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Location determinants of high-growth firms

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ABSTRACT

County-level location patterns of *INC*5000 companies provide one map of American entrepreneurship and innovativeness, and understanding the local factors associated with these firms' emergence is important for stimulating regional economic growth and innovation. We draw on the knowledge spillover theory of entrepreneurship to motivate our regression model, and augment this theory with additional regional features that have been found to be important in the firm location literature. Zero-inflated negative binomial regressions indicate that these firms exist in counties with larger average establishment size, higher educational attainment and more natural amenities. Income growth, a mix of higher paying industries, and more banks per capita are associated with a smaller presence of these types of firms, all else equal. We conclude that the local conditions favouring high-growth firms are likely to be different from those favouring new firms in general, and that these conditions differ significantly in urban and rural areas and by industrial sectors.

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Firm location; firm revenues; high-growth firms; *INC*5000 firms; negative binomial regression

1. Introduction

Rapidly growing firms have attracted the attention of academics and policy-makers in the USA and elsewhere because they provide evidence of a region's competitiveness and dynamism, and because of their potential to contribute to economic growth and job creation. For example, a higher proportion of 'Gazelle firms' in the same industry was found to enhance subsequent industry growth in the Netherlands (Bos and Stam 2014). In cross-country data, high-growth potential entrepreneurship is found to have significant impact on economic growth (Wong, Ho, and Autio 2005). Also, high-growth firms are found to contribute disproportionately to employment growth (see the review in Coad et al. 2014). While some high-growth firms could eventually become large multinational corporations and move overseas or to other states from their original location, many will mature into stable medium-sized corporations that support local employment growth, and generate primary and secondary multipliers and spillovers to their local and regional economies (e.g. see Acs and Varga 2005). Indeed, the group of high-growth firms we consider here, the *INC*5000, is dominated by newer firms that are likely to still locate in their original location. We submit that a systematic

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identification and analysis of the factors influencing locations of these successful firms has the potential to increase our understanding of regional growth dynamics in the 'new global economic era'. This study fills a gap in the emerging literature on the factors that support the appearance of high-growth firms by studying such firms in the USA.[1]

While Bos and Stam (2014) focus on the number of workers to define Gazelles, they point (149–150) out that other relevant indicators of fast growth such as 'sales, assets, productivity, and profits' are also important. Firm revenue growth measures a firm's ability to sell more of its products to customers, and it reflects a basic capacity to innovate and create new opportunities by effectively deploying new and emerging technologies or management strategies. The annual *INC*5000 list compiled by *INC* Magazine is one of the only sources of data on the fastest-growing US private firms. Yet with the exception of state-level analyses by Wheeler (1990), Lyons (1995) and Motoyama and Danley (2012), this list has not been thoroughly analysed in scholarly research.[2]

The location of these 5,000 high-growth firms is a map of creative innovation in the USA, which permits an analysis of the local factors that affect firms' ability to expand their sales rapidly. It is a map showing that modern firms can establish themselves even outside of large cities, a phenomenon that is also being observed in other large economies, including India and Brazil (Sridhar and Wan 2010). Data aggregated to the county-level provide the advantage of allowing us to examine how local conditions, such as availability of labour or historical demand shocks, affect the presence of such firms. Also, at the county level, local policy-makers may be able to apply potential policy levers that affect the emergence of high-growth firms. Furthermore, using county-level aggregates allows us to separately study the subset of firms located outside of large metropolitan areas and develop novel insights into high economic growth that depends on regional assets other than local agglomeration economies.

The article is structured as follows. Section 2 describes the basic conceptual model for analysing high-growth firm locations or creation determinants. Section 3 describes *INC* Magazine's 5,000 fastest-growing firms and presents descriptive statistics showing where they are located, while Section 4 describes our empirical methods. Section 5 presents and discusses results while conclusions, policy relevance and theoretical implications are presented in Section 6.

Our major conclusions are twofold and somewhat contrary to common perceptions about high-growth industries. First, rapidly growing firms (as defined here) are found in many sectors, not just high-technology. Second, although a growing concentration of such firms is evident in urban areas over time, high-growth firms are also found in smaller and more rural counties. Our regression results further support the conclusion that other factors besides agglomeration are important including human capital, natural amenities and other socio-economic characteristics.

2. Literature and conceptual framework: the location of (high-growth) firms

Building on the seminal work of Weber (1929) a large literature has developed around the general economics and geography of new and existing industry location. Arauzo-Carod, Liviano-Solis, and Manjón-Antolín (2010) suggest that the three basic firm locational determinants (see 702–705) are: (1) *neoclassical factors* such as agglomeration economies, the quality of human capital and transportation infrastructure; (2) *institutional factors* such as taxes and regulations and (3) *behavioural factors* including locational preferences of entrepreneurs.[3] They also note in this exhaustive survey of empirical studies that these factors have largely remained unchanged since the 1980s.

The geography of *new* firm formation is likewise generally understood to be influenced by a variety of local or regional factors, many of which can differ from the location of existing firms (see, *inter alia*, Malecki 1993; Lyons 1995; Audretsch, Hülsbeck, and Lehmann 2012; Kolympiris and Kalaitzandonakes 2013; Lasch, Robert, and Le Roy 2013; García 2014; Goetz and Rupasingha 2014).[4] Factors that influence the location of new firms may be more important in our assessment of high-growth firms because as we show below, these firms appear to be relatively new. In particular, conditions at the home location of the original owner(s) can play a key role in the initial formation of firms, even though it is not certain how much local socio-economic conditions affect future success. We expect entrepreneurs to take advantage of emerging market niches in new economic sectors and to draw on their own innovation activities, where applicable.

Considering both (1) overall patterns of regional economic conditions and (2) changing local economic and accessibility conditions, Acs and Armington (2006) model new firm locations based on a knowledge spillover theory of entrepreneurship that is in turn derived from a knowledge production function.[5] Although this framework is geared toward new, innovation-based firms, their empirical application uses the same three basic locational determinants as identified by Arauzo-Carod, Liviano-Solis, and Manjón-Antolín (2010) for all firms. By following Acs and Armington (2006), we essentially use the same categories of explanatory variables, though an advantage to their formulation is that its relative flexibility allows us to empirically augment their model below. Their basic equation is:

$$E_{\text{srt}} = \gamma\left(\delta^{*}(K,\theta,C) - w\right)/\beta, \tag{1}$$

where E represents entrepreneurial choice (the decision to start a firm – see also Goetz and Rupasingha 2009), parameter γ translates the earnings differential between entrepreneurship (δ^{*}) and wage employment (w) into the decision to start a firm, K represents knowledge inputs or the 'aggregate stock of knowledge' (R&D from universities and industry), θ is the 'share of knowledge not exploited by incumbents' and C measures entrepreneurial climate or culture. Parameter β represents 'institutional and individual barriers to entrepreneurship' (Acs and Armington 2006, 58–59). The authors' primary expectations were that a higher earnings differential, a greater stock of knowledge (both in aggregate and not used by incumbents) and a more favourable climate in the economy is associated with higher levels of entrepreneurship. While the Acs-Armington model guides our empirical specification, we are especially interested in testing whether the predictions of the model hold in the context of our high-growth firms. Specifically, we are interested in testing whether the role of agglomeration and knowledge spillovers in the literature may have been overstated. With the strong emphasis on high-technology firm growth of the last decades, knowledge accumulation and spillovers (e.g. Jofre-Monseny, Marín-López, and Viladecans-Marsal 2011; Alañón-Pardo and Arauzo-Carod 2013) have captured the attention of academics and policy-makers seeking to stimulate local economic growth by replicating the conditions that exist in places like Silicon Valley. Yet, the fundamental premise of agglomeration and associated spillovers is not without detractors (e.g. Knoben, Ponds, and van Oort 2011). Citing Kirchhoff (1994), Bos and Stam (2014) caution (p.147) that '(radical) innovation and firm growth are not necessarily related … (and) firms may very well innovate without growing significantly, and, conversely, grow without implementing much innovation.' Supporting this argument, Brewin, Monchuk, and Partridge (2009) find that rural food processors tend to focus on process innovation rather than on radical product innovation. The question remains whether agglomeration and knowledge spillovers matter for all industries, and whether high growth can occur even in places with limited agglomeration potential such as rural America.[6]

Local economic conditions (including agglomeration effects) would be less important if the activity in question primarily produces goods and services for export from the local area. For example, for firms to grow rapidly, they will eventually need to discover external markets to sustain their growth. For exports to broader markets, modern communications technology and greater market access may allow firms to emerge in areas where they were unable to in the past.[7] Additionally, modern transport infrastructure (e.g. airports or railroads) and services (such as non-stop flights) also facilitate location of firms in regions beyond big cities (Bel and Fageda 2008). However, if information technologies are complements for face-to-face contact (Gaspar and Glaeser 1998; McCann 2007), then recent trends may support the formation of high-growth firms in urban settings. Such urban advantages have been accelerating since 1950 in terms of population movements (Partridge et al. 2008) and they are primarily due to agglomeration productivity benefits for firms rather than households (Partridge et al. 2010). Because households do not appear to be attracted to urban areas to the same degree as firms are, greater accessibility may allow outdoor amenities, for example, to become potentially important determinants of firm locations that firms need to attract key workers (McGranahan, Wojan, and Lambert 2010). The relative importance of the competing mechanisms described above will be different in urban vs. rural areas.

Building on the literature review, we expand the Acs and Armington model with additional regional features that also are hypothesized to influence firm location. Specifically, we consider natural amenities, the influence of government and local geographic characteristics including remoteness and accessibility. We also augment their notion of knowledge spillovers and institutional capacity to include social capital, which has been argued to be essential in promoting learning (or transmitting knowledge) within regions by supporting openness to new ideas, interactions and trust (Malecki 2012; McKeever, Anderson, and Jack 2014; Goetz and Han 2015). Detailed controls for the strength of the local or regional economies are used. Using the county as the unit of analysis allows us to separately study metropolitan counties and non-metropolitan counties in order to explore the different mechanisms, outlined in the previous paragraph, through which high-growth firms emerge.

3. The *INC*5000 firms and their distribution across the USA

We focus on one particular type of high-growth firm, which is *Inc.* Magazine's published list of the 5,000 fastest-growing firms (*INC*5000) in terms of revenue. In order to be included on the list, candidate firms have to be located in the USA, be privately owned and not be subsidiaries or divisions of other companies (*INC Magazine* 2010). Firms chose whether or not to be considered for inclusion on the list, by providing verifiable revenue data to the magazine.

To evaluate the representativeness of the *INC*5000 data, we compare it to the Dynamics of Employment Change Data (DECD) from the US Census. In terms of spatial representativeness, we find that the total number of *INC*5000 firms in each county is highly correlated with both DECD firm birth and firm growth, with univariate correlations close to 0.8 for both measures. In

Table 1. Number of counties with INC5000 firms.

	All counties	Metro counties	Non-metro counties
All firms 2007	763	576	187
All firms 2009	642	494	148
All firms 2012	568	447	121
Industry level *INC*5000 firms 2012			
Business product	193	178	15
Energy	64	61	3
Engineering	64	59	5
Food and beverage	82	71	11
Government service	87	78	9
Health	169	157	12
IT service	200	191	9
Manufacturing	151	126	25
Software	125	119	6

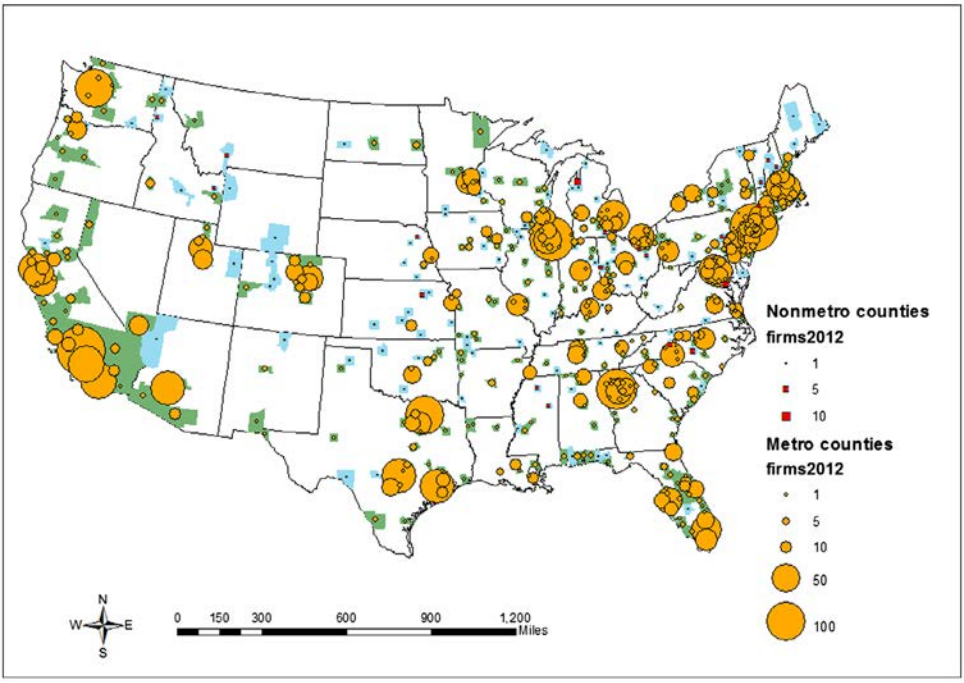

Figure 1. The distribution of INC5000 firms in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

terms of sectoral representativeness, the number of *INC*5000 firms in each two-digit industry is correlated (0.55) with firm birth and moderately correlated with firm growth (0.37).[8] As this is a study of firm locations, we suggest that spatial representativeness is more important than sectoral representativeness and that the *INC*5000 data are representative for our purposes.

It is important to note that we focus on revenue growth and not growth in employment or profits, for example. Indeed, various definitions have been used in the literature to define high-growth firms (e.g. Daunfeldt, Elert, and Johansson 2010). The advantage of using revenue as the growth metric is that it measures both expansion in the scale of operation and improvement in efficiency. Compared to the OECD definition which sets 20% revenue growth as the threshold for high-growth firms (Eurostat-OECD Manual on Business Demography 2007, 61, see Daunfeldt, Johansson, and Halvarsson 2015, for a cautionary note on this definition), 460 firms (9.2%) in the *INC*5000 data have lower revenue growth, with the lowest being 4.5%. As a sensitivity check, we also considered models that omitted these firms, but the results were virtually identical to our base results and we did not consider this sub-sample further.

Furthermore, the correlation between revenue and employment growth in our sample is 0.378, and it varies widely across industries, illustrating that other factors such as rapid productivity growth underlie high revenue growth. Kiviluoto (2013) is critical of the notion that sales growth reflects firm success and shows that relative growth of sales is not related to 14 other firm performance measures in the biotechnology and information technology industries. We conduct our analysis with these caveats in mind, though we note that Kiviluoto's analysis was based on a relatively small subset of fast-growing firms.[9]

The firms in our sample (for 2012, where we have the necessary detail) are mostly relatively young with an average age of 15 years (standard deviation of 15.4 years) and a range from 4 to 193 years (with 4 being the minimum to calculate revenue growth over 3 years). This compares with an average age of 25 years for the 'high impact' firms in Acs and Armington (2006) and illustrates the diversity of high-growth firms. The firms in our sample are slightly older than the Scottish firms studied by Mason and Brown (2013).

In general, the *INC*5000 firm location patterns are similar in 2007 (reflecting 2003–2006 revenue growth) and 2009 (2005–2008 revenue growth), and again in 2012, although some important changes appear across the five years.[10] For example, fewer firms were located in non-metropolitan counties and the sunshine states (CA and FL) while slightly more were found in the Washington DC area in 2009 compared to 2007. For California and Florida, these results may reflect the Great Recession and the housing bust that started at the end of 2007. By 2012, there were fewer *INC*5000 firms in non-metro areas compared to the earlier years. In fact, these firms have concentrated into fewer counties over time: from 763 in 2007 to 568 in 2012 (Table 1).

Firms are not only concentrating into fewer counties but non-metro counties are losing out more so than metro counties. Thus, since the Great Recession these firms are following more general population and labour concentration trends that also are occurring in the larger economy. Among the nine specific sectors for which we have data, manufacturing had the largest ratio of firms located in rural areas (19.8%), followed by food and beverage (15.5%) and government services (11.5%). IT services (4.7% rural), energy (4.9%) and software (5.0%) were the least likely to be found in rural areas. Hence, while rural areas may have some shortcomings in supporting rapidly growing firms, fast-growing firms, especially those in traditional sectors, are not precluded from locating or emerging in rural areas.

All 50 American states, the District of Columbia, and Puerto Rico are represented on the *INC*5000 list. Figure 1 shows the distribution of firms across the contiguous US counties and DC, while Appendix Figures A1–A9 show the maps by sector: Business Product, Energy, Engineering, Food and Beverage, Health, IT Services, Manufacturing and Software; we estimate separate regressions for the latter.

Table 2. Summary statistics and description of variables for 2012 regression.

Variable	Mean	Std. Dev	Definition	Source
Establish. size 08	12.1	4.3	Employment/establishments	CBP
IP index 08	24.1	9.1	Squared distance of local industrial employment shares from national shares.	CBP
Dropout 00	22.7	8.7	Pct. of adults (25+) with lower than high school education	Census
Bachelor 00	16.4	7.7	Pct. of adults (25+) with bachelor's degree or above	Census
Pop growth 05–08	1.7	4.5	Pct. of population growth	Census
PCI growth 05–08	18.7	10.6	Pct. of per capita personal income growth	BEA
Unemp 05	5.8	2.1	Unemployment rate	BEA
Population 08	98.7	311.6	2003 population (1000 persons)	BEA
Pop density 08	0.2	0.3	Thousand persons per square mile at CBSA level	Census
Proprietor 08	34.9	21.5	# of non-farm proprietors/Non-farm employment	BEA
Amenity	0.1	2.3	Amenity scale	USDA
Bank 08	0.5	0.3	# of commercial banks per 1000 persons	Census
Gov emp 08	0.8	2.4	Employment in public service (10,000 persons)	BEA
Pct urban 00	40.0	30.5	Pct. of population in urban area	Census
Pct urban^2	2527.0	2741.3	Pct urban squared	Census
Distance	37.3	37.0	Distance from county centroid to highway (km)	Authors
Ind mix 09–11	0.3	0.9	Industry mix growth rate	Authors
Ind mix 07–09	−3.0	2.5	Industry mix growth rate	Authors
Ind mix 00–07	5.8	4.3	Industry mix growth rate	Authors
Ind mix 90–00	14.2	5.3	Industry mix growth rate	Authors
Wage mix 08	1.1	0.2	Local wage mix	Authors
Social capital 09	0.0	1.3	Social capital score	RGF 2006*
Tax score 08	6.6	0.7	Tax score	Free-the-world.com
Market score 08	7.1	0.7	Market score	
Firms 09	1.6	8.6	# of *INC5000* firms in 2009	INC.com
BEA_#			BEA regional dummies NELD for New England; MEST for Mid-East; GLAK for Great_Lakes; PLNS for Planes; SEST for South-Est; SWST for South-West; RKMT for Rocky-Mountains	BEA

*Rupasingha, Goetz, and Freshwater (2006).

4. Empirical methods and data

While studying firm location at the firm-level (using discrete choice models, DCM) has the obvious advantage of being able to include firm characteristics, regional-level studies (using count data models, CDM) are also popular for data availability and empirical tractability. Because our data-set contains limited information about firm characteristics, and a large choice set of over 3,000 US counties, the cost of using DCMs outweighs the benefit and we therefore choose a CDM. As Guimarães, Figueirdo, and Woodward (2003), Guimaraes, Figueiredo, and Woodward (2004) note, if expected profit for firm j locating in county or region c (π_{cj}) is a random variable representing a linear combination of elements that are both stochastic and deterministic, a conditional logit model can be used to capture the likelihood of firm j choosing county c for its location. In this case, the conditional logit model can be estimated using a Poisson regression, which demonstrates the close relationship between the DCM and CDM.

When a CDM is used, the current state of the art in the firm location literature favours the hurdle negative binomial (HNB) model, with the zero-inflated negative binomial (ZINB) as a close second (Liviano and Arauzo-Carod 2013; Buczkowska and de Lapparent 2014). Both models accommodate over-dispersed data and allow excess zero observations to be determined by variables other than those determining the non-zero observations. The difference is that in HNB, all zeros are generated from the first (hurdle) stage while in ZINB, only some of the zeros are generated from the first (inflation) stage. As the cutoff point for high-growth firms in our data-set is artificial, it is not appropriate to model zeros as generated from a completely different process (if we just raise the bar for 'high-growth firms', some positive observations will become zeros). Therefore, we choose conceptual consistency over statistical goodness of fit and the ZINB over a HNB (see Bhat, Paleti, and Singh 2014, for new developments in modelling firms counts beyond HNB and ZINB models).

In the ZINB model, the distribution function for the number of *INC*5000 firms INC_{cj} is:

$$INC_{cj} \sim (1-\pi)^{*} \, f(INC_{cj}|AA, \boldsymbol{LF}, \boldsymbol{\beta}, r, p) + \pi^{*} I_{\pi}(\boldsymbol{IF}, \boldsymbol{\alpha}) \tag{2}$$

Here π is an indicator variable, I_{π} is the probability that $\pi = 0$, f (·) is the negative binomial distribution function, ***AA*** is the set of Acs and Armington entrepreneurial formation variables, ***LF*** includes amenities, government influence and geographic characteristics, $\boldsymbol{\beta}$ is a vector containing the parameters to estimated, and *r* and *p* are distribution parameters. Vector ***IF*** represents regressors in the inflation stage. A key regressor in the 2012 model is the number of *INC* firms in 2009, which captures the critical path dependence effects identified in Minniti (2004, 2005) and subsequently confirmed in work such as Chang, Chrisman, and Kellermanns (2011). Coefficients in the inflation stage are represented by vector $\boldsymbol{\alpha}$. Equation (2) is estimated for three samples: all US counties, metropolitan area counties and non-metropolitan counties, the latter defined as counties with code 3 or higher in the US Department of Agriculture Economic Research Service rural–urban continuum code.[11]

The specific independent variables included in the regression analysis are listed in Table 2, along with their definitions, summary statistics and sources. We use appropriate time lags, as necessary to mitigate endogeneity concerns. Because the *INC*5000 firm designation is based on revenue growth in the three preceding years (not counting the current year), we measure the independent variable four years earlier, unless data availability forces us to do otherwise. For some variables, such as the demand shocks described next, we use even longer lags. Specialization is measured by the Index of Inequality in Productive Structure (IP), which is commonly used (Palan 2010) in these types of studies. It is calculated as the squared distance of local two-digit industry employment shares from national shares. Population density, which is our measure of agglomeration economies, is constructed as the population density of the entire metropolitan area or micropolitan area for urban areas (which can be multiple counties) and as the county population density for non-metropolitan counties outside of micropolitan areas. The use of metropolitan and micropolitan area population density corresponds to the notion that these areas are defined as being economically integrated and thus firms may take advantage of the broader region's agglomeration effects. Conversely, non-metropolitan counties are by definition not economically linked to metropolitan areas, and thus we use their own population density to measure their agglomeration economies.

Another variable requiring further explanation is that of social capital, measured at the county-level. We use the index developed by Rupasingha, Goetz, and Freshwater (2006),[12] which reflects the local presence of social capital-generating establishments such as bowling alleys as well as civic organizations along with participation by local residents in elections as well as the decennial Census.

Local economic demand shocks vary over time and can produce divergent growth responses given that counties have diverse industry compositions that are differentially exposed to national or international shocks. We describe these processes here in more detail, because these variables have not previously been used in firm location studies such as this; instead they are conventionally used in regional growth models. Counties with 'favourable' industry compositions that experience positive demand shocks will grow faster than other counties, all else equal. If these local demand shocks are correlated with both the formation of *INC*5000 firms and other explanatory variables, then omitting local demand shocks would bias the results.

To account for differential demand shocks occurring in each county, we control for the widely used industry mix growth rate introduced to regression analysis by Bartik (1991); see also Malecki (1993, 126*ff*). The industry mix employment growth rate for a county '*c*' in period [*t*, *t* + *n*] is defined as:

$$INDMIX\_GR_{c,\,t,\,t+n} = \sum_i S_{ic^t} * [EMP\_GR]_{i,\,USA^{t,\,t+n}} \tag{3}$$

where $S_{ic}{}^{t}$ is the county employment share in (four-digit NAICS) industry *i* in the initial year *t* and $[EMP\_GR]_{i,\,USA^{t,\,t+n}}$ is the growth rate in industry *i* for the US in the period [*t*, *t* + *n*]. Our source for the four-digit data is the EMSI consulting firm.[13]

The resulting industry mix growth rate reflects the hypothetical employment growth rate if all of the county's industries were growing at the national average over the period. Changes in *national industry* demand are exogenous shifters, which is why the industry mix variable has commonly been used in the local labour market literature as an exogenous instrument for identifying local employment growth.[14] Including the industry mix growth rate in the model therefore removes a major source of omitted variables, while not introducing endogeneity.

Because the formation of *INC* firms may relate to local economic conditions that existed long in the past during the founding of the firm, as well as to very recent conditions that push the firm over the top in terms of revenue growth, we control for industry mix employment growth for the 1990–2000 and 2000–2007 periods. Depending on the model, we also control for 2007–2009 and 2009–2011 industry mix employment growth, allowing us to account for different (exogenous) effects both during and after the regression.

Finally, to capture the local wage structure, we control for the local wage mix. This mix is the sum across all four-digit industries of the product of the national average wage for that industry times the county's employment share in that industry. The wage mix represents the hypothetical average wage in the county if all of the county's industries paid the national average wage in each industry. Wage mix measures whether the county has a high- or low-paying composition of industries and accounts for the possibility that high wage structures may prevent *INC*5000 firms from emerging, or alternatively, high wage structures may support local demand for their product. Again, because it uses national wages, which are exogenous to the county, the wage mix variable should be exogenous, especially compared to the alternative of directly controlling for wages, which would likely cause endogeneity problems.

We consider the entire sample of counties but also examine metropolitan and non-metropolitan county subsamples to assess whether there are differences. We expect differences foremost because firms located in metropolitan areas have more access to agglomeration economies such as closer access to suppliers and customers, thicker labour markets and knowledge spillovers (Puga 2010). Such effects manifest themselves in many dimensions such as non-metropolitan (rural) areas having lower levels of educational attainment, a firm composition that favours the primary sectors, higher rural transportation and communication costs. However, these rural disadvantages, depending on the firm or the sector, are offset by lower input costs and possibly a greater abundance of natural amenities (or at least access to natural amenities).

Table 2 presents descriptive statistics of the variables used in the national model (all US counties and all industries). The 2012 data were provided by *INC* Magazine but did not include county FIPS codes.[15] We therefore matched the addresses of the ranked firms with their county locations. One concern with the *INC*5000 data is that the zip code identified as the location for the firm may represent the headquarters location or 'be little more than a post office box' (Lyons 1995, 391). However, to the extent that these companies are relatively small and working in the early stages of expansion (compared to established large companies), we argue that the probability of these firms being located in different counties is relatively small, or at least that the county location represents the place where the 'idea started' to create each firm.[16]

Data for other explanatory variables were obtained from the US Counties Database from US census.[17] To estimate the models, these variables were lagged in time to capture earlier socio-economic conditions so as to reduce potential endogeneity biases. While we are careful to lag the variables, we do not expect large feedback effects to bias these results because it would be difficult for the performance of one (usually small) firm to influence the demographic composition or other socio-economic conditions at the aggregated county level. The geographic variable distance (-to-interstate) was calculated using ArcGIS 9.3. The county shape files were obtained from the US Census Bureau Maps and Cartographic Resources[18] and the highway system shape files were retrieved from the Berkeley/UPenn Urban and Environmental Modeler's Datakit webpage.[19]

5. Results and discussions

Table 3 presents regression results for location determinants of the *INC*5000 firms in 2012 for all continental US counties, and the metro counties and non-metro subsamples.[20] Results for nine specific sectors are presented in Appendix Tables A1a–A1c. We include (BEA) regional fixed effects and report results of the first-stage regression (the probability of any *INC*5000 firm locating in a county) at the bottom of the table, along with estimated parameter ln α in those cases where its inclusion is warranted by a likelihood ratio test.

5.1. Benchmark regressions (all and metro/non-metro counties)

The parameter *ln*alpha differed statistically from zero in likelihood ratio tests in both the national ($n = 3,031$ counties) and metro-only (n=1,062 counties) regressions, with values of $\alpha = 0.765$ and 0.761, respectively.[21] Based on these tests, we report ZINB models for all and metro counties, and the zero inflated Poisson model for the non-metro counties.

The average *establishment size* variable is positive and statistically significant for all counties as well as for the metro subset. This indicates that counties with larger existing firms on average are more likely also to host *INC* firms, which is contrary to the Acs and Armington (2006) finding that county economies with more large firms spawn fewer new entrepreneurial ventures. The presence of large firms could be favourable to *INC* firms by providing potential space for joint ventures, clustering and commercial transactions (large firms may be

Table 3. Benchmark regression and sensitivity results for 2012.

Sample	All	Metro	Non-metro		All	Metro	Non-metro
Model	ZINB	ZINB	ZIP		Continued	Continued	Continued
Est size 08	0.147***	0.175***	0.0651	Wage mix 08	−2.044***	−1.988***	−1.429*
	(0.0188)	(0.0216)	(0.0452)		(0.428)	(0.509)	(0.791)
IP index 08	−12.94***	−14.53***	−8.739**	Tax score 08	0.00541	0.0703	−0.250
	(2.039)	(2.532)	(3.563)		(0.0814)	(0.0927)	(0.172)
Dropout 00	−0.051***	−0.051***	−0.0172	Market score 08	−0.0595	−0.112	−0.282
	(0.0127)	(0.0149)	(0.0302)		(0.113)	(0.126)	(0.234)
Bachelor 00	0.0610***	0.0600***	0.0620***	BEA_NELD	0.504*	0.372	1.364*
	(0.00848)	(0.00964)	(0.0217)		(0.272)	(0.297)	(0.776)
Pop growth 05–08	0.00835	0.00218	0.0752*	BEA_MEST	0.644**	0.682**	0.984
	(0.0123)	(0.0136)	(0.0394)		(0.272)	(0.303)	(0.790)
PCI growth 05–08	−0.0180*	−0.0237**	−0.00672	BEA_GLAK	0.532*	0.489	1.363*
	(0.00964)	(0.0117)	(0.0158)		(0.290)	(0.324)	(0.770)
Unemp 08	0.0558	0.0605	0.0310	BEA_PLNS	0.735**	0.698**	1.233
	(0.0376)	(0.0429)	(0.0803)		(0.300)	(0.330)	(0.780)
Pop density 08	0.270**	0.309***	4.739**	BEA_SEST	0.659**	0.756***	0.769
	(0.105)	(0.111)	(2.327)		(0.259)	(0.285)	(0.797)
Social capital 09	−0.442***	−0.366***	−0.353**	BEA_SWST	0.619**	0.763***	0.458
	(0.0832)	(0.101)	(0.150)		(0.252)	(0.283)	(0.755)
Proprietor 08	0.00627	0.0105*	−0.0123	BEA_RKMT	0.304	0.483*	0.218
	(0.00470)	(0.00551)	(0.0110)		(0.248)	(0.285)	(0.723)
Amenity	0.0732**	0.0791**	0.110	Constant	−1.383	−1.827	0.645
	(0.0297)	(0.0330)	(0.0716)		(1.111)	(1.300)	(2.292)
Bank 08	−1.671***	−2.987***	2.011**	*Inflation stage*			
	(0.561)	(0.693)	(0.897)	Bachelor 00	−0.0519**	−0.0921**	−0.0453*
Gov emp 08	0.0981***	0.0882***	0.361		(0.0213)	(0.0411)	(0.0241)
	(0.0139)	(0.0134)	(0.426)	Bank 08	−2.736**	−3.367**	1.966*
Distance	0.00205	0.00269	0.00353		(1.289)	(1.702)	(1.159)
	(0.00213)	(0.00305)	(0.00260)	Firms 09	−5.364	−3.479**	−17.64
Ind mix 09–11	0.238**	0.305**	0.210		(7.503)	(1.372)	(753.1)
	(0.116)	(0.143)	(0.223)	Population 08	−0.0111**	−0.000129	−0.00767
Ind mix 07–09	−0.0915*	−0.121**	−0.0185		(0.00554)	(0.00123)	(0.00703)
	(0.0499)	(0.0589)	(0.0938)	Pct urban 00	0.000318	−0.0177*	0.000515
Ind mix 00–07	0.0365	0.0682**	−0.0147		(0.00771)	(0.00911)	(0.00881)
	(0.0244)	(0.0298)	(0.0459)	Constant	3.543***	4.480***	1.568*
Ind mix 90–00	0.0341**	0.0300*	−0.00605		(0.684)	(1.104)	(0.869)
	(0.0147)	(0.0169)	(0.0304)	ln α	−0.352***	−0.409***	
					(0.0926)	(0.0950)	
				Observations	3.031	1.062	1.969

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

customers), and for attracting labour to the area. They could also be the source from which new firms are spun out (Dahlstrand 1997). Having larger firms also matters for spawning engineering and IT services (see below), which provide inputs and markets for *INC* 5000 companies within a county. In non-metro counties, in contrast, the effect of existing establishment size is not statistically different from zero.

The coefficient on the *specialization* variable (the IP index) is statistically different from zero in all three models, and negative.[22] Also contrary to what is expected based on Acs and Armington (2006), albeit using a different measure of specialization, this indicates that more specialization of existing firms within industries is associated with fewer rather than more *INC*5000 firms. Alternatively, counties with a relatively more diversified industrial base are more likely to host such high-growth firms.

The educational attainment variables, significant in all county types except non-metro for dropouts, have the expected signs: higher *dropout* rates from school are associated with fewer *INC*5000 firm locations (all counties and metros only), while the *per cent of population with bachelor degrees* significantly and statistically increases the number of *INC* firms across all geographies. This attests to the importance of formal educational attainment of the local workforce to entrepreneurial activity (see Audretsch, Hülsbeck, and Lehmann 2012) and regional growth in general (Simon and Nardinelli 2002), and to the extent that the workforce is drawn from the local population it represents a local return on investment in public education.

Of the other variables, lagged (2005–2008) *population growth* has no significant correlation with *INC*5000 firm presence except in the case of non-metro areas. The lagged (2005–2008) per capita *income growth* variable on the other hand has statistically significant and negative effects in all and in metro counties, consistent with the Acs and Armington model, which suggests that higher wage rates reduce the incentive for entrepreneurial initiatives Also, higher wage rates could cause difficulties for firms by raising labour costs.

The coefficient estimate for the *unemployment rate* variable is not statistically significant, suggesting that the formation and growth of *INC* firms is not necessarily triggered by a lack of jobs in particular counties. Entrepreneurship of *necessity*, which is consistent with Acs and Armington, is not typically perceived or found to be associated with successful firms (Figuero-Armijos, Dabson, and Johnson 2012), and our results reinforce these perceptions and finds.[23]

Population density has a positive and statistically significant effect in all of the county types, including in non-metropolitan counties.[24] This result not only underscores the significance of agglomeration economies, other factors held constant, but also suggests that these economies operate at the broader regional metropolitan and micropolitan area level rather than the county-level in urban settings. In fact, in unreported sensitivity analyses, when we measured density at the county level in urban settings, the resulting population density coefficient estimate was not statistically different from zero.

Kwon, Heflin, and Ruef (2013) as well as anecdotal evidence and popular belief suggest that communities with more social capital also spawn more entrepreneurial ventures, but our results do not bear this out. In fact, higher social capital stocks are associated with fewer *INC*5000 locations in 2012, and this effect is statistically significant. A sensitivity analysis reveals that the interaction between social capital and population density in all and in non-metro areas is positive and statistically significant.[25] Thus in the non-metro regions density contributes to the presence of high-growth firms by reinforcing positive effects of social capital positive. This dynamic is worth further exploration by rural researchers interested in understanding how to foster local entrepreneurship through social networks, for example.

Related to social capital is the idea that self-employed business owners more likely support other local businesses and also comprise a pool of firms from which *INC*5000 firms may emerge, but this is not supported by our initial results as the self-employment share of total employment is statistically insignificant, except in the case of metro areas.[26] At the same time, the natural *amenity* scale variable suggests the considerable importance of favourable geographic conditions in explaining the presence of *INC*5000 firms. This is the case across all counties and metro counties, as a group, but perhaps surprisingly not for non-metro counties. Yet, the non-metropolitan findings are consistent with Dorfman, Partridge, and Galloway's (2011) result that natural amenities are unrelated to the high-technology share of a non-metropolitan county workforce.

Another variable that is consistently significant across these models and, unexpectedly negative for all counties and metro counties, is the *number of commercial banks* per county. Counties with more banks are *less* likely to contain *INC*5000 firms as the local financial structure becomes more competitive and, conceivably, more sensitive to and supportive of firm creation and expansion. On the other hand, access to capital via commercial bank outlets does positively predict the presence of *INC* firms in the inflation stage regression and they are important in non-metro counties in the ZIP (zero inflation Poisson) model. One explanation is that *INC*5000 firms have more capital options other than just commercial banks in metropolitan areas, whereas banks are paramount as a source of their capital financing in rural areas. These findings across the different county types are generally consistent with results for US self-employment growth reported in Goetz and Rupasingha (2014), but at odds with those in Lee (2014), who finds for the UK that access to finance is a concern for firms.

Greater employment in government is associated with the presence of more rather than fewer *INC*5000 firms in all counties as well as in metro counties. Estrin, Korosteleva, and Mickiewicz (2013) find at the level of countries that a large public sector is important for enforcing property rights but that smaller government is more conducive to entrepreneurial firm formation. Thus, rather than crowding out the formation of fast-growing private firms, in our case a larger public sector presence may support it. One possibility may be that greater outsourcing of government functions provides more opportunities for private firms. This possibility is supported by the fact that the largest concentration of any one *INC*5000 sector is found in the Washington, DC area: government services. Results for the *distance* variable suggest that county accessibility measured from the county centroid to the nearest interstate highway is not a critical factor when predicting the numbers of the *INC* firms.

The industry mix employment growth variables suggest that metro and all counties with a concentration of industries between 1990 and 2000 that favoured job growth is positively associated with having more *INC*5000 firms, pointing to some possible persistence in economic conditions in the original founding of these firms and their eventual inclusion on the *INC*5000 list. Supporting the role of persistence is that having an overall composition of fast-growth industries in terms of employment growth in 2000–2007, 2007–2009 and 2009–2011 was not statistically associated with the number of 2012 *INC*5000 firms. This supports the notion that local conditions may matter when the firm is founded but less so as the firm identifies outside markets. Similarly, having a share of industries with a high-paying mix of jobs in 2008 was associated with the presence of fewer INC5000 firms in 2012 across all county types. This suggests that both higher labour costs of running a business when competing against high-paying firms and fewer incentives for workers to start their own firms in pursuit of higher earnings.

Last we note that our measures of state-level policy do not have any statistical effects in the benchmark model. This measure captures takings and discriminatory taxation as well as labour market freedom.[27] In both cases, a higher value of the variable means greater freedom. Earlier work, such as Stenholm, Acs, and Wuebker (2013) has found, at the level of nations, that different institutional arrangements do matter for high-impact entrepreneurship but less so for high-growth new ventures such as those studied here. In terms of BEA regional fixed effects, all regions except for the Rocky Mountains had more *INC*5000 firms than the excluded region (the Far West), all else equal.[28]

5.2. Regressions by sector

Next, we highlight results for the nine specific sectors, to shed light on whether different exogenous factors or policies may influence firm genesis by sector (Appendix Tables A1a–A1c below). Because of the small sample sizes, we do not have separate results for non-metro areas for any of the sectors, or for engineering in metro counties. A first major result is that the presence of energy, food and beverage products, and government services *INC*5000 firms is not associated with the average size of existing establishments in the community. Conversely, the average establishment size variable, as discussed above, was significant in the overall regressions and across areas. Relatedly, among the AA variables, sector specialization was not statistically significant for the engineering and government services sector. It does matter in the other sectors, but not always when metro areas are considered on their own. Where it is statistically significant, the direction of this effect is opposite to that predicted by AA.

The high school dropout rate for the most part had the expected negative association with the presence of rapidly growing firms in cases where its effect matters statistically. Yet for food and beverage products, a lower educational attainment share actually supports the emergence of high-growth firms, perhaps because it represents an available low-skilled labour force.[29] On the other hand, the presence of college graduates is positively associated with the number of *INC*5000 firms across all sectors except for government services (metro only), and this is a remarkably robust result.

Other noteworthy results include that a higher share of unemployed has a statistically significant effect only for government services, and the effect is negative. A higher share of self-employed has the expected positive association with *INC*5000 locations in the cases of business products, food and beverages (metro only), manufacturing and software firms. It is unclear whether these firms represent potential customers or they represent a more fertile seabed for the formation of *INC* firms.

Food and beverage firms are found to be the only sector to have a positive association with the banks per capita variable, suggesting that access to capital through commercial banks may be more important for these kinds of firms, but not for those in the other sectors, where the effect is in fact usually negative, as in the overall model. Distance to the nearest interstate highway from the county centroid was not statistically significant in the overall regressions, but this access variable does matter for business product firms. For this sector, overland transportation to markets is an important locational determinant.

Certain sectors are also more sensitive to government policy variables than others. For example, more freedom from statewide taxes and labour market regulations is, perhaps paradoxically, positively associated with the presence of government services firms. However, greater labour market freedom – surprisingly – is associated with fewer business product, manufacturing and software firms. In metro areas only, a lower tax burden enhances the presence of food and beverage firms, but greater labour market freedom reduces their presence.

6. Summary and conclusions

Our results suggest there is merit to examining systematically the self-reported *INC*5000 data of fastest-growing firms across US counties, and that such firm location patterns follow a certain economic logic. Perhaps most importantly, the data show that rapidly growing firms also are hosted in non-metro areas, although their number is declining over time, in line with increasing population concentration in metropolitan areas. Another key finding is that high-growth firms are also found in traditional sectors. Policy-makers should not overlook the potential opportunities of fostering innovation and growth in rural areas and in traditional sectors. In order to better exploit such opportunities, we need to understand the particular needs of firms in those areas and sectors, which this paper has started to identify.

While state-level policy variables turn out to have no significant effect, our other results demonstrate that local governments can play active roles in encouraging entrepreneurship and in helping firms succeed. For one thing, the size of the local government, measured by government employment shares, is positively linked to the formation of *INC*5000 firms. Early research has suggested that government activity can crowd out entrepreneurial private efforts. However, in this case it is shown that a strong local government is likely to support the emergence of high-growth firms. While it is ill-advised to blindly increase government employment, our results also suggest potential policy entries for governments to create favourable environments for high-growth firms. We find that a college-educated work force is essential to the presence of these firms, whereas a higher high school dropout rate is a statistically significant deterrent in all counties except those that are non-metro. The results for these two education related variables are remarkably consistent across industries. For policy-makers, this demonstrates once again that enhancing the quality of education is a valid long-term strategy to invigorate the economy.

Certain natural and socio-economic conditions are conducive to the emergence of high-growth firms. A mix of industries favouring rapid employment growth as far back as 1990–2000 is associated statistically with the presence of *INC*5000 firms today, suggesting that a strong local economy supports the initial founding of these firms. However, a higher mix of well-paying industries in the current period deters such firms from locating, suggesting that the labour environment is important. At the same time, natural amenities, a scarce resource in urban areas, are an attractive force for high-growth firms in all counties and metro counties but not in non-metro counties.

This paper also contributes to the theoretical understanding of the location of high-growth firms. Some of our findings are consistent with the predictions of Acs and Armington (2006). For example, greater population density is positively linked to the presence of *INC*5000 firms, consistent with the presence of agglomerate effects. The fact that population density is significant in both metro and non-metro counties shows that the mechanism through which high-growth firms emerge in rural areas is not entirely different from that in urban areas. Also consistent with the Acs and Armington model, we found that faster per capita income growth is associated with a lower presence of high-growth firms in all counties as well as in metro counties. The Acs and Armington model attributes this to lower incentives for entrepreneurship activities but the explanation could also be higher labour costs. The relative importance of these two interpretations could be a subject for future studies. Another measure of local economic dynamics, the population growth rate, turns out to be positive but insignificant except in non-metro counties. Thinner non-metro labour markets make it difficult for high-growth firms to recruit more employees to support rapid expansion, which highlights the different challenges faced by firms in urban and rural areas.

Some other results of this paper are contrary to predictions of the Acs and Armington model, suggesting that the regional assets required by high-growth firms (both new and existing) are different from those that support the growth of new firms more generally. For example, in our case, we find a positive association between the presence of larger existing firms and the number of high-growth firms in all and metro counties as well as in most industries. In the Acs and Armington (2006) study (59), the presence of larger firms is argued to be associated more with branch plants that carry out routine activities which are not conducive to entrepreneurship. In our case, the high-growth firms benefit from the presence of larger existing firms, in all counties as well as in metro counties. We argue that larger firms could be the suppliers, partners and customers of *INC*5000 firms, or the source from which successful new firms are spun out.

In our study of high-growth firms the degree of existing firm specialization also matters in a direction opposite to that predicted by knowledge spillover models, as in Acs and Armington (2006), and the result is robust across industries. They argue and their results confirm that more specialization (defined as the number of firms in a particular industry per capita) allows greater information spillovers and therefore supports new firm formation. For high-growth firms, the benefit of locating in a diverse economic environment seems to outweigh the benefit of learning from similar companies. Exactly how *INC* firms benefit from economic diversity could be an interesting question for further study.

Greater competition in the financial sector as measured by the number of banks per capita was associated with a statistically significant lower presence of *INC*5000 firms within all and metro counties, but it was associated with the presence of high-growth firms in non-metro areas. While the positive effect in non-metro counties is consistent with the expectation that high-growth firms need access to capital, the reason for the negative effect in metro counties is not obvious. The opposite results in metro and non-metro counties again point to the different conditions required for firms to succeed in urban and rural areas.

Notes

1. Existing studies mostly focus on European countries such as the UK (Lee 2014), France (Lasch, Robert, and Le Roy 2013), Scotland (Mason and Brown 2013), Italy (Bonaccorsi et al. 2014), Germany (Stuetzer et al. 2014), Spain (Lopez-Garcia and Puente 2012), as well as a study of 184 cities in 20 European countries (García 2014). There is also a literature, beyond the scope of our work, that examines internal strategies and characteristics of high-growth firms (Smallbone, Leig, and North 1995; Delmar, Davidsson, and Gartner 2003). Moreno and Casillas (2007) conduct a discriminant analysis to examine variables that separate high growth from other firms.
2. Starting in 1982, the magazine listed the 500 firms with highest revenue growth in the USA; in 2007, it expanded the list to 5,000 firms.
3. Examples of papers published since 2010 that use the same conceptual framework include Hanson and Rohlin (2011), Manjón-Antolín and Arauzo-Carod (2011), Frenkel (2012), Arauzo-Carod and Manjón-Antolín (2012), Arauzo-Carod (2013), Alañón-Pardo and Arauzo-Carod (2013), Basile, Benfratello, and Castellani (2013), Mota and Brandão (2013), Buczkowska and de Lapparent (2014), Liviano and Arauzo-Carod (2013, 2014).
4. At the same time, we note that factors contributing to firm emergence may not also ensure their long-term survival (see e.g. Brixy and Grotz 2007 for a sample of German firms).
5. See also Acs, Audretsch, and Lehmann (2013). For a cautionary statement about this theory, see Knoben, Ponds, and van Oort (2011).
6. The fact that the Tesla Company has bought large tracts of land in rural Nevada, both because of lower cost and to shield its research on batteries from competitors, is anecdotal evidence of the disadvantages of agglomeration.
7. Malecki (1993, 123) discusses how, in the past, lack of information about market conditions elsewhere created disadvantages especially for smaller firms.
8. Data are for 2007, which is the only year in which our *INC*5000 data contains NAICS codes. In other years, the *INC*5000 industry definition is not comparable to the NAICS definition used by the US Census.
9. As another extension, Pergelova and Angulo-Ruiz (2014) suggest that neither firm revenues nor profits are reliable guides for choosing firms to support with public financial resources. Their sample consists of new US firms.

10. Maps and analyses using 2007 and 2009 data, which we compiled from the website, are available from the authors upon request. We are grateful to *INC* Magazine for providing us with an electronic file containing the 2012 data.
11. The data are available here: http://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx (accessed August 12, 2014).
12. The data are available here: http://aese.psu.edu/nercrd/community/tools/social-capital (accessed August 12, 2014).
13. EMSI uses data from multiple sources including the BEA, BLS, *County Business Patterns,* and the *Quarterly Census of Employment and Wages* to fill 'suppression holes,' in which publically available sources do not report disaggregated industry employment and wage data, especially for rural counties to protect confidentiality. EMSI has developed an algorithm to fill these holes, and their data are reported to be relatively accurate (Dorfman, Partridge, and Galloway 2011; Fallah, Partridge, and Olfert 2011).
14. Note that the use of four-digit EMSI employment data allows us to more precisely measure industry mix demand shifts than is typical in the literature, which usually relies on one-digit or at best two-digit data.
15. http://www.inc.com/inc5000/2009/the-full-list.html.
16. In a sensitivity analysis described below, we included only the youngest firms to consider this possibility.
17. http://censtats.census.gov/usa/usa.shtml.
18. http://www.census.gov/geo/www/maps/.
19. http://dcrp.ced.berkeley.edu/research/footprint/.
20. Results using 2007 and 2009 data are not materially different, and available from the authors upon request. We also estimated models with interactions terms as part of our sensitivity analysis (see footnotes below).
21. In the zero inflation regressions, which are jointly estimated with the negative binomial regression, counties with more college graduates, banks per capita, *INC*5000 firms in 2009, and 2008 population as expected had statistically significant *greater* odds of also hosting one or more *INC* firms in 2012. Note that the inflation stage regression predicts the *absence* of firms.
22. These results also are robust to alternative measures of specialization, including the Hirschman–Herfindahl index and the Shannon Entropy index.
23. We do note that the coefficients' estimates on the unemployment rate in all and metro-only counties are positive, and not that far from being statistically significant.
24. The difference in the coefficients of metro and non-metro counties mostly reflects scaling in that population density is much higher in metropolitan counties. The elasticity of high-growth firm location and population density is 0.12 in metro counties and 0.19 in non-metropolitan counties. The larger non-metropolitan response is intuitive as we would expect non-metropolitan high-growth firms to benefit a little more at the margin from higher density because they have so relatively little to begin with.
25. Results are available from the authors.
26. Additional analysis shows that the association between proprietor or self-employment rates and the presence of *INC*5000 firms follows the shape of an inverted *U*. Conceivably, the presence of too many self-employed eventually crowds out opportunities for establishing rapidly growing firms, although at least initially the self-employed form a pool from which such firms are likely to emerge.
27. An important exception is that in the sensitivity analysis, where we include interactions among and non-linear effects of other variables, the effect of labour market freedom is statistically significant and *negative* in the model containing all counties. This may suggest that a policy of reduced labour market freedom creates incentives to start a high-growth firm. This could be explored in future research.
28. Young, smaller firms have been shown to drive a disproportionate share of US job growth (Haltiwanger, Jarmin, and Miranda 2013). Subtle differences emerged by metro and non-metro status of firms when we separately considered newer (<11 years) and older *INC*5000 firms (results available on request). For example, newer non-metro firms, establishment size and

prior (2005–2008) population growth each had a statistically significant and positive effect while neither had a statistical effect when all non-metro firms were considered together. Also, newer non-metro firms were less likely to emerge in counties with higher high school dropout rates, indicating that these firms require better-educated workers. When we considered only newer metro firms, a major difference was that industry specialization mattered, whereas it did not when all firms were considered together. Yet, the overriding theme was that the locational determinants between new and older fast growth firms were quite similar, suggesting that firm age is not a key intervening factor in their location. Another sensitivity test involving 2007 and 2009 data revealed largely consistent results. There is not enough variation in the dependent variable to permit estimating a panel data model.

29. Manufacturing is one sector for which the sample size is large enough to allow separate regressions for newer and older firms. Interestingly, for newer manufacturing firms, establishment size does not matter, and for newer metro-based manufacturing firms, the dropout rate is not statistically important.

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Appendix1.

Table A1a. Benchmark regressions for 2012, by sector detail.

	Business product		Energy		Engineering
Sample	All	Metro	All	Metro	All
Model	ZINB	ZINB	NBREG	NBREG	ZIP
Est size 08	0.151***	0.152***	0.0578	0.0461	0.214***
	(0.0302)	(0.0326)	(0.0690)	(0.0774)	(0.0620)
IP index 08	−10.75***	−10.74**	−42.81***	−46.36***	−14.87
	(3.911)	(4.239)	(12.69)	(14.56)	(9.394)
Dropout 00	−0.0218	−0.00459	−0.0136	0.00540	0.0385
	(0.0231)	(0.0248)	(0.0425)	(0.0462)	(0.0483)
Bachelor 00	0.0610***	0.0649***	0.0861***	0.0947***	0.0692**
	(0.0136)	(0.0144)	(0.0265)	(0.0288)	(0.0292)
Pop growth 05-08	−0.0133	−0.0209	0.0443	0.0340	0.0163
	(0.0216)	(0.0224)	(0.0382)	(0.0414)	(0.0418)
PCI growth 05-08	−0.00867	−0.0176	−0.0355	−0.0356	0.0227
	(0.0175)	(0.0191)	(0.0334)	(0.0378)	(0.0296)
Unemp 08	0.0357	0.0320	0.131	0.105	0.0497
	(0.0729)	(0.0782)	(0.0971)	(0.104)	(0.162)

(*Continued*)

Table A1a. (*Continued*)

	Business product		Energy		Engineering
Pop density 08	0.130	0.124	−0.258	−0.356	−0.452
	(0.148)	(0.152)	(0.269)	(0.283)	(0.317)
Social capital 09	−0.160	−0.0629	−0.687**	−0.703**	−0.183
	(0.144)	(0.157)	(0.300)	(0.334)	(0.269)
Proprietor 08	0.0189**	0.0215**	0.0180	0.0201	0.0263
	(0.00863)	(0.00915)	(0.0119)	(0.0127)	(0.0199)
Amenity	0.0816*	0.0765	0.0130	−0.00947	0.145
	(0.0457)	(0.0477)	(0.0918)	(0.0966)	(0.0961)
Bank 08	−1.804	−1.694	−3.708*	−4.566*	−4.905
	(1.250)	(1.257)	(2.132)	(2.450)	(3.259)
Gov emp 08	0.0550***	0.0525***	0.0535***	0.0524**	0.0218
	(0.00920)	(0.00913)	(0.0200)	(0.0207)	(0.0174)
Distance	−0.00806*	−0.00933*	−0.00329	−0.00289	0.00888
	(0.00477)	(0.00553)	(0.00748)	(0.00857)	(0.00769)
Ind mix 09-11	0.154	0.195	0.410	0.520	0.778
	(0.237)	(0.265)	(0.446)	(0.566)	(0.555)
Ind mix 07-09	−0.135	−0.168*	0.0559	−0.0323	−0.450**
	(0.0863)	(0.0918)	(0.184)	(0.211)	(0.212)
Ind mix 00-07	0.0536	0.0805*	0.0947	0.108	0.163*
	(0.0437)	(0.0473)	(0.0889)	(0.102)	(0.0908)
Ind mix 90-00	0.0544**	0.0528**	0.0545	0.0508	−0.0752
	(0.0253)	(0.0267)	(0.0528)	(0.0593)	(0.0529)
Wage mix 08	−1.138	−1.272	−2.140	−2.323	2.128
	(0.769)	(0.830)	(1.432)	(1.565)	(1.780)
Tax score 08	0.114	0.151	−0.370	−0.333	0.0933
	(0.137)	(0.143)	(0.274)	(0.287)	(0.275)
Market score 08	−0.404**	−0.499**	−0.192	−0.279	0.0804
	(0.193)	(0.201)	(0.459)	(0.490)	(0.423)
BEA_NELD	0.282	0.172	0.623	0.653	1.182
	(0.394)	(0.401)	(0.816)	(0.848)	(0.827)
BEA_MEST	0.328	0.267	1.148	1.195	1.747*
	(0.422)	(0.435)	(0.822)	(0.863)	(0.920)
BEA_GLAK	0.403	0.264	−0.0204	−0.552	1.725*
	(0.453)	(0.469)	(0.951)	(1.040)	(0.975)
BEA_PLNS	0.658	0.625	1.261	1.111	1.726*
	(0.457)	(0.471)	(0.945)	(0.994)	(1.002)
BEA_SEST	0.866**	0.844**	−0.203	−0.185	0.887
	(0.401)	(0.413)	(0.824)	(0.861)	(0.895)
BEA_SWST	0.414	0.518	1.111	1.071	0.198
	(0.384)	(0.400)	(0.718)	(0.754)	(0.795)
BEA_RKMT	0.377	0.475	−0.536	−0.436	0.600
	(0.402)	(0.422)	(0.943)	(0.969)	(0.822)
Constant	−3.207	−3.158	−1.778	−1.383	−13.54***
	(1.958)	(2.101)	(3.933)	(4.269)	(4.684)
VARIABLES	inflate	inflate			inflate
Bachelor 00	0.00539	0.00730			−0.160**
	(0.0198)	(0.0213)			(0.0701)
Bank 08	−0.449	0.0713			2.618
	(1.913)	(2.302)			(6.264)
Firms 09	−0.220***	−0.205***			−0.409*
	(0.0768)	(0.0684)			(0.217)
Population 08	−0.00221*	−0.00205*			0.00250
	(0.00117)	(0.00116)			(0.00254)
Pct urban 00	−0.0132	−0.0131			−0.0361
	(0.00915)	(0.0107)			(0.0231)
Constant	2.579***	2.321**			7.354***
	(0.905)	(1.059)			(2.632)
ln α	−1.484***	−1.540***	−0.0541	−0.0863	
	(0.359)	(0.358)	(0.446)	(0.455)	
Observations	3.031	1.062	3.031	1.062	

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table A1b. Benchmark regressions for 2012, by sector detail.

	Food and Beverage		Government Service		Health	
Sample	All	Metro	All	Metro	All	Metro
Model	ZIP	ZIP	ZINB	ZINB	ZINB	ZINB
Est size 08	0.0410	0.0677	0.0672	0.0183	0.186***	0.185***
	(0.0473)	(0.0571)	(0.0622)	(0.0714)	(0.0363)	(0.0391)
IP index 08	−16.90**	−12.47	−1.800	13.38	−19.79***	−25.08***
	(8.274)	(11.33)	(7.078)	(10.86)	(5.424)	(6.694)
Dropout 00	0.0570*	0.0776**	−0.120***	−0.146***	−0.0672**	−0.0623**
	(0.0335)	(0.0381)	(0.0437)	(0.0534)	(0.0278)	(0.0299)
Bachelor 00	0.0560**	0.0663**	0.0497*	0.0186	0.0418**	0.0441**
	(0.0237)	(0.0277)	(0.0267)	(0.0298)	(0.0165)	(0.0174)
Pop growth 05-08	0.0858**	0.0517	−0.0782**	−0.0735*	0.0274	0.0219
	(0.0348)	(0.0439)	(0.0374)	(0.0399)	(0.0213)	(0.0223)
PCI growth 05-08	−0.00238	−0.0186	−0.0522*	−0.0322	0.00280	0.000454
	(0.0290)	(0.0388)	(0.0280)	(0.0302)	(0.0188)	(0.0197)
Unemp 08	0.0538	0.0293	−0.252*	−0.408**	0.0536	0.0656
	(0.116)	(0.143)	(0.152)	(0.174)	(0.0842)	(0.0929)
Pop density 08	−0.0110	0.0698	0.0829	0.00652	0.116	0.116
	(0.232)	(0.254)	(0.304)	(0.330)	(0.170)	(0.175)
Social capital 09	−0.350*	−0.366	−0.422	−0.377	−0.348**	−0.401**
	(0.199)	(0.239)	(0.299)	(0.342)	(0.151)	(0.164)
Proprietor 08	0.0135	0.0297*	−0.00106	−0.000790	0.00245	0.00750
	(0.0120)	(0.0155)	(0.0173)	(0.0221)	(0.00992)	(0.0106)
Amenity	0.0525	0.0813	0.141	0.199*	0.0563	0.0560
	(0.0726)	(0.0867)	(0.0940)	(0.103)	(0.0517)	(0.0533)
Bank 08	5.689***	6.156**	−3.641*	−5.740**	−3.396**	−2.194
	(2.005)	(2.495)	(2.211)	(2.585)	(1.501)	(1.589)
Gov emp 08	0.0252**	0.0213*	0.0808***	0.0719***	0.0485***	0.0462***
	(0.0106)	(0.0114)	(0.0263)	(0.0236)	(0.0116)	(0.0116)
Distance	−0.000956	−0.00368	0.00876	−0.00638	0.00514	0.00872
	(0.00614)	(0.00781)	(0.00729)	(0.0117)	(0.00448)	(0.00553)
Ind mix 09–11	−0.260	−0.0665	0.174	0.512	−0.294	−0.0802
	(0.439)	(0.540)	(0.377)	(0.500)	(0.270)	(0.284)
Ind mix 07–09	0.121	−0.0483	0.0181	0.00131	−0.0430	−0.0896
	(0.173)	(0.216)	(0.155)	(0.176)	(0.111)	(0.124)
Ind mix 00–07	0.00777	0.0703	0.0502	−0.0229	0.125**	0.143**
	(0.0720)	(0.0857)	(0.0747)	(0.0939)	(0.0512)	(0.0571)
Ind mix 90-00	0.0919**	0.0662	−0.0378	−0.0168	0.0269	0.00113
	(0.0466)	(0.0575)	(0.0397)	(0.0446)	(0.0303)	(0.0323)
Wage mix 08	−2.717**	−1.892	0.315	0.873	−2.088**	−1.310
	(1.168)	(1.439)	(1.369)	(1.702)	(0.879)	(0.951)
Tax score 08	0.169	0.431*	0.165	0.0803	0.0364	0.0491
	(0.218)	(0.258)	(0.296)	(0.330)	(0.155)	(0.162)
Market score 08	−0.603	−0.833*	0.771**	0.759*	−0.326	−0.196
	(0.377)	(0.434)	(0.388)	(0.440)	(0.215)	(0.228)
BEA_NELD	0.863	0.592	0.722	0.808	0.407	0.576
	(0.655)	(0.724)	(0.912)	(0.961)	(0.468)	(0.476)
BEA_MEST	−0.239	−0.0988	1.642*	1.552	0.952**	1.052**
	(0.716)	(0.815)	(0.892)	(0.947)	(0.470)	(0.482)
BEA_GLAK	0.0775	0.00311	1.022	1.561	0.919*	0.793
	(0.717)	(0.800)	(1.042)	(1.109)	(0.484)	(0.495)
BEA_PLNS	0.344	0.335	0.0439	−0.102	0.924*	0.994*
	(0.785)	(0.893)	(1.152)	(1.263)	(0.511)	(0.527)
BEA_SEST	−0.404	−0.0991	1.798**	1.656*	1.406***	1.295***
	(0.676)	(0.772)	(0.888)	(0.940)	(0.437)	(0.448)
BEA_SWST	−0.715	−0.644	1.137	1.295	0.779*	0.607
	(0.649)	(0.727)	(0.803)	(0.818)	(0.426)	(0.430)
BEA_RKMT	0.410	0.678	0.768	0.936	−0.00210	0.153
	(0.553)	(0.593)	(0.776)	(0.805)	(0.461)	(0.477)
Constant	−2.106	−4.996	−7.130**	−3.835	−1.498	−3.646
	(3.285)	(3.970)	(3.633)	(4.296)	(2.363)	(2.575)
Inflation stage						
Bachelor 00	−0.0251	−0.0273	0.0563	−0.0148	−0.00387	−0.0250
	(0.0262)	(0.0291)	(0.0550)	(0.0499)	(0.0274)	(0.0289)

(*Continued*)

Table A1b. (*Continued*)

	Food and Beverage		Government Service		Health	
Bank 08	6.372***	5.171	−4.600	−3.063	−3.852	−2.269
	(2.116)	(3.189)	(4.032)	(4.982)	(3.098)	(2.871)
Firms 09	−0.0507	−0.0513	−1.350**	−0.547*	−0.241**	−0.177**
	(0.0364)	(0.0412)	(0.618)	(0.312)	(0.116)	(0.0775)
Population 08	−0.00408***	−0.00441**	−0.00111	−0.00111	−0.00380*	−0.00343*
	(0.00149)	(0.00210)	(0.00259)	(0.00242)	(0.00216)	(0.00177)
Pct urban 00	0.0112	−0.00190	−0.0356	−0.0654**	0.0116	0.0115
	(0.0125)	(0.0164)	(0.0222)	(0.0297)	(0.0142)	(0.0158)
Constant	0.607	2.120	4.628**	8.153***	2.280**	2.240*
	(1.211)	(1.527)	(2.219)	(3.098)	(1.156)	(1.331)
ln α			0.476*	0.149	−1.193***	−1.343***
			(0.278)	(0.346)	(0.384)	(0.404)
Observations	3.031	1.062	3.031	1.062	3.031	1.062

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table A1c. Benchmark regressions for 2012, by sector detail.

	IT services		Manufacturing		Software	
Sample	All	Metro	All	Metro	All	Metro
Model	ZINB	ZINB	ZINB	ZINB	ZINB	ZINB
Est size 08	0.235***	0.237***	0.0914**	0.138***	0.132***	0.145***
	(0.0341)	(0.0362)	(0.0386)	(0.0464)	(0.0455)	−0.0484
IP index 08	−15.04***	−13.75***	−12.22***	−20.20***	−14.06**	−11.35
	(4.114)	(4.275)	(4.241)	(6.614)	(6.620)	−7.403
Dropout 00	−0.0420*	−0.0381	−0.0923***	−0.106***	0.00115	0.0107
	(0.0247)	(0.0263)	(0.0292)	(0.0330)	(0.0326)	−0.0346
Bachelor 00	0.0828***	0.0852***	0.0305*	0.0415**	0.0767***	0.0831***
	(0.0161)	(0.0170)	(0.0175)	(0.0200)	(0.0206)	−0.0218
Pop growth 05–08	−0.0185	−0.0207	−0.0204	−0.0374	0.0364	0.0375
	(0.0213)	(0.0221)	(0.0274)	(0.0320)	(0.0295)	−0.0304
PCI growth 05–08	−0.00565	−0.00932	0.0372**	0.0719***	−0.00482	0.00375
	(0.0170)	(0.0183)	(0.0182)	(0.0255)	(0.0252)	−0.0262
Unemp 08	0.0795	0.0926	0.126	0.152	0.0271	0.0351
	(0.0786)	(0.0817)	(0.0795)	(0.104)	(0.107)	−0.115
Pop density 08	0.202	0.173	0.0730	0.0830	0.00980	−0.0133
	(0.153)	(0.156)	(0.196)	(0.204)	(0.208)	−0.213
Social capital 09	−0.392***	−0.399***	−0.339**	−0.216	−0.260	−0.233
	(0.145)	(0.152)	(0.167)	(0.184)	(0.191)	−0.205
Proprietor 08	0.0150	0.0152	0.0159*	0.0302***	0.0264*	0.0296*
	(0.0100)	(0.0108)	(0.00846)	(0.0112)	(0.0155)	−0.0166
Amenity	0.0529	0.0494	0.114*	0.0856	0.0588	0.086
	(0.0490)	(0.0504)	(0.0620)	(0.0663)	(0.0607)	−0.0637
Bank 08	−3.733***	−3.564***	−1.349	−1.182	−4.167**	−3.962**
	(1.195)	(1.241)	(1.230)	(1.600)	(1.826)	−1.804
Gov emp 08	0.0542***	0.0549***	0.0758***	0.0576***	0.0389***	0.0388***
	(0.0117)	(0.0119)	(0.0162)	(0.0129)	(0.0122)	−0.0125
Distance	0.00367	0.00563	−0.00834	−0.00631	0.00344	0.00381
	(0.00480)	(0.00533)	(0.00546)	(0.00781)	(0.00535)	−0.00598
Ind mix 09–11	0.106	−0.0155	0.400*	−0.0617	−0.0701	−0.0049
	(0.262)	(0.290)	(0.233)	(0.322)	(0.381)	−0.402
Ind mix 07–09	−0.163*	−0.136	−0.248**	−0.353***	−0.0990	−0.172
	(0.0952)	(0.102)	(0.103)	(0.132)	(0.138)	−0.145
Ind mix 00–07	0.0978**	0.0991*	−0.0613	−0.0524	0.0761	0.0944
	(0.0488)	(0.0531)	(0.0500)	(0.0599)	(0.0654)	−0.07
Ind mix 90–00	0.0278	0.0297	0.0267	0.0228	0.0900**	0.0735
	(0.0273)	(0.0288)	(0.0295)	(0.0391)	(0.0441)	−0.0463
Wage mix 08	−1.949**	−2.470***	−1.133	−0.460	−0.547	−0.529
	(0.800)	(0.846)	(0.866)	(1.064)	(1.129)	−1.199
Tax score 08	0.122	0.126	0.265	0.234	0.0801	0.119
	(0.136)	(0.140)	(0.173)	(0.190)	(0.192)	−0.202
Market score 08	−0.148	−0.180	−0.510**	−0.790***	−0.627**	−0.626**
	(0.202)	(0.209)	(0.249)	(0.283)	(0.303)	−0.308
BEA_NELD	0.515	0.548	0.622	0.518	0.297	0.452
	(0.415)	(0.425)	(0.550)	(0.565)	(0.545)	−0.554

(*Continued*)

Table A1c. (*Continued*)

	IT services		Manufacturing		Software	
BEA_MEST	1.036**	1.092**	1.150**	0.863	0.00480	0.221
	(0.444)	(0.454)	(0.556)	(0.581)	(0.606)	−0.623
BEA_GLAK	0.819*	0.826*	1.212**	0.965	0.336	0.479
	(0.479)	(0.490)	(0.580)	(0.606)	(0.614)	−0.628
BEA_PLNS	0.467	0.503	0.569	0.402	0.689	0.806
	(0.509)	(0.522)	(0.623)	(0.665)	(0.693)	−0.712
BEA_SEST	1.041**	1.077**	1.185**	1.625***	0.714	0.795
	(0.423)	(0.432)	(0.533)	(0.561)	(0.572)	−0.582
BEA_SWST	0.411	0.432	1.208**	1.347**	0.0642	0.0128
	(0.411)	(0.421)	(0.499)	(0.530)	(0.529)	−0.55
BEA_RKMT	0.168	0.169	0.326	1.006*	0.785	0.875*
	(0.444)	(0.461)	(0.513)	(0.554)	(0.508)	−0.53
Constant	−5.888***	−5.341**	−2.196	−2.055	−3.483	−4.787
	(2.054)	(2.154)	(2.303)	(2.878)	(3.018)	−3.278
Inflation stage						
Bachelor 00	−0.0115	0.00229	−0.0841*	0.0118	−0.0367	−0.0386
	(0.0339)	(0.0369)	(0.0483)	(0.0252)	−0.0265	−0.0292
Bank 08	−1.342	−1.030	−1.037	0.250	−1.471	−3.254
	(2.177)	(2.331)	(2.298)	(2.158)	−2.466	−2.693
Firms 09	−0.599***	−0.617**	−2.911**	−0.143	−0.219**	−0.215**
	(0.223)	(0.253)	(1.177)	(0.0904)	−0.0872	−0.0904
Population 08	−0.000431	−0.00119	0.00358	−0.00178	−0.000326	−0.000609
	(0.00139)	(0.00260)	(0.00271)	(0.00145)	−0.00077	−0.000825
Pct urban 00	−0.0207	−0.0127	−0.0103	−0.00786	−0.0252*	−0.0255
	(0.0138)	(0.0185)	(0.0131)	(0.0106)	−0.0132	−0.0158
Constant	3.440***	2.630	3.533**	1.647	4.890***	5.575***
	(1.307)	(1.623)	(1.408)	(1.060)	−1.265	−1.529
ln α	−0.924***	−0.907***	−0.447	−2.085*	−1.000***	−1.004***
	(0.232)	(0.231)	(0.330)	(1.116)	−0.353	−0.354
Observations	3.031	1.062	3.031	1.062	3.031	1.062

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

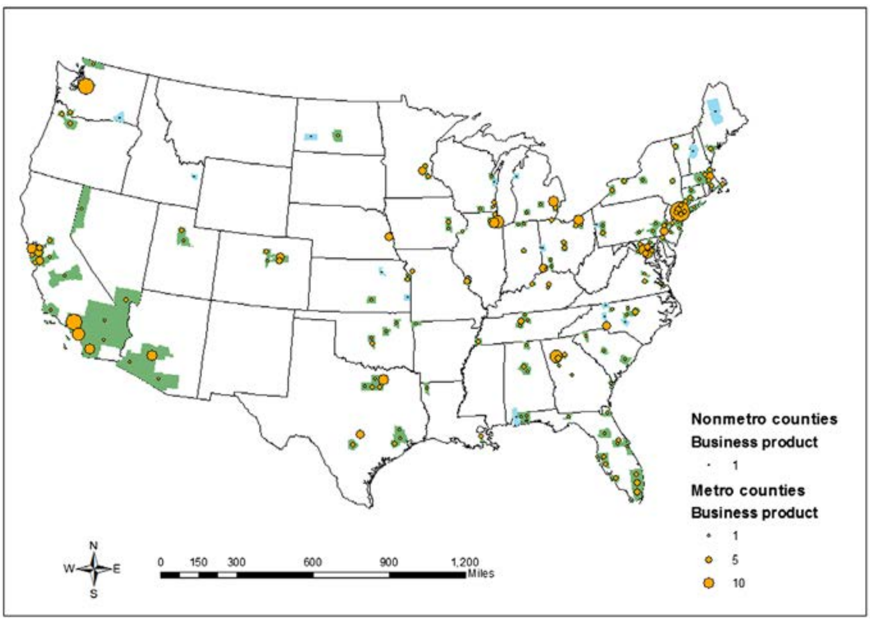

Figure A1. The distribution of INC5000 in the business product sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

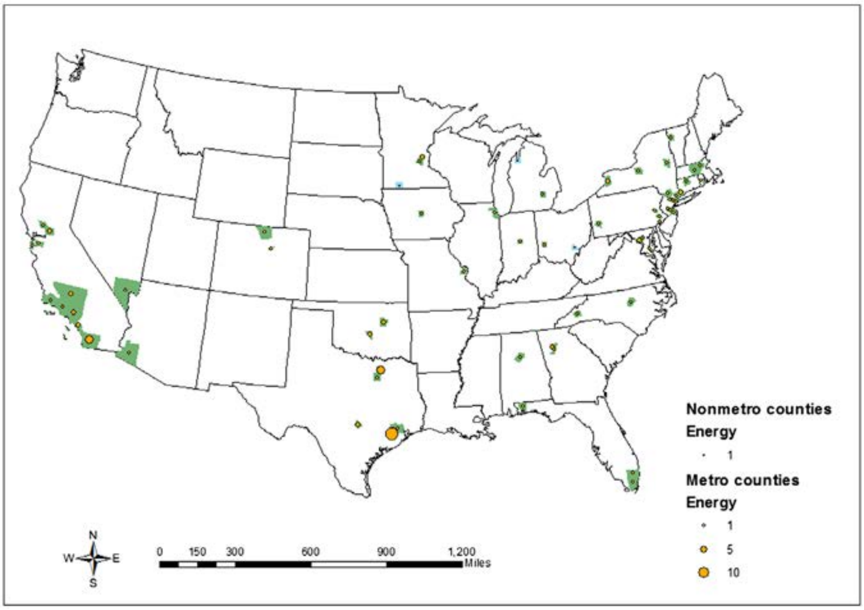

Figure A2. The distribution of *INC*5000 in the energy sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

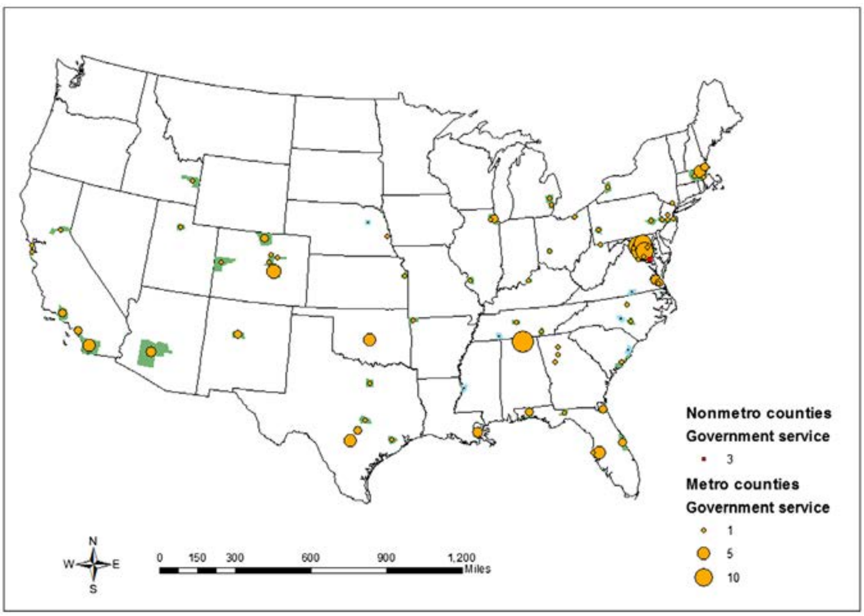

Figure A3. The distribution of *INC*5000 in the engineering sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

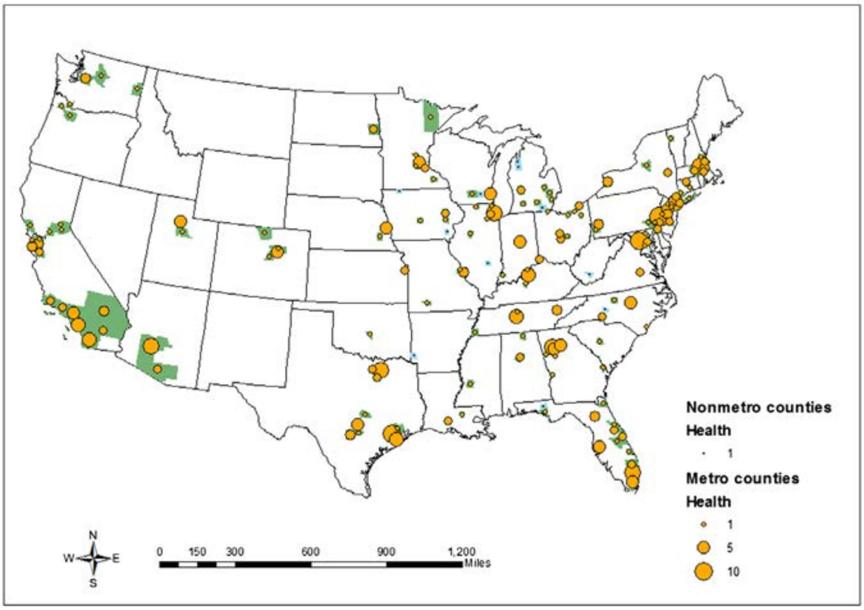

Figure A4. The distribution of *INC*5000 in the food and beverage sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

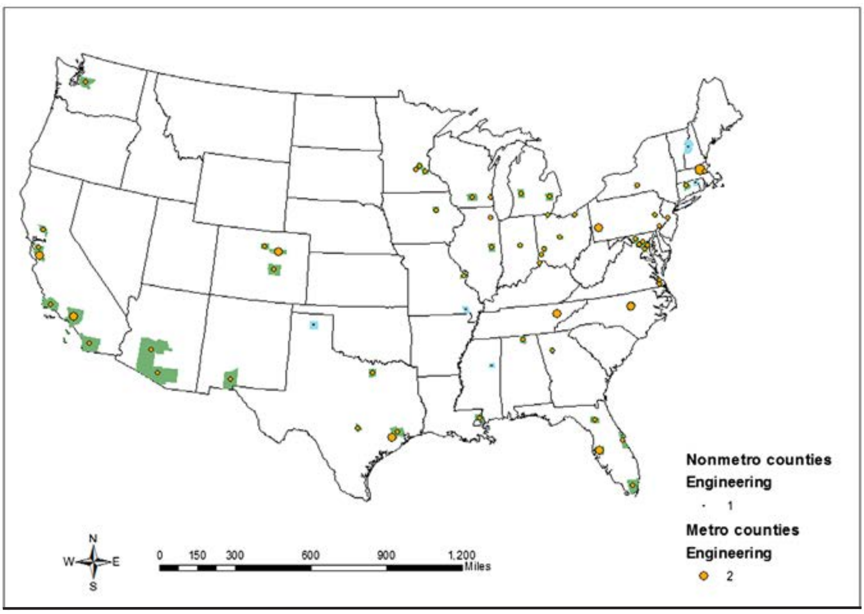

Figure A5. The distribution of *INC*5000 in the government service sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

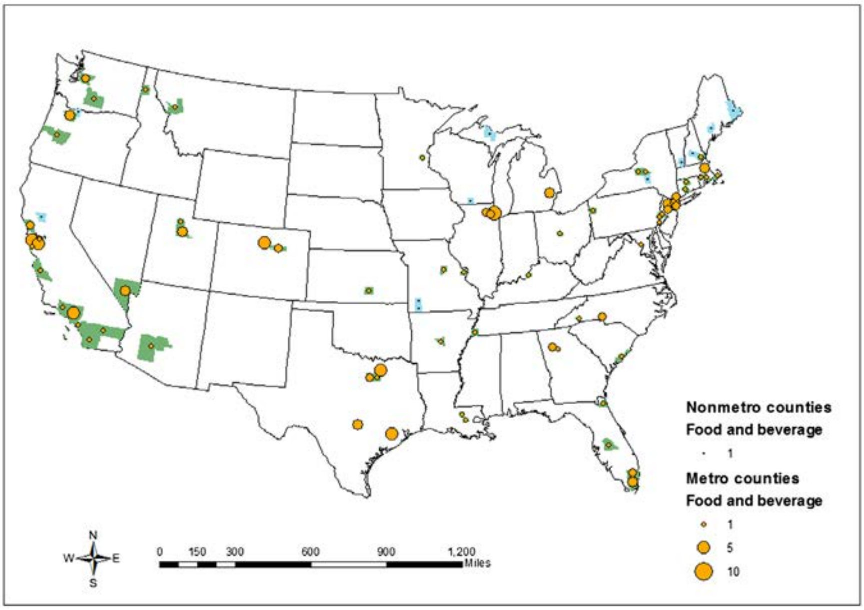

Figure A6. The distribution of *INC*5000 in the health sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

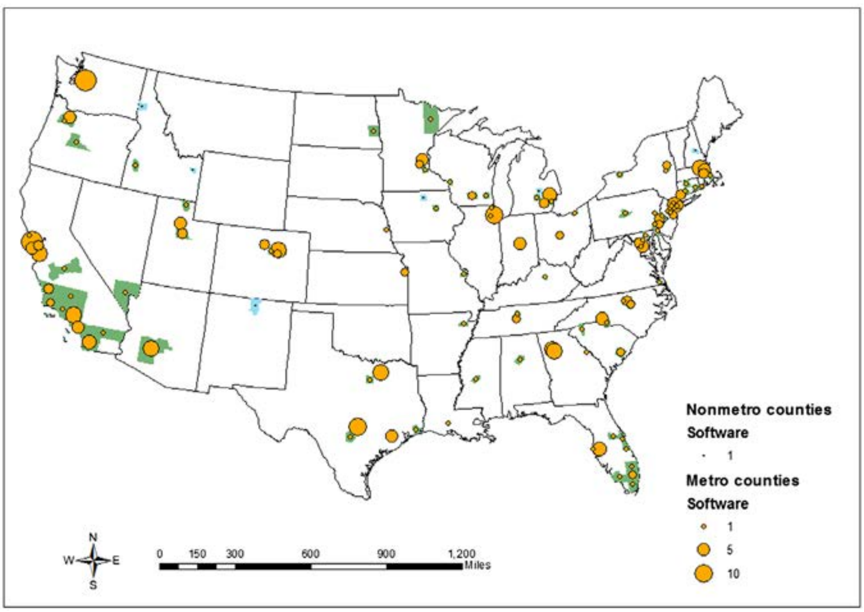

Figure A7. The distribution of *INC*5000 in the IT service sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

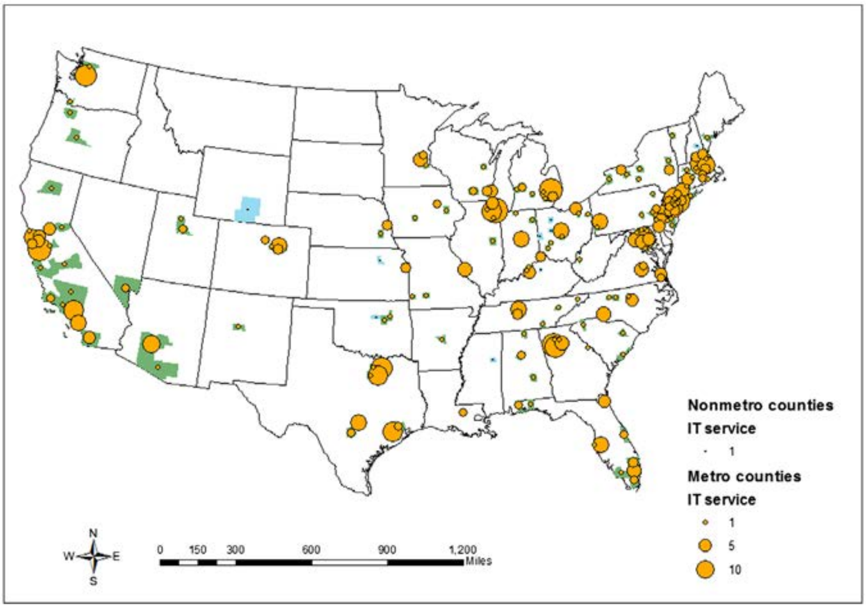

Figure A8. The distribution of *INC*5000 in the manufacturing sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)

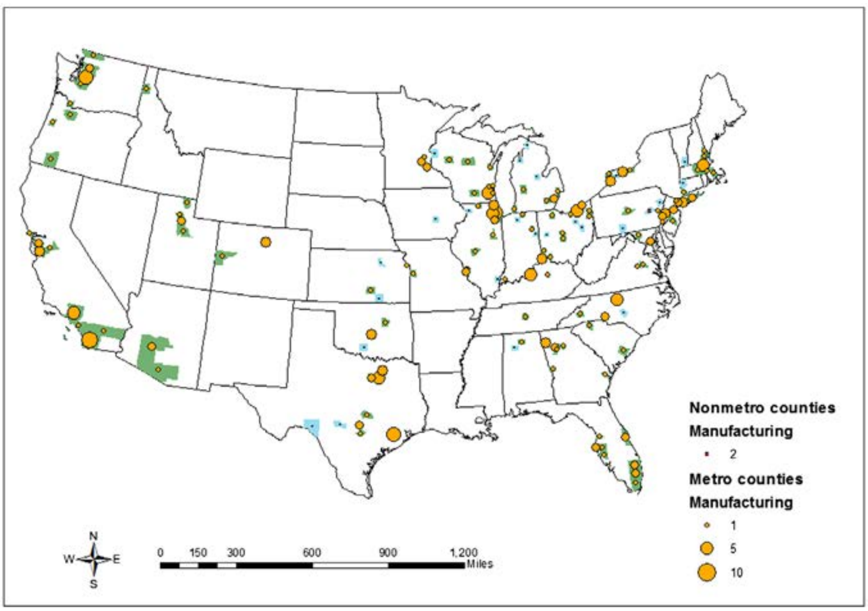

Figure A9. The distribution of *INC*5000 in the software sector in 2012.
Please see the online article for the colour version of this figure: http://dx.doi.org/10.1080/08985626.2015.1109003.
Note: Green area indicates metro counties and blue area indicates non-metro counties. (Source: The authors created Figures 1 and A1-9 from data that are publicly available at http://www.inc.com/inc5000. No third party was involved in their creation.)