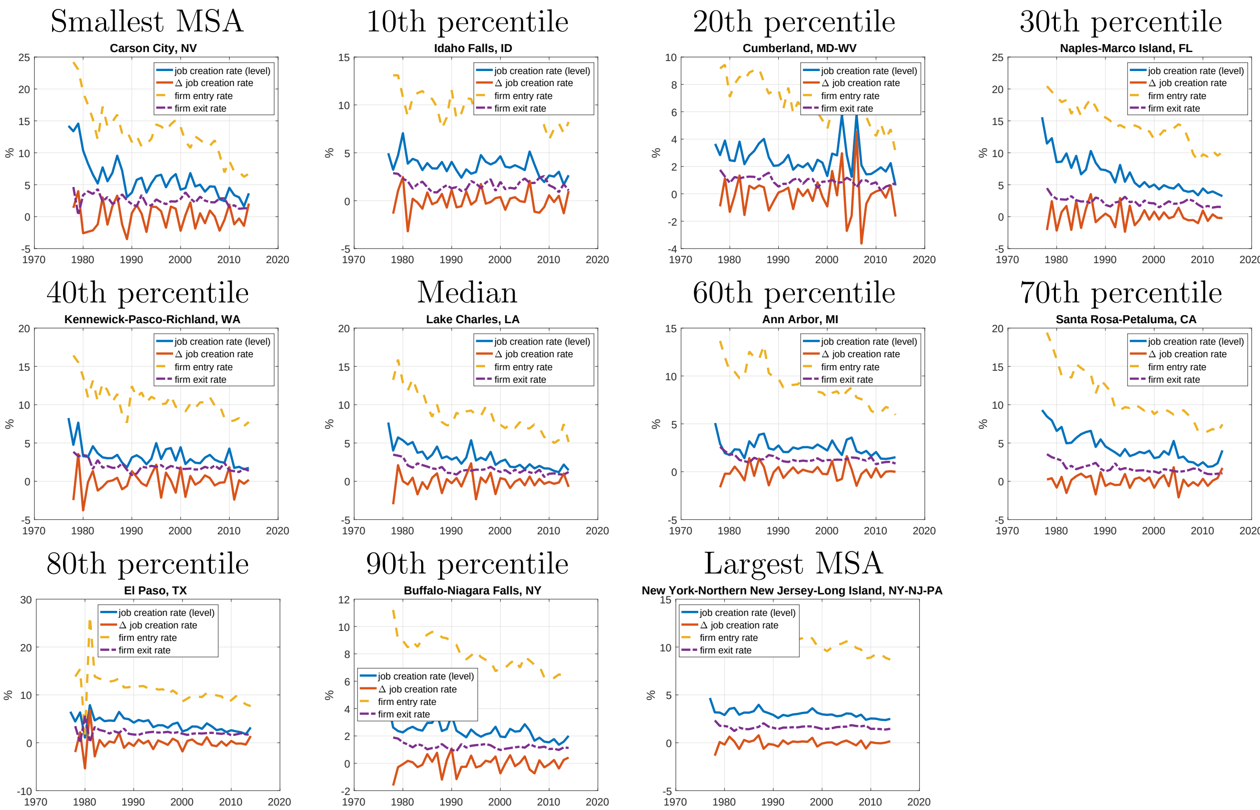
For most periods, population growth and the net migration rate track each other in MSAs. Given that the two series move closely together for most periods, we interpret the occasional deviations of the net migration rate from the population growth rate as measurement error. We show the MSAs with the smallest and largest population in 1986, the start of the migration series, and MSAs next to the deciles of the population size distribution.

Figure A.1: Net migration rate and population growth rate for MSAs of various sizes



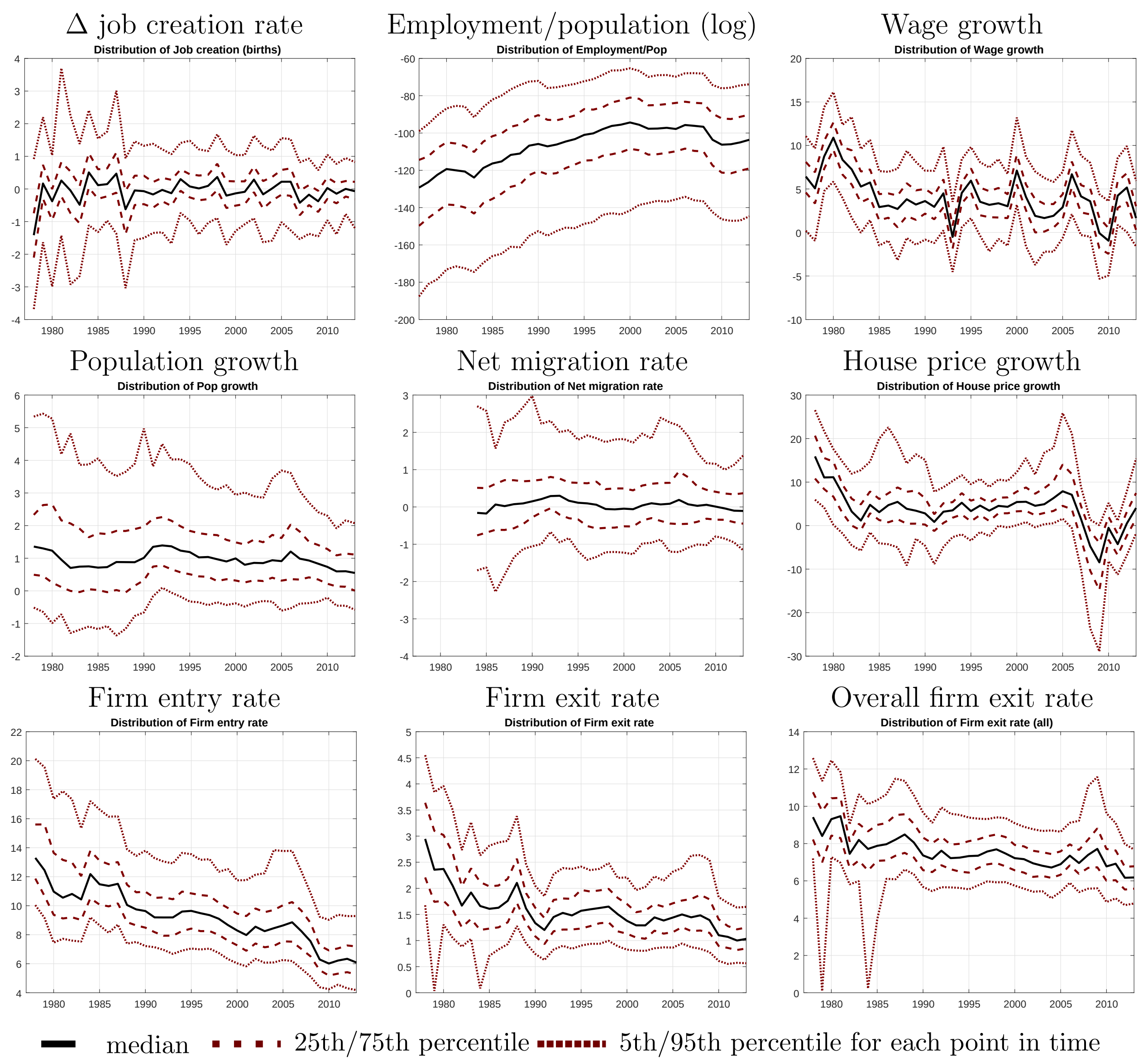
County Business Pattern (CBP) employment measures and Business Dynamics Statistics employment (BDS) track each other closely. Population levels change smoothly. We show the MSAs with the smallest and largest population in 1986, the start of the migration series, and MSAs next to the deciles of the population size distribution.

Figure A.2: Population, CBP employment, and BDS employment for MSAs of various sizes



Firm entry rates show a trend decline, whereas job creation rates are almost stable in many MSAs such as New York, NY, or Ann Arbor, MI. Focusing on the change in job creation by startups, converted to a rate relative to overall employment, we see stationary series. Firm exit rates also appear stationary. We show the MSAs with the smallest and largest population in 1986, the start of the migration series, and MSAs next to the deciles of the population size distribution.

Figure A.3: startup activity for MSAs of various sizes



The variables in our VAR and its periphery have regional variation that we model and use for identification. We show the median across MSAs along with the inner 50% and 90% for each point in time.

Figure A.4: Cross-sectional distribution of variables in VAR over time

MSA, state(s)	Initial density Pop. per sq mi	Entry rate (% of firms) Initial	2013	Avg. startup size Initial	2013	Patents Median #	Trademarks Median #
Abilene, TX	49	15.0	6.1	5.3	6.9	5	x
Akron, OH	736	11.8	5.6	5.8	5.4	276	191
Albany, GA	73	12.5	5.1	5.0	6.6	x	x
Albany-Schenectady-Troy, NY	276	10.5	7.0	4.4	4.7	328	95
Albuquerque, NM	52	16.0	6.9	5.7	6.1	144	85
Alexandria, LA	75	11.7	4.4	5.9	12.8	5	x
Allentown-Bethlehem-Easton, PA-NJ	432	10.6	5.9	5.0	6.2	249	108
Altoona, PA	261	8.8	5.0	5.9	7.8	7	9
Amarillo, TX	47	14.6	6.5	5.4	4.6	12	13
Ames, IA	122	13.1	4.9	6.6	15.2	46	x
Anchorage, AK	7	21.4	7.1	5.2	5.3	22	18
Ann Arbor, MI	365	13.7	6.6	5.4	5.0	239	96
Anniston-Oxford, AL	186	14.6	4.4	5.4	4.6	3	x
Appleton, WI	161	12.2	4.9	5.0	5.4	60	45
Asheville, NC	133	14.8	7.5	4.6	4.9	54	44
Athens-Clarke County, GA	105	14.3	7.1	5.0	5.9	19	15
Atlanta-Sandy Springs-Marietta, GA	262	16.6	9.2	5.4	5.1	372	1144
Atlantic City-Hammonton, NJ	341	12.9	6.2	4.0	6.8	12	34
Auburn-Opelika, AL	118	13.2	8.2	5.9	8.5	13	x
Augusta-Richmond County, GA-SC	109	13.6	5.6	5.6	10.7	33	26
Austin-Round Rock-San Marcos, TX	126	15.8	10.7	5.7	5.3	556	279
Bakersfield-Delano, CA	46	17.2	7.3	5.2	5.1	57	32
Baltimore-Towson, MD	846	11.9	6.9	4.6	5.6	431	499
Bangor, ME	40	13.3	5.3	3.2	5.0	5	8
Barnstable Town, MA	351	15.5	6.4	4.0	4.1	37	38
Baton Rouge, LA	136	13.3	6.3	6.0	6.2	147	46
Battle Creek, MI	202	10.1	4.6	5.5	5.4	22	19
Bay City, MI	275	10.3	4.2	5.1	5.5	22	x
Beaumont-Port Arthur, TX	173	12.1	5.9	6.1	5.6	29	x
Bellingham, WA	47	19.8	6.9	11.6	4.1	27	37
Bend, OR	16	27.4	8.3	5.2	3.6	20	18
Billings, MT	24	13.5	6.5	5.0	4.2	8	x
Binghamton, NY	219	10.8	5.4	5.4	5.3	113	20
Birmingham-Hoover, AL	172	14.0	6.2	5.8	9.7	33	112
Bismarck, ND	21	17.1	7.5	5.7	5.2	7	x
Blacksburg-Christiansburg-Radford, VA	117	14.6	5.3	7.0	7.7	37	x
Bloomington, IN	106	13.3	5.6	5.3	7.0	22	17
Boise City-Nampa, ID	22	16.7	8.6	5.3	5.2	53	62
Boston-Cambridge-Quincy, MA-NH	1132	11.3	6.9	5.6	5.2	1846	1502
Bowling Green, KY	92	12.8	7.9	8.7	5.1	x	16
Bremerton-Silverdale, WA	319	18.9	7.6	4.5	4.8	22	22
Bridgeport-Stamford-Norwalk, CT	1297	11.8	7.1	4.6	5.5	488	534
Brownsville-Harlingen, TX	219	13.8	7.0	6.0	5.9	5	x
Brunswick, GA	53	16.4	6.7	5.5	5.3	x	5
Buffalo-Niagara Falls, NY	824	11.2	6.4	5.2	6.1	273	172
Burlington, NC	232	11.3	5.2	3.9	5.1	13	26
Burlington-South Burlington, VT	118	16.4	5.7	7.0	4.5	90	55
Canton-Massillon, OH	414	12.3	5.1	5.1	4.7	65	63
Cape Coral-Fort Myers, FL	222	21.4	10.6	5.8	4.5	32	46
Cape Girardeau-Jackson, MO-IL	54	13.2	6.0	4.4	4.3	x	4
Carson City, NV	189	24.2	6.2	5.4	3.4	10	24
Casper, WY	12	15.6	5.6	5.9	4.8	5	x
Cedar Rapids, IA	105	11.9	5.2	5.5	4.5	74	43
Champaign-Urbana, IL	105	14.2	5.8	5.9	5.8	40	29
Charleston, WV	129	12.3	4.4	4.6	7.4	48	14
Charleston-North Charleston-Summerville, SC	157	15.5	8.1	6.3	5.4	52	67
Charlotte-Gastonia-Rock Hill, NC-SC	262	13.8	8.7	5.2	5.3	161	306
Charlottesville, VA	74	13.9	5.8	4.3	5.0	33	44
Chattanooga, TN-GA	197	13.1	6.5	5.7	5.5	34	76
Cheyenne, WY	25	16.6	8.8	5.3	4.8	x	x
Chicago-Joliet-Naperville, IL-IN-WI	1118	12.0	7.8	6.0	5.1	2372	3414
Chico, CA	79	17.0	7.0	4.0	4.1	12	15
Cincinnati-Middletown, OH-KY-IN	393	11.6	6.3	5.1	6.3	412	499
Clarksville, TN-KY	77	13.0	6.4	4.3	5.5	7	15
Cleveland, TN	99	13.0	4.5	4.1	4.9	15	7
Cleveland-Elyria-Mentor, OH	1108	10.8	5.5	6.1	7.6	606	670
Coeur d'Alene, ID	41	22.1	7.3	5.0	4.5	10	x
College Station-Bryan, TX	50	13.5	7.1	5.4	6.5	32	x
Colorado Springs, CO	115	18.0	8.0	4.9	4.1	34	85
Columbia, MO	91	14.3	7.8	5.5	3.9	22	17
Columbia, SC	129	14.9	6.6	4.7	5.7	54	61
Columbus, GA-AL	131	12.5	5.8	4.9	4.6	9	18
Columbus, IN	153	11.9	4.2	5.6	7.3	29	x
Columbus, OH	318	12.6	7.3	5.0	7.0	292	356
Corpus Christi, TX	182	12.8	6.2	5.7	9.7	28	11
Corvallis, OR	97	19.2	5.9	6.7	4.0	47	11
Crestview-Fort Walton Beach-Destin, FL	116	16.9	8.0	4.2	5.2	9	13
Cumberland, MD-WV	143	9.2	4.7	4.4	8.8	4	x
Dallas-Fort Worth-Arlington, TX	311	15.7	9.5	6.1	6.7	1085	1459
Dalton, GA	129	17.1	4.9	6.5	5.1	4	28
Danville, IL	109	10.8	3.4	4.5	5.1	6	x
Danville, VA	110	10.7	4.1	4.1	5.5	x	x
Davenport-Moline-Rock Island, IA-IL	176	12.1	5.3	5.8	5.3	49	52
Dayton, OH	484	12.0	5.2	5.2	5.9	238	145
Decatur, AL	92	15.7	5.8	5.3	7.2	11	x
Decatur, IL	226	11.3	4.9	5.0	6.8	17	14
Deltona-Daytona Beach-Ormond Beach, FL	208	17.0	8.1	5.0	4.1	28	48
Denver-Aurora-Broomfield, CO	182	16.0	9.3	5.8	4.9	597	884
Des Moines-West Des Moines, IA	135	13.6	6.3	5.9	5.3	43	110
Detroit-Warren-Livonia, MI	1119	12.8	7.5	6.1	6.7	1537	796
Dothan, AL	65	14.5	5.3	6.4	7.2	x	7
Dover, DE	164	11.9	7.3	4.5	4.5	8	27

Table A.1: List of MSAs included (continued on the next page. . .)

MSA, state(s)	Initial density Pop. per sq mi	Entry rate (% of firms) Initial	2013	Avg. startup size Initial	2013	Patents Median #	Trademarks Median #
Dubuque, IA	155	11.5	4.7	5.6	3.7	13	11
Duluth, MN-WI	35	11.6	4.1	6.0	6.0	15	30
Durham-Chapel Hill, NC	160	13.3	7.0	5.2	5.0	145	112
Eau Claire, WI	77	13.9	6.0	4.8	7.9	31	21
El Centro, CA	21	14.2	5.7	4.8	3.8	7	6
Elizabethtown, KY	111	15.4	7.8	3.8	4.0	x	x
Elkhart-Goshen, IN	288	11.3	5.4	6.2	6.9	47	51
Elmira, NY	244	10.5	4.7	4.6	4.2	40	x
El Paso, TX	444	13.8	8.0	6.0	5.2	23	36
Erie, PA	350	9.7	3.7	4.7	5.6	63	24
Eugene-Springfield, OR	55	20.0	6.3	5.3	6.5	51	63
Evansville, IN-KY	137	13.2	5.6	5.0	5.7	25	29
Fairbanks, AK	8	20.5	7.2	6.3	5.6	x	x
Fargo, ND-MN	47	13.2	6.8	4.8	4.4	18	23
Farmington, NM	13	15.9	5.3	6.4	13.8	6	x
Fayetteville, NC	252	14.0	6.0	4.6	6.4	8	x
Fayetteville-Springdale-Rogers, AR-MO	60	16.2	8.5	4.9	4.9	22	44
Flagstaff, AZ	4	14.4	6.5	4.8	6.5	x	x
Flint, MI	701	12.3	5.7	5.8	5.9	56	30
Florence, SC	122	12.9	5.2	5.1	5.5	21	11
Florence-Muscle Shoals, AL	103	13.6	4.9	4.3	7.6	14	23
Fond du Lac, WI	122	11.2	3.8	4.3	5.0	22	x
Fort Collins-Loveland, CO	51	20.4	8.7	4.8	4.8	128	61
Fort Smith, AR-OK	52	12.0	5.7	4.8	6.6	11	x
Fort Wayne, IN	249	11.6	5.4	4.9	7.0	31	57
Fresno, CA	82	16.2	6.8	5.6	5.2	33	67
Gadsden, AL	187	12.0	3.7	8.1	7.5	3	x
Gainesville, FL	116	17.4	7.8	5.7	6.1	70	28
Gainesville, GA	181	12.1	7.5	4.8	4.9	12	x
Glens Falls, NY	65	11.9	5.6	3.6	5.9	22	13
Goldsboro, NC	171	10.7	5.0	4.6	4.6	3	x
Grand Forks, ND-MN	30	11.3	5.0	4.9	9.0	x	x
Grand Junction, CO	21	17.5	5.9	5.8	3.6	9	x
Grand Rapids-Wyoming, MI	199	11.9	6.0	5.5	6.6	131	167
Great Falls, MT	32	13.6	5.5	5.5	5.6	x	x
Greeley, CO	28	13.9	9.2	4.7	4.2	20	20
Green Bay, WI	117	12.1	5.4	7.7	5.9	34	52
Greensboro-High Point, NC	239	13.1	6.2	5.5	4.9	49	121
Greenville, NC	105	14.4	5.9	4.7	5.4	x	x
Greenville-Mauldin-Easley, SC	201	13.3	6.9	5.2	6.2	120	121
Gulfport-Biloxi, MS	124	14.3	5.4	6.7	6.5	11	x
Hagerstown-Martinsburg, MD-WV	164	10.3	5.0	4.2	5.6	13	x
Hanford-Corcoran, CA	52	13.6	5.1	4.5	4.8	x	x
Harrisburg-Carlisle, PA	268	10.0	5.5	4.7	8.9	118	62
Harrisonburg, VA	87	11.5	6.0	4.4	5.7	5	9
Hartford-West Hartford-East Hartford, CT	687	11.5	5.8	4.8	6.7	424	285
Hattiesburg, MS	59	12.8	6.4	5.6	7.6	7	x
Hickory-Lenoir-Morganton, NC	157	13.1	4.8	5.5	5.6	40	49
Hinesville-Fort Stewart, GA	38	24.4	5.7	5.1	9.9	x	x
Hot Springs, AR	100	13.0	5.6	6.0	4.5	x	x
Houma-Bayou Cane-Thibodaux, LA	72	13.3	4.5	5.6	6.1	16	x
Houston-Sugar Land-Baytown, TX	318	17.0	9.6	6.3	7.1	800	804
Huntington-Ashland, WV-KY-OH	174	12.4	5.2	4.1	7.0	21	12
Huntsville, AL	174	14.6	6.6	4.7	5.7	87	26
Idaho Falls, ID	26	13.1	7.1	4.9	3.8	24	18
Indianapolis-Carmel, IN	308	13.1	7.6	5.6	5.8	357	335
Iowa City, IA	84	14.5	6.5	6.0	5.3	25	10
Ithaca, NY	182	13.8	5.0	4.4	4.7	70	17
Jackson, MI	214	9.5	4.2	5.0	8.7	28	14
Jackson, MS	105	14.9	6.8	5.2	4.9	19	33
Jackson, TN	100	11.9	5.3	5.7	7.3	8	6
Jacksonville, FL	220	14.8	9.5	6.0	4.8	70	150
Jacksonville, NC	153	15.5	6.5	4.5	6.6	x	x
Janesville, WI	192	11.8	4.3	5.3	6.4	27	21
Jefferson City, MO	47	13.4	5.5	4.9	4.5	7	x
Johnson City, TN	175	12.1	4.8	4.4	6.1	20	x
Johnstown, PA	276	9.0	3.9	5.6	7.0	8	x
Jonesboro, AR	61	14.2	6.9	4.8	6.0	5	x
Joplin, MO	98	12.2	6.7	4.9	3.7	15	13
Kalamazoo-Portage, MI	233	12.1	4.9	5.0	5.2	97	50
Kankakee-Bradley, IL	150	11.1	5.1	6.0	5.1	9	x
Kansas City, MO-KS	189	14.0	7.9	5.7	5.6	160	558
Kennewick-Pasco-Richland, WA	41	16.4	7.2	5.0	4.0	43	11
Killeen-Temple-Fort Hood, TX	83	13.2	6.8	6.1	6.1	x	x
Kingsport-Bristol-Bristol, TN-VA	133	13.6	5.2	5.2	5.2	90	25
Kingston, NY	140	11.1	6.0	3.6	4.6	49	28
Knoxville, TN	260	15.2	6.1	5.4	5.9	59	91
Kokomo, IN	188	10.5	4.3	5.4	6.2	40	x
La Crosse, WI-MN	106	12.1	5.0	6.2	7.3	17	13
Lafayette, LA	175	15.3	7.0	5.4	6.9	31	20
Lake Charles, LA	70	13.2	7.5	5.1	6.0	12	x
Lake Havasu City-Kingman, AZ	3	20.3	7.3	4.4	4.5	x	7
Lakeland-Winter Haven, FL	165	15.6	7.4	4.7	6.3	28	31
Lancaster, PA	372	11.0	5.7	4.9	4.8	100	65
Lansing-East Lansing, MI	238	12.7	5.9	5.3	5.1	43	52
Laredo, TX	27	12.5	9.0	5.9	4.5	x	x
Las Cruces, NM	23	15.6	5.8	6.2	5.7	10	x
Las Vegas-Paradise, NV	49	17.6	12.0	7.9	7.0	59	364
Lawrence, KS	138	13.6	5.1	6.0	4.5	18	15
Lawton, OK	108	12.4	4.7	5.3	8.5	x	x
Lebanon, PA	299	8.5	4.3	4.2	5.1	14	9
Lewiston, ID-WA	32	12.5	5.3	4.6	3.8	x	x

Table A.1: List of MSAs included (continued on the next page. . .)

MSA, state(s)	Initial density Pop. per sq mi	Entry rate (% of firms) Initial	 2013	Avg. startup size Initial	 2013	Patents Median #	Trademarks Median #
Lewiston-Auburn, ME	210	11.2	5.0	4.9	9.7	6	x
Lexington-Fayette, KY	210	14.0	7.2	5.6	4.7	72	52
Lima, OH	274	9.4	3.7	4.7	5.4	8	x
Lincoln, NE	142	13.4	6.5	5.0	4.9	46	46
Little Rock-North Little Rock-Conway, AR	115	13.9	7.1	5.2	6.0	33	68
Logan, UT-ID	33	14.5	6.9	5.5	3.6	33	22
Longview, TX	87	14.3	6.0	6.0	5.3	21	9
Longview, WA	65	15.8	5.8	4.9	8.7	7	7
Los Angeles-Long Beach-Santa Ana, CA	1869	16.5	9.2	6.1	6.0	2689	4536
Louisville/Jefferson County, KY-IN	254	12.0	6.3	6.0	6.5	68	198
Lubbock, TX	118	14.0	6.5	5.1	6.1	25	16
Lynchburg, VA	88	11.9	5.7	4.9	3.6	38	19
Macon, GA	114	11.9	5.7	4.0	6.2	14	12
Madera-Chowchilla, CA	25	17.3	6.3	4.6	4.3	x	7
Madison, WI	137	13.1	6.1	5.5	5.3	76	151
Manchester-Nashua, NH	300	15.7	6.1	4.8	5.2	170	83
Manhattan, KS	58	12.7	5.2	4.3	7.9	10	6
Mankato-North Mankato, MN	65	10.2	4.1	5.7	6.0	10	16
Mansfield, OH	264	9.4	4.3	4.0	5.3	12	10
McAllen-Edinburg-Mission, TX	165	13.4	9.4	6.4	5.9	x	10
Medford, OR	44	20.1	6.6	5.4	4.5	16	26
Memphis, TN-MS-AR	211	13.0	6.4	5.8	6.4	104	227
Merced, CA	65	13.6	5.8	4.2	5.5	x	8
Miami-Fort Lauderdale-Pompano Beach, FL	579	19.6	11.4	6.0	4.8	630	1459
Michigan City-La Porte, IN	181	11.0	3.7	4.9	3.8	15	12
Midland, TX	82	14.4	9.4	6.3	6.9	13	7
Milwaukee-Waukesha-West Allis, WI	958	11.5	6.0	5.1	6.6	390	382
Minneapolis-St. Paul-Bloomington, MN-WI	352	13.9	7.1	6.2	5.8	1399	1470
Missoula, MT	27	17.7	6.2	5.4	5.4	10	12
Mobile, AL	287	15.7	5.0	5.7	6.6	22	19
Modesto, CA	165	18.6	7.3	5.1	4.6	34	35
Monroe, LA	104	12.8	5.9	4.8	6.8	13	9
Monroe, MI	237	11.8	5.3	4.4	4.4	27	14
Montgomery, AL	101	15.5	5.7	6.6	7.0	8	26
Morgantown, WV	101	12.4	5.9	4.0	10.0	12	x
Morristown, TN	131	12.8	6.0	5.3	6.4	x	x
Mount Vernon-Anacortes, WA	33	19.1	5.4	8.7	3.8	10	18
Muncie, IN	332	10.3	4.2	6.6	6.4	10	14
Muskegon-Norton Shores, MI	315	11.0	4.6	4.9	5.1	22	13
Myrtle Beach-North Myrtle Beach-Conway, SC	83	18.6	8.1	5.9	4.8	8	20
Napa, CA	129	15.2	6.9	4.1	6.5	15	86
Naples-Marco Island, FL	35	20.4	9.5	5.3	5.0	x	19
Nashville-Davidson–Murfreesboro–Franklin, TN	151	15.4	8.4	5.3	6.7	89	308
New Haven-Milford, CT	1254	11.2	5.8	4.7	9.3	326	206
New Orleans-Metairie-Kenner, LA	417	12.4	6.7	6.4	7.1	109	133
New York-Northern New Jersey-Long Island, NY-NJ-PA	2482	11.5	8.9	4.9	5.0	4009	7869
Niles-Benton Harbor, MI	308	11.4	4.0	6.7	8.3	40	33
North Port-Bradenton-Sarasota, FL	236	18.4	9.3	5.6	5.7	73	107
Norwich-New London, CT	363	11.2	5.9	4.1	5.8	100	32
Ocala, FL	69	17.2	8.1	4.8	5.4	15	x
Ocean City, NJ	311	15.6	6.1	3.4	2.6	5	x
Odessa, TX	117	14.5	8.2	6.3	5.8	5	x
Ogden-Clearfield, UT	182	16.4	8.2	6.0	5.4	72	53
Oklahoma City, OK	149	14.4	7.7	5.8	6.4	81	121
Olympia, WA	148	19.4	7.0	5.4	3.9	9	13
Omaha-Council Bluffs, NE-IA	151	12.4	6.8	5.6	5.3	40	184
Orlando-Kissimmee-Sanford, FL	209	18.7	10.8	5.3	5.9	176	321
Oshkosh-Neenah, WI	301	11.8	4.7	7.1	5.1	64	43
Owensboro, KY	112	12.4	4.9	5.3	6.1	6	x
Oxnard-Thousand Oaks-Ventura, CA	260	18.3	7.9	5.1	5.1	143	268
Palm Bay-Melbourne-Titusville, FL	238	20.6	8.7	5.6	3.7	103	46
Panama City-Lynn Haven-Panama City Beach, FL	123	15.8	6.6	4.9	5.0	11	x
Parkersburg-Marietta-Vienna, WV-OH	121	12.0	4.3	4.2	6.8	26	13
Pensacola-Ferry Pass-Brent, FL	171	15.3	7.2	5.1	4.9	30	28
Peoria, IL	155	11.4	4.6	5.1	5.5	112	32
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1144	11.5	7.0	5.4	6.9	1764	1943
Phoenix-Mesa-Glendale, AZ	97	17.8	9.5	6.0	6.2	516	610
Pine Bluff, AR	53	11.8	5.1	5.0	6.8	x	x
Pittsburgh, PA	508	10.8	5.3	4.7	6.0	644	465
Pittsfield, MA	156	11.8	4.2	4.3	4.7	37	23
Pocatello, ID	27	12.2	5.5	5.7	3.6	6	x
Portland-South Portland-Biddeford, ME	179	13.8	6.2	4.8	4.4	67	87
Portland-Vancouver-Hillsboro, OR-WA	186	17.1	8.2	5.2	4.4	356	499
Port St. Lucie, FL	114	20.0	9.6	5.9	4.8	41	29
Prescott, AZ	7	20.3	7.3	4.3	4.4	15	17
Providence-New Bedford-Fall River, RI-MA	896	10.8	6.0	6.1	5.1	293	348
Provo-Orem, UT	36	16.7	11.2	6.0	6.2	52	141
Pueblo, CO	52	14.2	6.5	4.5	4.9	x	x
Punta Gorda, FL	69	21.9	8.9	5.4	4.0	x	x
Racine, WI	516	11.4	5.3	8.5	4.7	24	54
Raleigh-Cary, NC	178	15.2	8.8	4.6	5.0	241	144
Rapid City, SD	15	17.8	7.0	5.7	4.8	6	x
Reading, PA	358	9.4	5.4	5.5	6.7	61	54
Redding, CA	27	21.9	5.3	4.1	5.6	12	10
Reno-Sparks, NV	26	17.4	7.4	7.1	5.7	52	129
Richmond, VA	144	13.2	7.2	5.0	5.3	100	177
Riverside-San Bernardino-Ontario, CA	49	19.4	9.3	5.5	5.8	254	255
Roanoke, VA	138	12.0	5.0	4.6	6.3	23	25
Rochester, MN	76	12.9	6.1	4.6	4.8	77	23
Rochester, NY	334	11.6	6.6	5.1	5.0	856	183
Rockford, IL	345	11.4	5.3	5.5	6.1	103	44
Rocky Mount, NC	116	12.1	5.1	4.3	6.5	4	8

Table A.1: List of MSAs included (continued on the next page. . .)

MSA, state(s)	Initial density Pop. per sq mi	Entry rate (% of firms) Initial	2013	Avg. startup size Initial	2013	Patents Median #	Trademarks Median #
Rome, GA	158	12.4	5.9	6.3	8.3	5	7
Sacramento–Arden-Arcade–Roseville, CA	196	18.9	8.3	5.5	5.1	207	200
Saginaw-Saginaw Township North, MI	284	11.2	4.5	5.0	7.0	37	15
St. Cloud, MN	74	13.3	5.1	5.5	4.6	13	16
St. George, UT	9	15.1	10.8	5.8	5.4	x	x
St. Joseph, MO-KS	73	12.3	7.1	4.8	6.3	6	17
St. Louis, MO-IL	291	12.1	8.7	5.6	4.5	506	804
Salem, OR	119	18.2	6.6	4.8	5.9	29	26
Salinas, CA	86	16.0	5.8	4.8	5.2	31	68
Salisbury, MD	119	12.7	5.8	3.7	5.0	5	11
Salt Lake City, UT	62	15.3	8.9	6.2	5.5	225	341
San Angelo, TX	31	12.8	6.5	5.6	4.8	x	x
San Antonio-New Braunfels, TX	151	13.8	8.6	5.9	6.6	134	257
San Diego-Carlsbad-San Marcos, CA	408	20.9	8.9	5.2	5.8	849	971
Sandusky, OH	312	8.9	4.5	4.9	5.8	12	8
San Francisco-Oakland-Fremont, CA	1295	15.7	8.3	5.7	5.1	1347	1861
San Jose-Sunnyvale-Santa Clara, CA	468	17.8	8.8	5.5	4.9	2032	835
San Luis Obispo-Paso Robles, CA	42	20.6	6.5	4.3	4.6	26	47
Santa Cruz-Watsonville, CA	393	20.8	6.1	4.9	5.1	86	89
Santa Fe, NM	38	15.4	6.1	4.8	6.3	20	39
Santa Rosa-Petaluma, CA	173	19.4	6.4	4.7	5.4	74	149
Savannah, GA	168	13.6	7.2	5.6	5.5	14	16
Scranton–Wilkes-Barre, PA	346	10.5	5.2	5.6	5.0	40	48
Seattle-Tacoma-Bellevue, WA	326	18.1	8.7	6.3	4.4	678	884
Sebastian-Vero Beach, FL	100	17.0	7.6	6.1	4.2	12	18
Sheboygan, WI	197	11.1	4.2	9.1	4.6	39	27
Sherman-Denison, TX	90	11.4	7.0	3.6	4.9	17	x
Shreveport-Bossier City, LA	134	11.6	6.0	5.6	7.4	22	18
Sioux City, IA-NE-SD	67	11.6	4.8	5.7	5.8	8	15
Sioux Falls, SD	52	14.7	6.8	4.6	5.2	7	25
South Bend-Mishawaka, IN-MI	304	11.8	4.8	5.9	7.5	73	41
Spartanburg, SC	242	12.4	5.5	4.5	7.2	57	34
Spokane, WA	182	15.7	6.5	4.7	4.7	45	57
Springfield, IL	159	10.1	4.7	5.0	7.8	18	16
Springfield, MA	352	9.7	5.4	6.1	4.1	103	106
Springfield, MO	82	15.9	8.5	5.6	4.5	30	63
Springfield, OH	379	9.2	4.1	5.1	5.0	15	12
State College, PA	102	11.4	5.2	4.4	4.4	26	18
Stockton, CA	231	15.0	6.6	4.9	6.1	27	50
Sumter, SC	130	11.7	5.3	5.6	7.2	x	x
Syracuse, NY	271	10.8	6.0	5.0	5.0	149	81
Tallahassee, FL	82	15.7	7.1	4.8	5.6	19	30
Tampa-St. Petersburg-Clearwater, FL	588	17.3	9.6	5.5	5.1	218	431
Terre Haute, IN	119	10.1	4.0	5.2	7.7	4	10
Texarkana, TX-Texarkana, AR	73	11.9	5.2	5.2	7.3	x	x
Toledo, OH	404	10.6	5.2	5.5	8.5	155	122
Topeka, KS	62	13.2	4.3	4.8	11.3	6	26
Trenton-Ewing, NJ	1387	9.7	7.3	4.3	4.5	289	134
Tucson, AZ	53	16.6	6.5	6.9	5.4	192	117
Tulsa, OK	104	14.3	7.0	5.2	5.5	87	122
Tuscaloosa, AL	60	14.3	6.3	7.6	4.8	7	10
Tyler, TX	127	12.7	7.3	6.2	6.0	12	15
Utica-Rome, NY	125	10.3	4.6	3.9	6.1	27	34
Valdosta, GA	56	12.6	5.1	5.0	7.2	x	x
Vallejo-Fairfield, CA	249	16.9	6.1	5.5	5.1	31	34
Victoria, TX	38	14.7	7.3	5.6	7.8	x	x
Vineland-Millville-Bridgeton, NJ	279	10.8	5.3	4.7	7.3	7	14
Virginia Beach-Norfolk-Newport News, VA-NC	440	14.4	6.9	4.6	5.3	120	135
Visalia-Porterville, CA	47	16.0	6.2	4.2	4.2	11	22
Waco, TX	158	12.5	6.0	5.7	5.4	11	27
Warner Robins, GA	197	12.7	6.9	3.6	6.0	x	x
Washington-Arlington-Alexandria, DC-VA-MD-WV	599	14.0	7.9	5.8	5.5	743	1800
Waterloo-Cedar Falls, IA	115	12.9	4.7	4.6	5.2	23	15
Wausau, WI	69	13.1	4.1	6.6	6.1	16	12
Wenatchee-East Wenatchee, WA	14	14.5	7.5	3.6	3.1	x	8
Wheeling, WV-OH	197	8.7	4.0	3.6	7.9	9	7
Wichita, KS	109	13.6	6.0	5.3	5.6	35	86
Wichita Falls, TX	53	11.1	4.7	5.2	7.2	11	x
Williamsport, PA	96	9.8	5.1	4.0	9.9	23	13
Wilmington, NC	82	15.0	7.9	6.8	4.4	32	30
Winchester, VA-WV	62	12.2	5.4	3.6	4.5	7	15
Winston-Salem, NC	217	13.8	5.9	4.8	5.2	87	93
Worcester, MA	425	9.8	5.8	5.7	4.9	209	130
Yakima, WA	38	16.1	5.5	4.7	4.0	13	19
York-Hanover, PA	333	9.6	5.6	5.1	6.3	58	63
Youngstown-Warren-Boardman, OH-PA	392	10.4	4.6	4.8	7.9	61	46
Yuba City, CA	79	16.6	6.1	5.3	5.3	5	x
Yuma, AZ	14	13.3	5.4	6.1	7.2	3	x
Minimum	3	8.5	3.4	3.2	2.6	3	4
25th percentile	73	11.9	5.3	4.8	4.8	12	16
Median	134	13.3	6.1	5.2	5.5	31	34
75th percentile	239	15.6	7.2	5.7	6.5	87	113
Maximum	2482	27.4	12.0	11.6	15.2	4009	7869

Table A.1: List of MSAs included with MSA characteristics

B Proof of Proposition 1

Here we re-state and then prove Proposition 1.

Proposition 1 (Identifying shocks.)**.** *Let $V = \tilde{B}\tilde{B}'$ and $\Gamma = V'_{q+1:q+q_z,1:q}$. Partition $\Gamma = [\Gamma_1', \Gamma_2]'$, where Γ_1 is $q_z \times q_z$. Assume Γ_1 is invertible, so that $\kappa = \Gamma_2\Gamma_1^{-1}$ is well defined.*

(a) If we only use the first instrument for identification of the first shock, we have $\beta_{[1]} = [1, (\Gamma_2 e_1)' \frac{1}{\Gamma_1 e_1}]' \times \bar{c} \propto \Gamma e_1$ for $\bar{c} > 0$ defined below.

(b) Let $q_1 = \bar{c}_1(I - \eta\kappa)\Gamma_1 e_1$. Let $q_2 = F chol(\Lambda)$, where F are the $q_z - 1$ eigenvectors and Λ the diagonal matrix of strictly positive eigenvalues of $S_1S_1' - q_1q_1'$. Then the first identified shock equals the shock identified using only the first instrument, i.e., $\beta_{[1]}e_1 \propto \Gamma e_1$.

Proof. **Part (a):** The treatment in Stock and Watson (2012) shows most clearly that with a single shock, the impact response is proportional to Γ. But even if it requires more algebra, we now also show how this follows from (3.8). Here, we follow the notation in Drautzburg (2016, Appendix A), except for substituting β for α.

To identify a single shock from (3.8), set $q_z = 1$. $\eta = \beta_{12}\beta_{22}^{-1}$ and $\kappa = \beta_{21}\beta_{11}^{-1} = \Gamma_2\Gamma_1^{-1}$. It follows that $S_1 = (\beta_{11} - \beta_{12}\beta_{22}^{-1}\beta_{21})$. By construction, β_{11} is the conditional standard deviation of the first variable attributable to the identified shock: $\beta_{11} = \sqrt{\Sigma_{11} - f(\Sigma, \kappa)}$, normalizing the sign of the shock so that the impact-response is positive. $\kappa = \Gamma_2\Gamma_1^{-1}$, and $f(\Sigma, \kappa) \equiv \beta_{12}\beta_{12}' = (\Sigma_{12}' - \kappa\Sigma_{11})'(ZZ')^{-1}(\Sigma_{12}' - \kappa\Sigma_{11})$ with $ZZ' = \begin{bmatrix}\kappa & -I_{m-m_z}\end{bmatrix}\Sigma\begin{bmatrix}\kappa' \\ -I_{m-m_z}\end{bmatrix}$ (Drautzburg, 2016, Appendix A).

To prove that $\beta_{21} = \Gamma_2$ is as desired, use the Woodbury matrix identify to write

$$
\begin{aligned}
(I - \kappa\eta)^{-1} &= I + \kappa(I - \eta\kappa)^{-1}\eta \\
&= I + \kappa\eta(I - \eta\kappa)^{-1}
\end{aligned}
$$

where the second equality uses that $(I - \eta\kappa)^{-1}$ is a scalar with $q_z = 1$.

Consequently:

$$
\begin{aligned}
\beta_{21} &= (I - \kappa\eta)^{-1}\kappa S_1 \\
&= \kappa S_1 + \kappa\eta\kappa(I - \eta\kappa)^{-1}S_1 \\
&= \kappa S_1 + \kappa(\eta\kappa - I + I)(I - \eta\kappa)^{-1}S_1 \\
&= \kappa S_1 - \kappa(I - \eta\kappa)(I - \eta\kappa)^{-1}S_1 + \kappa(I - \eta\kappa)^{-1}S_1 \\
&= \kappa(I - \eta\kappa)^{-1}S_1 \equiv \kappa\beta_{11} \equiv \Gamma_2\frac{\beta_{11}}{\Gamma_1}.
\end{aligned} \tag{B.1}
$$

Therefore, $\beta_{[1]} = [\Gamma_1, \Gamma_2']'\frac{\beta_{11}}{\Gamma_1}$.

In Proposition 1 we consider $q_z > 1$, so that we need to replace the scalar Γ_1 here with $[\Gamma_1]_{11} = e_1'\Gamma_1 e_1$. Consequently, the constant in Proposition 1 is given by $\bar{c} = \frac{\beta_{11}}{[\Gamma_1]_{11}}$ where $\beta_{11} = \sqrt{\Sigma_{11} - f(\Sigma, \kappa)}$, normalizing the sign of the shock so that the impact-response is positive.

Part (b): We proceed in two parts. First, we prove that $[q_1, q_2][q_1, q_2]' = S_1S_1'$. Second, we prove that for $(S_1S_1')^{1/2} = [q_1, q_2]$ it holds that $\beta_{[1]}e_1 \propto \Gamma e_1$.

(1) Note that the $q_z \times q_z$ matrix $S_1 S_1' - q_1 q_1'$ is symmetric of rank $q_z - 1$. Therefore:

$$S_1 S_1' - q_1 q_1' = \begin{bmatrix} F & f_\perp \end{bmatrix} \begin{bmatrix} \Lambda & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} F_1' \\ f_\perp' \end{bmatrix} = F \Lambda F',$$

where F are $q_z - 1$ normed $q_z \times 1$ eigenvectors associated with the strictly positive eigenvalue λ_i, where $\Lambda = \text{diag}([\lambda_i]_{i=1}^{q_z-1})$. Because the eigenvectors are normed $F'F = I_{q_z-1}$, $f_\perp' f_\perp = 1$ and $F' f_\perp = 0$. Therefore $q_2 = F \text{chol}(\Lambda)$ satisfies $q_2 q_2' = S_1 S_1' - q_1 q_1'$ as desired.

(2) Rewrite $\beta_{[1]} e_1$:

$$\beta_{[1]} e_1 = \begin{bmatrix} (I - \eta\kappa)^{-1} \\ (I - \kappa\eta)^{-1}\kappa \end{bmatrix} q_1.$$

By construction:

$$(I - \eta\kappa)^{-1} q_1 = (I - \eta\kappa)^{-1} \bar{c}_1 (I - \eta\kappa) \Gamma_1 e_1 = \bar{c}_1 \Gamma_1 e_1, \tag{B.2}$$

as desired.

It remains to show that

$$(I - \kappa\eta)^{-1} \kappa q_1 = \bar{c}_1 \Gamma_2 e_1 \tag{B.3}$$

to ensure the same factor of proportionality. Plugging in for q_1:

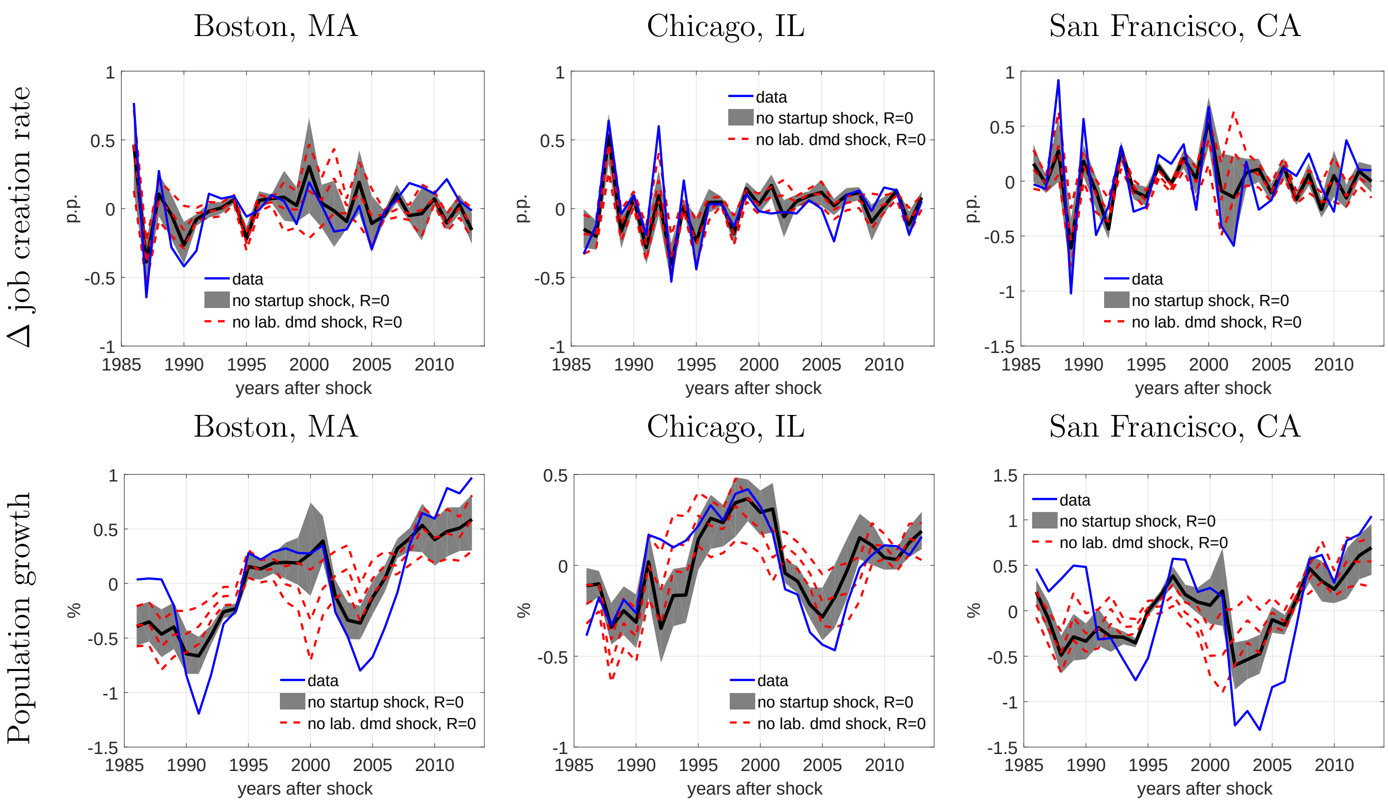
$$\begin{aligned} (I - \kappa\eta)^{-1} \kappa \bar{c}_1 (I - \eta\kappa) \Gamma_1 e_1 &= \bar{c}_1 \Gamma_2 e_1. \\ \Leftrightarrow \bar{c}_1 (\kappa - \kappa\eta\kappa) \Gamma_1 e_1 &= \bar{c}_1 (I - \kappa\eta) \Gamma_2 e_1. \\ \Leftrightarrow \bar{c}_1 (I - \kappa\eta) \kappa \Gamma_1 e_1 &= \bar{c}_1 (I - \kappa\eta) \Gamma_2 e_1. \\ \Leftrightarrow \bar{c}_1 (I - \kappa\eta) \Gamma_2 e_1 &= \bar{c}_1 (I - \kappa\eta) \Gamma_2 e_1. \end{aligned}$$

The second to last equality uses that $\kappa = \Gamma_2 \Gamma_1^{-1}$. Combining (B.2) and (B.3) it follows that $\beta_{[1]} e_1 \propto \Gamma e_1$. □

C Additional estimates

Section C.1 presents additional results for our baseline model. Section C.2 presents various alternative specifications for our baseline model. Section C.3 shows additional results when we split MSAs by initial density. Section C.4 shows all results when we split MSAs by initial firm entry. Section C.6 contains additional results that examine the link between innovation and startups.

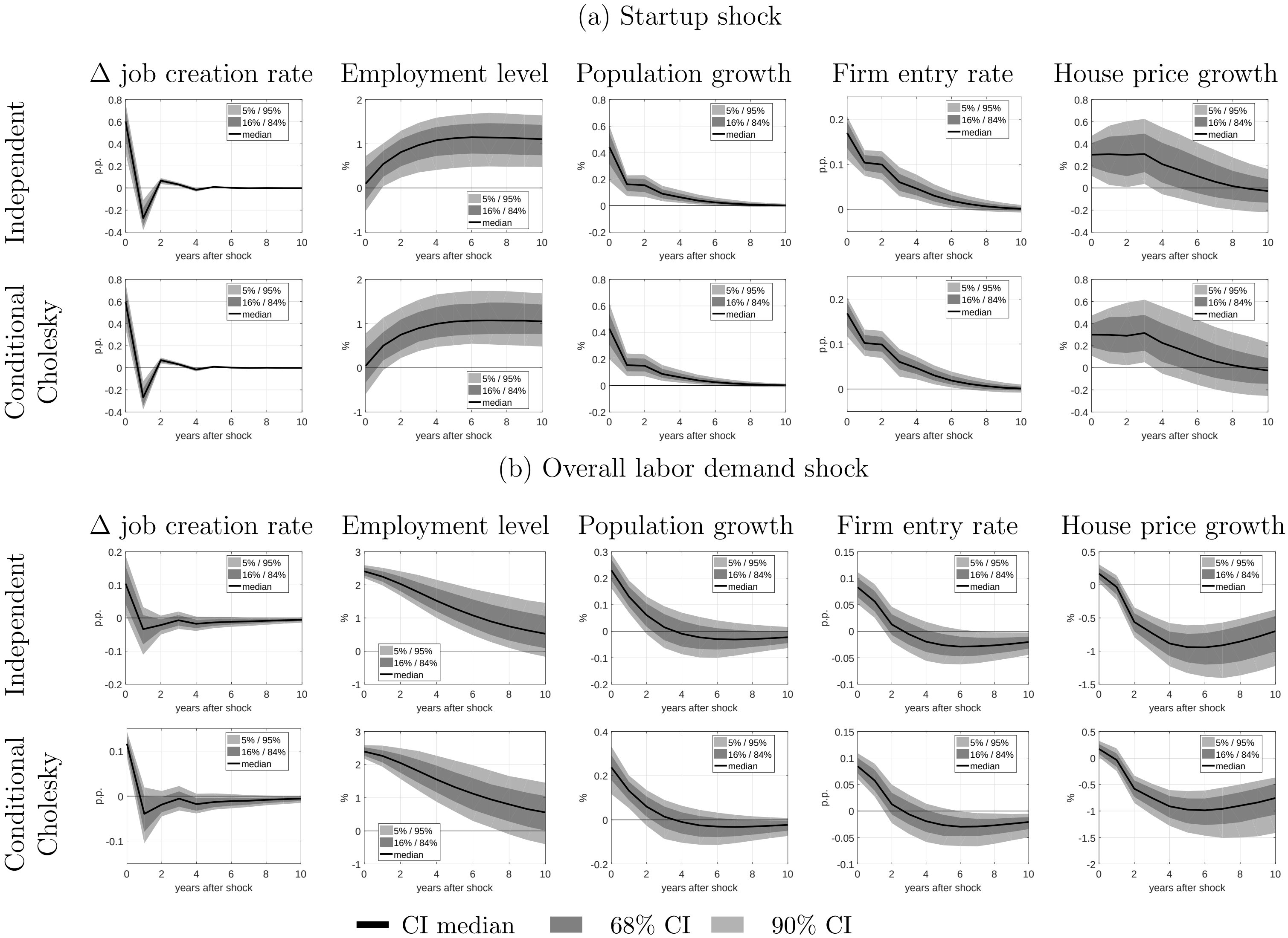
C.1 Additional baseline results



This plot quantifies the importance of startup shocks and overall labor demand shocks for three MSAs while turning off the spatial correlation. Compared to Figure 5, we find that turning off the spatial correlation brings the counterfactuals closer to zero, highlighting the role of spatial correlation in explaining outcomes. All variables in deviations net of MSA and year fixed effects. We show 68% confidence intervals.

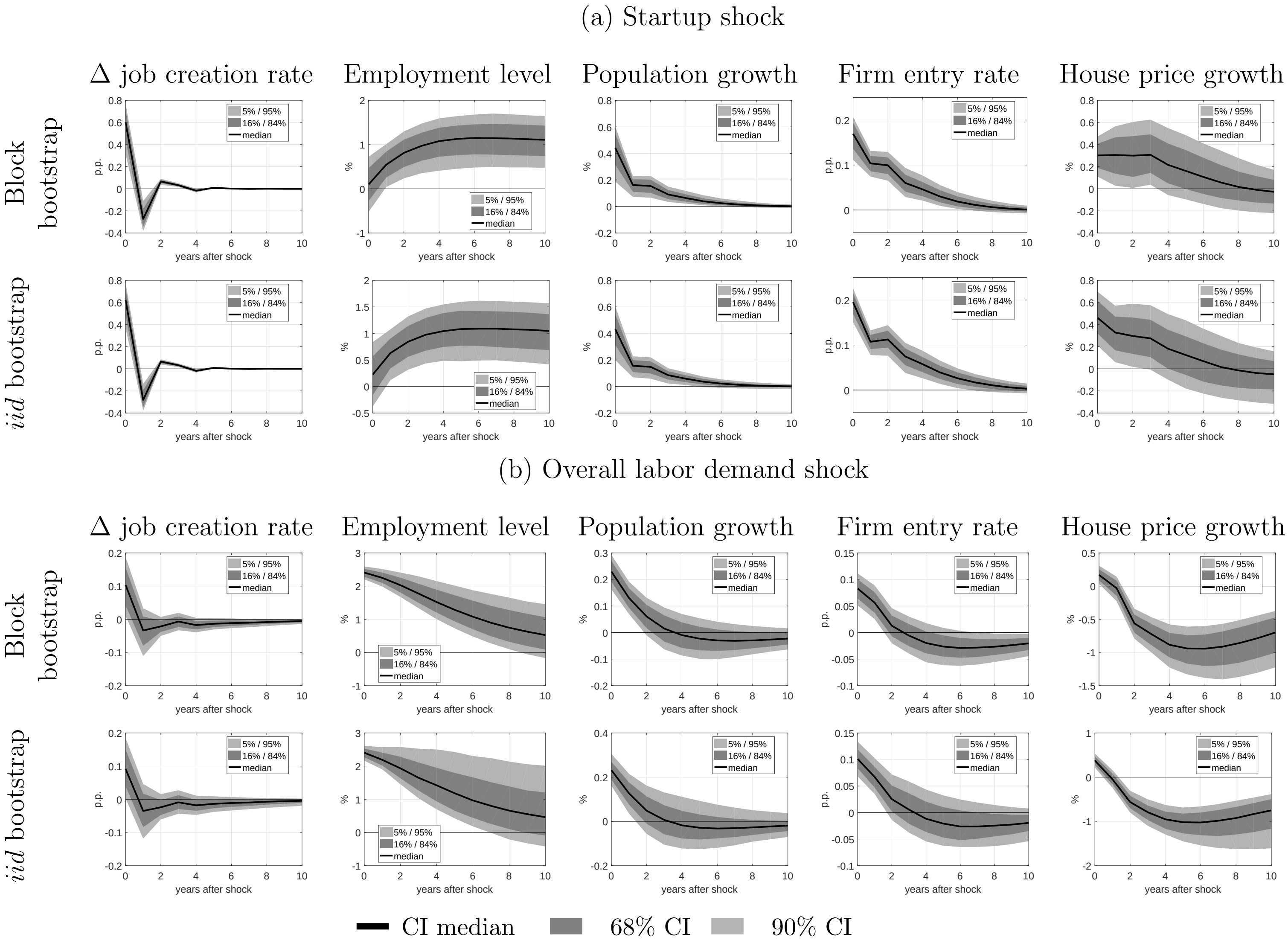
Figure C.1: Historical contributions to the change in the job creation rate and population growth: Comparison of three large MSAs, 1986–2013. No spatial spillovers ($\tilde{R} = 0$).

C.2 VAR specification



We compare two ways to factor the two identified shocks: In our baseline ("independent"), we attribute all the variation in the standard Bartik (1991) instrument to the overall labor demand shock. In the alternative, we choose a Cholesky factorization of the variance attributable to the two identified shocks that orders the overall labor demand shock first ("conditional Cholesky"). Both give almost identical answers. House price data are from CoreLogic Solutions.

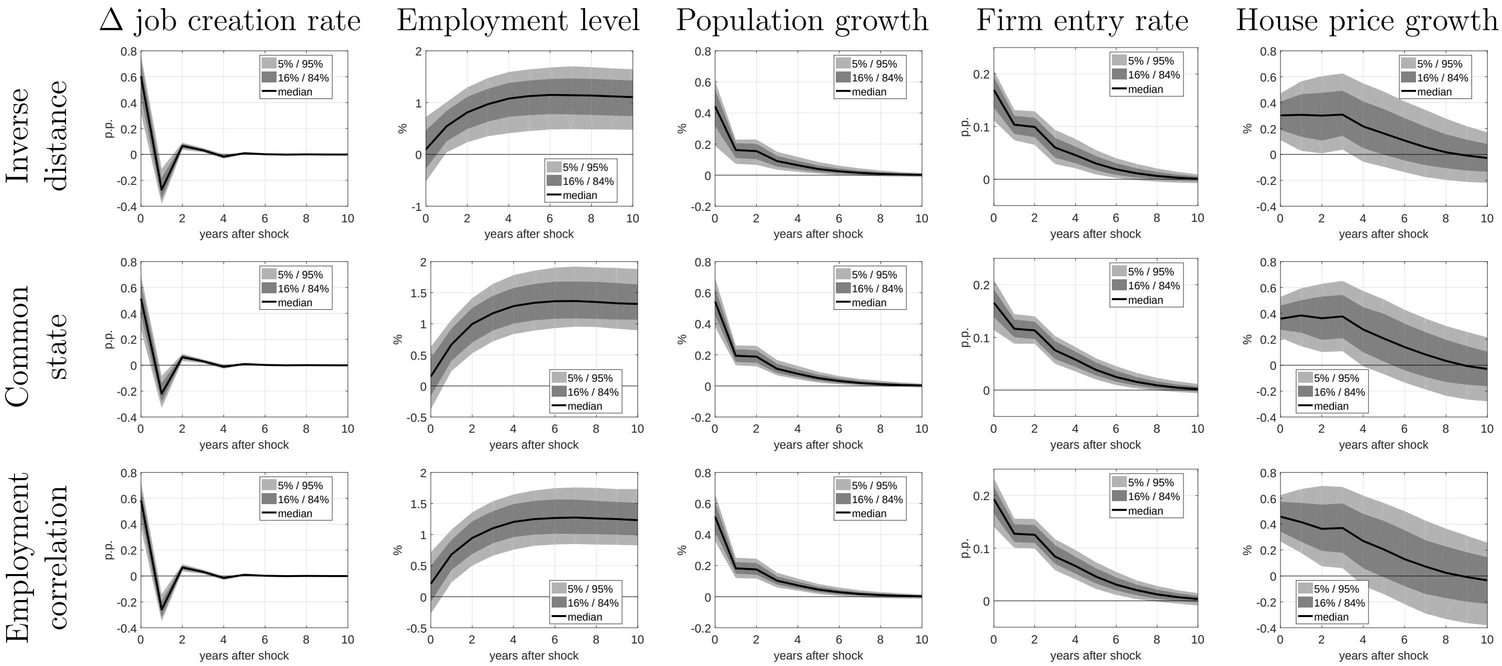
Figure C.2: Impulse-responses in baseline VAR: Treating the standard Bartik IV as independent vs. ordering it first in a conditional Cholesky factorization.



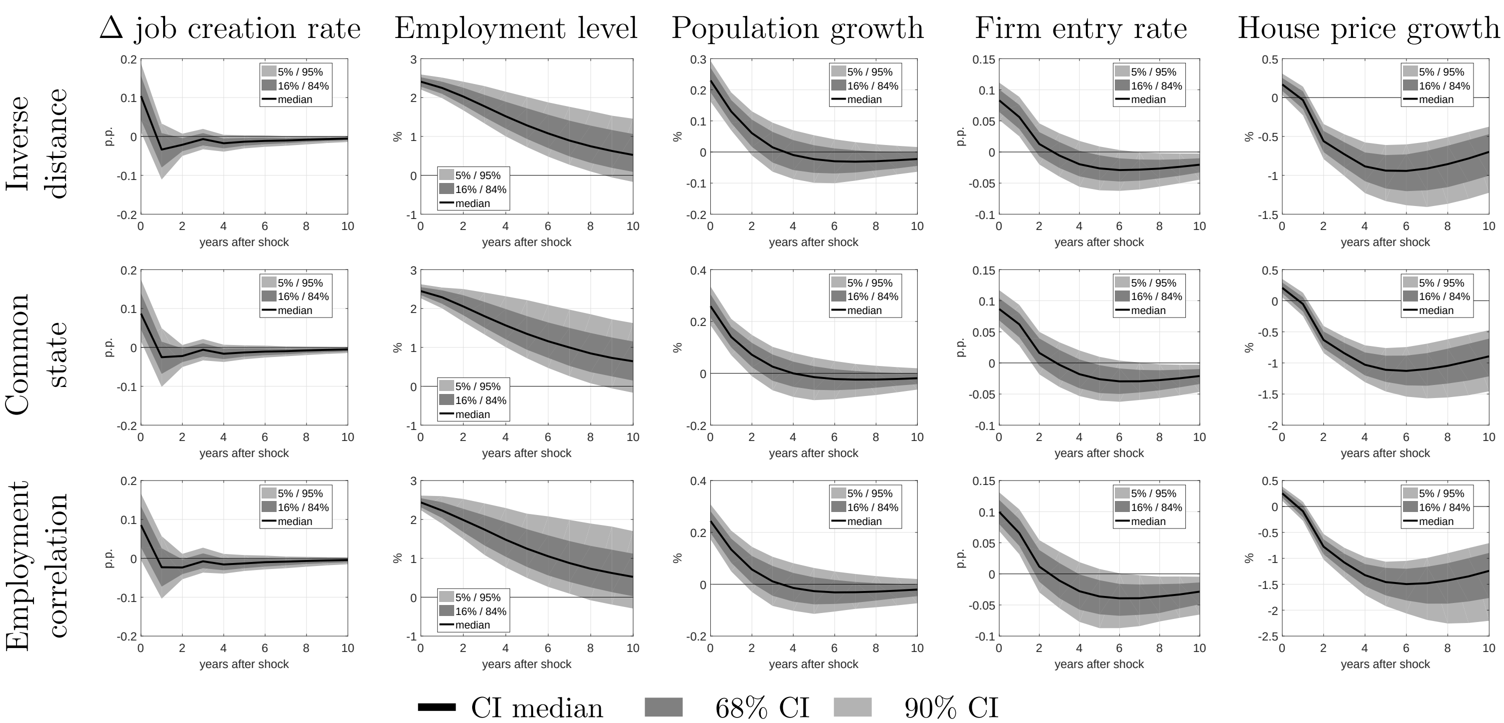
We compare two bootstrap schemes: In our baseline, we sample blocks of three years at a time. In the *iid* bootstrap, we sample year by year independently. We find that the two schemes give very similar answers. We would expect this if the VAR captured dynamics well and the instruments had little autocorrelation. House price data are from CoreLogic Solutions.

Figure C.3: Impulse-responses in baseline VAR: 3-period block bootstrap (baseline) vs. *iid* bootstrap.

(a) Startup shock



(b) Overall labor demand shock



We compare three different proximity measures: The inverse Euclidian distance between MSA centroids (our baseline measure), treating MSAs with a common state as neighbors, and using the correlation of HP-filtered employment levels. All three give very similar identical answers. House price data are from CoreLogic Solutions.

Figure C.4: Impulse-responses in baseline VAR: Inverse Euclidean distance vs common state or employment correlation as proximity measure.

Table C.1: First-stage F-statistics: Baseline VAR with various lag lengths

	$2\ln(L_c^E/L_c^S)/N$	
Specification	Distance vs. common state	Distance vs. correlation of employment
Common spatial correlation	5.4	28.0
Variable-specific spatial correlation	5.0	24.3

The concentrated log-likelihood clearly favors the inverse Euclidean distance as a proximity measure. With variable-specific spatial autocorrelation, the likelihood ratio is 5.4, and with common spatial correlation the ratio is 5.0. The differences are much larger when using the correlation of cyclical employment to compute correlations. The models are not nested, but the distance-based measure increases the fit significantly. House price data are from CoreLogic Solutions.

Table C.2: First-stage F-statistics in patent VAR for two different shock factorizations

(a) Patent variation independent

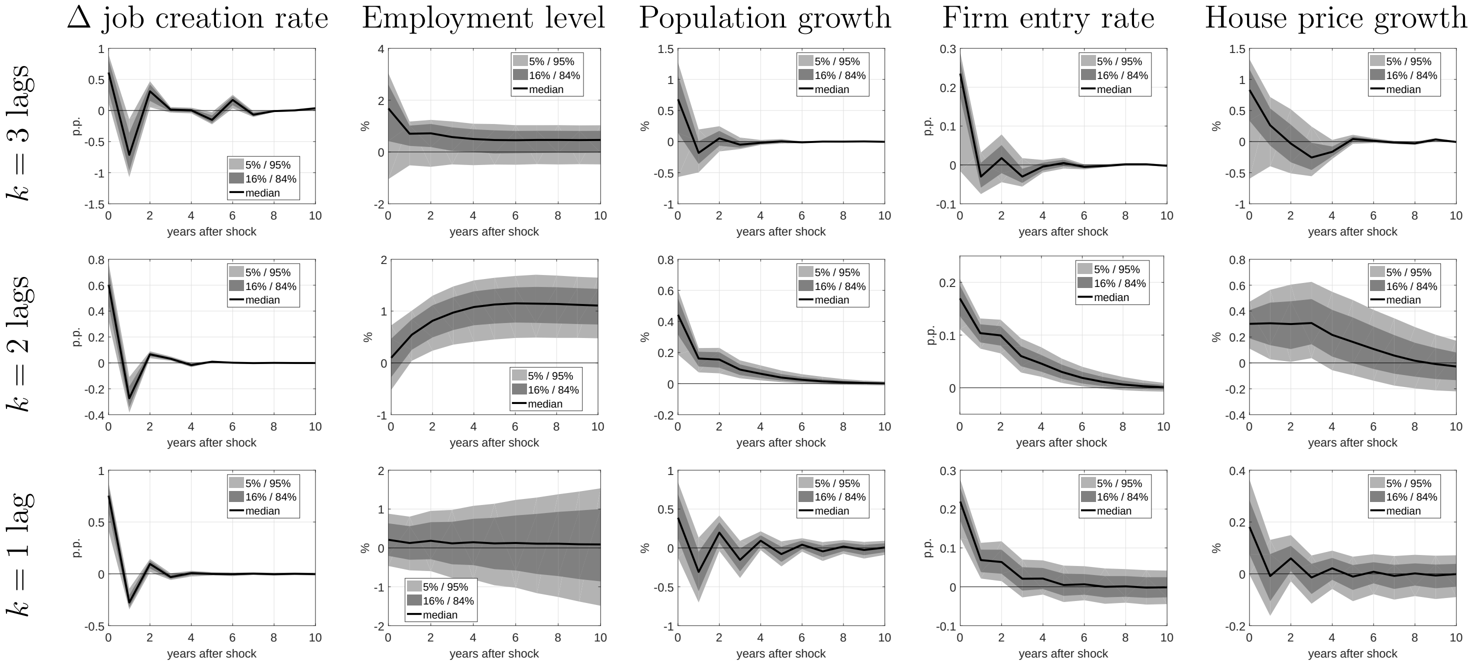
	Point		Confidence interval			
Variable	estimate	5%	16%	Median	84%	95%
Patent growth	10.3	5.9	7.8	11.1	14.6	17.4
Employment/Pop (log, BDS)	23.5	13.1	16.2	23.4	31.3	37.3

(b) Standard Bartik variation independent

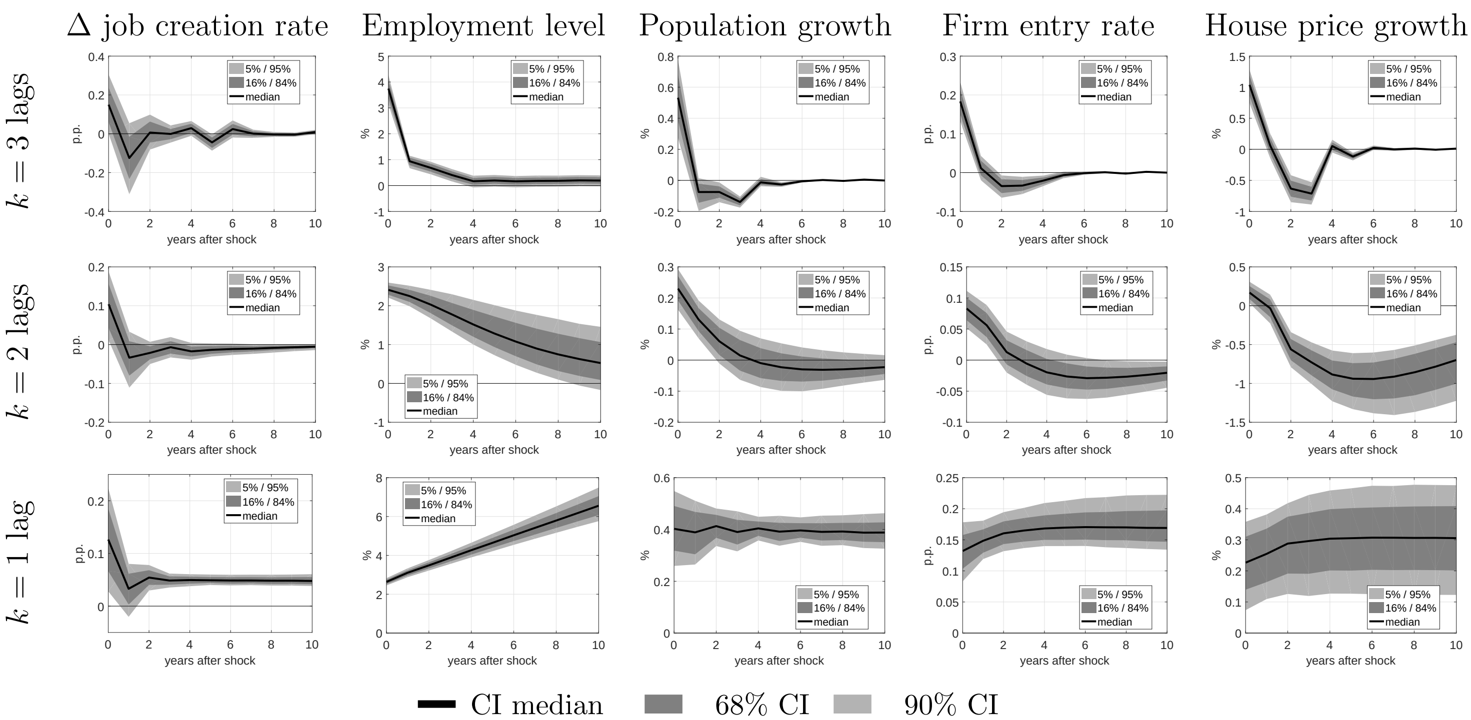
	Point		Confidence interval			
Variable	estimate	5%	16%	Median	84%	95%
Patent growth	10.3	5.9	7.7	11.1	14.6	17.4
Employment/Pop (log, BDS)	23.5	13.1	16.3	23.6	31.7	37.8

The F-statistics that measure how well the instruments identify the structural shocks are very similar for both factorizations of the joint variance spanned by the startup and overall labor demand shocks.

(a) Startup shock

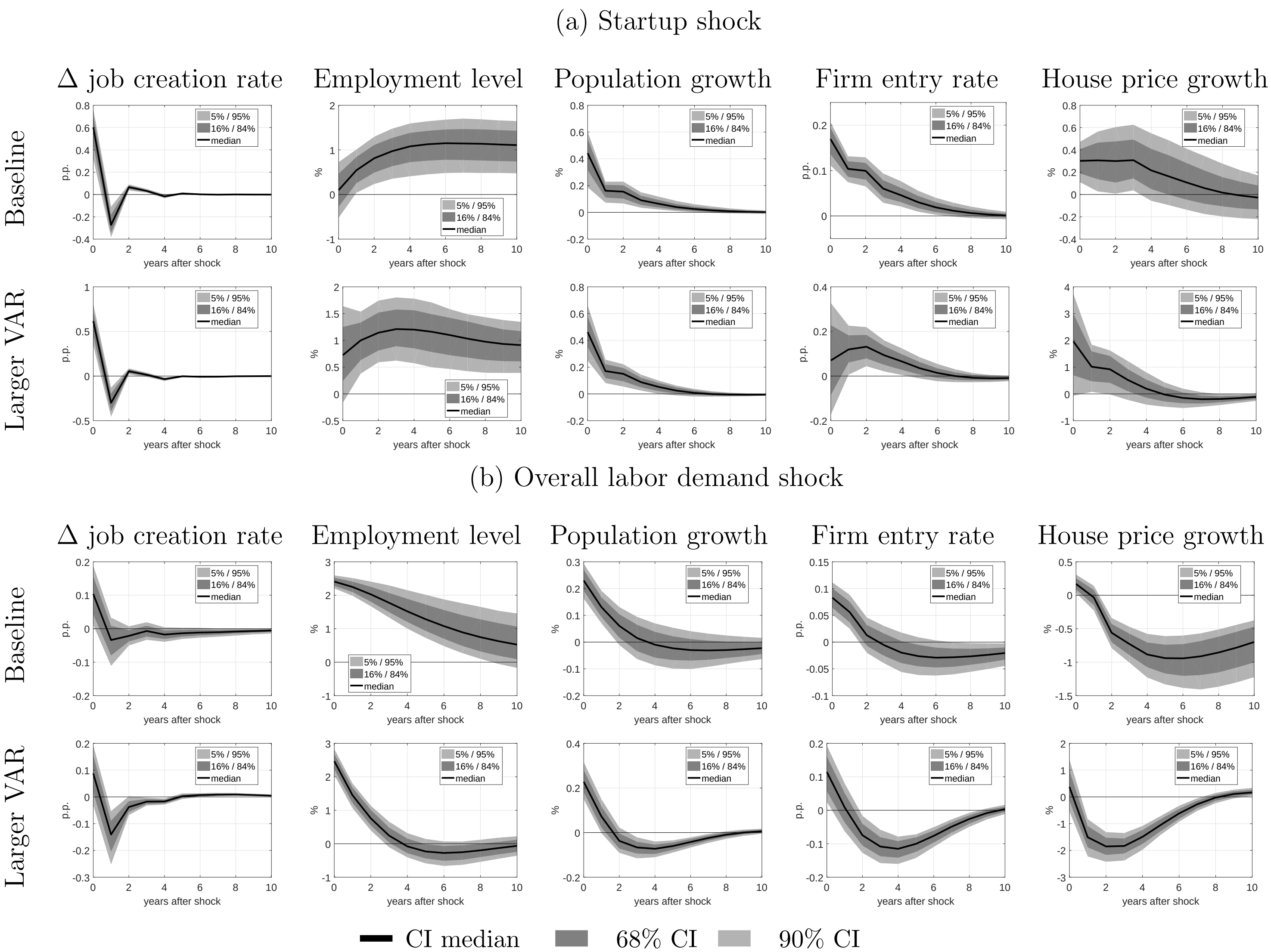


(b) Overall labor demand shock



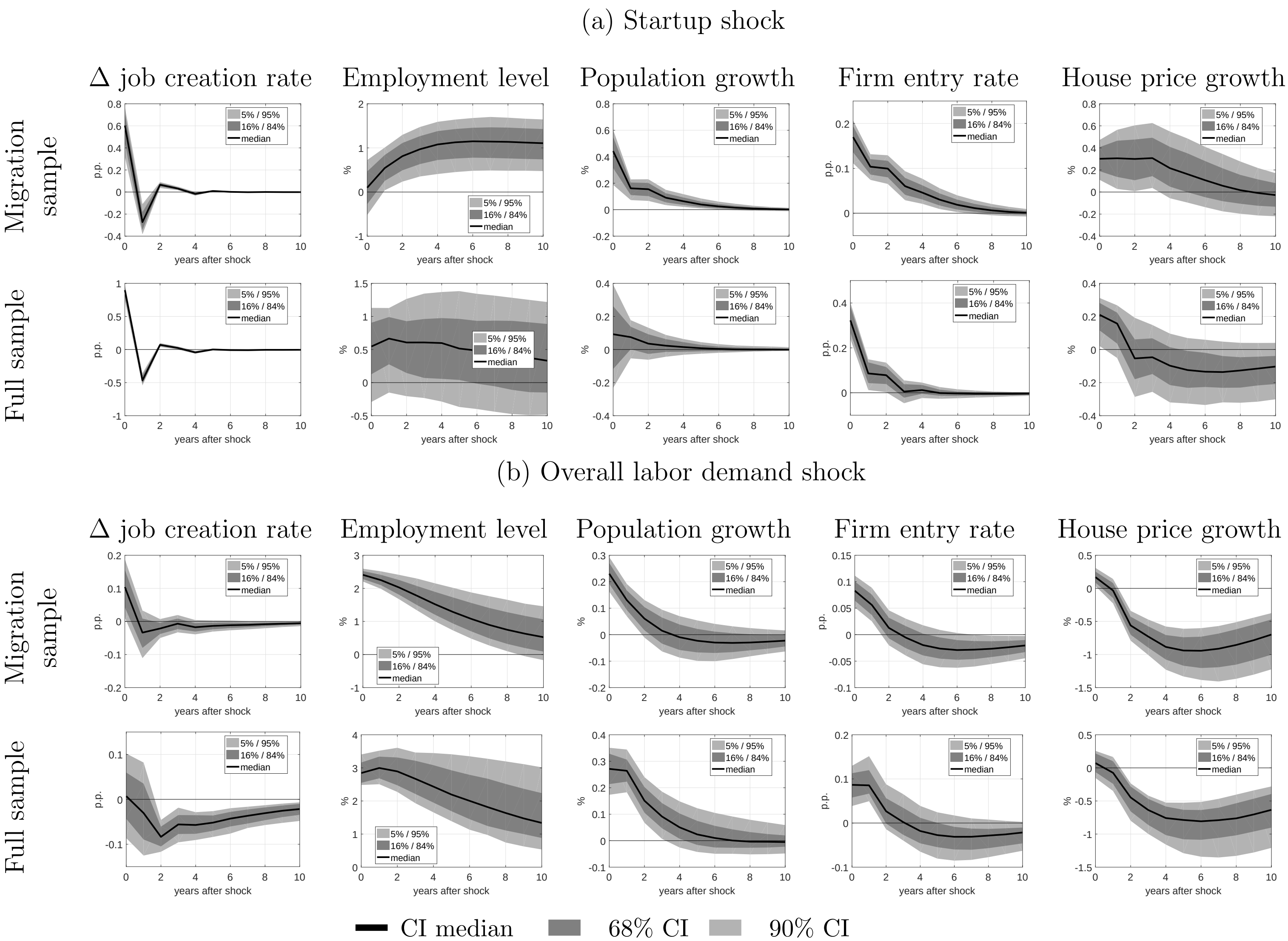
We compare our baseline model with two lags to specifications with one or three lags. With a single lag, the VAR seems close to unstable and shock responses are qualitatively different from our baseline estimates. In contrast, with three lags we find qualitatively similar responses. Because theory suggests that we need a rich enough VAR specification, we conclude that we need at least two lags to capture the structural impulse-response functions well. House price data are from CoreLogic Solutions.

Figure C.5: Impulse-responses in baseline VAR: Comparing the lag length



In our baseline VAR, we model firm entry rate, house price growth, and other variables without allowing them to feed back into the VAR. When we include entry and house prices in the core VAR, the responses of the original VAR variables changes little. The responses of the entry rate and house price growth change slightly, but the larger model has less precise estimates whose confidence intervals are consistent with the estimates from the smaller model. House price data are from CoreLogic Solutions.

Figure C.6: Impulse-responses in baseline VAR and in larger VAR with entry rate and house prices.



Here we drop the migration rate from the peripheral VAR to begin the estimation in 1980. We find qualitatively similar results, but noisier effects of the startup shock on employment and population growth. House price data are from CoreLogic Solutions.

Figure C.7: Impulse-responses in baseline VAR: Migration sample (1986–2013) vs. full sample (1980–2014).

Table C.3: First-stage F-statistics in baseline VAR and large VAR

(a) Baseline

Variable	Point estimate	Confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	16.2	7.0	10.0	14.8	20.7	26.0
Employment/Pop (log, BDS)	84.3	34.3	47.3	72.6	92.9	104.7

(b) Large VAR

Variable	Point estimate	Confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	7.7	2.4	3.7	6.1	9.4	12.6
Employment/Pop (log, BDS)	42.2	11.7	20.8	33.5	43.9	50.3

The F-statistics that measure how well the instruments identify the structural shocks drop in the larger VAR. Intuitively, the identification problem becomes harder when we try to tell the two shocks apart from four other shocks, rather than two other shocks.

Table C.4: Variance decomposition: Comparison of baseline and large wage VARs. Standard Bartik independent. 1986–2013. 2 lags. 68% Confidence interval

(a) Baseline VAR

	Startup shock		Overall labor demand		Other VAR shocks		Idiosyncratic shock	
Gross job creation (births)	53.0	(28.8, 76.2)	1.9	(0.3 , 3.5)	45.0	(22.2, 68.8)	0.0	(0.0 , 0.0)
Employment/Pop (log, BDS)	3.8	(0.2 , 7.9)	70.4	(64.0, 77.4)	25.8	(18.1, 33.3)	0.0	(0.0 , 0.0)
Pop growth	39.5	(18.1, 61.3)	10.8	(6.9, 14.6)	49.8	(27.6, 71.0)	0.0	(0.0 , 0.0)
Wage growth	6.2	(0.2, 12.7)	20.4	(14.7, 26.1)	73.4	(64.5, 82.5)	0.0	(0.0 , 0.0)
Firm entry rate	6.8	(4.4 , 9.0)	1.7	(1.0 , 2.4)	2.4	(0.7 , 4.0)	89.2	(87.7, 90.7)
House price growth	0.7	(0.2 , 1.1)	0.2	(0.0 , 0.4)	0.7	(0.3 , 1.1)	98.4	(97.9, 98.9)
Firm exit rate	0.1	(0.0 , 0.1)	0.1	(0.0 , 0.3)	0.3	(0.1 , 0.4)	99.5	(99.3, 99.7)
Net migration rate	13.9	(6.3, 21.8)	6.2	(4.2 , 8.2)	18.5	(10.1, 27.5)	61.3	(56.6, 66.2)
Firm exit rate (all)	0.8	(0.1 , 1.5)	1.9	(1.4 , 2.5)	1.9	(0.9 , 3.0)	95.3	(93.9, 96.8)

(b) Large VAR

	Startup shock		Overall labor demand		Other VAR shocks		Idiosyncratic shock	
Gross job creation (births)	48.4	(27.8, 68.9)	1.6	(0.1 , 3.1)	50.1	(29.7, 70.5)	0.0	(0.0 , 0.0)
Employment/Pop (log, BDS)	3.1	(0.1 , 6.1)	46.4	(36.7, 55.6)	50.5	(40.8, 60.6)	0.0	(0.0 , 0.0)
Pop growth	39.5	(21.8, 57.2)	9.9	(5.7, 14.1)	50.7	(32.0, 69.0)	0.0	(0.0 , 0.0)
Wage growth	4.6	(0.2 , 9.2)	25.6	(18.6, 32.6)	69.8	(61.3, 78.1)	0.0	(0.0 , 0.0)
Firm entry rate	5.9	(0.3, 11.9)	3.3	(0.7 , 5.6)	90.8	(83.5, 97.4)	0.0	(0.0 , 0.0)
House price growth	11.9	(1.3, 21.2)	1.2	(0.0 , 2.5)	86.9	(78.1, 96.9)	0.0	(0.0 , 0.0)
Firm exit rate (all)	2.8	(0.8 , 4.9)	2.8	(1.7 , 3.9)	8.4	(5.9, 10.9)	86.0	(83.6, 88.4)
Firm exit rate	0.5	(0.1 , 1.0)	0.7	(0.4 , 1.0)	2.9	(2.0 , 3.7)	95.9	(94.9, 96.9)
Net migration rate	17.4	(9.3, 26.2)	6.8	(4.3 , 9.4)	22.7	(13.5, 31.1)	53.1	(48.2, 57.8)

Estimating a larger VAR leads to a similar variance decomposition for the variables that we model only in the periphery in our baseline but include in the larger VAR. The identified shocks still explain less 15% of house price growth and less than 10% of firm entry. House price data are from CoreLogic Solutions.

Table C.5: First-stage F-statistics: Baseline VAR with various lag lengths

$k = 3$

Variable	Point estimate	Confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	18.4	2.2	3.0	5.2	7.6	9.5
Employment/Pop (log, BDS)	39.6	18.5	23.5	31.9	41.7	47.3

$k = 2$

Variable	Point estimate	Confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	16.2	7.0	10.0	14.8	20.7	26.0
Employment/Pop (log, BDS)	84.3	34.3	47.3	72.6	92.9	104.7

$k = 1$

Variable	Point estimate	Confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	14.0	3.9	6.6	11.4	16.7	21.0
Employment/Pop (log, BDS)	83.6	24.8	40.5	68.7	89.0	102.2

The F-statistics measuring the strength of the identification vary little with the number of lags included in the VAR and are always above 10.0. However, with three lags the bootstrapped distribution of the F-statistic shifts to the left.

C.3 Differences in initial density

Table C.6: Spatial autocorrelation: Coefficients estimates by variable; split by density

(a) Point estimates and confidence intervals for model with varying ρs: Low density

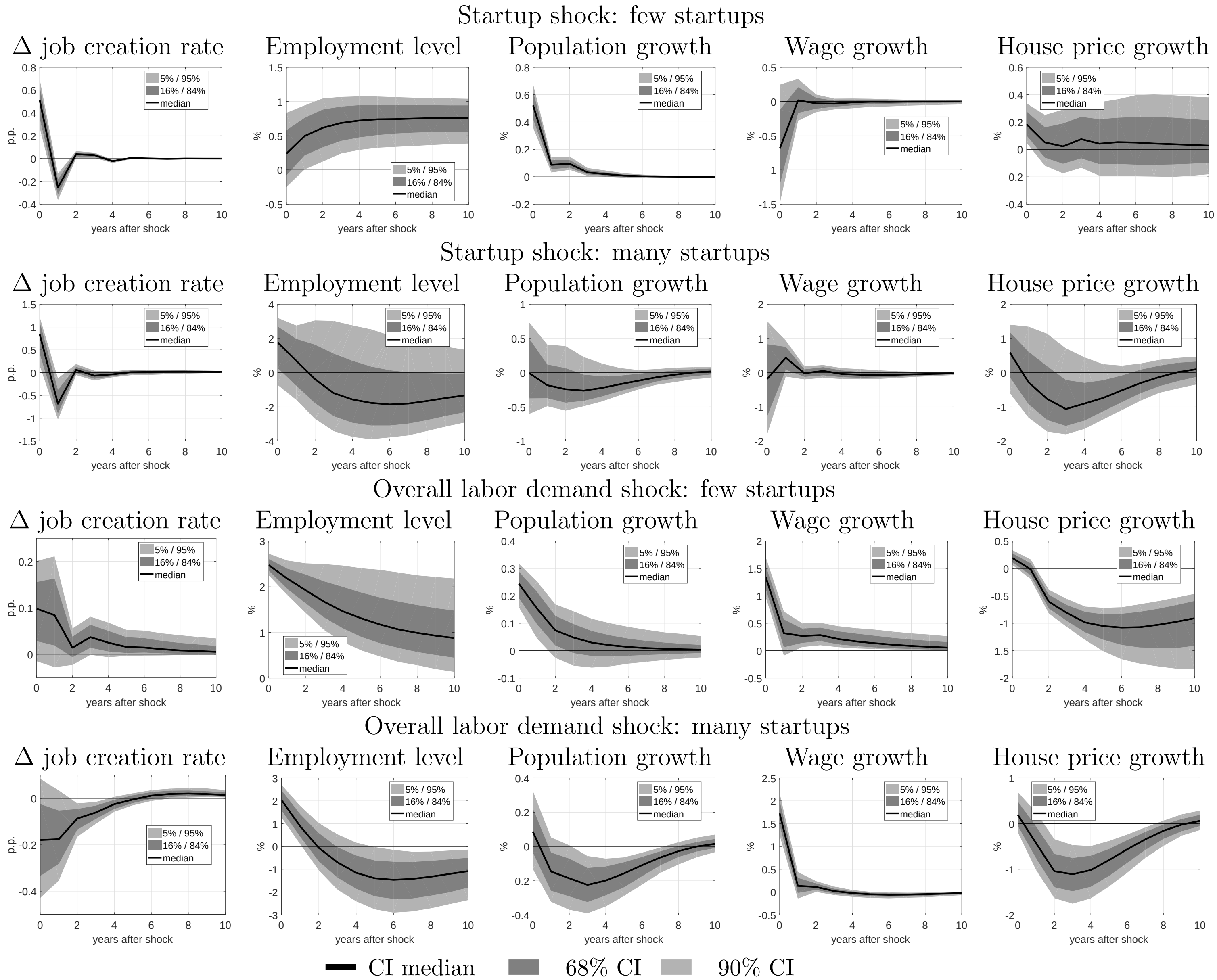
Variable	Point estimate	Avg. bias	Bias-corrected confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	-0.02	0.01	-0.03	-0.02	-0.01	-0.00	0.00
Employment/Pop (log, BDS)	-0.07	0.03	-0.06	-0.05	-0.04	-0.03	-0.02
Pop growth	-0.14	0.06	-0.12	-0.10	-0.08	-0.06	-0.05
Wage growth	-0.06	0.02	-0.05	-0.05	-0.04	-0.03	-0.02
Firm entry rate	-0.10	0.05	-0.06	-0.06	-0.05	-0.04	-0.02
House price growth	-0.16	0.06	-0.11	-0.11	-0.10	-0.09	-0.08
Firm exit rate	-0.06	0.02	-0.05	-0.04	-0.03	-0.03	-0.02
Net migration rate	-0.14	0.08	-0.08	-0.07	-0.06	-0.05	-0.04
Firm exit rate (all)	-0.12	0.06	-0.07	-0.07	-0.06	-0.05	-0.05
Bartik: Entrant's job creation	-0.08	0.03	-0.06	-0.05	-0.04	-0.04	-0.03
Bartik: Employment	-0.11	0.05	-0.08	-0.07	-0.06	-0.05	-0.05

(b) Point estimates and confidence intervals for model with varying ρs: High density

Variable	Point estimate	Avg. bias	Bias-corrected confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	0.17	-0.10	-0.03	0.01	0.07	0.14	0.19
Employment/Pop (log, BDS)	0.50	-0.21	0.15	0.21	0.28	0.35	0.42
Pop growth	0.92	-0.34	0.35	0.40	0.54	0.70	0.80
Wage growth	0.40	-0.12	0.17	0.21	0.27	0.33	0.38
Firm entry rate	0.66	-0.30	0.17	0.25	0.33	0.39	0.44
House price growth	1.00	-0.33	0.58	0.61	0.66	0.71	0.75
Firm exit rate	0.40	-0.16	0.16	0.19	0.24	0.29	0.33
Net migration rate	0.90	-0.49	0.25	0.32	0.41	0.49	0.54
Firm exit rate (all)	0.78	-0.36	0.34	0.37	0.42	0.48	0.50
Bartik: Entrant's job creation	0.56	-0.23	0.22	0.26	0.32	0.38	0.42
Bartik: Employment	0.73	-0.30	0.33	0.37	0.43	0.49	0.52

The estimated spatial correlation is small for low density cities, but larger than in the baseline estimates for high density areas. For high density MSAs, the spatial correlation varies significantly across variables. House price data are from CoreLogic Solutions.

C.4 Differences in initial entry rate



We split MSAs by their initial firm entry rate. The distribution is skewed to the right, and we set the cutoff at the 75th percentile. The effects of both shocks differ across MSAs with stronger effects in the MSAs with an initially lower startup rate. For MSAs with low initial startup rates, our results mirror our baseline estimates. For MSAs with many startups, our estimates of the effects of startup shocks are very noisy, and we find in Table C.8 that the corresponding F-statistic is low. We conclude that our identification is likely driven by MSAs with lower initial entry rates. House price data are from CoreLogic Solutions.

Figure C.8: Impulse-responses to startup and overall labor demand shocks for MSAs grouped by their initial entry rate.

Table C.7: Spatial autocorrelation: Coefficients estimates by variable; split by startup entry rate

(a) Point estimates and confidence intervals for model with varying ρs: Low density

Variable	Point estimate	Avg. bias	Bias-corrected confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	-0.02	0.01	-0.02	-0.02	-0.01	-0.00	0.00
Employment/Pop (log, BDS)	-0.04	0.01	-0.04	-0.04	-0.03	-0.02	-0.01
Pop growth	-0.07	0.01	-0.07	-0.06	-0.05	-0.04	-0.04
Wage growth	-0.03	0.01	-0.02	-0.02	-0.01	-0.01	-0.00
Firm entry rate	-0.13	0.02	-0.11	-0.11	-0.10	-0.09	-0.09
House price growth	-0.14	0.02	-0.13	-0.12	-0.11	-0.11	-0.10
Firm exit rate	-0.07	0.02	-0.07	-0.06	-0.06	-0.05	-0.04
Net migration rate	-0.17	0.03	-0.16	-0.15	-0.14	-0.13	-0.12
Firm exit rate (all)	-0.08	0.02	-0.07	-0.07	-0.06	-0.05	-0.05
Bartik: Entrant's job creation	-0.11	0.03	-0.09	-0.09	-0.08	-0.07	-0.06
Bartik: Employment	-0.08	0.02	-0.07	-0.07	-0.06	-0.05	-0.05

(b) Point estimates and confidence intervals for model with varying ρs: High density

Variable	Point estimate	Avg. bias	Bias-corrected confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	0.10	-0.05	-0.03	0.00	0.05	0.10	0.14
Employment/Pop (log, BDS)	0.25	-0.07	0.09	0.13	0.17	0.22	0.26
Pop growth	0.40	-0.08	0.23	0.27	0.31	0.36	0.38
Wage growth	0.17	-0.08	0.00	0.04	0.08	0.13	0.15
Firm entry rate	0.69	-0.12	0.50	0.53	0.57	0.61	0.63
House price growth	0.75	-0.11	0.57	0.60	0.64	0.67	0.70
Firm exit rate	0.43	-0.10	0.27	0.29	0.33	0.37	0.40
Net migration rate	0.86	-0.12	0.66	0.70	0.75	0.79	0.82
Firm exit rate (all)	0.49	-0.13	0.29	0.32	0.35	0.39	0.42
Bartik: Entrant's job creation	0.60	-0.14	0.38	0.42	0.47	0.51	0.54
Bartik: Employment	0.49	-0.12	0.28	0.31	0.36	0.41	0.44

The estimated spatial correlation is small for MSAs with few startups, but comparable to the baseline estimates for areas with high entry rates. For high entry MSAs, the spatial correlation varies significantly across variables. House price data are from CoreLogic Solutions.

Table C.8: First-stage F-statistics split by initial entry rates

(a) Low initial entry rate

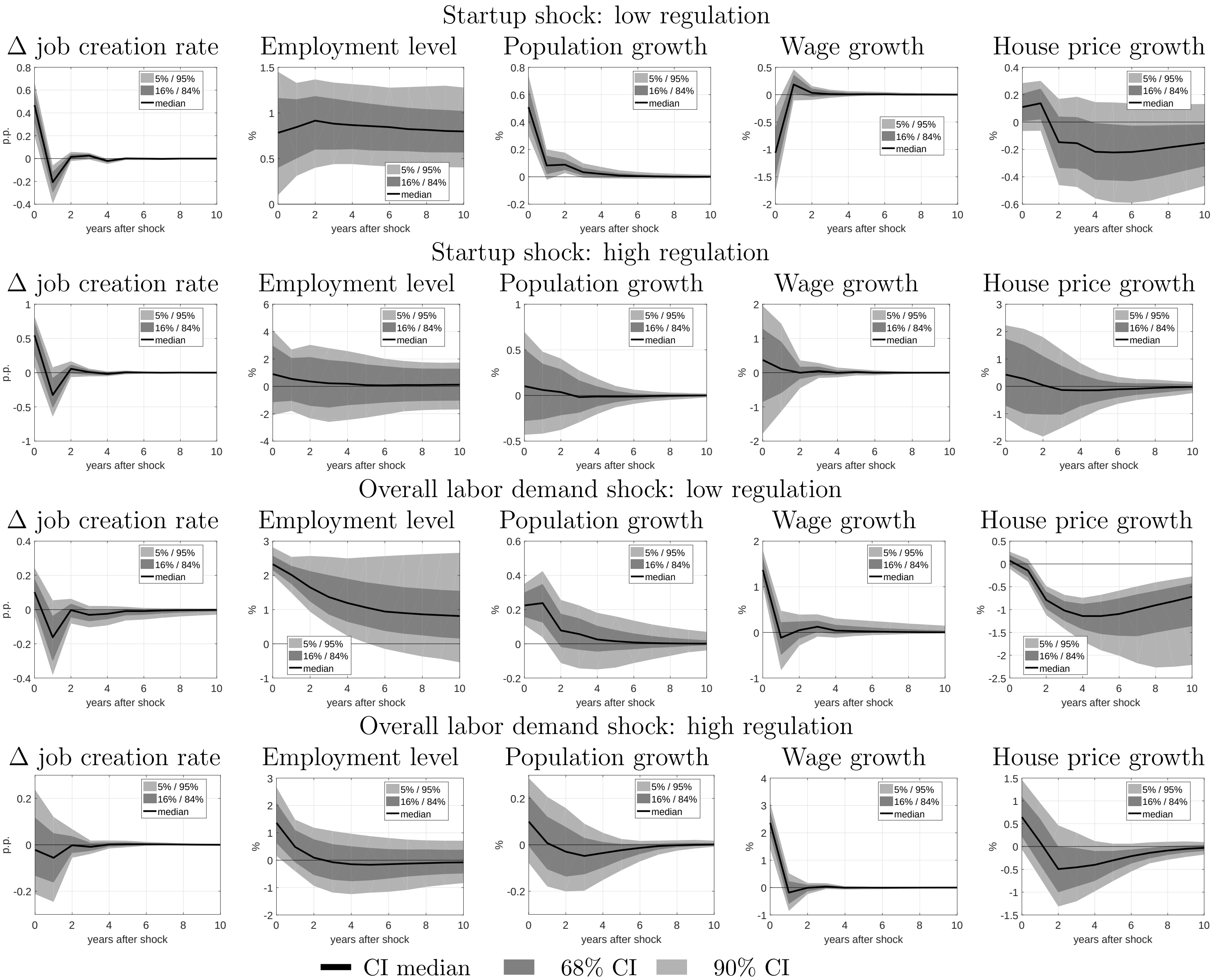
	Point	Confidence interval				
Gross job creation (births)	24.1	9.6	14.0	22.2	30.9	38.9
Employment/Pop (log, BDS)	88.7	33.9	48.2	69.5	90.1	110.1

(b) High initial entry rate

	Point	Confidence interval				
Gross job creation (births)	5.6	1.8	3.0	5.8	10.0	12.9
Employment/Pop (log, BDS)	25.9	12.7	16.6	23.9	32.5	39.5

The F-statistics measuring the strength of the identification indicate that our instruments predict the identified shocks well, except for startup shocks in high entry MSAs.

C.5 Differences in Wharton Regulation Index



We split MSAs by their initial firm entry rate. The distribution is skewed to the right, and we set the cutoff at the 67th percentile. The effects of both shocks differ across MSAs with stronger effects in the MSAs with an initially lower startup rate. For MSAs with low regulation, our results are similar to our baseline estimates, but stronger. For MSAs with high regulation, our estimates of the effects of startup shocks are very noisy, and we find in Table C.10 that the corresponding F-statistic is low. We conclude that our identification is likely driven by MSAs with lower regulation. Higher regulation MSAs, however, also show a weaker response to overall labor demand shocks. House price data are from CoreLogic Solutions.

Figure C.9: Impulse-responses to startup and overall labor demand shocks for MSAs grouped by their Wharton Regulation Index number.

Table C.9: Spatial autocorrelation: Coefficients estimates by variable; split by Wharton Regulation Index

(a) Point estimates and confidence intervals for model with varying ρs: Low density

Variable	Point estimate	Avg. bias	Bias-corrected confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	-0.06	0.03	-0.07	-0.06	-0.04	-0.02	-0.01
Employment/Pop (log, BDS)	-0.17	0.03	-0.16	-0.14	-0.12	-0.10	-0.09
Pop growth	-0.17	0.07	-0.13	-0.12	-0.10	-0.07	-0.05
Wage growth	-0.07	0.02	-0.08	-0.07	-0.05	-0.03	-0.02
Firm entry rate	-0.27	0.07	-0.23	-0.22	-0.20	-0.18	-0.17
House price growth	-0.31	0.07	-0.26	-0.25	-0.24	-0.22	-0.21
Firm exit rate	-0.17	0.04	-0.17	-0.15	-0.13	-0.11	-0.10
Net migration rate	-0.36	0.09	-0.30	-0.29	-0.27	-0.25	-0.23
Firm exit rate (all)	-0.27	0.10	-0.20	-0.19	-0.18	-0.16	-0.15
Bartik: Entrant's job creation	-0.29	0.10	-0.23	-0.21	-0.19	-0.17	-0.16
Bartik: Employment	-0.19	0.08	-0.15	-0.13	-0.11	-0.09	-0.07

(b) Point estimates and confidence intervals for model with varying ρs: High density

Variable	Point estimate	Avg. bias	Bias-corrected confidence interval 5%	16%	Median	84%	95%
Gross job creation (births)	0.18	-0.08	0.02	0.05	0.11	0.16	0.20
Employment/Pop (log, BDS)	0.45	-0.09	0.26	0.29	0.34	0.40	0.43
Pop growth	0.45	-0.18	0.15	0.21	0.28	0.33	0.36
Wage growth	0.21	-0.06	0.06	0.10	0.15	0.20	0.24
Firm entry rate	0.74	-0.19	0.46	0.50	0.54	0.59	0.62
House price growth	0.83	-0.19	0.58	0.60	0.64	0.68	0.71
Firm exit rate	0.46	-0.11	0.29	0.32	0.37	0.41	0.46
Net migration rate	0.94	-0.22	0.61	0.66	0.73	0.77	0.80
Firm exit rate (all)	0.74	-0.26	0.40	0.43	0.48	0.53	0.55
Bartik: Entrant's job creation	0.78	-0.26	0.43	0.47	0.53	0.58	0.62
Bartik: Employment	0.52	-0.21	0.21	0.25	0.31	0.37	0.41

The estimated spatial correlation is slightly negative for MSAs with low regulation, but comparable to the baseline estimates for areas with high regulation. For both high and low regulation MSAs, the spatial correlation varies significantly across variables. House price data are from CoreLogic Solutions.

Table C.10: First-stage F-statistics split by Wharton Regulation Index

(a) Low Wharton Regulation Index

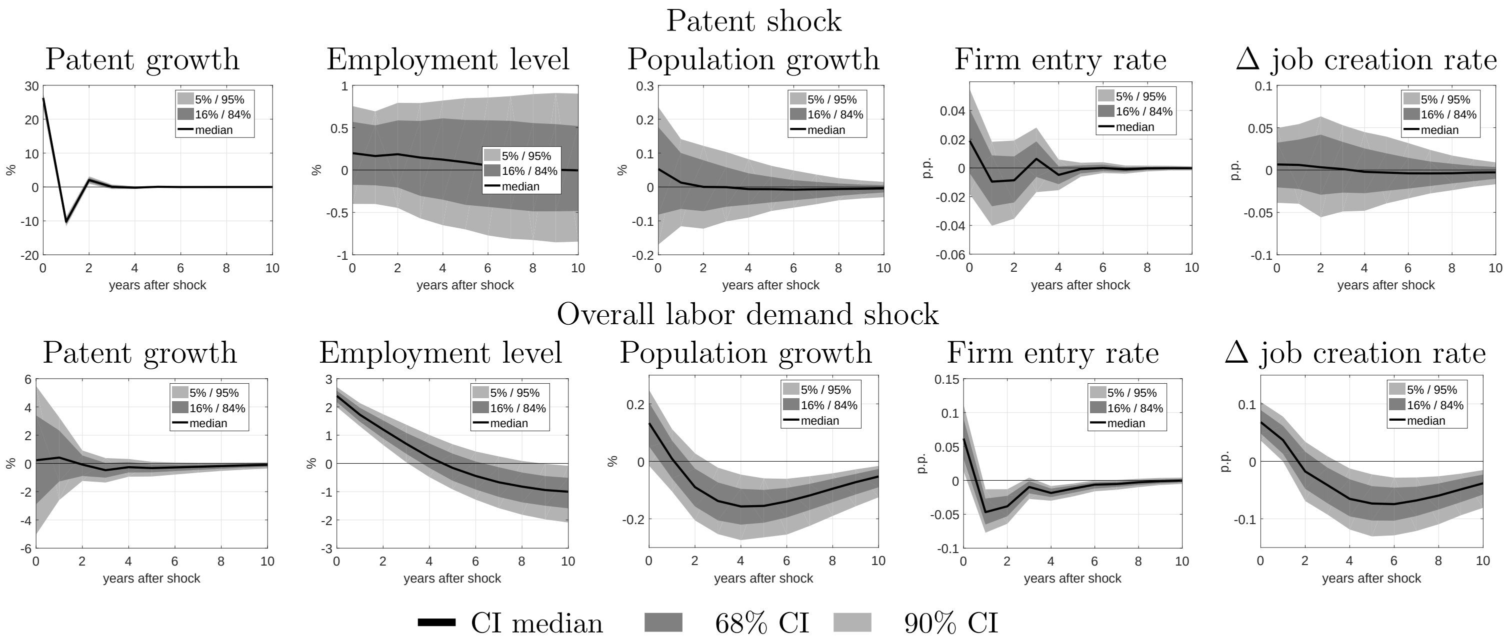
	Point	Confidence interval				
Gross job creation (births)	17.2	5.3	9.0	15.4	21.9	26.5
Employment/Pop (log, BDS)	61.6	23.1	29.0	43.0	58.0	71.9

(b) High Wharton Regulation Index

	Point	Confidence interval				
Gross job creation (births)	4.9	1.3	2.2	4.4	7.2	9.3
Employment/Pop (log, BDS)	13.4	7.0	9.9	14.9	21.6	28.3

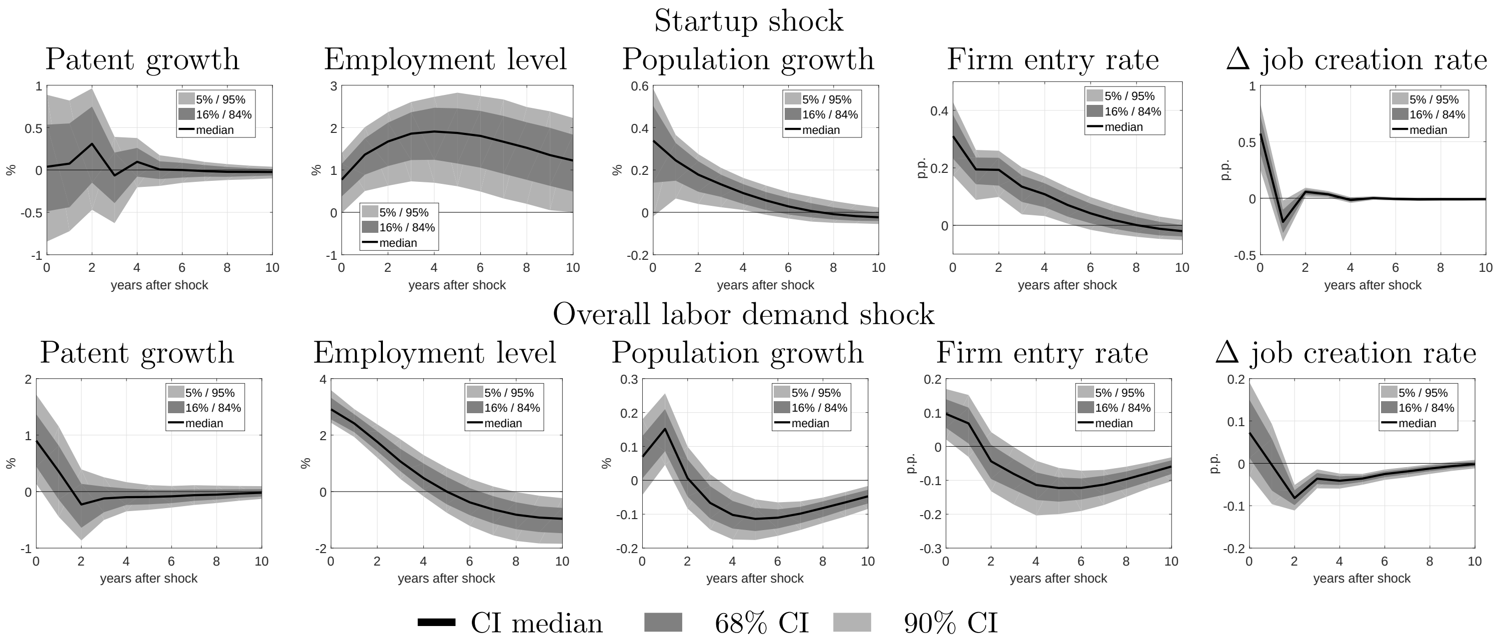
The F-statistics measuring the strength of the identification indicate that our instruments predict the identified shocks well, except for startup shocks in highly regulated MSAs.

C.6 Innovation



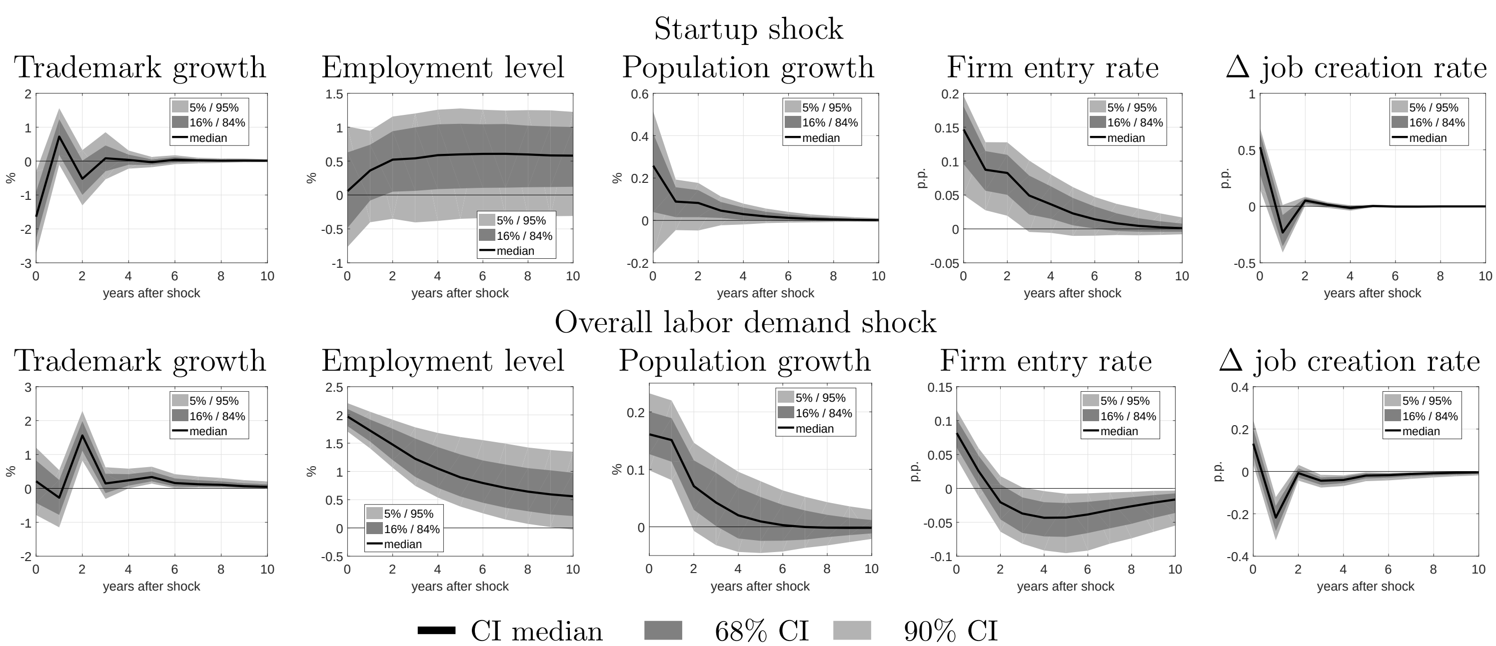
Here we show the responses in a model with patenting shock when we identify the overall labor demand shock as in our baseline. We find less significant effects on startups, but also on economic activity overall. This cautions against assuming strong effects of innovative activity on local labor markets.

Figure C.10: Impulse-responses to patenting shocks and overall labor demand shocks in our patenting VAR with the labor demand shock identified as in our baseline VAR.



Here we estimate our baseline model in the patent sample and include patenting in the periphery. We find that patenting does not respond to identified startup shocks, suggesting that much of startup activity does not lead to measurable increases in innovation.

Figure C.11: Impulse-responses to startup shocks and overall labor demand shocks in our baseline VAR estimate for MSAs with patenting data: 1980–2001.



Here we estimate our baseline model in the trademark sample and include trademark filings in the periphery. We find that trademarking does not respond to identified startup shocks, suggesting that much of startup activity does not lead to measurable increases in innovation.

Figure C.12: Impulse-responses to startup shocks and overall labor demand shocks in our baseline VAR estimate for MSAs with trademark data.