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## Entrepreneurs and City Growth

by

Naomi Hausman

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בנין פרץ נפתלי, קמפוס האוניברסיטה העברית, הר הצופים, ירושלים 9190501  
The Hebrew University Campus, MT. Scopus, 9190501 Jerusalem, Israel  
[www.falk.huji.ac.il](http://www.falk.huji.ac.il)

# Entrepreneurs and City Growth\*

By

Naomi Hausman  
The Hebrew University of Jerusalem

## Abstract

Entrepreneurs are often thought to be important drivers of economic growth. This paper shows that local entrepreneurs have strong complementarities with national industry tailwinds in generating city growth. Although substantial literature on national industry shocks to local labor markets suggests a city's growth is largely determined by the national performance of its prominent industries, in fact the local growth response is importantly mediated by the local employment distribution across firm types within industry. Cities with more winning industry employment in small, incorporated firms grow more in response to an equally sized national shock. Having illustrated this empirical feature of cities, the paper presents evidence on three sets of theories aiming to explain the importance of entrepreneurs: (1) that entrepreneurs encourage entry, (2) that entrepreneurs facilitate knowledge spillovers and innovation, and (3) that entrepreneurs simply represent human capital, already a central feature of growth models. Microdata from the U.S. Census' LBD, which permits examination of establishment and firm dynamics, indicates an important role of entrepreneurs in encouraging growth from entry of new establishments. LBD-linked surveys providing new insight into cross-firm interactions – based on R&D activities, innovation and technology transfer, IT investment, and IT use – lend support to the knowledge spillovers theory of entrepreneurship effects. Local availability of human capital, in contrast, cannot explain the entrepreneurship effect.

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# 1 Introduction

Entrepreneurs bring new ideas to life. Indeed, substantial theory and evidence suggest the importance of entrepreneurs for growth. That entrepreneurship predicts subsequent entry and city growth is now a robust empirical regularity (Glaeser et al. (1992, 2010); Rosenthal and Strange (2003, 2010)), although only isolated evidence has established a causal link (Glaeser et al. (2015)). Meanwhile, substantial literature on city dynamics suggests that a locality’s growth is largely determined by the national performance of its prominent industries (Bartik (1991); Blanchard and Katz (1992); Autor et al. (2013)).

This paper presents a new fact that casts both of these views in a new light: the effect of national industry shocks on city growth is largely determined by the ex-ante employment share of entrepreneurial firms in affected industries. Entrepreneurs have a striking complementarity with national industry tailwinds in generating city growth. To build intuition for this result, consider the example of Provo-Orem, Utah and State College, Pennsylvania in the 1990s. Although both cities had similar ex-ante shares of employment in the “computer systems design and related services” industry (NAICS 5415), this industry in Provo, UT had a larger share of its employment in small firms, whereas in State College, PA it was dominated by larger firms. The 1990s were strong years for the computer systems design industry, nationally, but Provo was better able to capitalize on these favorable national growth currents than was State College: overall city employment grew by 69% in Provo but only 9.3% in State College over the decade. The large literature on city dynamics that follows Bartik (1991) in taking advantage of shift-share instruments would, however, predict similar outcomes for these two cities based on their similar initial employment shares in that industry and similar overall labor demand shocks (calculated by summing weighted shocks across all industries).

Why entrepreneurs are so critical in helping cities capitalize on growth opportunities is the natural question raised by this complementarity. In addition to illustrating this empirical feature of cities, the paper presents evidence on three sets of theories behind the importance of entrepreneurs: (1) that entrepreneurs encourage entry, (2) that entrepreneurs facilitate knowledge spillovers and innovation, and (3) that entrepreneurs simply represent human capital, already a central feature of growth models.

First, to convey the primary importance of entrepreneurial firms, the paper builds on two existing literatures – one on entrepreneurship effects and another on national industry shocks to local labor markets – and it decomposes the standard Bartik shock into parts that reflect not only the city’s industry employment distribution but also the extent to which a city’s employment is distributed in more versus less entrepreneurial firms. In each Bartik component, a city’s ex-ante employment shares in an industry-firm-type category – say, biotech employment in small, incorporated firms – are interacted with mean-zero national (not city  $j$ ) industry-specific employment growth shocks (as are typically used in Bartik instruments) and summed across industries. In words: does a city that experiences a positive shock to its small-incorporated-firm-heavy industry grow more than another city that experiences a positive shock to its large-incorporated-firm-heavy industry, for example? City employment growth is then regressed on a vector of these firm-type “Bartik shocks,” implementing on a large scale – across cities, industries, and decades – the thought experiment described above. This strategy provides a test of the hypothesis that a city’s ex-ante distribution of production across firm types affects its growth: if the firm type distribution is immaterial, the coefficients on these firm-type Bartik shocks will be equal.

Highly detailed and confidential Census data on U.S. businesses in the three decades from 1982 to 2012 provide a wealth of variation as well as establishment and firm characteristics with which to study this question. In particular, the confidential microdata allow for tracking of establishments and their firm linkages over time to fully capture their growth dynamics and their appropriate classification into size and age groups in the base year or year of entry. These data are uniquely suited to study the growth response of 317 U.S. cities to their varying degrees of ex-ante entrepreneurship.

Results indicate that that small establishments – and in particular, small, incorporated establishments – have an outsized effect in generating city employment growth, while the unincorporated tend to have a negative or zero effect. These effects exist over and above the previously documented predictive power of the city-wide ex-ante size distribution of employment. Although entrepreneurs are sometimes thought of as new and young rather than small firms, per se, evidence indicates that age does not explain this effect; the group of small, incorporated firms is more important for growth than the young, old, large, unincorporated, or any other combination of these categories.

Several theories aim to explain how entrepreneurs generate local growth. First, entrepreneurs may facilitate growth of their area through entry, by thickening markets for support services, passing

entrepreneurial skills to their children, or generating an entrepreneur-friendly culture in which starting your own firm brings status (Vernon (1960); Chinitz (1961)). A second set of theories, advanced heavily by Jane Jacobs, AnnaLee Saxenian, and many others, is that entrepreneurs generate knowledge spillovers – that the economy becomes more dynamic because of the increased local idea flows that occur because economic activity is organized into more, smaller, outward-facing firms (Marshall (1890); Jacobs (1969); Saxenian (1994)). These idea flows may result, for example, from higher labor mobility between small firms or from supply chain linkages: entrepreneurs are more likely to need to source inputs for production or R&D from outside the firm, and they may make their niche in providing these inputs for others. These kinds of interactions between firms may be evident in their use of information technology (IT) to organize activity across firms and in their engagement in joint R&D projects and transfer of intellectual property. A third hypothesis regarding the source of the entrepreneurship effect relates to measurement. It may be that entrepreneurs don't create growth, per se, but that they represent the ready local availability of human capital, which economists have long considered instrumental in growth. Entrepreneurs tend to be highly educated, and more educated areas tend to have both more entrepreneurship and more highly educated entrepreneurs (Fairlie and Robb (2008); Doms et al. (2010)).<sup>1</sup> A key issue in providing evidence on this hypothesis is thus the ability to distinguish clearly in the data between entrepreneurship and human capital.

The paper provides new evidence on these potential mechanisms by linking to the LBD additional confidential Census data sets on R&D, IT investment, and IT use. The Business Research and Development and Innovation Survey (BRDIS) provides firm-level data on R&D spending and activities, including engagement in joint projects with other firms, universities, or governments, and production and transfer of intellectual property. The Annual Survey of Manufactures (ASM) and Computer and Network Use Survey (CNUS) supply information on multiple categories of IT investment as well as use of internal and external networks for management of operations.

In support of the knowledge spillovers theory, estimates indicate local growth complementarities between small, incorporated firms, on one hand, and measures of knowledge spillovers from R&D, IT investment in small firms, and external network use in small firms, on the other. That small, incorporated firms facilitate entry also finds substantial support in the data: the entire city growth

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<sup>1</sup>See VanDerShuis et al. (2008) for a review of the literature on education and entrepreneurship.

effect from these firms comes from employment growth in establishments that enter over the course of the decade. The evidence contradicts the notion that these entrepreneurial firms may simply reflect local human capital; when the two are independently measured and included together in growth regressions, human capital has no positive effect in explaining growth.

The ability to pinpoint and measure entrepreneurial firms is an important contribution of the paper. “Entrepreneurship” has a wide variety of measures which tend to vary according to the type of information available in any particular data set – from the self-employed, to entrants and young firms, to small businesses – despite scholars’ awareness that many non-entrepreneurs are captured in these measures (Guzman and Stern (2015, 2017); Levine and Rubinstein (2017)). While previous studies using firm data have used firm size and/or age to measure entrepreneurs, they have tended to ignore the fact that a firm’s legal form of organization provides key information about the firm’s intentions. Firms that wish to take risks and/or to recruit funds from external investors must incorporate to limit the personal liability of the firm’s owners. Because innovation generally requires upfront investment with uncertain payoffs, entrepreneurs aiming to generate economic change and growth are likely to incorporate. Levine and Rubinstein (2017) show in individual-level data that although the self-employed, as a whole, look negatively selected from the group of salaried workers on human capital and wages, the incorporated self-employed fit the image of high-skilled risk-takers described by our models of entrepreneurs. Accordingly, the present work uses information on firms’ legal form of organization and size to improve measurement of entrepreneurs in business-side data and provide evidence that this measure is appropriate. Indeed, not only do small, incorporated firms exhibit the greatest complementarity with national industry growth shocks, but they also predict growth distinctly from and more strongly than local human capital.

The paper’s results are relevant both directly for policy as well as for future research. Local policy makers everywhere are interested in the factors that contribute to city success – including accelerators (Hochberg and Fehder (2015); Hochberg (2016)), venture capital (Chen et al. (2010)), educated workers (Moretti (2004)), universities (Hausman (2018)), and “Innovation Districts” or economic “Empowerment Zones” (Busso et al. (2013)) – but most attempts to stimulate innovative industrial clusters have failed at huge cost (Lerner (2009)). Being able to pinpoint the entrepreneurs that are most likely to contribute to growth and the mechanisms through which they do so can aid policy development to focus on more efficient initiatives. These may, for example, complement

existing channels of knowledge flows or increase accessibility of the ecosystem that supports small, incorporated entrants as opposed to spinning wheels on support for mom and pop shops. Pinpointing the growth-generating entrepreneurs is also important for future research that relies on identifying entrepreneurs in business data. Researchers may improve the precision of their measures by taking advantage not only of establishment and firm size measures, but also of legal form of organization, a measure often included in industry data.

Finally, previous research has suggested that using incorporation to disaggregate the self-employed resolves three apparent discrepancies between theory and empirics regarding entrepreneurs' human capital, liquidity constraints, and activity relative to the business cycle (Levine and Rubinstein (2018)). This paper shows that using incorporation status shrinks the gap between theory and empirics not only regarding selection into entrepreneurship, as in Levine and Rubinstein (2018), but also regarding the growth effects of entrepreneurs. Schumpeterian growth, driven in theory by entrepreneurs replacing old innovation with new (Schumpeter (1942)), is captured here in a city-wide growth measure which allows firms to interact, transmit ideas, create, destruct, and generate growth not only internally but also in other firms that benefit from them. Empirically, small firms that signal their growth orientation by incorporating are the ones that generate the greatest gains for their cities in response to national shocks, encourage the most new-establishment entry to their city, and exhibit the strongest growth complementarities with local measures of knowledge spillovers – all of which accord with our theories of entrepreneurs.

The paper is structured as follows. Section 2 presents the central fact of the paper on the critical role of entrepreneurs in mediating national industry shocks, setting up and executing the basic test. Section 3 motivates the research question in more detail, discussing several alternative theories of the ways in which entrepreneurs may generate local growth. Section 4 provides tests and evidence on these theories from rich confidential Census data that permit the examination both of firm dynamics over decades and of detailed firm activities that may potentially generate growth. Section 5 concludes.

## 2 Entrepreneurs and Growth Effects of National Industry Shocks

### 2.1 Bartik shocks and local growth

Since at least Bartik (1991), a substantial body of work has shown that cities and regions respond to national industry employment changes in proportion to their own ex-ante distribution of employment across industries. Cities with more ex-ante employment in nationally growing industries experience more employment growth city-wide. Accordingly, “Bartik shocks,” or “shift-share instruments,” which are weighted sums across industries of national industry employment changes, where the weights are ex-ante local industry employment shares, have become an exceedingly common tool among applied economists. While some researchers construct these Bartik shocks for the purpose of directly studying regional response to change (Blanchard and Katz (1992); Autor et al. (2013); Notowidigdo (2013)), many others use them as local labor demand shiftors for the purpose of understanding other features of cities. Such features have included, for example, the effects of housing supply elasticity on housing prices, population growth, and diverging location choices by skill (Glaeser et al. (2006); Saiz (2010); Diamond (2016)); changes in real wages inequality (Moretti (2013)); and local effects of advanced internet adoption (Forman et al. (2012)). These examples, as well as many others, all indicate that the interaction of ex-ante local industry employment distributions with national industry employment growth is a strong predictor of employment and wage growth for the locality as a whole.

Another literature, meanwhile, emphasizes the importance of entrepreneurs for city growth. That the presence of entrepreneurs predicts subsequent local growth is by now a robust empirical regularity. This relationship holds whether entrepreneurship is measured as small average establishment size, the share of employment in new or young firms, or entrant counts (Glaeser et al. (1992, 2010); Rosenthal and Strange (2010)).<sup>2</sup> Almost no causal evidence of this effect exists, except for one nice piece of recent evidence using proximity to historic mines and the “company town” culture they engender as an instrument for long term entrepreneurship rates (Glaeser et al. (2015)). The theoretical underpinnings for this literature relate to agglomeration economies, which make firms in cities more productive, and the notion that the way in which production is organized into

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<sup>2</sup>Other important work debates the role of small versus young firms in job creation (Davis et al. (1996); Neumark et al. (2011); Haltiwanger et al. (2013))



firms may affect the type and extent of increasing returns in a location. (I discuss some of these theories in greater detail in section 3.) In short, the organization of production into more small, entrepreneurial firms as opposed to older behemoths may improve knowledge flows or ease supply chain linkages for potential entrants, thus increasing the productivity of the location, making it more attractive to both firms and workers, and generating local growth.

This paper links these two literatures, providing a test of the importance of entrepreneurs within the regional growth framework of Bartik (1991). Using a common mathematical approximation, one can perfectly decompose the “standard” Bartik shock into parts that reflect firm-type-specific shocks. A regression of city growth on the vector of these firm-type-specific shocks then provides a test of whether the ex-ante distribution of industry employment across these firm types – and not just across industries – affects the city’s growth response to national industrial changes. Consider, for example, a simple decomposition by firm size.<sup>3</sup> Intuitively, this decomposition represents a natural experiment comparing two cities that look similar along all other dimensions – including their overall firm size distributions – but one has a concentration of small firms in industry A, while the other has a concentration of small firms in industry B. Meanwhile, industry growth evolves independently in the rest of the nation, causing these two cities to be treated by the resulting vector of industry-specific labor demand shocks. Industry A may grow nationally more rapidly than does industry B, causing the first city randomly to receive a bigger demand shock to its concentration of small firms. If small firms disproportionately generate growth, then the first city should experience faster growth than the second in response to this vector of national industry shocks.

The more general analogue to this experiment, originally formulated by Bartik (1991), is commonly constructed as follows, using, for any particular decade, cross-city variation in industry employment distributions and time variation in national industry employment. (The latter source of variation is considered to be plausibly random with respect to any particular city (Borusyak et al. (2018)).)<sup>4</sup> The predicted growth in labor demand in an MSA is calculated as a weighted

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<sup>3</sup>Of course, one can use this method for decompositions along any number of dimensions of firm heterogeneity within industry. In practice, this paper allows for several alternative definitions of “entrepreneurs,” conducting decompositions along dimensions of firm age, firm size, legal form of organization, and combinations of these. For ease of exposition, I use firm size in delineating the estimation.

<sup>4</sup>The conditions necessary to make causal statements using shift-share instruments, and their plausibility in this context, are discussed further in section 2.6.

average of growth rates of national industry employment, where the weights are the lagged share of MSA employment in each industry. To be precise, the original Bartik shock is defined as

$$\Delta B_{jt}^* = \sum_{ind} \frac{emp_{j,t-10}^{ind}}{emp_{j,t-10}} \Delta \ln \left( N_{-j,t}^{ind} \right)$$

where  $emp_{j,t-10}^{ind}$  is the total employment in industry  $ind$  in MSA  $j$  in year  $t - 10$  and  $emp_{j,t-10}$  is total employment across all industries in MSA  $j$  in year  $t - 10$ .  $\Delta N_{-j,t}^{ind}$  is the national industry shock defined as:

$$\Delta \ln \left( N_{-j,t}^{ind} \right) = \ln \left( emp_{-j,t}^{ind} \right) - \ln \left( emp_{-j,t-10}^{ind} \right)$$

where  $emp_{-j,t}^{ind}$  is the total national employment in industry  $ind$ , excluding MSA  $j$ , in year  $t$ , and  $emp_{-j,t-10}^{ind}$  is total national employment in industry  $ind$ , excluding MSA  $j$ , in year  $t - 10$ .

To estimate the effect on MSA employment growth of a shock to labor demand, we commonly regress:

$$(1) \quad \ln \left( \frac{emp_{jt}}{emp_{jt-10}} \right) = \beta \Delta B_{jt}^* + \varepsilon_{jt},$$

The intuition behind the basic industry share Bartik,  $\Delta B_{jt}^*$ , is that cities with a higher proportion of employment in industries that are growing nationally are likely to experience larger positive shocks to labor demand. A Bartik modified to help us learn about the growth effects of the firm-size distribution within industries has a similar feel. Cities with a higher proportion of small firm employment in industries that are growing nationally are expected to experience more growth under the hypothesis that small firms generate city growth. To implement this comparison, I calculate the Bartik shock separately for different firm size categories and regress city employment growth on these firm size Bartiks.

Using the fact that  $\ln(1+x) \approx x$ , one can exactly decompose the industry employment share Bartik shock into several establishment size group employment share Bartiks. This approximation implies:

$$\ln \left( \frac{emp_{jt}}{emp_{jt-10}} \right) = \ln \left( \frac{emp_{jt-10} - emp_{jt-10} + emp_{jt}}{emp_{jt-10}} \right) = \ln \left( 1 + \frac{\Delta emp_{jt}}{emp_{jt-10}} \right) \approx \frac{\Delta emp_{jt}}{emp_{jt-10}},$$

$$\Delta \ln \left( N_{-j,t}^{ind} \right) = \ln \left( \frac{emp_{-j,t-10}^{ind} - emp_{-j,t-10}^{ind} + emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}} \right) = \ln \left( 1 + \frac{\Delta emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}} \right) \approx \frac{\Delta emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}}.$$

Thus, the Bartik shock can be redefined as:

$$(2) \quad \Delta B_{jt} = \sum_{ind} \frac{emp_{j,t-10}^{ind}}{emp_{j,t-10}} \frac{\Delta emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}} \approx \Delta B_{jt}^*,$$

and substituted into equation 1 to create a benchmark for the firm size Bartik regressions:

$$(3) \quad \frac{\Delta emp_{jt}}{emp_{jt-10}} = \beta \Delta B_{jt} + \varepsilon_{jt},$$

It is now straightforward to decompose this regression in ways that can be informative on the extent to which small firms contribute to their city's growth. I first decompose the right hand size of the regression into firm size group Bartik instruments in order to answer the question of whether small firms disproportionately cause city growth. In section 4.1.1, I use a further decomposition into components of city growth, on the left hand side, to investigate the hypothesis that small firms may generate growth primarily by encouraging entry.

## 2.2 Testing for Firm Size Effects

The lagged industry shares that form the standard Bartik instrument in equation (3) are actually composed of several groups of establishments. For ease of exposition, establishments are categorized here as belonging to small, medium, or large firms.<sup>5</sup> Note that:

$$\frac{emp_{j,t-10}^{ind}}{emp_{j,t-10}} = \frac{emp_{j,t-10}^{ind,S}}{emp_{j,t-10}} + \frac{emp_{j,t-10}^{ind,M}}{emp_{j,t-10}} + \frac{emp_{j,t-10}^{ind,L}}{emp_{j,t-10}}.$$

Plugging this expression into equation 2 yields

$$\Delta B_{jt} = \sum_{ind} \frac{emp_{j,t-10}^{ind}}{emp_{j,t-10}} \frac{\Delta emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}} = \sum_{ind} \left( \frac{emp_{j,t-10}^{ind,S}}{emp_{j,t-10}} + \frac{emp_{j,t-10}^{ind,M}}{emp_{j,t-10}} + \frac{emp_{j,t-10}^{ind,L}}{emp_{j,t-10}} \right) \frac{\Delta emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}}.$$

<sup>5</sup>About two-thirds of employer firms are single-unit firms, meaning the establishment and firm are equivalent; the remaining third are multi-unit firms that may have establishments in multiple cities such that establishments in any particular city must be categorized according to their firm's size in order to conduct tests of the importance of firm-size distribution.

which leads to the the definition of “small”, “medium”, and “large” Bartik shocks as:

$$\begin{aligned}\Delta B_{jt}^S &= \sum_{ind} \left( \frac{emp_{j,t-10}^{ind,S}}{emp_{j,t-10}} \right) \frac{\Delta emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}}, \\ \Delta B_{jt}^M &= \sum_{ind} \left( \frac{emp_{j,t-10}^{ind,M}}{emp_{j,t-10}} \right) \frac{\Delta emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}}, \\ \Delta B_{jt}^L &= \sum_{ind} \left( \frac{emp_{j,t-10}^{ind,L}}{emp_{j,t-10}} \right) \frac{\Delta emp_{-j,t}^{ind}}{emp_{-j,t-10}^{ind}}.\end{aligned}$$

Thus, the overall Bartik shock is the sum of the size specific Bartik shocks:

$$\Delta B_{jt} = \Delta B_{jt}^S + \Delta B_{jt}^M + \Delta B_{jt}^L.$$

Plugging this expression into (3), distributing, and adding controls for a city’s overall firm size distribution provides an estimating equation to test the extent to which the within-industry firm size distribution affects growth:

$$(4) \quad \frac{\Delta emp_{jt}}{emp_{jt-10}} = \beta^S \Delta B_{jt}^S + \beta^M \Delta B_{jt}^M + \beta^L \Delta B_{jt}^L + \sum_g \frac{emp_{j,t-10}^g}{emp_{j,t-10}} + \varepsilon_{jt},$$

In practice, the national industry growth component of each Bartik is de-meanded to satisfy independence conditions. The new term in this equation,  $\sum_g \frac{emp_{j,t-10}^g}{emp_{j,t-10}}$ , where  $g$  is the firm size group, controls for the overall (as opposed to industry-specific) ex-ante firm size distribution in each city  $j$  in order to account for the fact that some cities may be skewed overall towards smaller or larger firms and thus isolate the effect of experiencing a national growth shock to a small-firm heavy industry. If the firm size distribution doesn’t matter, then each firm-size Bartik should have a similar effect on city growth. If, on the other hand, small firms generate more growth than others in response to national labor demand shocks, the small firm Bartik coefficient should be larger than the others. Formally, these predictions amount to testing the null hypothesis that

$$(5) \quad \beta^S = \beta^M = \beta^L.$$

where  $\beta^S > \beta^M$ ,  $\beta^S > \beta^L$  is expected if small firms generate greater growth.

## 2.3 Measuring Entrepreneurs

Who is an entrepreneur? That’s the million dollar question – whether explicitly stated as such or not – underlying much empirical research on entrepreneurship (Glaeser and Kerr (2009)).

In individual-level data, entrepreneurs are variously measured as small-business owners, founders of “start-ups,” or the self-employed, depending on context and data availability, although it’s generally understood that each of these definitions mismeasures the group of “entrepreneurs” in one way or another. Levine and Rubinstein (2017) show that using indicators for self-employment, alone, generates a misleading view of entrepreneurs: the self-employed as a whole are negatively selected from the group of salaried workers on human capital and wages, while economists’ theories of entrepreneurs suggest they should be positively selected. However, if one also uses information about the self-employed’s legal form of organization (hereafter, LFO), one can identify the subset that is truly entrepreneurial because LFO provides key information regarding intentions. Entrepreneurs that wish to take risks and/or to raise funds from external investors must incorporate to limit the personal liability of the firm’s owners. Because innovation generally requires upfront investment with uncertain payoffs, entrepreneurs aiming to effect economic change – which is in turn what creates growth – are likely to incorporate. (Schumpeterian growth models, for example, specifically describe growth from innovating entrepreneurs who bring creative destruction Schumpeter (1911); Aghion et al. (2014)). Indeed, the subset of the self-employed that incorporate more closely resemble our theoretical image of entrepreneurs in that they are positively selected on human capital and wages, while the remainder of the self-employed are negatively selected (Levine and Rubinstein (2017)). Measuring entrepreneurs as the subset of self-employed who incorporate similarly resolves two other empirical puzzles regarding (1) the effects of liquidity constraints on entrepreneurship and (2) entrepreneurial activity relative to the business cycle (Levine and Rubinstein (2018)).

Although information on LFO exists in many business-side data sets, incorporation status tends not to be used to measure entrepreneurs in establishment- or firm-level data. Instead, measures vary, including small average establishment size, the share of employment in small establishments or firms, the share of employment in entrants, or entrant counts (Glaeser et al. (1992, 2010); Rosenthal and Strange (2003, 2010); Delgado et al. (2010)). There is also some debate over whether small or new and young firms matter most, although this debate is somewhat distinct from the current

research because of its focus on job creation – employment additions within firms – as opposed to city- or region-wide growth in which firms interact and may generate growth in others in addition to growing, themselves (Davis et al. (1996); Neumark et al. (2011); Haltiwanger et al. (2013)). A strong correlation exists between each of these measures and subsequent entry and/or city employment growth, and each of them accords in some way with our theories on who entrepreneurs are, so it is a priori unclear which measure is best. Nevertheless, it is of obvious import to measure entrepreneurs well if we are to make progress in empirical research on this group that is thought to be a critical input to growth.

While it seems logical that incorporation is likely to be an important predictor of entrepreneurship, this paper is otherwise ex-ante agnostic about the best way to measure entrepreneurs. Two of the leading measures – small firms and young firms – are highly correlated with each other empirically, leading me to let the data do the talking. In practice, I conduct several alternative decompositions of the standard Bartik shock into firm-type Bartik shocks along dimensions of firm size, firm age, firm incorporation status, and combinations of the three. I then regress city growth on each of these vectors of firm-type Bartiks separately and then together, in a sort of horse-race to understand which categorizations matter the most for identifying the entrepreneurs that generate growth.<sup>6</sup>

## 2.4 The U.S. Census Bureau’s Longitudinal Business Database

Estimating the entrepreneur effect using the methodology described above requires data in at least two years, a decade apart, on employment at the MSA-industry level nationwide. The more detailed are the industry categories, the richer is the variation available. Public use industry data tend to come highly aggregated, as they are often censored at a more detailed industry level and in less-populated geographic areas.<sup>7</sup> This paper uses as the backbone of its analysis NAICS 4-digit industry data over three decades from the confidential Longitudinal Business Database (LBD) of the U.S. Census Bureau, enabling the use of detailed industry variation.

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<sup>6</sup>All estimations have been replicated using categorizations by establishment size/age as opposed to firm size/age. Results are the same in almost every case, as would be expected given that two-thirds of firms are single-units. The exception comes when studying entry in section 4.1 because a small single-unit entrant has different potential theoretical interpretations than a small multi-unit entrant.

<sup>7</sup>Before the 1990s, the public use County Business Patterns (CBP) data is usable nationwide only at the 2-digit SIC level.

The data contain employment as of March 12 and annual payroll data for every non-farm employer establishment in the U.S., as well as each establishment’s detailed location, industry, year of entry, and year of exit. I use data from 1982-2012, which provides three decades of industry change and allows any given city-industry to go through more and less entrepreneurial times within the period of observation.

These data allow the construction of industry and industry-firm size group employment shares by metropolitan statistical area (MSA) and nationally for the years 1982, 1992, 2002, and 2012 – economic census years in which the data are most reliable. These employment shares and national employment changes then form both the standard Bartik shock as in equation 3 and the firm-type Bartik shock as in equation 4. Because Bartik shocks are best-used with decadal changes rather than in closer intervals, I employ data for this purpose from the four economic census years listed above (although data from intermediate years are used to understand entry dynamics, as described in section 4.1.1). National employment changes over closer intervals have higher serial correlation and thus are less useful as plausibly random demand shocks to cities. Decadal changes also are less likely to pick up business cycle swings and more likely to pick up secular changes, such that the demand changes measured are not temporary.

There are several advantages to using the confidential LBD data over public use data sets on establishments. An important one for accurately measuring industrial activity by geographic area over long periods of time is that the LBD data aren’t censored. Public use data sets on firms censor area-year-industry-establishment size group cells when the number of establishments represented is small; this type of censoring is quite frequent in certain locations and industries, especially in the earlier years of the sample period. In addition, public use data tend to aggregate establishments to higher level industry groups; the detail of the LBD enables measurement of industry activity consistently at the 4-digit NAICS level over these three decades.<sup>8,9</sup>

Finally, the LBD allows tracking of establishments and their firm linkages over time for a deeper understanding of entry and growth dynamics (to be discussed in depth in section 4.1.1). The ability

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<sup>8</sup>The data are reported at yet more detailed industry codes, but because codes change over time, a concern arises that using the additional detail would introduce excessive noise.

<sup>9</sup>Note that the ability to assign establishments consistently to 4-digit NAICS codes over four decades is not to be taken for granted, even in the LBD. The U.S. Census Bureau switched their industry classification system from SIC to NAICS in 1997, making it difficult to work with samples that span that year. I am grateful to have been able to take advantage of a new algorithm that assigns NAICS-2002 codes to every establishment in the LBD from 1976 onwards (Fort (2015)). This work allows me to use the entire sample period without any discontinuity.

to measure both which firms *cause* growth and which establishments and firms *themselves* grow – in the sense of adding employment – is possible only because each establishment’s path can be traced from year to year. This type of analysis would not be possible with public use data.

#### 2.4.1 Main Estimation Sample

The main sample used in estimation is comprised of industrial employment changes in NAICS 4-digit industries over three decades: 1982-92, 1992-2002, and 2002-12. To capture city dynamics, I focus on the largest 317 MSAs, excluding those that are non-city remainder areas of states. Observing growth in these 317 MSAs over three decades generates a sample of 951 observations.

Employment and wage growth in these cities conform to the patterns we expect given our knowledge of the most quickly growing and declining types of places in the US over the last several decades.

Sunbelt cities top the employment growth list of MSAs in all three decades. Some of the highest growth cities are, in particular, university towns in the south and southwest. Greenville, NC – home to the second-largest UNC campus – and Provo, UT, – home to Brigham Young University – were both in the top 25 fastest growing MSAs in 1992. The latter moved up the growth ranks in 2002 and was joined by Austin, TX (UT Austin), Boulder, CO (UC Boulder), and Raleigh-Durham-Chapel Hill, NC – home to the Research Triangle, UNC-Chapel Hill, NC State, and Duke University. Provo and Austin continue to rank highly in 2012.

Of course the high employment growth cities in these decades in general are those with elastic housing supply, nice weather and/or outdoors amenities, and in a substantial number of cases, energy deposits (e.g. Texan cities). The slowest growing cities in terms of employment are also unsurprising: rust belt either literally or in spirit. These are largely northern industrial manufacturing towns that have declined: Flint, MI, Buffalo, NY, Dacatur, IL, Pittsfield, MA, Detroit, MI. Though Dayton, OH now has significant R&D in aeronautical and astronautical engineering, for example, that has not been quite enough to save it from large reductions in employment through 2012 as its main advantage – central location for manufacturers, suppliers, and shippers – has declined in importance.

Because of variation in housing supply elasticity across MSAs, one would not necessarily expect the highest employment growth places to be the highest wage growth places, and indeed they



usually aren't. San Francisco and Boston, for example, rank low on employment growth but very highly on wage growth in 2012. Over the decade from 2002-2012, Boston ranks 187th out of 317 MSAs in employment growth, but 29th in wage growth. San Francisco ranks 284th in employment growth but 10th in wage growth in the same decade.

## 2.5 Results: The Importance of Small, Incorporated Firms

The basic results are presented in Table 1. Column 1 begins with the standard industry share Bartik regression for comparison: a 1% increase in predicted industry employment growth leads to a 1.37% increase in city employment growth, indicating a small multiplier effect from stimulating growth. The stimulative effects of the firm-type Bartik instruments can be compared to this benchmark estimate – as well as to each other – to understand whether firm-type matters.

Not shown are regressions of city employment growth on ex-ante employment shares by firm size group. These regressions are analogous to the wealth of previous evidence showing that the presence of small firms predicts subsequent city growth (Glaeser et al. (1992, 2010)), and they show the same substantive result. When there is more employment in small firms – those with 1-10 employees or 11-100 employees – the city subsequently grows faster. All regressions presented in this paper with firm-type Bartiks also control for these ex-ante firm-type employment shares and thus indicate an effect beyond the previously-shown correlations.

Column 2 presents the basic firm-size Bartik regression. The coefficient on the smallest firm size group (1-10 employees) is largest, at 4.37 (substantially higher than the 1.37 of the standard Bartik), and the coefficient sizes decline monotonically as firm size grows. An F-test rejects that the coefficients on these firm-size Bartiks are equal ( $p = 0.00$ ). Column 3 decomposes the standard Bartik along two dimensions – firm size and LFO – to test the Levine and Rubinstein (2017) claim that incorporation status helps to identify entrepreneurs. This regression provides strong support for the claim: the incorporated firm Bartiks have strongly positive and significant effects on employment growth, while the unincorporated firm Bartiks have a zero or negative effect. In addition, the small, incorporated firm coefficient is much larger in magnitude than (and statistically distinct from) the large, incorporated firm coefficient: 4.81 versus 0.86. It seems that small, incorporated firms are more complementary with national shocks in producing local growth than are large or unincorporated firms. Regressions with city population growth on the left hand side

(columns 4-6) resemble the employment growth regressions, although the breakdown indicates a starker distinction between the smallest firms and the rest.

Some scholars of entrepreneurship argue that firm age, rather than firm size, is what really matters for employment gains. Haltiwanger et al. (2013), for example, shows that new and young firms, rather than small firms per se, are responsible for much of the economy's year-to-year job flows. The present work does not directly address their point because it examines longer-run, city-wide employment gains that may occur in an establishment of *any* size *due* to small firms. Nevertheless, the point that new and young firms may well be more important than small firms in generating growth should be considered seriously. Theoretically speaking, young firms may be the ones with the newest, most innovative, highest potential-upside ideas. Or, empirically, the group of recent entrants may simply better capture the entrepreneurs with the most growth potential.

To evaluate this possibility, I run a horse race between Bartiks decomposed by firm size groups, as above, and Bartiks decomposed by firm age groups. The four (exhaustive) age groups are 0 years old (entrants this year), 1-5 years old, 6-10 years old, and more than 10 years old.<sup>10</sup> The detail of the LBD data allow the categorization of every establishment exactly into its appropriate firm size and firm age bin.

Table 2 presents the results on firm age. Column 1 shows a regression of city employment growth on the vector of firm age Bartiks alone, indicating a pattern quite different from the one we see with firm size Bartiks. Although (Haltiwanger et al. (2013)) show that the youngest firms are responsible for the most year-to-year job additions in their own firms, the results in table 2 indicate they do not seem to generate city-wide employment growth over a decade at all. The coefficients on the newest entrants (0 years) and on firms age 1-5 years are indistinguishable from 0. That these firms don't generate a longer run effect could be due to the fact that they're the most volatile or to a lack of complementarity with national growth shocks. It may also be that negative national shocks are least favorable for these young firms. Older firms and, in particular, older incorporated firms seem to be more complementary to national shocks. Column 3 indicates negative, insignificant effects for young and old unincorporated firms alike, positive but insignificant effects of young incorporated firms, but larger positive and significant effects of old, incorporated

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<sup>10</sup>Age is right-censored in the LBD because the data are left-censored. The LBD begins in 1976, and firms that entered beforehand are known only to have entered at the latest in 1976.

firms.

When the age Bartiks go head to head with the firm size Bartiks, however, they do not fare well. Column 2 presents a horse race of age versus size, with no incorporation breakdown. There we see the size coefficients only get stronger relative to column 2 of table 1, and no significance remains for any of the age Bartiks.<sup>11</sup> Column 5 runs a similar horse race but includes incorporation-by-size and incorporation-by-age breakdowns. Although the old firm Bartiks are omitted due to collinearity, it is easy to see that, once again, the small, incorporated Bartik has the strongest positive coefficient: 5.145% city employment growth for each 1% of predicted growth. This effect is substantially larger, again, than the standard Bartik in table 1, column 1. The age Bartiks provide little additional explanatory power when added to the regression with size Bartiks, and they are not significant. Thus, although it is reasonable to guess that firm age rather than size may be what matters for growth, these data do not provide the support when one uses this methodology based on labor demand changes.

## 2.6 Conditions for Causal Interpretation and Suggestive Evidence

The central fact presented by this paper is that a city's growth response to national industry shocks is importantly determined not only by its ex-ante distribution of employment across industries – as a wealth of prior evidence has indicated – but also by its ex-ante distribution of employment across firm types within industries. Cities grow more when small, incorporated firms have higher employment shares in growth-shocked industries. Thus far, I have presented this fact as a sort of complementarity between local firms and national tailwinds, but under certain conditions, this effect can be considered a causal effect of small, incorporated firms on local growth. This section discusses those conditions and provides evidence that can alleviate key endogeneity concerns that would make one hesitate to draw causal conclusions.

The most basic issue that arises with the use of shift share instruments for exogenous variation in labor demand is that the ex-ante employment distribution in a city may be related to a number of other city features that may also affect growth. See Bartik (1991); Blanchard and Katz (1992); Glaeser et al. (2006); Saiz (2010); Forman et al. (2012); Autor et al. (2013); Moretti (2013); Notowidigdo (2013) and Diamond (2016) for a variety of uses of these instruments in urban

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<sup>11</sup>One of the age Bartiks is omitted here due to collinearity.

and labor economics and for discussions of their potential shortcomings. Considering the classic industry share Bartik, a city with a high 1970 manufacturing share would experience a negative labor demand shock over the next decade and be predicted to decline, but it is also likely to have low education levels which would put negative pressure on growth. In the case of the modified firm-type Bartik, one might be concerned that the local firm size and productivity distribution may respond to market size, which may in turn be related to growth (Melitz (2008); Melitz and Ottaviano (2008)). Alternatively, growing cities may have more small, incorporated firms, perhaps because entrepreneurs anticipate growth and disproportionately enter those places.

Even if one were to suppose that ex-ante employment shares are endogenous to growth outcomes, however, the shift-share instrument can still take a causal interpretation because it draws its exogenous variation from the national industry employment shocks. As long as the national industry employment changes (that are interacted with the ex-ante industry employment shares) are mean-zero, the overall Bartik shock can satisfy conditions for exogeneity (Borusyak et al. (2018)). Accordingly, I de-mean the national changes in calculating all Bartik shocks, as mentioned in section 2.2.

In addition, I provide two pieces of evidence suggesting the potential endogeneity of the ex-ante firm size distribution is not a big concern. First, I ask whether, empirically, entrants seem to anticipate growth by systematically entering growing cities. Table 3 shows regressions of city employment growth (column 1) and city wage growth (column 2) from year  $t-10$  to  $t$  on the employment share of entrants in year  $t$ , in years  $t-5$  to  $t-1$ , and in years  $t-10$  to  $t-6$ . If firms systematically enter cities that are *currently* growing, then these coefficients should be strongly positive. In fact, all coefficients in the two regressions are varying forms of precise and imprecise zeros, some slightly positive and some slightly negative. It does not seem that firms systematically enter cities that are currently growing, which makes it hard to believe they manage to anticipate growth more than ten years forward and systematically enter in advance.

Second, I re-estimate the basic firm size Bartik equation using only employment shares from the first year of the sample, 1982. This strategy aims to remove the component of the correlation between firm size Bartiks and growth that may be due to an endogenously evolving firm size distribution over time as the city grows. Table 4 shows that the main firm size result is nearly identical when fixing 1982 shares in calculating the Bartik shocks for each decade. The coefficient

on the small firm (1982 shares) Bartik is 4.844 (1.324), while the coefficient on the small firm Bartik with t-10 shares is 4.372 (1.309). The evolution of the firm size distribution with city growth cannot explain the result. Any story of endogeneity of the ex-ante employment distribution would have to explain why this distribution should be systematically related to city outcomes four decades later.

Thus the small, incorporated firm effect on growth presented in this paper can be considered plausibly causal to the extent one believes either, (1) that national “not j” industry shocks provide plausibly exogenous variation in labor demand to cities, *or* (2) that the endogeneity of ex-ante firm type employment shares isn’t driving the result.

### 3 Entrepreneurs and Growth

Economists have long studied agglomeration economies as a source of growth in cities (see Rosenthal and Strange (2004) for a review). Firms cluster together, paying the costs of congestion, because of the productivity advantages that stem from savings in transport of goods, people, and ideas. Thus, in studying the factors that generate growth of industrial clusters, economists have typically focused on understanding the roles of the “Marshallian factors:” input-output relationships, labor pooling, and knowledge spillovers.

One way to organize our theories on the contributions of entrepreneurs to city growth, then, is to consider how an organization of production into smaller, more entrepreneurial firms may especially facilitate these agglomeration economies. If small firms are better than large ones at generating these externalities, they may disproportionately feed city growth, which may come from incumbent employment gains or from entrants. Although in principle any of these agglomeration economies may result in local productivity advantages and stronger entry incentives, I distinguish in the following exposition between knowledge spillovers – which may generate continuing incumbent growth and should attract entry of small and large firms alike – and other externalities created by small firms which should disproportionately attract more entrepreneurs and perpetuate the entrepreneurial nature of the city.

In this section, I discuss a number of theories and associated evidence on how small firms may disproportionately contribute to agglomeration and growth. The first set of theories regards entrepreneurs as generating growth through entry, especially that of other entrepreneurs. The second

set bears on entrepreneurs as instruments of growth due to their ability to facilitate knowledge spillovers. Finally, I elaborate on the possibility that the “entrepreneurship effect” is really a local human capital effect in disguise. In section 4, I then describe my methodology for distinguishing between these theories and present the associated evidence.

Chinitz (1961), in comparing New York to Pittsburgh, proposed several reasons for the perpetuation of entrepreneurship in a locality. First, the entrepreneurial spirit may be transmitted intergenerationally: company men are less likely to pass an entrepreneurial drive down to their kids, such that company towns persist. Second, and subtly distinct from within-family transmission of human capital, is that the organization of business carries with it a culture. Chinitz observed that entrepreneurs in company towns are surrounded by an “aura of second-class citizenship.” In contrast, anyone who has spent time in lively start-up clusters such as San Francisco or Tel Aviv knows how typical it is for young men in those places to dream aloud about their next venture. In those places, being an entrepreneur brings status. Third, small firms generally need to source intermediate goods and services from the local economy more than do large firms, which often source internally or from a distance (the fixed cost of distance is spread over larger purchases in big firms). The presence of more local small firms means that there will already be an infrastructure of local input suppliers that can serve small entrants.

All of Chinitz’s points regarding the observed persistence in entrepreneurship can be thought of as mechanisms by which entrepreneurs ease entry for other entrepreneurs. Glaeser et al. (2015) provide evidence that differences in initial local levels of entrepreneurship, driven by the company towns that resulted from the high fixed costs of mining, are perpetuated to some extent over decades and lead to substantial differences in long run city growth.

Since Chinitz, a number of others have further developed the “intermediate goods” mechanism of the entrepreneurship effect. Helsley and Strange (2007) present a model in which agglomeration and the degree of firms’ vertical integration are jointly determined; agglomeration is a substitute for integration because it provides external supply chain linkages. Empirically, higher local industry concentrations are associated with greater purchased input intensity (Holmes (1999)). These “intermediate goods” can also be considered more generally, as pointed out by Helsley and Strange (2011), to be the multi-dimensional skills of human and entrepreneurial capital or something like urban diversity as in Jacobs (1969). In each case, local market thickness can substitute for sourc-

ing the entire range of necessary skills and inputs from within the firm. Some types of ancillary services – legal, real estate, financial, technical – which most firms are likely to need at some point, are often provided in-house in large firms but would be prohibitively expensive for small firms to carry full-time. A local abundance of such support services could reduce fixed costs of entry for entrepreneurs and increase their local presence (Glaeser et al. (2010)).

Access to capital – especially early stage capital – is a good example of an input that is particularly important to entrepreneurs and is disproportionately locally sourced. Entrepreneurs tend to be capital constrained, which may make entry more difficult where there isn't already a concentration of entrepreneurs and financing opportunities. Petersen and Rajan (1994, 1995) show how local banking conditions influence the local rates of entrepreneurship and financing. Chen et al. (2010) show that venture capital firms locate where investment opportunities are good – in terms of concentrations of promising entrepreneurs – and then they invest disproportionately locally. In fact, portfolio companies not local to a VC fund must pass a higher threshold for investment: they systematically outperform local investments. Home bias is common across a variety of types of investment funds, including also private equity and public equity, in terms both of the location of the sub-investment managers chosen and the location of the ultimate assets held (Coval and Moskowitz (2002); Brown et al. (2015); Hochberg and Rauh (2013)). Bernstein et al. (2016) provide evidence that, at least in some cases, this home bias is likely to be justified by the increased monitoring and mentoring that is enabled by on-site interaction. Given the critical nature of financing to entrepreneurs, the evidence on investment funds and early stage capital is quite convincing on the attractiveness of existing entrepreneurial clusters to new start-ups.

Whether small or large firms are likely to have an advantage in generating growth through knowledge spillovers is debatable. There are reasons to think large firms would have an edge. Schumpeter (1942) points out that large firms may have an advantage in producing new ideas because they can spread the fixed costs of R&D over a larger number of innovations. Jones (2008) notes that as innovations get more complex, innovators have to specialize more, such that there may be human capital complementarities of which large firms can take advantage when they hire more workers. Large firms may have better access to university ideas, as they may have better infrastructure for navigating universities' institutional intricacies and engaging them in joint R&D activities (Hausman (2018)).

But a small firm advantage in along this same dimension – idea production – can be readily illustrated with the example of spinoffs. Their new idea doesn’t have to fit into any particular scope, as does that of a large firm, but rather can be evaluated on its own merits and developed independently. Large firms may produce large numbers of new ideas but can only develop the small fraction of them that accord with their other business interests. The Wall Street Journal reported in 2002, for example, that GE researchers had proposed more than 2,000 new products in 2001, but only 5 proposals had been selected for development.<sup>12</sup>

More generally, local knowledge spillovers derive not just from knowledge production but also from knowledge transmission. Smaller firms are likely to have a distinct advantage over larger ones in this respect because they inherently have more outward-facing interactions, at a minimum for the supply chain reasons discussed above. In addition, a modular organization of production resulting in more, smaller firms is likely to encourage job hopping (Saxenian (1994); Fallick et al. (2006)). Mobile workers bring with them the human capital and ideas acquired at their previous employers.

Acquiring knowledge from others in the local ecosystem when a firm is in its infancy is of primary import in the well-known “nursery cities” model of Duranton and Puga (2001). In this model, young firms locate in expensive, congested, but diverse and idea-ridden cities to try out prototypes until they find their optimal production process, at which point they move to a cheaper, specialized city to mass produce (implicitly, at a larger size). Henderson (2002) provides consistent empirical evidence, using confidential U.S. Census Bureau data from the manufacturing sector to show that single plant firms both benefit more from and generate greater external benefits than do corporate plants because of their greater reliance on external environments. These effects are strongest in knowledge-based industries (high-tech) but disappear in machinery. Case studies support the importance of knowledge flows between entrepreneurs; Sorenson and Audia (2000) point to the footwear industry as an example in which entrepreneurs enter nearby other footwear manufacturers to feed their need for tacit knowledge, social ties, and self-confidence. The transmission of knowledge across firms is of course crucial for harvesting the positive externalities of idea production; without this component, Marshall’s “mysteries of the trade” remain mysteries. Indeed, large firms seem to have a tendency

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<sup>12</sup>Of course, spinoffs may also be one reason for local complementarities between small and large firms (Agrawal et al. (2014)).



to keep their “mysteries” close to their chests: Agrawal et al. (2010) show that there is a smaller overall impact and fewer knowledge spillovers from inventions in large firms because they’re mostly appropriated by the inventing firms themselves. This effect is especially true for large firms in company towns, where there are fewer surrounding small firms, perhaps because nearby small firms are typically those that learn of and build on large firms’ inventions.

A third theory of entrepreneurship effects on local growth is that measures of entrepreneurs are really picking up the ready availability of local human capital, which economists have long included directly in growth models. Substantial evidence suggests that entrepreneurs tend to be highly skilled.<sup>13</sup> Levine and Rubinstein (2017, 2018) show that entrepreneurs, measured by the incorporated self-employed, score higher on aptitude tests as youth, earn more per hour, and work more hours than their unincorporated self-employed and salaried counterparts. The relationship between skills and entrepreneurship holds both at the individual level and at the city level. Metro areas with higher levels of education have higher entrepreneurship rates, and more educated entrepreneurs locate in areas with higher human capital workforces (Acs and Armington (2004); Doms et al. (2010)).

It may be that more educated areas produce more entrepreneurs, but one would also expect entrepreneurs to be attracted to educated areas, since they would benefit from more educated workers. Evidence suggests that educated workers have better access to information (Wozniak (2010)), are better at implementing new ideas (Bartel and Lichtenberg (1987)), and adopt new technologies more quickly (Doms and Lewis (2006)). Concentrations of skilled workers can also lower search costs for specialized skills.

A positive relationship between education and entrepreneurial success would further drive the empirical correlation of skills with the presence of entrepreneurs, as the less skilled would systematically drop out of the pool of observed entrepreneurs. The same logic would apply at the city level if firms’ success were related to local education rates. As one might expect, the evidence supports this relationship as well. Fairlie and Robb (2008) show that businesses with more educated owners have higher sales and profits, are more likely to hire employees, and are more likely to survive. Doms et al. (2010) provide further support for this conclusion as well as suggestive evidence that

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<sup>13</sup>See VanDerSluis et al. (2008) for a review of the empirical literature on the relationship between education and entrepreneurship.

area education encourages success as well.

Overall, the strong relationship between skills and entrepreneurship presents the need to address the hypothesis that the entrepreneurship effect on city growth may actually be driven more by general skills than by entrepreneurial skills, per se. Previous empirical evidence on entrepreneurship persistence indicates that local human capital can't explain the relationship between initial entrepreneurship rates and subsequent entry (Glaeser et al. (2010)). Nevertheless, in section 4 I propose and conduct tests of the importance of human capital versus entrepreneurs along with those that examine entrepreneurs' roles as agents of entry and facilitators of knowledge spillovers.

## 4 Evidence on Mechanisms of the Entrepreneurship Effect

As discussed in the previous section, several theories have been proposed in the literature to explain how entrepreneurs may generate local growth. In particular, they may ease entry for other establishments and firms; they may facilitate knowledge spillovers in a locality; or they may simply represent the ready local availability of human capital, but not generate growth beyond what their high skill level would predict. This section presents evidence on these three hypotheses and discusses the special features of the data used in the process.

### 4.1 Do Entrepreneurs Ease Entry?

#### 4.1.1 Measurement using Longitudinal Links in the LBD

To investigate whether entrepreneurs generate growth through entry, I take advantage of the richness of the LBD and measure the extent to which the small firm growth effect comes from growth in incumbent establishments versus entrant establishments. The decadal city growth measure on the left-hand-side of the regressions presented in Tables 1- 4 reflects the underlying employment changes of establishments that existed in the city in year  $t-10$  as well as those of establishments that entered the city between  $t-10$  and  $t$  and still exist in year  $t$ . If most of the decadal growth from small, incorporated firms comes from growing incumbents, then the entrepreneur effect likely works through some mechanism that stimulates existing firms to become more productive. On the other hand, a growth effect driven mostly by growth from entrants would suggest that entrepreneurs may help their cities by encouraging entry.

I use the longitudinal establishment links of the LBD to categorize each establishment in city  $j$  and year  $t$  according to the year in which entered the city and the size of the firm to which it belonged in the year of entry or the base year ( $t-10$ ).<sup>14</sup> Entrants are those establishments that entered city  $j$  between  $t-10$  and  $t$ . Incumbent establishments, which were already located in city  $j$  in year  $t-10$ , are categorized according to their firm's size in  $t-10$ . I can thus decompose city growth in each decade into growth from incumbents and growth from entrants in total and within each firm size category. Doing so will allow me to understand not only which types of firms are *generating* growth – by the Bartik coefficients, as before – but now also which types of establishments are *growing*.

Note that in addition to informing us on the entry hypothesis, any cross-category effects in this analysis also support spillovers: employment gains in one category as a result of the presence of another. For instance, it may be that small, incorporated firms stimulate growth primarily in larger establishments through their market interactions. This kind of story is highly plausible in an innovative industry in which small firms generate and develop new ideas that they can pass on to larger ones to mass produce and market, or in which larger firms buy out small ones to integrate their ideas and expand market presence.

Formally, the decomposition of overall city growth into growth of each establishment type works as follows. City growth in each decade – from  $t - 10$  to  $t$  – is composed of employment changes from surviving incumbents, from dying incumbents, and from entrants. Categorizing incumbents according to their  $t - 10$  firm size, and categorizing entrants according to their year-of-entry firm size (they were not observed in  $t - 10$ ), one can formally decompose city growth into growth from establishments belonging to small, medium, and large firms:

$$(6) \quad \frac{\Delta emp_{jt}}{emp_{jt-10}} = \frac{\Delta emp_{jt}^S}{emp_{jt-10}} + \frac{\Delta emp_{jt}^M}{emp_{jt-10}} + \frac{\Delta emp_{jt}^L}{emp_{jt-10}}.$$

It is then possible to estimate a separate regression for each size group:

$$(7) \quad \frac{\Delta emp_{jt}^S}{emp_{jt-10}} = \beta^{SS} \Delta B_{jt}^S + \beta^{SM} \Delta B_{jt}^M + \beta^{SH} \Delta B_{jt}^L + \varepsilon_{jt},$$

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<sup>14</sup>Recall that establishment and firm size coincide for single-unit firms but not for multi-unit firms, and that approximately two-thirds of employer firms are single-units. I have conducted all of this analysis also where I categorize establishments instead according to *establishment* size. The results have the same substantive conclusion for entry.

$$(8) \quad \frac{\Delta emp_{jt}^M}{emp_{jt-10}} = \beta^{MS} \Delta B_{jt}^S + \beta^{MM} \Delta B_{jt}^M + \beta^{MH} \Delta B_{jt}^L + \varepsilon_{jt},$$

$$(9) \quad \frac{\Delta emp_{jt}^L}{emp_{jt-10}} = \beta^{LS} \Delta B_{jt}^S + \beta^{LM} \Delta B_{jt}^M + \beta^{LH} \Delta B_{jt}^L + \varepsilon_{jt}.$$

Note that the estimates from equations (7), (8), and (9) should sum to those from equation (4):

$$\begin{aligned} \beta^{SS} + \beta^{MS} + \beta^{LS} &= \beta^S, \\ \beta^{SM} + \beta^{MM} + \beta^{LM} &= \beta^M, \\ \beta^{SL} + \beta^{ML} + \beta^{LL} &= \beta^L. \end{aligned}$$

This decomposition gives an intuitive breakdown of the estimated effects. For example, a large  $\beta^{SS}$  would imply that establishments of small firms make up a large share of the growth response to a demand shock in cities with a high initial share of small firms.

As in section 2, all specifications include decade fixed effects to absorb national changes in employment growth and controls for lagged employment shares of each firm type group. Standard errors are clustered by MSA, as before. Because these controls are included, the coefficients on the small firm size Bartik shocks measure the differential growth effects of having the city's small firms in industries that are nationally growing more versus less quickly, holding constant the city's overall firm size distribution in the base period.

#### 4.1.2 Results: Entry Effects of Entrepreneurs

Table 5 presents the results of this decomposition. Panel A presents growth in all establishments, decomposed only into firm size categories. Panels B and C decompose growth in incumbents and entrants by firm size category. In each panel, coefficients are presented for firm-size cross incorporation status Bartiks, since small, incorporated firms were shown to have the largest impact on overall city growth of any firm-type group. In addition, the standard industry share Bartik coefficient is presented in each panel and column for comparison. Coefficients in columns 1-4 sum to the same-row coefficient in column 5, as is expected from the decomposition.

Panel A, column 5 reproduces the results from table 1, column 3, which show that small, incorporated firms have an outsized effect on overall city growth relative to large or unincorporated

firms and relative to the standard industry Bartik. This effect, 4.808% for a 1% predicted increase, comes mostly from establishments in the smallest and largest firm size categories, in which the coefficients are 1.313 and 1.768, respectively. Both of these coefficients are large relative to the standard industry share Bartiks for each category, 0.408 and 0.607, respectively. A similar decomposition by establishment size category indicates that, as one might expect, the growth from larger firm sizes shown in column 4 is actually coming from small establishments of large, multi-unit firms (table A1, panel A). Large, incorporated firms have positive and significant effects on growth in all categories, but these effects are an order of magnitude smaller in all cases than the small, incorporated firm effect, and they are also always smaller than the standard industry Bartik for the relevant group. Although small, unincorporated firms seem to generate some growth in the smallest firm size category, they generate only moderate growth in the middle two categories and such strong negative growth in the largest category that overall they have no positive effect on city growth. Large, unincorporated firms have negative effects on growth in all firm size categories.

Panel B, column 5, shows that none of the city growth effect comes from incumbents. The coefficient on the standard industry share Bartik is an insignificant  $-0.089$  (0.064), nor are any of the coefficients on the firm type Bartiks significant for overall incumbent growth.

Indeed, the entire city growth effect is driven by entrants, as can be seen in panel C, column 5. The coefficient on the standard industry share Bartik, 1.460, is of the same magnitude as that for overall city growth, 1.371. The same goes for the coefficients on the firm type Bartiks when predicting total entrant growth versus overall city growth. And, again, the small, incorporated firm Bartik has a coefficient that is 3.25 times the magnitude of that on the standard industry share Bartik and nearly 5 times the magnitude of that on the large, incorporated firm Bartik. The coefficients on the unincorporated firm Bartiks when predicting entrant growth are again zero and highly negative for small and large firms, respectively.

Of course, entry of establishments into a particular city reflects both new firm creation and expansion of existing firms. Both generate growth for the city and are thus important. While new firm creation may reflect local innovation, expansions create local presence for what are likely higher productivity firms, on average, as well as within-firm connections to other cities and the associated knowledge flows. But the type of entrants could provide clues as to the mechanisms by which entrepreneurs encourage entry. If entrant establishments are predominantly single-units,

then it may be that existing entrepreneurs create a sort of ecosystem with support services that make it easier for new entrepreneurs to enter. On the other hand, an entry effect driven largely by expansions of existing firms – which may be more likely to have their own internal services or existing lines of support – is more likely to be due to positive productivity spillovers from knowledge flows or labor pooling. Large firms expanding to a city may specifically be looking for small firms with new ideas to subsume for growth.

To understand the extent to which growth from entry comes from new firm creation versus multi-unit expansion, I further decompose entrant growth by these groupings and present the results in table 6. Columns 5 and 6 indicate very similar effects of small, incorporated firms, overall, on single-unit entry (2.694 (0.274)) versus multi-unit expansion (2.045 (0.294)), with slightly more multi-unit employment growth. When these effects are further decomposed by firm size, one can see that single-unit entry is the prominent form of entry among small firms, while multi-unit expansion dominates among larger firms, as one might expect (row 1 of columns 1-4). Although large, incorporated firms, generate a similar pattern of growth among single- and multi unit entrants of small versus large firms, they generate an order of magnitude less growth among single-unit entrants than do small, incorporated firms. Naturally, large firms would be less likely to create the ecosystem that would support entry of new small firms. In sum, it seems there is support for both mechanisms, discussed above, by which entrepreneurs may ease entry.

## **4.2 Do Entrepreneurs Facilitate Knowledge Spillovers?**

### **4.2.1 Complementarities between Entrepreneurs and Knowledge Spillovers**

One of the mechanisms by which entrepreneurs may generate growth comes from their relatively small size and their resulting interaction with other firms. Smaller firms, for instance, are more likely to need to buy inputs and services rather than making them themselves, and they may also be more likely to produce inputs used by other firms. If entrepreneurs are good producers of new ideas, other firms may want to locate nearby to learn from them, and larger firms in particular may be able to take these new ideas to a more advanced stage of development and mass production. Local areas that are more “open,” in the sense of having more inter-firm connections because of input-output relationships, joint R&D agreements, intellectual property transfer, and communication

systems infrastructure may especially benefit from the new ideas and outward-facing nature of entrepreneurs. Put differently, there may be complementarities between entrepreneurs and proxies for inter-firm interactions in generating local growth.

To test this possibility, I generate proxies for local openness based on firms' IT expenditures, networked internet use, and intellectual property transfer. I then test for growth complementarities between these proxies and entrepreneurs, measuring the latter both by average establishment size of incorporated firms and by the employment share in small, incorporated firms. This analysis is conducted at the zoomed-in level of the county, since IT use (Forman et al. (2012)) and other openness measures vary across county even within an MSA, and since spillovers are likely to operate at a localized level. Formally, I regress employment growth in county  $c$  from year  $t-10$  to  $t$  on  $OP_c$ , a county level measure of openness, the share of employment in small, incorporated firms, the share of employment in small, unincorporated firms, the interactions of each of these shares with the openness measure, and set of county level controls,  $X_{c,t-10}$ <sup>15</sup>:

$$\begin{aligned}
 \frac{\Delta emp_{ct}}{emp_{c,t-10}} &= \alpha_0 + \alpha_1(OP_c) + \alpha_2 \left( Empshr_{c,t-10}^{sm,inc} \right) + \alpha_3 \left( Empshr_{c,t-10}^{sm,uninc} \right) \\
 &+ \alpha_4(OP_c) * \left( Empshr_{c,t-10}^{sm,inc} \right) + \alpha_5(OP_c) * \left( Empshr_{c,t-10}^{sm,uninc} \right) \\
 (10) \quad &+ X_{c,t-10}\delta + \nu_{ct},
 \end{aligned}$$

where the employment share for group  $g$  is defined as

$$(11) \quad Empshr_{c,t-10}^g = \left( \frac{emp_{c,t-10}^g}{emp_{c,t-10}} \right)$$

and where entrepreneurs are alternatively measured by average establishment size and average incorporated establishment size. Because the openness measures come from surveys that are available only beginning in the 1990s and 2000s, I estimate this regression just for 2002-2012 county growth.

$\alpha_4$  is expected to be positive if entrepreneurs are complementary with local openness in generating growth, in contrast with  $\alpha_5$ , which is expected to be non-positive given the previous findings

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<sup>15</sup>The county level controls,  $X_{c,t-10}$ , include ex-ante income, education, fraction of the population in an engineering degree program, enrollees in a Carnegie 1 university, fraction of population in professional occupations, number of local patents produced in the 1980s, fraction of the population over age 65, fraction black, population density, net migration, home internet use, and several controls on commercial IT use from aggregated Harte Hanks data, including penetration of basic commercial internet, penetration of advanced commercial internet, and PCs per employee.

that small, unincorporated firms do not seem either theoretically or empirically to be Schumpeterian entrepreneurs.

#### **4.2.2 Measuring Knowledge Spillovers in LBD-Linked Surveys**

To measure openness of localities, I use several LBD-linked surveys on firms' IT investment, IT use, engagement in joint R&D projects, and intellectual property transfer.

IT investment and use are meant to reflect the potential connectedness of firms. Areas with greater IT investment may have lower costs of between-firm communications and supply chain relationships, which may facilitate spillovers. IT systems may particularly complement small firms, which are more likely to need to “buy” rather than “make,” and which may especially need cheaper sales mechanisms – such as e-selling – both to other businesses and direct to consumer to pick up market share (McElheran (2015)). The Census' Annual Survey of Manufactures (ASM) since 2006 contains establishment-level data on dollar amounts of total IT spending as well as IT spending in particular categories such as computers and data processing equipment, hardware, software, and purchased IT services for the manufacturing sector. One piece of evidence that already suggests the outward-facing nature of small firms is that their IT expenditures tend to be more heavily weighted towards purchased IT services, whereas that of large firms tends to tilt towards hardware and equipment. In fact, the flexibility of purchased IT services may increase the survival and growth of young and small firms who can now save on the enormous fixed costs of owned IT systems, and this effect is particularly strong in local areas with high concentrations of IT services (Jin and McElheran (2017)). I thus use county-level and county-firm size averages of IT spending in these different categories to proxy for the local infrastructure connecting firms.

An even more direct measure of communication infrastructure comes from the 1999 Computer and Network Use Supplement (CNUS) to the ASM. The CNUS contains information on actual computer network type (EDI, Internet, both), use of networks for conducting any of over 20 business processes (such as procurement, payroll, inventory, etc.), and whether the networks are used for internal versus external management of operations. I use broad categorizations of “any network use,” “internal network use,” and “external network use” to capture both the use of communication infrastructure, generally, and the use of this infrastructure for outward-facing interactions that could generate spillovers, specifically. The data exist in only one year, but that year is well-timed before



the decade over which I examine growth in this exercise, and the data cover the entire manufacturing sector, surveying approximately 50,000 plants with a response rate of 82%. I calculate county- and county-firm-size level measures of network use as a proxy for local openness.

In addition, I take advantage of the Census' Business Research and Development and Innovation Survey (BRDIS), which provides a high level of detail on firms' engagement in joint R&D projects, intellectual property production, and intellectual property transfer. The survey provides information on the R&D activity of approximately 45,000 firms per year, sampling with certainty those that were known to have engaged in R&D in the prior year and with some probability the rest, in a stratified sampling methodology. Among other things, the survey asks specifically about joint R&D agreements with other U.S. firms, with U.S. or foreign governments, U.S. or foreign universities, customers, vendors, and competitors. Relatedly, it asks about R&D that's outsourced to other firms or that the firm is conducting for others. An entire section of the survey covers intellectual property, technology transfer, and innovation. Although there are many rich measures in the data, I focus on those most aptly reflecting knowledge transfer, as opposed to knowledge production, for the purpose of proxying for local openness. Specifically, I generate an index of intellectual property transfer to reflect the extent of explicit knowledge flows in the county. The index includes answers to a series of nine questions on transfer or receipt of IP to/from others not owned by the company, transfer or receipt of IP to/as a spin-off, acquisition of a small or large financial interest in another company for IP, participation in cross-licensing agreements, and allowing free use of IP or making use of free IP. The richness of these questions provides an unprecedented opportunity to study the complementarities of local knowledge spillovers with entrepreneurs.

### **4.2.3 Results: Entrepreneurs and Knowledge Spillovers**

Table 7 presents results of county employment growth regressions, 2002-2012, when average total IT expenditures in the county are used as the measure of local openness. Column 1 shows a basic complementarity of openness with small firms: the interaction of average total IT spending and average establishment size is negative and significant on growth, indicating that counties with smaller establishments and more IT investment grow especially quickly. (The relevant main effects for all interactions in this table are of course included in all regressions.) Column 2 supports the evidence presented in section 2.5 that entrepreneurs are even better measured by the subset

of small firms that is incorporated. When average establishment size is measured separately for incorporated and unincorporated establishments, we see an even stronger negative effect on the interaction between IT investment and average incorporated establishment size, while we see no significant effect on the interaction with average unincorporated establishment size. Considering average IT investments in small firms in particular, there continues to be a complementarity with small incorporated establishments but not for small unincorporated establishments, which seem to exhibit the reverse effect (column 3).

This pattern holds, with even stronger effect size, when using the employment share in small (or small, incorporated) establishments as the measure of entrepreneurship rather than average establishment size. Column 5 shows the positive and significant interaction of IT investment with small establishment employment share, while column 6 shows the effect decomposed by incorporation status as well – positive and significant for the incorporated small establishment share, and not significant for the unincorporated establishment share interaction. The effect for the small, incorporated employment share interaction is more than 2.5 times as large when measuring specifically IT investment in local small firms rather than all local firms (column 7). And the significance of the effect disappears when using only IT spending in large firms. These results suggest a complementarity between small, incorporated firms and spending on the technological infrastructure that may connect them.

Table 8 focuses on a component of IT spending that is relatively more important for small firms. Entrepreneurs' IT spending tends to be more heavily weighted towards purchased IT services, which allow these capital-poor firms to take advantage of cloud services and networks while avoiding the high fixed costs of purchasing the hardware and equipment themselves (Jin and McElheran (2017)). In addition to being disproportionately important to the IT use of entrepreneurs, purchased IT services also themselves involve between-firm interactions in procurement. The pattern of results with this more specific measure of IT investment is similar to that in the previous table, with even stronger coefficients on all the small, incorporated establishment share interactions (columns 6-8). The complementarity between entrepreneurs and IT investments in generating growth is stronger for measures of IT investment that more specifically relate to entrepreneurs' usage.

In Table 9, I further hone in on between-firm connections, measuring openness of a local area by actual internet network use of firms, both in general and specifically for external information

sharing. I measure average network use separately among small and large firms in a county. Column 1 shows a positive and significant correlation between county growth and ex-ante average network use by small firms, while there is no significant correlation between growth and average network use by large firms. Column 6 shows the analogous result for network use specifically for external information sharing. Columns 2 and 7 indicate complementarities between small average establishment size for incorporated firms and network use, in general and for external communications, respectively. The same complementarities show up when using employment shares of small, incorporated firms to measure entrepreneurs (columns 4 and 9). Small, unincorporated firms do not exhibit this complementarity with network use, however (columns 2, 4, 7, and 9). Meanwhile, network use among large firms does not seem to follow this pattern, with insignificant small incorporated firm interactions in 3/4 cases and insignificant small unincorporated firm interactions in 4/4 cases (columns 3, 5, 8, and 10). These network use complementarities exist even while controlling for another important measure of local spillovers, which is the IP sharing index discussed in more depth with respect to the next table. The interpretation is that the entrepreneurship effect is larger in counties with more network use among small firms, even among counties that already have high levels of knowledge sharing.

Finally, in table 10, I investigate how the entrepreneurship growth effect varies across counties with more versus less intellectual property transfer across firms. As a reminder, the IP index used here reflects 9 survey questions on IP transfer and receipt across firms, including whether firms have made use of IP produced and made available for free by another firm, or vice versa. Column 1 shows the basic strong, positive correlation between this index and county growth: places with more IP sharing across firms grow more. This coefficient is supportive of knowledge spillovers as a source of growth-generating agglomeration economies. Column 2 adds an interaction term between the IP index and average establishment size, which has a strong negative correlation with growth and suggests that counties with more IP sharing grow especially quickly when firms are smaller. The same is true when entrepreneurs are measured by the share of employment in small establishments, as in column 4. The complementarity is stronger, again, when measuring entrepreneurs by the share of employment specifically in small, incorporated firms: column 5 shows a strong positive and significant coefficient on the interaction of the IP index and the small incorporated establishment share and a negative and significant coefficient on the interaction of the IP index and the small,

unincorporated establishment share. Growth complementarities are strongest where there is a high level of knowledge sharing *and* a high concentration of entrepreneurs, precisely measured.

Across a variety of measures of local openness, or proclivity towards spillovers – from investment in IT infrastructure, to network use, to IP sharing – these results provide consistent support for strong complementarities between entrepreneurs and openness in generating local growth. In each case, these complementarities seem strongest specifically for small, incorporated firms, which further lends credibility to using this group for the measurement of entrepreneurs.

### 4.3 Entrepreneurial Human Capital

Although the previous two sections presented evidence in support of two potential mechanisms through which entrepreneurs generate growth, either of these channels could theoretically be facilitated by high local concentrations of human capital. Skilled workers are an important factor drawing firms to cities, and they also are well-known to generate local spillovers both generally (Moretti (2004)) and specifically through their knowledge production (Jaffe et al. (1993)). Since entrepreneurs tend to be highly educated, one would want to be sure that the entrepreneurship effect measured here isn't just a human capital effect in disguise. This section presents two types of evidence to distinguish the role of entrepreneurs from that of local skills.

The first approach returns to regressions from section 2 and constructs a new set of decomposed Bartik shocks based on shares of firm counts in each firm-type category as opposed to shares of employment. The logic is that each entrepreneurial firm is really based on some new idea from a skilled individual – the more skilled workers in a city, the more “lottery tickets” that city will have, in a sense, for new business ideas which may or may not succeed. It may be that having a lot of lottery tickets – from having a highly skilled population – is what matters more than the employment density in entrepreneurial firms.

Table 11 presents results from these Bartik regressions over the three decadal changes from 1982 to 2012. Column 1 shows results from a regression of city employment growth on firm count Bartiks for small and large incorporated firms and small and large unincorporated firms, showing a somewhat different pattern than that in previous results. The incorporated firm Bartiks are still more important for growth overall, with strong positive effects, while the large unincorporated Bartik has an extremely large, negative, and significant effect. But when firm counts are used, the

large, incorporated group becomes twice as important as the small, incorporated group, reversing the previous result (column 1). When the count Bartiks are put head to head with the employment share Bartiks in column 3, however, the coefficients on the employment share Bartiks remain almost unchanged from their original values (reproduced in column 2). The small, incorporated count Bartik loses any significance, while the large count Bartik declines in magnitude by 1/3 and remains positive and significant.

I draw several conclusions from these results. First, the “lottery ticket” hypothesis that the small, incorporated firm effect is driven just by large numbers of ideas from skilled locals doesn’t hold any weight. It’s clear that these firms have to have succeeded at least enough to have significant employment share, which results from the development work of entrepreneurs as opposed to just the seed of the idea from human capital. Second, although having lots of a city-industry’s employment share in large, incorporated firms does not seem to advance growth much – perhaps because these firms then become dominant and preclude entrepreneurship – having some large, incorporated firms does seem to matter. Agrawal et al. (2014) suggests that local ecosystems are actually stronger when comprised of many small firms and at least one large lab, which both advances the development of some small firms’ ideas and spins off new small firms whose ideas are outside its scope. These results support that notion. Third, none of the alternative firm groupings or Bartik shock calculations has been able to wipe out the basic small, incorporated employment share Bartik effect. This group of firms both logically represents entrepreneurs and contributes importantly to local growth in a robust way across all specifications.

The second approach I take to distinguishing entrepreneurship effects from human capital effects is to measure which seems to be most complementary with the local “openness” or knowledge spillovers measures from the previous section. If my measures of entrepreneurs are actually just representing local human capital, then adding human capital interactions with openness should wipe out the importance of the entrepreneurship interaction terms (note that, of course, the main effects of local human capital were already included in all regressions shown in section 4.2).

Table 12 presents the results of these regressions for each measure of openness: IT investment, network use, and the index of intellectual property transfer. Human capital is measured by the county’s share of college graduates, and entrepreneurs are measured both by average incorporated establishment size and the employment share of small, incorporated establishments. The results are

quite consistent across specifications and measures. In each case, the interaction of BA share with the openness measure is either zero or negative, while the interaction of local entrepreneurship with the openness measure is of the predicted direction (negative for average establishment size, positive for employment share) and, if anything, becomes stronger. In none of the cases does the BA share interaction wipe out the entrepreneurship effect on growth. The result holds in columns 1 and 2 for the IP sharing index, in columns 3 and 4 for IT investment, and in columns 5 and 6 for internet network usage. This analysis provides strong support for the notion that my entrepreneurship measures reflect something distinct from local human capital, and that it is this entrepreneurship that seems to be complementary to local knowledge spillovers in generating growth.

## 5 Discussion

This paper provides new evidence on role of entrepreneurs in city growth. It presents a new fact that leads to a reinterpretation of the literatures both on labor demand shocks and on entrepreneurs, and it uses rich data to test between alternative explanations of this fact. A large body of research since Bartik (1991) has shown us that city growth responds to national industry shocks in proportion to the ex-ante shares of employment in shocked industries. Meanwhile, the literature on entrepreneurship has been robust in finding that entrepreneurs predict subsequent city growth, with some causal evidence that places with higher long-run levels of entrepreneurship grow faster (Glaeser et al. (1992, 2010); Rosenthal and Strange (2003, 2010); Glaeser et al. (2015)). This paper shows that a city's distribution of employment within industries across firm type is a critical determinant of the city's growth response to shocks, above and beyond the effect of the distribution of employment across industries. Entrepreneurs may predict city growth, as a wealth of research shows, precisely because they are key mediators of national growth shocks.

Although there is much debate over whether growth-generating entrepreneurs are best measured as small or young firms, this paper shows in several ways that these entrepreneurs are best measured as small, incorporated firms. This result builds on previous work by Levine and Rubinstein (2017, 2018) showing the importance of using incorporation in individual-level data to identify properly entrepreneurs from among the self-employed so that stylized facts on entrepreneurs from data match the theory. An important contribution of this paper is to show that distinguishing between

incorporated and unincorporated small firms leads to substantial improvement in the ability to identify the entrepreneurs that are instrumental in growth. This distinction can be used in future research on entrepreneurs in business-side data.

The paper demonstrates, in addition, that the entrepreneurs identified as small, incorporated firms, empirically fit several important theoretical features economists have thought entrepreneurs to exhibit. In particular, entrepreneurs seem to generate local externalities that encourage entry: nearly the entire city growth effect from entrepreneurs comes from entrants to the locality. This effect may occur because entrepreneurs engender an ecosystem filled with suppliers, support services, and other infrastructure that reduces entry costs. Entrepreneurs in theory are also credited with facilitating productive local knowledge flows because of their outward-facing nature. Small, incorporated firms are in practice shown here to be highly complementary to a variety of measures of local “openness” in generating growth, presumably taking advantage of lower-cost opportunities to interact with and learn from other firms. Greater local IT investments, internet network use, and intellectual property transfer may reduce these interaction costs and increase knowledge spillovers when entrepreneurs are present to leverage them. Furthermore, it does not appear that local human capital exhibits these complementarities, which lends confidence to the notion that the measured effect is really about entrepreneurs.

In addition to being useful to researchers looking for stronger local labor demand instruments or better measurement of entrepreneurs, the results presented here are relevant to policy makers interested in boosting local growth. This work suggests support efforts can be focused on incorporated small firms, rather than the long-term unincorporated that are unlikely to take much risk or bring new ideas to market. The local ecosystem is likely to matter, and infrastructure that reduces entry costs or improves connections between firms is likely to promote growth. Importantly, entrepreneurship seems to beget entrepreneurship, so planting a seed of a cluster under conditions of strong communication infrastructure and openness for knowledge transfer may well bear fruit. Worldwide, numerous programs have been implemented by local policy makers aiming to generate local industrial clusters, including starting accelerators, attracting venture capital, providing tax advantages to large firms, supporting local universities, and creating Innovation Districts and Enterprize and Empowerment Zones (Hochberg and Fehder (2015); Hochberg (2016); Chen et al. (2010); Greenstone et al. (2010); Hausman (2018); Neumark and Kolko (2010); Busso et al. (2013)).

These projects have met with mixed success – despite evidence from economists that many of these factors contribute to local growth – perhaps because of differences in the environmental contexts. My results suggest the importance of having numerous entrepreneurs present to capitalize on stimulative programs.

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Table 1: City Growth and Firm Size

	City Employment Growth			City Population Growth		
	1	2	3	4	5	6
Standard Industry Share Bartik	1.371*** (0.149)			0.948*** (0.097)		
Firm Size Bartik, 1-10 Emp		4.372*** (1.309)			5.304*** (0.805)	
Firm Size Bartik, 11-100 Emp		3.308*** (0.858)			0.879* (0.488)	
Firm Size Bartik, 101-1000 Emp		1.350*** (0.487)			0.730** (0.342)	
Firm Size Bartik, >1000 Emp		0.683*** (0.204)			0.718*** (0.123)	
Small, Inc. Firm Bartik			4.808*** (0.677)			3.042*** (0.424)
Large, Inc. Firm Bartik			0.862*** (0.169)			0.765*** (0.124)
Small, Uninc. Firm Bartik			1.024 (0.772)			0.504 (0.519)
Large, Uninc. Firm Bartik			-1.437*** (0.531)			-1.052*** (0.398)
Constant	0.274*** (0.012)	0.035 (0.067)	-0.312*** (0.114)	0.174*** (0.009)	0.186*** (0.047)	-0.076 (0.101)
Lagged Emp Share Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	951	951	951	951	951	951
R-squared	0.45	0.52	0.54	0.19	0.25	0.27
F eq. of coeffs		10.778	11.96		17.465	11.13
p-val eq. of coeffs		0.00	0.00		0.00	0.00

Note: Observations in the regressions are MSA-years for the 317 largest MSAs in the U.S. for the years 1992, 2002, and 2012 (thus covering the three decades from 1982-2012). Bartik shocks are calculated using decadal changes in employment and are de-meant to satisfy exogeneity conditions; their construction is detailed in section 2 of the text. Lagged employment share controls and year fixed effects are included in all specifications. Standard errors are clustered by MSA. Significance levels: \* 10% \*\* 5% \*\*\* 1%

Table 2: The Importance of Firm Size vs. Firm Age

	City Employment Growth				
	1	2	3	4	5
Firm Age Bartik, 0 Yrs	0.638 (1.191)	-0.661 (0.921)			
Firm Age Bartik, 1-5 Yrs	0.961 (1.237)	-0.6 (0.762)			
Firm Age Bartik, 6-10 Yrs	1.385*** (0.243)	0.236 (0.199)			
Firm Age Bartik, >10 Yrs	0.887*** (0.174)				
Firm Size Bartik, 1-10 Emp		5.837*** (1.302)			
Firm Size Bartik, 11-100 Emp		3.154*** (0.850)			
Firm Size Bartik, 101-1000 Emp		1.141** (0.473)			
Firm Size Bartik, >1000 Emp		0.709*** (0.201)			
Young, Inc. Firm Bartik			1.118 (1.039)		-0.677 (0.687)
Old, Inc. Firm Bartik			1.419*** (0.197)		
Young, Uninc. Firm Bartik			-1.376 (1.418)		-0.715 (0.863)
Old, Uninc. Firm Bartik			-0.378 (0.585)		
Small, Inc. Firm Bartik				4.808*** (0.677)	5.145*** (0.726)
Large, Inc. Firm Bartik				0.862*** (0.169)	0.980*** (0.165)
Small, Uninc. Firm Bartik				1.024 (0.772)	1.349 (0.905)
Large, Uninc. Firm Bartik				-1.437*** (0.531)	-1.161* (0.617)
Constant	-0.152** (0.068)	-0.192*** (0.071)	0.125 (0.139)	-0.312*** (0.114)	-0.349*** (0.138)
Lagged Emp Share Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	951	951	951	951	951
R-squared	0.49	0.54	0.48	0.54	0.54
F eq. of age barts	1.6	0.83	0.07	11.96	26.78
p-val eq. of age barts	0.19	0.48	0.79	0	0
F eq. of emp barts		13.85			
p-val eq. of emp barts		0			

Note: Observations in the regressions are MSA-years for the 317 largest MSAs in the U.S. for the years 1992, 2002, and 2012 (thus covering the three decades from 1982-2012). Bartik shocks are calculated using decadal changes in employment and are de-meanned to satisfy exogeneity conditions; their construction is detailed in section 2 of the text. Lagged employment share controls and year fixed effects are included in all specifications. Standard errors are clustered by MSA. Significance levels: \* 10% \*\* 5% \*\*\* 1%



Table 3: Do Entrants Predict City Growth?

	1	2
	City Emp Growth t-10 to t	City Wage Growth t-10 to t
MSA Emp Share Year t Entrant Estabs	-0.0000021* (0.0000011)	0.0000036** (0.0000017)
MSA Emp Share Years t-5 to t-1 Entrant Estabs	0.0000023*** (0.0000006)	-0.0000011 (0.0000007)
MSA Emp Share Years t-10 to t-6 Entrant Estabs	-0.0000024*** (0.0000005)	0.0000002 (0.0000006)
Year FE	Yes	Yes
Observations	951	951
R-squared	0.23	0.33

Note: Observations in the regressions are MSA-years for the 317 largest MSAs in the U.S. for the years 1992, 2002, and 2012 (thus covering the three decades from 1982-2012). Bartik shocks are calculated using decadal changes in employment and are de-meant to satisfy exogeneity conditions; their construction is detailed in section 2 of the text. Lagged employment share controls and year fixed effects are included in all specifications. Standard errors are clustered by MSA. Significance levels: \* 10% \*\* 5% \*\*\* 1%

Table 4: City Growth and Firm Size, Fixing 1982 Employment Shares

	City Employment Growth		City Population Growth	
	1	2	3	4
Standard Industry Share Bartik, 1982 shares	1.042*** (0.119)		0.655*** (0.081)	
Firm Size Bartik, 1982 shares, 1-10 Emp		4.844*** (1.324)		5.216*** (0.763)
Firm Size Bartik, 1982 shares, 11-100 Emp		3.165*** (0.877)		0.955** (0.461)
Firm Size Bartik, 1982 shares, 101-1000 Emp		1.298*** (0.474)		0.846** (0.335)
Firm Size Bartik, 1982 shares, >1000 Emp		0.600*** (0.200)		0.606*** (0.117)
Constant	0.292*** (0.014)	0.015 (0.055)	0.180*** (0.011)	0.095** (0.043)
Lagged Emp Share Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	951	951	951	951
R-squared	0.43	0.52	0.13	0.27
F eq. of coeffs		12.94		18.948
p-val eq. of coeffs		0		0

Note: Observations in the regressions are MSA-years for the 317 largest MSAs in the U.S. for the years 1992, 2002, and 2012 (thus covering the three decades from 1982-2012). Bartik shocks are calculated using decadal changes in employment but fixed 1982 firm size employment shares. They are de-meanned to satisfy exogeneity conditions; their construction is detailed in section 2 of the text. Lagged employment share controls and year fixed effects are included in all specifications. Standard errors are clustered by MSA. Significance levels: \* 10% \*\* 5% \*\*\* 1%

Table 5: Growth Decomposition by Firm Size Group and Incumbency Status

Panel A: Growth from All Establishments, by Firm Size Group

	Employment Growth				City Emp Growth <sub>5</sub>
	Size 1-10 <sub>1</sub>	Size 11-100 <sub>2</sub>	Size 101-1000 <sub>3</sub>	Size >1000 <sub>4</sub>	
Small, Inc. Firm Bartik	1.313*** (0.160)	1.062*** (0.203)	0.665*** (0.157)	1.768*** (0.312)	4.808*** (0.677)
Large, Inc. Firm Bartik	0.200*** (0.041)	0.099*** (0.036)	0.087*** (0.033)	0.476*** (0.099)	0.862*** (0.169)
Small, Uninc. Firm Bartik	1.136*** (0.223)	0.891*** (0.219)	0.535*** (0.186)	-1.537*** (0.464)	1.024 (0.772)
Large, Uninc. Firm Bartik	-0.278*** (0.102)	-0.149 (0.117)	-0.045 (0.127)	-0.965*** (0.352)	-1.437*** (0.531)
Standard Industry Share Bartik	0.408*** (0.040)	0.195*** (0.032)	0.161*** (0.029)	0.607*** (0.080)	1.371*** (0.149)

Panel B: Growth from Incumbent Establishments, by Firm Size Group

	Incumbent Emp Growth				Total Incumbent Emp Growth <sub>5</sub>
	Size 1-10 <sub>1</sub>	Size 11-100 <sub>2</sub>	Size 101-1000 <sub>3</sub>	Size >1000 <sub>4</sub>	
Small, Inc. Firm Bartik	-0.102* (0.058)	0.12 (0.117)	0.222** (0.105)	-0.171 (0.221)	0.068 (0.365)
Large, Inc. Firm Bartik	-0.008 (0.010)	-0.061*** (0.018)	-0.042* (0.023)	-0.033 (0.061)	-0.143* (0.075)
Small, Uninc. Firm Bartik	0.058 (0.073)	0.276** (0.124)	0.449*** (0.130)	-0.478 (0.297)	0.305 (0.402)
Large, Uninc. Firm Bartik	0.047 (0.048)	0.15 (0.096)	0.153* (0.086)	-0.119 (0.352)	0.232 (0.520)
Standard Industry Share Bartik	-0.101*** (0.016)	-0.155*** (0.025)	-0.007 (0.022)	0.175*** (0.061)	-0.089 (0.064)

Panel C: Growth from Entrant Establishments, by Firm Size Group

	Entrant Emp Growth				Total Entrant Emp Growth <sub>5</sub>
	Size 1-10 <sub>1</sub>	Size 11-100 <sub>2</sub>	Size 101-1000 <sub>3</sub>	Size >1000 <sub>4</sub>	
Small, Inc. Firm Bartik	1.415*** (0.152)	0.942*** (0.133)	0.443*** (0.127)	1.939*** (0.230)	4.739*** (0.498)
Large, Inc. Firm Bartik	0.208*** (0.043)	0.160*** (0.031)	0.129*** (0.032)	0.508*** (0.072)	1.005*** (0.142)
Small, Uninc. Firm Bartik	1.077*** (0.194)	0.615*** (0.161)	0.086 (0.140)	-1.059*** (0.365)	0.72 (0.587)
Large, Uninc. Firm Bartik	-0.325*** (0.122)	-0.300*** (0.081)	-0.198** (0.079)	-0.846*** (0.196)	-1.669*** (0.353)
Standard Industry Share Bartik	0.510*** (0.050)	0.350*** (0.033)	0.168*** (0.022)	0.432*** (0.058)	1.460*** (0.128)

Note: Observations in the regressions are MSA-years for the 317 largest MSAs in the U.S. for the years 1992, 2002, and 2012 (thus covering the three decades from 1982-2012). Bartik shocks are calculated using decadal changes in employment and are de-meanned to satisfy exogeneity conditions; their construction is detailed in section 2 of the text. The decomposition of city growth is described in section 4.1.1. Lagged employment share controls and year fixed effects are included in all specifications. Standard errors are clustered by MSA. Significance levels: \* 10% \*\* 5% \*\*\* 1%

Table 6: Growth Decomposition of Entrants by Firm Size Group and Number of Establishments per Firm

	Firm Size 1-10		Firm Size >1000		Total Multi-Unit Emp Growth 5	Total Single-Unit Emp Growth 6	Total Entrant Emp Growth 7
	Multi-Unit Entrant Growth 1	Single-Unit Entrant Growth 2	Multi-Unit Entrant Growth 3	Single-Unit Entrant Growth 4			
Small, Inc. Firm Bartik	0.089*** (0.023)	1.326*** (0.144)	1.886*** (0.206)	0.053 (0.094)	2.694*** (0.274)	2.045** (0.294)	4.739*** (0.498)
Large, Inc. Firm Bartik	0.032*** (0.007)	0.176*** (0.039)	0.489*** (0.068)	0.02 (0.022)	0.641*** (0.089)	0.364*** (0.074)	1.005*** (0.142)
Small, Uninc. Firm Bartik	0.147*** (0.043)	0.931*** (0.179)	-0.913*** (0.333)	-0.146 (0.162)	-0.392 (0.395)	1.111*** (0.311)	0.72 (0.587)
Large, Uninc. Firm Bartik	-0.018 (0.017)	-0.307*** (0.117)	-0.837*** (0.192)	-0.009 (0.036)	-1.108*** (0.232)	-0.561*** (0.178)	-1.669*** (0.353)
Constant	-0.002 (0.007)	-0.089*** (0.034)	0.073 (0.066)	0.012 (0.015)	0.096 (0.080)	-0.087 (0.055)	0.01 (0.115)
N	951	951	951	951	951	951	951
R-squared	0.21	0.72	0.41	0.01	0.54	0.67	0.65
F eq. of emp barts	1.03	2.51	41.83	0.76	35.01	3.48	22.53
p-val eq. of emp barts	0.31	0.11	0	0.38	0	0.06	0

Note: Observations in the regressions are MSA-years for the 317 largest MSAs in the U.S. for the years 1992, 2002, and 2012 (thus covering the three decades from 1982-2012). Bartik shocks are calculated using decadal changes in employment and are de-meanned to satisfy exogeneity conditions; their construction is detailed in section 2 of the text. The decomposition of city growth is described in section 4.1.1. Lagged employment share controls and year fixed effects are included in all specifications. Standard errors are clustered by MSA. Significance levels: \* 10% \*\* 5% \*\*\* 1%

Table 7: IT Investment and Entrepreneurs – All Expenditure Categories

	County Employment Growth							
	1	2	3	4	5	6	7	8
IT Spending	-0.034***							
× Avg. Establishment Size	(0.013)							
IT Spending		-0.042***						
× Avg. Incorp. Establishment Size		(0.014)						
IT Spending		0.002						
× Avg. Unincorp. Establishment Size		(0.003)						
Small Firm IT Spending			-0.038**					
× Avg. Incorp. Establishment Size			(0.017)					
Small Firm IT Spending			0.009**					
× Avg. Unincorp. Establishment Size			(0.005)					
Large Firm IT Spending				-0.035***				
× Avg. Incorp. Establishment Size				(0.012)				
Large Firm IT Spending				0.001				
× Avg. Unincorp. Establishment Size				(0.003)				
IT Spending					0.098**			
× Small Establishment Emp. Share					(0.040)			
IT Spending						0.105*		
× Small Incorp. Establishment Emp. Share						(0.060)		
IT Spending						0.086		
× Small Unincorp. Establishment Emp. Share						(0.084)		
Small Firm IT Spending							0.265***	
× Small Incorp. Establishment Emp. Share							(0.081)	
Small Firm IT Spending							-0.157*	
× Small Unincorp. Establishment Emp. Share							(0.089)	
Large Firm IT Spending								0.061
× Small Incorp. Establishment Emp. Share								(0.048)
Large Firm IT Spending								0.103
× Small Unincorp. Establishment Emp. Share								(0.071)
N	2,700	2,700	2,700	2,700	2,700	2,700	2,700	2,700
R-sq	0.1704	0.1723	0.1630	0.1700	0.1720	0.1723	0.1703	0.1709

Note: Observations in the regressions are counties, with growth measured over the decade 2002-2012 and firm size and employment shares measured in the base year, 2002. Data on IT expenditures by firm and spending category come from the Census' Annual Survey of Manufactures (ASM). All regressions include the main effects relevant for each interaction term, controls for penetration of basic commercial internet, advanced commercial internet, and PCs per employee (from Harte Hanks aggregates), a control for home internet penetration in the county, and ex-ante county-level demographics, including median per capital income and per capita income squared, BA share, HS share, fraction of population in an engineering degree program, enrollees in a Carnegie 1 university, fraction of population in professional occupations, number of local patents produced in the 1980s, fraction over age 65, population density, and net migration.

Table 8: IT Investment and Entrepreneurs – Purchased IT Services

	County Employment Growth							
	1	2	3	4	5	6	7	8
Purchased IT Exp.	-0.031**							
×Avg. Establishment Size	(0.013)							
Purchased IT Exp.		-0.034**						
×Avg. Incorp. Establishment Size		(0.016)						
Purchased IT Exp.		0.001						
×Avg. Unincorp. Establishment Size		(0.004)						
Small Firm Purchased IT Exp.			-0.049**					
×Avg. Incorp. Establishment Size			(0.021)					
Small Firm Purchased IT Exp.			0.001					
×Avg. Unincorp. Establishment Size			(0.008)					
Large Firm Purchased IT Exp.				-0.031**				
×Avg. Incorp. Establishment Size				(0.013)				
Large Firm Purchased IT Exp.				0.001				
×Avg. Unincorp. Establishment Size				(0.004)				
Purchased IT Exp.					0.085**			
×Small Establishment Emp. Share					(0.043)			
Purchased IT Exp.						0.142*		
×Small Incorp. Establishment Emp. Share						(0.075)		
Purchased IT Exp.						0.014		
×Small Unincorp. Establishment Emp. Share						(0.094)		
Small Firm Purchased IT Exp.							0.342***	
×Small Incorp. Establishment Emp. Share							(0.112)	
Small Firm Purchased IT Exp.							-0.254**	
×Small Unincorp. Establishment Emp. Share							(0.124)	
Large Firm Purchased IT Exp.								0.136**
×Small Incorp. Establishment Emp. Share								(0.065)
Large Firm Purchased IT Exp.								0.064
×Small Unincorp. Establishment Emp. Share								(0.080)
N	2,700	2700	2700	2700	2700	2700	2700	2700
R-sq	0.1636	0.1618	0.1608	0.1627	0.1664	0.1672	0.1681	0.1687

Note: Observations in the regressions are counties, with growth measured over the decade 2002-2012 and firm size and employment shares measured in the base year, 2002. Data on IT expenditures by firm and spending category come from the Census' Annual Survey of Manufactures (ASM). All regressions include the main effects relevant for each interaction term, controls for penetration of basic commercial internet, advanced commercial internet, and PCs per employee (from Harte Hanks aggregates), a control for home internet penetration in the county, and ex-ante county-level demographics, including median per capita income and per capita income squared, BA share, HS share, fraction of population in an engineering degree program, enrollees in a Carnegie 1 university, fraction of population in professional occupations, number of local patents produced in the 1980s, fraction over age 65, population density, and net migration.

Table 9: Networked Internet Adoption and Entrepreneurs

	County Employment Growth									
	Using Any Network					Using Internet for External Information Sharing				
	1	2	3	4	5	6	7	8	9	10
Fraction of Small Firms Using	0.021** (0.011)	0.149*** (0.048)		-0.066** (0.033)		0.025* (0.014)	0.147*** (0.049)		-0.084* (0.046)	
Fraction of Large Firms Using	-0.004 (0.021)		0.104 (0.075)		-0.046 (0.042)	-0.007 (0.013)		0.057 (0.073)		-0.060 (0.045)
Fraction of Small Firms Using × Avg. Incorp. Establishment Size		-0.123*** (0.040)					-0.093** (0.039)			
Fraction of Small Firms Using × Avg. Unincorp. Establishment Size		0.007 (0.018)					-0.023 (0.030)			
Fraction of Large Firms Using × Avg. Incorp. Establishment Size			-0.135* (0.074)					-0.079 (0.075)		
Fraction of Large Firms Using × Avg. Unincorp. Establishment Size			0.028* (0.016)					0.024 (0.020)		
Fraction of Small Firms Using × Small Incorp. Establishment Emp. Share				0.890*** (0.283)					0.886*** (0.315)	
Fraction of Small Firms Using × Small Unincorp. Establishment Emp. Share				-0.388 (0.261)					-0.163 (0.367)	
Fraction of Large Firms Using × Small Incorp. Establishment Emp. Share					0.047 (0.263)					0.057 (0.314)
Fraction of Large Firms Using × Small Unincorp. Establishment Emp. Share					0.349 (0.308)					0.563 (0.356)
Index of IP Sharing Across Firms	0.480*** (0.183)	0.424** (0.183)	0.442** (0.182)	0.336* (0.183)	0.356** (0.179)	0.480*** (0.183)	0.436*** (0.125)	0.430** (0.182)	0.336*** (0.126)	0.343* (0.180)
N	2,700	2,700	2,700	2,700	2,700	2,700	2,700	2,700	2,700	2,700
R-sq	0.1469	0.1740	0.1735	0.1794	0.1743	0.1472	0.1697	0.1681	0.1769	0.1746

Table 10: Intellectual Property Transfer, Knowledge Spillovers, and Entrepreneurs

	County Employment Growth				
	1	2	3	4	5
Index of IP Sharing Across Firms	0.523*** (0.184)	1.333*** (0.444)	1.441*** (0.468)	0.796*** (0.307)	0.507 (0.614)
IP Index × Avg. Establishment Size		-1.123*** (0.440)			
IP Index × Avg. Incorp. Establishment Size			-0.759* (0.449)		
IP Index × Avg. Unincorp. Establishment Size			-0.456* (0.272)		
IP Index × Small Establishment Emp. Share				1.227* (0.649)	
IP Index × Small Incorp. Establishment Emp. Share					1.971*** (0.561)
IP Index × Small Unincorp. Establishment Emp. Share					-0.678** (0.339)
N	2,700	2,700	2,700	2,700	2,700
R-sq	0.134	0.164	0.162	0.180	0.186

Note: Observations in the regressions are counties, with growth measured over the decade 2002-2012 and firm size and employment shares measured in the base year, 2002. Firm-level data on intellectual property transfer and sharing across firms come from the Census' Business Research and Development and Innovation Survey (BRDIS). All regressions include the main effects relevant for each interaction term, controls for penetration of basic commercial internet, advanced commercial internet, and PCs per employee (from Harte Hanks aggregates), a control for home internet penetration in the county, and ex-ante county-level demographics, including median per capita income and per capita income squared, BA share, HS share, fraction of population in an engineering degree program, enrollees in a Carnegie 1 university, fraction of population in professional occupations, number of local patents produced in the 1980s, fraction over age 65, population density, and net migration



Table 11: Entrepreneurial Capital and the Role of the Number of Small Firms

	City Employment Growth		
	1	2	3
Small, Inc. Firm Count Bartik	3.218*** (0.495)		-0.126 (0.664)
Large, Inc. Firm Count Bartik	6.127*** (0.994)		3.911*** (1.098)
Small, Uninc. Firm Count Bartik	2.781*** (0.512)		1.538** (0.724)
Large, Uninc. Firm Count Bartik	-14.254*** (3.904)		-6.072* (3.556)
Small, Inc. Firm Bartik		4.808*** (0.677)	3.643*** (1.035)
Large, Inc. Firm Bartik		0.862*** (0.169)	0.644*** (0.188)
Small, Uninc. Firm Bartik		1.024 (0.772)	-1.348 (1.479)
Large, Uninc. Firm Bartik		-1.437*** (0.531)	-1.206** (0.579)
N	951	951	951
R-squared	0.45	0.54	0.55
F eq. of age barts	5.96	11.96	9.27
p-val eq. of barts	0.02	0.00	0.00

Note: Observations in the regressions are MSA-years for the 317 largest MSAs in the U.S. for the years 1992, 2002, and 2012 (thus covering the three decades from 1982-2012). Bartik shocks are calculated using decadal changes in employment and are de-meanded to satisfy exogeneity conditions; their construction is detailed in section 2 of the text. Lagged employment share controls and year fixed effects are included in all specifications. Standard errors are clustered by MSA. Significance levels: 10% 5% 1%

Table 12: Human Capital versus Entrepreneurial Capital: Interaction with Local R&D, IT Investment, and IT use

	County Employment Growth					
	1	2	3	4	5	6
IP Sharing Index × BA Share	-7.674** (3.228)	-7.172** (2.939)				
IP Sharing Index × Avg. Incorp. Establishment Size	-1.096** (0.493)					
IP Sharing Index × Avg. Unincorp. Establishment Size	-0.353 (0.258)					
IP Sharing Index × Small Incorp. Emp. Share		2.090*** (0.511)				
IP Sharing Index × Small Unincorp. Emp. Share		-0.574 (0.355)				
IT Spending × BA Share			-0.230** (0.106)	-0.187 (0.114)		
IT Spending × Avg. Incorp. Establishment Size			-0.043*** (0.014)			
IT Spending × Avg. Unincorp. Establishment Size			0.003 (0.003)			
IT Spending × Small Incorp. Emp. Share				0.138** (0.065)		
IT Spending × Small Unincorp. Emp. Share				0.041 (0.081)		
Frac. Small Firms using Any Network × BA Share					0.006 (0.290)	-0.010 (0.296)
Frac. Small Firms using Any Network × Avg. Incorp. Establishment Size					-0.122*** (0.040)	
Frac. Small Firms using Any Network × Avg. Unincorp. Establishment Size					0.007 (0.018)	
Frac. Small Firms using Any Network × Small Incorp. Emp. Share						0.892*** (0.283)
Frac. Small Firms using Any Network × Small Unincorp. Emp. Share						-0.392 (0.266)
N	2,700	2,700	2,700	2,700	2,700	2,700
R-sq	0.165	0.188	0.178	0.176	0.174	0.179

Note: Observations in the regressions are counties, with growth measured over the decade 2002-2012 and firm size and employment shares measured in the base year, 2002. Data on IP sharing come from the BRDIS; data on IT expenditures come from the ASM; data on network use come from the CNUS. All regressions include main effects relevant for each interaction term, controls for penetration of basic commercial internet, advanced commercial internet, and PCs per employee (from Harte Hanks aggregates), a control for home internet penetration in the county, and ex-ante county-level demographics, including median per capita income and per capita income squared, BA share, HS share, fraction of population in an engineering degree program, enrollees in a Carnegie 1 university, fraction of population in professional occupations, number of local patents produced in 1980s, fraction over age 65, population density, and net migration.

# Appendix

Table A1: Growth Decomposition by Establishment Size Group and Incumbency Status

Panel A: Growth from All Establishments, by Firm Size Group

	Employment Growth				City Emp Growth 5
	Size 1-10 1	Size 11-100 2	Size 101-1000 3	Size >1000 4	
Small, Inc. Estab Bartik	1.376*** (0.143)	1.465*** (0.187)	0.818*** (0.146)	0.168 (0.174)	3.827*** (0.485)
Large, Inc. Estab Bartik	0.199*** (0.059)	0.150** (0.063)	0.173*** (0.058)	0.065 (0.077)	0.587*** (0.194)
Small, Uninc. Estab Bartik	0.763** (0.324)	0.031 (0.334)	-0.268 (0.226)	-0.838** (0.328)	-0.312 (0.767)
Large, Uninc. Estab Bartik	-0.352*** (0.124)	-0.427** (0.178)	0.037 (0.149)	-0.467 (0.348)	-1.208** (0.532)
Standard Industry Share Bartik	0.522*** (0.048)	0.362*** (0.049)	0.312*** (0.038)	0.175*** (0.058)	1.371*** (0.149)

Panel B: Growth from Incumbent Establishments, by Firm Size Group

	Incumbent Emp Growth				Total Incumbent Emp Growth 5
	Size 1-10 1	Size 11-100 2	Size 101-1000 3	Size >1000 4	
Small, Inc. Estab Bartik	-0.054 (0.050)	0.117 (0.111)	0.249** (0.098)	-0.339** (0.143)	-0.027 (0.267)
Large, Inc. Estab Bartik	0.005 (0.014)	-0.079*** (0.026)	-0.078* (0.045)	0.013 (0.073)	-0.139 (0.086)
Small, Uninc. Estab Bartik	-0.036 (0.078)	0.024 (0.176)	0.128 (0.167)	0.144 (0.261)	0.261 (0.388)
Large, Uninc. Estab Bartik	0.043 (0.061)	0.166 (0.138)	0.306*** (0.106)	-0.269 (0.340)	0.245 (0.522)
Standard Industry Share Bartik	-0.113*** (0.018)	-0.200*** (0.032)	0.085** (0.034)	0.140** (0.062)	-0.089 (0.064)

Panel C: Growth from Entrant Establishments, by Firm Size Group

	Entrant Emp Growth				Total Entrant Emp Growth 5
	Size 1-10 1	Size 11-100 2	Size 101-1000 3	Size >1000 4	
Small, Inc. Estab Bartik	1.430*** (0.134)	1.348*** (0.128)	0.569*** (0.119)	0.508*** (0.130)	3.854*** (0.341)
Large, Inc. Estab Bartik	0.194*** (0.061)	0.229*** (0.055)	0.251*** (0.049)	0.051 (0.056)	0.726*** (0.159)
Small, Uninc. Estab Bartik	0.799*** (0.301)	0.006 (0.244)	-0.396** (0.180)	-0.982*** (0.310)	-0.573 (0.601)
Large, Uninc. Estab Bartik	-0.394*** (0.133)	-0.593*** (0.159)	-0.269** (0.129)	-0.197** (0.098)	-1.453*** (0.335)
Standard Industry Share Bartik	0.636*** (0.060)	0.561*** (0.049)	0.227*** (0.030)	0.035 (0.038)	1.460*** (0.128)

Note: Observations in the regressions are MSA-years for the 317 largest MSAs in the U.S. for the years 1992, 2002, and 2012 (thus covering the three decades from 1982-2012). Bartik shocks are calculated using decadal changes in employment and are de-meant to satisfy exogeneity conditions; their construction is detailed in section 2 of the text. The decomposition of city growth is described in section 4.1.1. Lagged employment share controls and year fixed effects are included in all specifications. Standard errors are clustered by MSA. Significance levels: \* 10% \*\* 5% \*\*\* 1%