

IFN Working Paper No. 1290, 2019

## **Local Rates of New Firm Formation: An Empirical Exploration using Swedish Data**

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# LOCAL RATES OF NEW FIRM FORMATION

- an empirical exploration using Swedish data

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June 12, 2019

## ABSTRACT

We assess the empirical literature on the determinants of spatial variations in new-firm formation rates by undertaking a systematic empirical analysis of the relative roles of different demand- and supply-side factors. Using instrumental variables to address endogeneity, we find that local growth drives local entrepreneurship exclusively in services industries. Average establishment size has a robust negative influence on local new-firm formation rates, but its effect varies across industries. Local industry diversity is only positive for new-firm formation in high-tech and knowledge-intensive activities. There is also some evidence of that longer distances to urban centers is associated with higher new-firm formation rates. The only local factor with a consistent positive effect on new-firm formation across industries is local density of skilled workers. We conclude that industry structure, geography and agglomeration matter, but in the end, new firms are started by people, so it is unsurprising that the main factor driving local entrepreneurship is the characteristics of the local residents.

**JEL:** R11, L26, M13, R30

**Keywords:** entrepreneurship, new firm formation, geography, human capital, agglomeration, local growth, startups

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**Acknowledgements:** We are grateful for constructive comments from seminar participants at the Swedish Entrepreneurship Forum, BTH and the WRSA conference 2019 in February, Napa Valley, US. Martin Andersson recognizes funding from the Kamprad foundation in Sweden.

## 1. INTRODUCTION

The literature on “geography of entrepreneurship” has long focused on understanding the sources of variations in new-firm formation across cities and regions (Plummer and Pe’er 2010, Audretsch and Fritsch 1994). A key message from this analysis is that there are large spatial variations in the rate of new business formation that are governed by spatial heterogeneity in various local supply- and demand-side conditions, such as local demand growth, local presence of input suppliers, supply of potential entrepreneurs, agglomeration factors (e.g. Armington and Acs 2002, Glaeser 2009), as well cultural and policy differences (Fritsch and Wyrwich 2014, Davidsson and Wiklund 1997).

While it is well established that these factors matter, less is known about their relative importance and, in particular, whether their relative importance varies by industry. One reason is that rather few analyses assess the various arguments in the literature and systematically evaluate their importance in explaining how local factors affect local entrepreneurship. One exception is Glaeser’s (2009) assessment of the relative importance of four factors: local supply of entrepreneurial human capital; entrepreneurial culture; local availability of inputs; and size of the local customer base. His main conclusion is that local entrepreneurship in US metropolitan areas is primarily driven by labor supply, especially the supply of potential entrepreneurs and the supply of labor inputs. Likewise, a number of studies show that there is heterogeneity in how various factors influence entrepreneurship across industries (Nyström 2007, Johnson 2004, Westlund et al 2014). Yet, there is relatively scant evidence of how this industry heterogeneity is affected by local factors.

This paper contributes to the literature with a systematic empirical analysis of the relative importance of how different local factors explain local entrepreneurial activity. In contrast to Glaeser (2009) who uses indicators on the local stock of self-employed and small firms, we directly measure the rate of new firm formation. New-firm formation has the advantage of capturing the essence of entrepreneurship, and its policy relevance is magnified because new-firm formation has a disproportionate influence on aggregate national new-job creation (Haltiwanger et al., 2013). There are similar findings about how small firms enhance aggregate *net* national job growth (Nuemark et al., 2011), which means that *gross* job creation from small-firm births more than offset any job losses from small-firm deaths.

Turning to local effects, firm start-ups and greater densities of self-employment are associated with greater *subsequent* local economic growth (Bunton et al., 2015; Fleming and Goetz, 2011; Goetz et al., 2012; Komarek and Loveridge, 2014, 2015; Rupasingha and Goetz, 2012). In addition, greater densities of small businesses and self-employment have been found to be especially important in enhancing growth in lagging and remote regions (Stephens and Partridge, 2011; Stephens et al., 2013). Various explanations have been put forth for why new and small firms are especially important for local economies including their propensity to buy inputs locally, their profits remain local, and it signals future

growth opportunities in the local economy. Finally, Tsvetkova et al. (2019) find that small and new business formation is linked to much larger local job and income multipliers than equivalent changes for existing businesses. Taken together, this motivates analyzing the drivers of the local rate of new firm formation.

Using data on Swedish municipalities, we analyze the relative empirical relevance of four local factor groups: (i) local economic conditions, (ii) industry structure, (iii) geography, and (iv) wider agglomeration. Local economic conditions refer to basic characteristics such as local job growth, educational attainment, and the local economy's overall diversity. Industry structure reflects the employment composition across broad industry categories as well as average establishment size. Geography consists of indicators aimed to capture a municipality's position in the urban hierarchy including measures of distance to nearest urban centers. Finally, wider agglomeration consists of variables reflecting conditions in the wider functional region to which a municipality belongs. These categories of factors represent various theoretical perspectives that influence local entrepreneurship.

One of our key local economic characteristics is local employment growth. Although this variable is standard in many empirical analyses, it is plagued with conceptual ambiguity as well as potential endogeneity. Conceptually, one argument is that local growth creates opportunities for new firms, for instance because local job growth increases local demand for various goods and services. The other argument is that local job growth increases the opportunities for regular wage employment, and thereby reducing local entrepreneurship activity. Hence, the *net* effect is ambiguous. Empirically, endogeneity may arise because, as discussed above, local job growth supports local entrepreneurship, but local entrepreneurial activity also creates employment (Fritsch 2013, Glaeser et al 2015, Fritsch and Wyrwich 2017). Thus, we employ an instrumental variable (IV) approach and use a shift-share local employment growth variable to instrument for local employment growth (cf. Bartik 1991, Blanchard and Katz 1992). This instrument is known as the so-called 'Bartik-instrument', and the main idea is to use national-growth-weighted local industry shares to isolate the part of the variation in local employment growth that is exogenous.

Our main findings can be summarized as follows. First, all four local-factor groups influence overall new-firm formation. We find strong evidence of the role of people with the local density of skilled workers being strongly associated with higher overall local new-firm formation rates. These results are in line with Glaeser (2009), who emphasized how skills explain spatial variations in US local entrepreneurship. Our IV estimates also show that local growth has robust positive influence on the local rate of new-firm formation. That is, the local rate of firm formation appears to be stimulated by local job growth, even after accounting for endogeneity. We also find that average establishment size is critical in explaining spatial variations in new-firm formation. Large average establishment size is a strong

predictor of low rates of local firm formation. This is consistent with the argument that a local density of small-scale business is conducive for the emergence of a ‘culture of entrepreneurship’ and a thick local input market (Chinitz 1961, Rosenthal and Strange 2010). The industry composition is of less empirical relevance. Additionally, we find that a municipality’s position in the urban hierarchy and conditions in surrounding areas matter. Foremost, there is a ‘distance protection’ effect in that longer distances to the closest urban center is associated with greater new-firm formation rates. We also find evidence suggesting that there is competition for skilled labor from nearby areas. This points to a relevance of urban backwash effects that operate within functional labor market regions in understanding the geography of new-firm formation (cf. Gaile 1980, Partridge et al 2007).

Second, the relative importance of different local factors in explaining the new-firm formation differs significantly across industries. Local job growth only supports new-firm formation in services, and in particular low-end services like retail and wholesale trade that depend on local demand. The ‘distance-protection’ effect is present in all industries except high-tech manufacturing and knowledge-intensive services, perhaps due to less reliance on local markets, and also because they have a stronger dependence on the rich resources offered by large cities and city centers. Therefore, longer distance to urban centers is not advantageous for their rate of new firm formation. Moreover, indicators of local industry structure add explanatory power, especially for services. Services also differ from manufacturing due to a greater tendency for services to ‘cluster’. New-firm formation in services tend to be higher where services have greater local employment shares, but not manufacturing firm formation. Another clear result is that local industry diversity is only positively associated with new-firm formation in high-tech and knowledge-intensive industries, corroborating findings from several studies (c.f. Feldman and Audretsch 1999, de Groot et al 2016).

The results at the industry level also confirm the central role of human capital in local firm formation—i.e., local average educational attainment is the only local factor with a consistently positive relation on new-firm formation across all industry subgroups. Our conclusion is that industry structure, geography, and agglomeration matter, but in the end, people start new firms and their characteristics are the main factor driving local entrepreneurship.

The rest of the paper is structured as follows: Section 2 presents background and motivation as well as a discussion of the role of the four groups of local factors that are assumed to primarily affect local rates of new-firm formation. Section 3 presents the data, variables, and the empirical strategy underpinning the econometric analysis. Section 4 presents the results and Section 5 concludes.

## 2. BACKGROUND AND MOTIVATION

### 2.1. The importance of the local rate of new firm formation

There are two main motivations for studying the factors that drive the local rate of new firm formation, and how they differ across industries. First, a growing empirical literature shows that small business activity and new-firm formation has a causal positive effect on long-run economic growth and development of regions. Glaeser et al (2015) analyze the connection between local rates of small business activity and job growth in US cities. Using distance to historical mines as an instrument, they find a significant causal effect of a city's initial average establishment size and the initial start-up employment share on long-term employment growth. Fritsch and Wyrwich (2017) study German regions, finding a significant long-run effect of start-up activity on job growth. Other recent studies find similar results (Tsvetkova et al., 2019; Lee (2017). Tsvetkova et al. (2019) compare the local employment effects from exogenous net changes in self-employment with similar changes in regular wage employment in US counties. They find that self-employment indeed has a significant positive effect on local job growth and their results suggest that stimulating self-employment is likely to generate much larger effects stimulating regular wage employment. Lee (2017) uses an IV-approach to assess the influence of small business births on US metropolitan area job and wage growth. He finds quantitatively substantial positive effects on both employment and wages and that these effects are not confined to the initially created businesses – they also spill over to the wider local economy. The main message from these studies is that we have reasons to ask, “what drives local new firm formation?” given its import for growth of local jobs and incomes.

Second, recent studies point to not only the importance of new-firm formation in high-tech, innovative, and knowledge-intensive industries, but also for more mundane types of new firms and small business activity. For example, the studies cited above examine the overall rate of new-firm formation, small business density, and self-employment rates. These measures are more likely to capture everyday entrepreneurship, rather than “radical” and high-potential startups associated with venture capital and potential ‘gazelles’ (cf. Henrekson and Sanandaji 2014). The positive effect of overall new-firm formation on regional development and growth can be understood from the multifaceted functions of small businesses and new-firms in local economies. Schumpeterian (1934) creative destruction suggests that a main way that entrepreneurship influences growth and economic dynamism is through its function of disrupting markets, challenging established business models, and introducing new technologies and innovations.

The Schumpeterian perspective entails a focus on innovative, technology-based, and high-potential new firms and small businesses that may employ venture capital. These business types have also been the

main focus of recent entrepreneurship research, which has recently been criticized for overlooking the importance of more mundane forms of entrepreneurial activity (Aldrich and Ruef 2018). Kirzner (1973), for instance, emphasizes how entrepreneurship also has an equilibrating role in the economy. Locally, examples could refer to small businesses and new firms such as coffee shops, restaurants, electricians, carpenters, that develop and grow in response to rising local demand. Such mundane forms of entrepreneurship matter at the local level even if the growth potential of individual firms may be limited. For example, entrepreneurship in these activities is a key way for a local area or city to develop a variety of services and cultural venues that in turn help shape the overall attractiveness of local areas for firms and individuals (including entrepreneurs).<sup>4</sup> Entrepreneurial activity generally also implies the development of local role models and knowledge and information about the practice of running a business, which may help to develop a local ‘culture of entrepreneurship’ (Sorenson and Audia 2000, Andersson and Larsson 2016, Minniti 2005). Moreover, a local presence of entrepreneurs and frequent startup activity may create pressure on local policymakers to develop regulations and enforcement procedures that are more business friendly (Andersson and Henrekson 2015).

The upshot is that there are reasons to not only study start-ups and small business activity in industries typically associated with innovation and knowledge, but also in low-end industries and more basic activities (c.f. Stephens and Partridge, 2011). As discussed below, these different types of activities are also likely to differ with respect to their dependence on both local supply- and demand-side conditions, including local knowledge and agglomeration, which further motivates an industry-disaggregated analysis of the drivers of local entrepreneurship.<sup>5</sup>

## 2.2. Determinants of the local rate of new firm formation

As stated in the introduction, our empirical analyses assess the relative importance of four groups of local factors on the local new-firm formation rates. They are (i) local economic conditions, (ii) industry structure, (iii) geography and (iv) wider agglomeration. We now briefly motivate and discuss the role of each group of factors.

### *Local economic conditions*

Economic focus is on size, human capital, employment growth, and the local economy’s overall industry diversity. Size, typically measured as either total population or employment, is related to both the supply- and demand-sides of a local economy. On the supply-side, it is well established that larger cities and regions offer various agglomeration benefits from ‘sharing’, ‘matching’, and ‘learning’ effects

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<sup>4</sup> For example, Oner (2017) shows that a local variety of retailers enhances the attractiveness of cities.

<sup>5</sup> These analyses are also relevant for policy aiming to stimulate local entrepreneurship in small and more specialized cities and regions that lack industry variety and knowledge bases. Therefore, such policy efforts focus on particular industrial areas.

(Duranton and Puga 2004; Rosenthal and Strange 2004). Although the past empirical focus of agglomeration studies is on productivity, agglomeration benefits are also likely to influence entrepreneurship. For example, matching effects could spur entrepreneurship because new firms are more likely to find needed human capital. Learning effects could stimulate local entrepreneurship as individuals may be more likely to develop good ideas for a new business when operating in larger cities, in which ideas and information may easily spread.

On the demand-side, population also reflects the scale of local demand. Large local markets may stimulate new firms by allowing for narrower specializations and making activities with large fixed startup costs economically viable.<sup>6</sup> Another aspect of the role of size stresses the local variety of customers. Transaction-cost theory posits a relationship between vertical integration and ‘market thickness’ (Pirrong 1993, McLaren 2000). Thick markets in this context occur when many firms have arm’s length arrangements, so that a firm has many potential customers. This implies that problems related to hold-up are reduced, which stimulates startup activity due to the greater number of alternative customers (cf. Andersson and Hellerstedt 2009).<sup>7</sup> On the other hand, large size comes with potential costs, such as crime, pollution, congestion and higher housing prices, which may deter new firm formation. In empirical applications, the size variables capture the *net* influence of these effects.

Human capital plays a central role in local new-firm formation rates (e.g. Armington and Acs 2002). Local human capital is typically measured as average educational attainment of the workforce. Besides being a local measure of the supply of skilled workers, it also measures the local supply of potential entrepreneurs when entrepreneurial intentions or capabilities are reflected by education or human capital. Individual-level studies of factors that influence whether individuals switch from regular wage employment to become entrepreneurs has often found a positive education effect, possibly due to entrepreneurial absorptive capacity.<sup>8</sup> Qian and Acs (2011) define such capacity as “the ability of an entrepreneur to understand new knowledge, recognize its value, and commercialize it by creating a firm”, and is indeed likely associated with years of schooling. At the aggregate regional level, Qian et al (2013) conceptualize human capital as representing the local absorptive capacity to develop and act on business opportunities, especially in regard to knowledge-based entrepreneurial activity in US metropolitan areas.

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<sup>6</sup>Positive transport costs and scale economies in production theoretically imply a significant role for market size in explaining geographical start-up patterns across industries. Market size pertains to the potential to recover fixed costs associated with a start-up. Larger markets allow such fixed costs to be spread over larger sales, such that unit costs fall. If the market is too limited relative to a start-up’s fixed costs, it can imply that an entrepreneurial opportunity will go unrealized, even though the same opportunity is economically viable in larger markets. This argument is naturally most important for firms selling product or services that depend on local markets.

<sup>7</sup>If there are few customers, an arm’s length arrangement means that the supplying firm is at the risk of being ‘held-up’ by the customer who may use its strong negotiation position to enforce low prices and affect the supplying firm’s profitability. These risks can deter startup activity.

<sup>8</sup> See e.g. Andersson and Larsson (2016) or Koster and Andersson (2018) for such analyses using Swedish data.



Local growth has been shown to be a key factor in affecting regional new firm formation. Reynolds et al (1994) report that a key factor explaining regional variations in new-firm formation rates across several different countries is local growth, measured as population or job growth, or in-migration. The typical explanation for the positive influence of local growth is its effect on local demand and overall business opportunities. Still, a problem with many of early studies is that they pay little attention to endogeneity associated with the link between local growth and new firm formation.

Overall industry diversity is another typical variable when assessing the geography of entrepreneurship. Jacobs (1969) proposed that cities foster innovation and economic dynamism because their greater variety and diversity stimulate cross-fertilization of ideas, knowledge, and information. These ideas were formalized by Duranton and Puga (2001) in the context of firm process innovations, where large and diverse cities are portrayed as “nurseries” for new products and services. A wide array of industries in a city would then be advantageous for new firm formation. Bosma and Sternberg (2014) use GEM-data for urban areas in 12 EU countries and find evidence that diversity of urban regions stimulate entrepreneurship, in particular opportunity-based.

### *Industry structure*

The industry structure vector includes various local industry employment shares, as well as the region’s average establishment size. Regional industrial employment shares influence entrepreneurship for a variety of reasons. One possible reason is that larger concentrations of high-tech and knowledge-intensive activities are linked to higher rates of new firm formation (Audretsch and Lehmann 2005). The ‘knowledge spillover theory of entrepreneurship’ (KSTE) suggests that entrepreneurial opportunities are created endogenously through knowledge investments (Acs et al 2009). Accordingly, “... entrepreneurial activity will be greater where investments in new knowledge are relatively high, since start-ups will exploit spillovers from the source of knowledge production” (Acs et al., 2009, p. 17). Because firms active in knowledge-intensive and high-tech industries typically invest more in R&D and other intangible assets, regions with higher employment concentrations in these industries are expected to have higher new-firm formation rates, which is a key underlying factor behind sources of ‘Schumpeterian’ entrepreneurship.

The average size of local establishments is another structural characteristic. A robust empirical finding is regions with smaller average establishment sizes (or regions with high density of SMEs) have higher new-firm formation rates (Reynolds et al 1994; Rosenthal and Strange 2010). One reason is that local density of small firms implies there are more opportunities for workers to develop entrepreneurial human capital. For example, employees in SMEs are more likely to be exposed to the whole business process, making them better equipped to start a firm. They are also more likely to be in contact with the firm’s

founder(s) who could serve as role model(s) and promote an entrepreneurial attitude (cf. Wagner 2004). Indeed, the literature confirms that employees in small firms are more likely to switch from wage employment to be entrepreneurs (Hyytinen and Maliranta 2008, Elfenbein et al 2011, Wagner 2004). Another reason is the social interaction across local small firms may facilitate new-firm creation, which benefits from a greater density of established entrepreneurs that serve as potential role models that can transmit knowledge through social networks (Minniti 2004, Sorenson and Audia 2000, Andersson and Larsson 2016).<sup>9</sup> Third, a local density of SMEs may indicate that the local economy has thicker input markets. As Chinitz (1961) argues, large firms are more integrated and therefore less dependent on external local suppliers (and they may have already established external supply chains). Chinitz claimed that “dollar for dollar, their business is less of stimulus for a community of independent suppliers” (ibid, p. 288; and see Fleming et al., 2011 for empirical evidence). Thus, regional economies dominated by large firms will have narrower input markets than regions dominated by SMEs, which have a local presence of input suppliers that is important for firm births (c.f. Rosenthal and Strange 2010; Glaeser 2009; Glaeser and Kerr 2009).

### *Geography*

The Geography vector aims to capture a region’s position in the urban hierarchy. This perspective is motivated by a long tradition in urban and regional research that emphasizes urban-rural interdependencies in regional growth and business dynamics (Berry 1970, Parr 1973, Irwin et al 2010; Partridge et al, 2007). That is, local areas do not operate in isolation, but rather their development is largely influenced by their position in the wider urban hierarchy, in particular their proximity to urban areas that determine their access to agglomeration benefits. Proximity to urban centers can have offsetting effects on local development. For example, the literature typically refers to ‘spread’ and ‘backwash’ to describe these offsetting effects (Gaile 1980). Spread refers to positive effects when the urban benefits diffuse to a proximate hinterland. Backwash refers instead to negative effects when urban proximity deters development, for example when firms and individuals instead choose to locate in the urban area.

There are several arguments supporting both the existence of spread and backwash effects that affect firm formation. Spread effects could, for example, be generated from “rural” entrepreneurs having access to nearby large cities with agglomeration benefits—e.g., access to a diversity of business services, while paying lower rents. As skilled workers are also typically drawn to urban areas (Ahlin et. al 2018), access to skilled workers for a startup is enhanced in the vicinity of larger urban centers, supporting start-ups in “rural” areas closer to urban centers. On the other hand, backwash effects are associated with

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<sup>9</sup>Minniti (2005) argues that such local social networks effect are important and could imply that a city or local area develops a ‘local entrepreneurship culture’: “entrepreneurship creates a ‘culture’ of itself that influences individual behavior in its favor” (ibid, p.3).

supply- and demand-side competition. Demand-side competition arises when proximity to urban areas provide greater choice of consumer and producer services and products, which imply that consumers prefer to travel to nearby urban centers.

Classic central-place theory suggests, for example, that central cities produce goods and services of higher order and offer more opportunities for multi-purpose shopping (e.g. Dicken and Lloyd 1990). Supply-side urban competition effects refer to firms in the vicinity of urban centers find it more difficult to attract skilled workers because they prefer to work and live in the urban center. That is, proximity to the urban centers means that resources concentrate in the urban center, creating backwash effects that suppress new firm formation in areas closer to urban centers. In empirical applications, measures of distance to urban centers will capture the *net* effect of spread and backwash effects, revealing which effect dominates.

While the role of agglomeration factors is typically “described” in the literature on the geography of entrepreneurship, issues of rural-urban interdependencies and distance to urban centers are often not explicitly addressed. Lavesson (2018) is an exception. He studies how distance to urban centers influence Swedish start-ups. The main finding is that larger distance from urban centers is generally associated with higher new-firm formation rates, and this is explained by a “distance protection” effect from urban competition.<sup>10</sup> His analysis suggests that the dominating influence is backwash effects.

### *Wider agglomeration*

The last group of determinants of the local new-firm formation is the role of wider agglomeration. This group assesses the role of characteristics of the wider functional region to which a local area belongs. Because we empirically focus on Swedish municipalities, they represent in economic terms a rather small spatial level of analysis. Most Swedish municipalities are part of a larger local labor market. A functional region consists of municipalities that together forms an integrated local labor market through a high frequency of commuting between them (cf. Karlsson and Olsson 2006). If municipalities that are part of a local labor market region are fully integrated, then that could mean that *regional* labor market characteristics matter more than those for the municipality. Thus, we will also account for basic economic characteristics of the wider functional region to which a municipality belongs.

## 2.3. Differences across industries

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<sup>10</sup>Lavesson (2018) only finds that longer distance deters local new firm formation when he considers distances to “large” urban centers, i.e. Stockholm, Malmö and Göteborg, which are Sweden’s largest urban areas. The explanation of this finding is that remote regions cannot access the agglomeration benefits that large cities offer, and that rural regions draw on urban resources, but mainly from larger agglomerations.

Conceptually, industries vary in two main ways that bear on the relative importance of differing determinants of new firm formation discussed above. First, there are differences across industries in terms of their reliance on various supply-side factors—e.g., agglomeration benefits. Second, industries differ in terms of the extent to which they rely on the local or regional market.

### *Variations in supply-side factors across industries*

Firms differing in the face of supply-side constraints is a classic conjecture. For example, Nelson and Winter (1982) introduced the notion of ‘technological regimes’ to describe how industries differ with regards to technological opportunity—i.e., how easy technology can be accessed through learning and innovation. Classic studies of innovation across industries also suggest that industries indeed differ in terms of the relative role of suppliers, universities, and customers when it comes to the sources of information, knowledge, and technology (e.g. Pavitt 1984, Breschi et al 2001). Moreover, the literature on “industry-life cycles” has for a long time claimed that firm resource needs and their behavior change over the course of their industry’s life cycle (Klepper 1996 and 1997, Agrawal and Gort 2002, Tavassoli 2015). Because there is spatial heterogeneity in the local availability of various resources, it is also natural that industries differ in their location patterns, including those of startups.

The research on location of different types of industries and activities shows that there are significant differences that emanate from industry heterogeneity regarding different supply-side factors. For example, innovation activities are more concentrated geographically than other types of activities, and that they tend to concentrate in diverse regions rich in knowledge resources and skilled labor (Audretsch and Feldman 1996, Feldman 2000). A typical finding in the literature is also that growth and productivity of high-tech and knowledge-intensive industries is more dependent on industry diversity, whereas specialization appears to matter more for low-tech industries (De Groot et al 2016). Neffke et al (2011) argue that industry life-cycle perspectives are important and show that the importance of local diversity declines as industries mature. This suggests that startups in young industries that rely on knowledge and technology are more likely to occur in resource-rich regions with strengths in knowledge or technology (cf. Audretsch and Lehmann 2005).

Another reason why supply-side factors, in particular labor skills, are to some extent industry-specific is because relevant knowledge, experiences, and skills may have an industry component (cf. Boschma 2017). New firms need local availability of knowledge to emerge and such availability is likely enhanced in regions with more established firms in similar or related industries. A main argument is that the local presence of related industries implies that there is a local pool of workers with relevant experiences and

skills that the new firms in an industry can employ (Xiao et al 2018).<sup>11</sup> To extent that industry-specific knowledge is critical, then startups in an industry will be more likely when regions have greater concentrations in related (or similar) industries.

### *Variations in demand-side factors across industries*

Industries differ widely in terms of how much their sales depend on local demand. This perspective is, for example, critical in understanding classic issues such as ‘minimum efficient scale’ in analyzing the location of different industries. Some services like coffee shops, hairdressers, and restaurants are in principle ‘non-traded’ and are largely dependent on the scale of local demand. Other industries like high-tech manufacturing are export-intensive with an international market.

Basic non-traded consumer services, whose demand is likely predominantly local, are likely to be responsive to local demand growth. There are also arguments that more advanced business services are also dependent on the size and growth of the local market. For example, knowledge intensive and high-tech business services often supply non-standardized services and may involve intensive customer contacts and ‘face-to-face’ interaction during the sales process (Andersson and Hellerstedt 2009). Such distance-sensitive activities are likely attracted to large local markets and respond to local demand growth.<sup>12</sup> At the same time, industries that rely more on external demand are likely to be non-responsive to local-demand factors.

## 3. EMPIRICAL STRATEGY

### 3.1. Data

We use data on new firm formation in Swedish municipalities between 1993 to 2012. Our data are obtained from Statistics Sweden (SCB). Swedish municipalities are the finest geographical unit that possess administrative rights. There are 286 municipalities (i.e., the number existing in 1993), while the corresponding figure for labor market regions is 75.

A firm is considered new if its organization number did not exist before (for years  $< t$ ) in the data and if it is classified as new in the so-called FAD-register (cf. Andersson and Klepper 2013). To distinguish between broad industry categories, we use the Eurostat (2009) classification to group new firms into

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<sup>11</sup> Hidalgo (2015) claims that this is one reason why there is interdependence between local industries and local knowledge and: “knowledge and knowhow need the presence of industries as much as industries need the presence of knowledge and knowhow” (ibid. p.142). This idea associates to Marshall’s argument of a local pool of workers regarding the benefits of local industry clusters.

<sup>12</sup> Coffey and Bailly (1991: 109) remark for instance that “... it is the cost of maintaining face-to-face contacts between the producer on the one hand, and their inputs and markets, on the other hand, that is potentially the most expensive element of intermediate-demand service production”.

five categories: (i) high-tech manufacturing (HT-man), (ii) low-tech manufacturing (LT-man), (iii) knowledge intensive services (KIS), (iv) less knowledge intensive services (LKIS), and (v) other industries (Others). The last category is comprised of new firm start-ups in agriculture, fishery and construction.

To measure a municipality's new-firm formation rate, the number of start-ups is normalized to the working-age (20-65 years) municipal population (1000s) (c.f. Audretsch and Fritsch 1994). We then compute weighted averages over 1993-2012. There are two reasons for this: a) to smooth out erratic yearly fluctuations and b) our empirical model will include time-invariant variables, like distance to urban centers, which means that we cannot exploit the time dimension in the data to control for time-invariant municipal effects.

### 3.2. Model and variables

To assess the relative importance of the four groups of factors discussed in Section 2 in explaining local rates of new firm formation, we set-up the following baseline empirical model:

$$y_i = \alpha + \beta_1 \mathbf{LOCAL}_i + \beta_2 \mathbf{INDUSTRY}_i + \beta_3 \mathbf{GEOGRAPHY}_{ij} + \mathbf{W\_AGGLOMERATION}_{LMA(-i)} + \varepsilon_i$$

where  $y_i$  the average rate of new firm formation in municipality  $i$  between 1993 and 2012.  $\mathbf{LOCAL}_i$ ,  $\mathbf{INDUSTRY}_i$ ,  $\mathbf{GEOGRAPHY}_{ij}$  and  $\mathbf{W\_AGGLOMERATION}_{LMA(-i)}$  represent local economic conditions, industry structure, geography and wider agglomeration, respectively. Subscripts  $i$  and  $j$  indicate distance relationships between municipality  $i$  and nearest urban center  $j$  while the subscript  $-i$  show that the contribution from the pertinent municipality  $i$  is deducted in the calculation of wider agglomeration variables (i.e., labor market region). We estimate this model for the overall rate of new-firm formation, as well as across the five industry categories. A number of tests to assess the explanatory power of each of the four groups of factors will be undertaken.

The first group of independent variables  $\mathbf{LOCAL}_i$  is comprised of six variables. First, municipal employment growth between 1993 and 2012 ( $\mathbf{EmpGr93\_12}_i$ ) is a key indicator of local growth. We address endogeneity concerns by employing an IV approach with a Bartik shift-share predictor (see below and Appendix A). We measure overall industry diversity with an inverted Herfindahl index ( $\mathbf{InvHerfindahl}_i$ ). This indicator equals the sum of squared industry employment shares. Agglomeration effects are captured by the total number of employees (in logs) of each municipality ( $\mathbf{LNDayPop}_i$ ). To capture local human capital, we measure the total number of employees with a long university education ( $\geq 3$  years) as a fraction of the total workforce ( $\mathbf{HighEDshare}_i$ ), as well as an indicator variable for whether the municipality hosts a local university ( $\mathbf{University}_i$ ). As a general

control, we include the working-age (20-64) resident share in the municipality, (**WorkShare<sub>i</sub>**). It reflects the pool of potential entrepreneurs in working age, and could also be claimed to capture the trade-off between starting a new firm and taking wage employment. If it is positive in the regressions it means that potential workers involve in firm start-ups rather than in wage employment, while a negative influence means the opposite.

**INDUSTRY<sub>i</sub>** consists of the industry employment shares and average establishment size. Employment shares in high-tech manufacturing (**HT\_Share<sub>i</sub>**), low-tech manufacturing (**LT\_Share<sub>i</sub>**), knowledge-intensive services (**KIS\_Share<sub>i</sub>**), and low-knowledge intensive services (**LKIS\_Share<sub>i</sub>**) are included. The share of individuals employed in agriculture, fishery, and construction industries (**Others\_Share<sub>i</sub>**) constitutes the reference group. Average establishment size equals total employees divided by the total number of establishments. In the analyses for different industries, we use two measures of average establishment size: (i) average establishment size in the same industry (**AvEstSize\_Int<sub>i</sub>**) and (ii) average establishment size outside the industry (**AvEstSize\_Ext<sub>i</sub>**). By separating the two measures, we can test if the effect of small-scale businesses is internal to an industry or if it also works across industries.

**GEOGRAPHY<sub>i</sub>** represents variables that focus on a municipality's distance to urban centers of various size, as well as indicators of the municipality's position in its functional region (local labor market). Regarding the distance variables, we consider three urban-center types: (i) small, (ii) medium, and (iii) large (c.f. Lavesson, 2018 and Partridge et al., 2008). Medium-sized urban centers comprise municipalities classified as urban (using the Swedish Board of Agriculture's definition) with at least 50,000 inhabitants (37) while large urban centers are urban municipalities with at least 250,000 inhabitants (3). The remaining 53 urban centers are classified as small.

The three distance variables account for how access to urban centers influence local firm start-ups, where access is measured as the distance in kilometers between the population centroids of municipalities (cf. Niedomysl et al. 2017). The variable **DistNearUC<sub>i</sub>** measures the geographical distance to nearest urban center (regardless of size), while **AddMedium<sub>i</sub>** and **AddLarge<sub>i</sub>** account for marginal effects from (additional) distance to medium-sized and large urban centers. The variables that capture marginal effects of distance comprise the difference between reaching the nearest urban center (of any size) and reaching a medium-sized urban center on the one hand (**AddMedium<sub>i</sub>**), and a large urban center on the other hand (**AddLarge<sub>i</sub>**). By definition, **AddMedium<sub>i</sub>** is zero for municipalities classified as medium-sized urban centers. Similarly, **AddLarge<sub>i</sub>** is zero for Stockholm, Malmö, and Göteborg. We also include an indicator variable for the largest municipality in the labor market area, (**Central<sub>i</sub>**). **LargestUrban<sub>i</sub>** is another dummy for being one of Sweden's three largest municipalities, i.e. Stockholm, Malmö or Göteborg.

**W\_AGGLOMERATION**<sub>LMA(-i)</sub> include similar variables as in **LOCAL**<sub>i</sub>, but measured at the level of local labor market regions (LMA), excluding the municipality in question. At this level, we include total employment (**LNDayPopLMA**<sub>i</sub>), individuals of working age (**WorkShareLMA**<sub>i</sub>), human capital (**HighEDshareLMA**<sub>i</sub>) as well as industry employment shares (**HT\_ShareLMA**<sub>i</sub>, **LT\_ShareLMA**<sub>i</sub>, **KIS\_ShareLMA**<sub>i</sub> and **LKIS\_ShareLMA**<sub>i</sub>).

### *Endogeneity concerns – instrumenting local employment growth*

As stated above, there are possible endogeneity issues between job growth and firm start-ups. To address this, municipal employment growth is instrumented with a shift-share instrument (Bartik 1991). The Bartik-instrument is constructed by allowing municipal industries, as defined in Eurostat (2009), to grow at the national industry average. The idea is that by allowing sectoral employment growth to follow the corresponding national growth rates, the part of variation that is exogenous to municipal firm start-ups is isolated.<sup>13</sup> The Bartik instrument is the predicted employment growth is all of the municipality’s industries (using Eurostat, 2009) grow at their respective national employment growth rate. Because the national growth rate is exogenous to a given municipality, the instrument is valid.

Two requirements need to be fulfilled for an IV estimator to be useful. First, there needs to be a strong first-stage—i.e., a strong correlation is required between the instrumental variable (IV) and the endogenous variable. Following convention, the first-stage requirement is tested using a traditional F-test in the empirical analysis. Second, the exclusion restriction must be fulfilled so that the instrument is uncorrelated with the residual. Because the model is exactly identified, this requirement cannot be formally tested but is usually satisfied (see e.g. Blanchard and Katz 1992). We also employ the Kleibergen and Paap (2006) test to assure that that the IV estimator does not suffer from underidentification.

### 3.3. New firm formation across municipalities in Sweden

Table A1 in Appendix presents summary statistics for the empirical analysis, including the Bartik-instrument. An average Swedish municipality experiences about 11 new firms per 1000 working-age individuals. Still, spatial heterogeneity is significant with new-firm formation rates ranging from 5 to 21 new firms per 1000 working-age individuals.

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<sup>13</sup> The formula for the Bartik-IV is:

$$\mathbf{IVEmpGr93\_12}_i = \sum_{\text{sector } j} e_{ij1993} g_{j1993,2012}^{\text{National}}$$

where  $e_{ij1993}$  is municipality  $i$ ’s employment share in sector  $j$  in 1993 and  $g_{j1993,2012}^{\text{National}}$  is the national sectoral employment growth rates between 1993 and 2012.



As in many other countries, new firms tend concentrate in service industries. Table 1 presents the distribution of startups by industry in 1993 and 2012. In 1993, the fraction of service startups was 55% and in 2012, this figure increased to over 64 %. At the same time, manufacturing startups are rare and constitute only about 3-5 % of all new firms, reflecting the rising move to services in OECD economies (cf. Schettkat 2007). About 23 percent of new service-oriented firms were knowledge intensive (KIS) in 1993, increasing 11.2 percentage points to 34 percent in 2012.

**Table 1.** The distribution of new firms across industries 1993 and 2012.

INDUSTRY	Share	
	1993	2012
High-tech manufacturing	0.015	0.004
Low-tech manufacturing	0.047	0.032
Knowledge intensive-services	0.228	0.340
Less knowledge intensive-services	0.329	0.303
Other industries	0.381	0.321

**Note:** Industry categories based on Eurostat (2009).

On average during the study period, 5.34 out of 10.9 new firms per working-age individual occur in KIS or LKIS. Firm start-ups in agriculture, fishery and construction appear to be common. An average Swedish municipality experiences about 4.85 new firms, per working-age individual in these industries. However, the range (maximum – minimum value) indicates that this is a result partly driven by high numbers in a few municipalities.

Figure 1 maps new-firm formation rates in total and by industry. The maps show that there is significant spatial variation in the rates of new-firm formation—both in total and by industry. The maps clearly show that new-firm rates formation in knowledge-intensive service industries tend to be high in larger cities, whereas new-firm formation in other services as well as low-tech manufacturing is comparatively high in smaller and remote areas, like the northeastern parts.

Figure 2 presents Kernel density estimates of total firm start-ups and firm start-ups by industry. The distributions are all positively skewed (a-f) with a rather long right tail. In each industry, there are some municipalities that perform very well in terms of new-firm formation compared to others. The average rates are substantially higher than the mean, indicating the existence of new-firm formation ‘hot-spots’.

As Figure 1, Figure 2 also illustrate significant industry differences. For example, new-firm formation rates in knowledge-intensive services stand out as having a very long right-hand tail, with as many as 188 of the 286 municipalities having below average rates. Hence, in this industry, there are a number of

municipalities that are clear ‘hot-spots’, even though the underlying data is the weighted-average rate of new-firm formation over the whole period 1993-2012, which smooths out short-run variations.

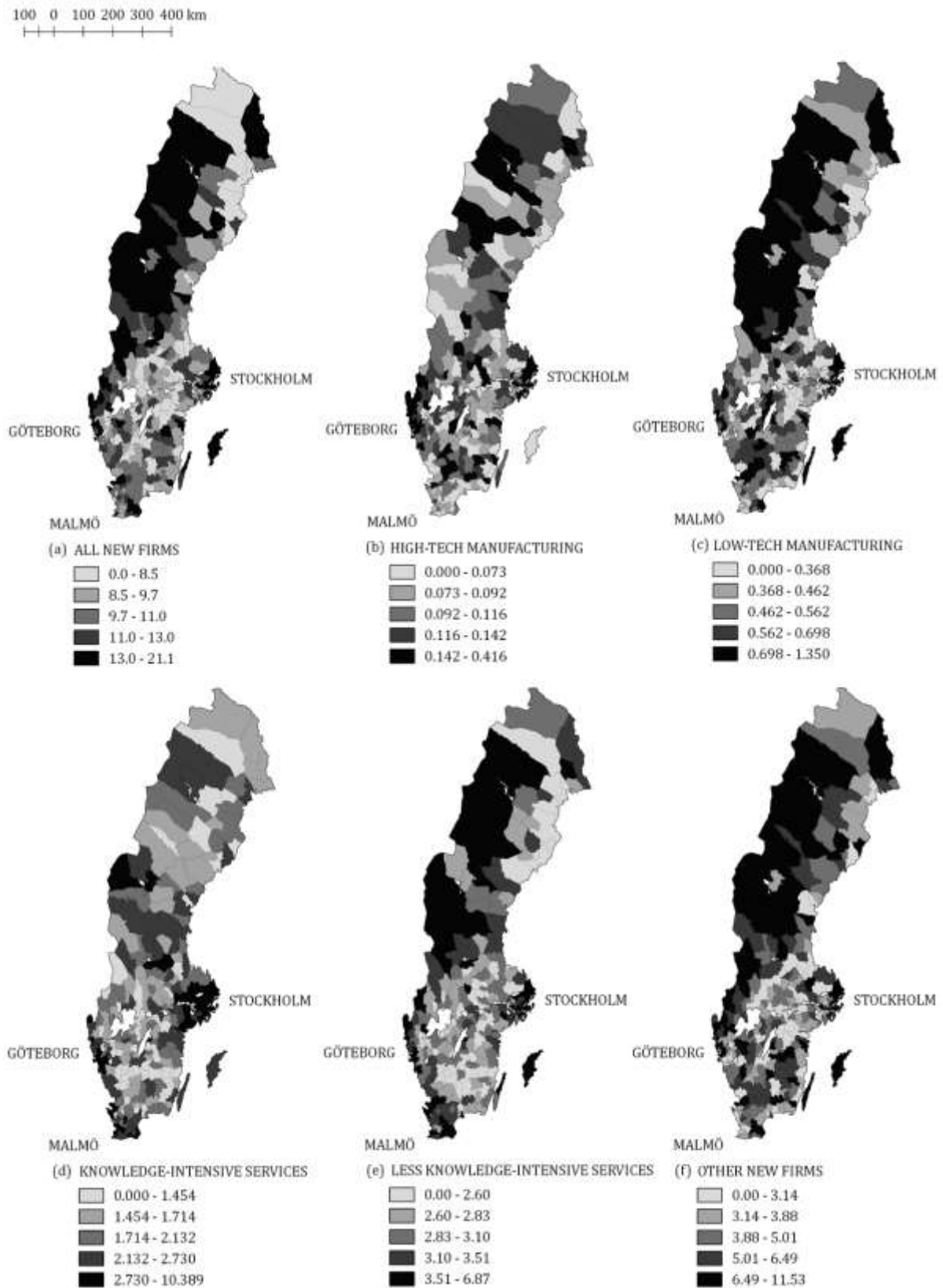
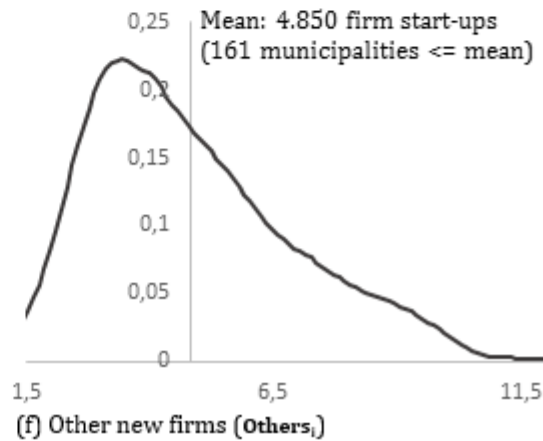
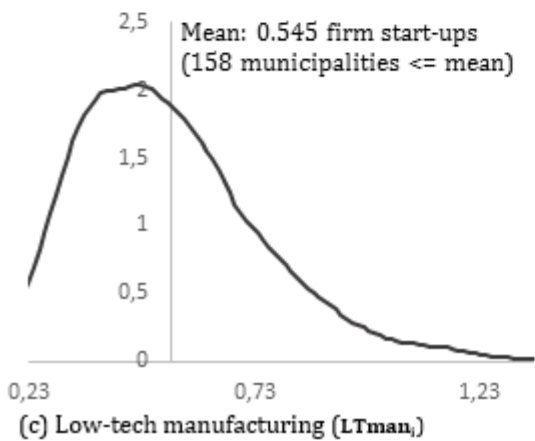
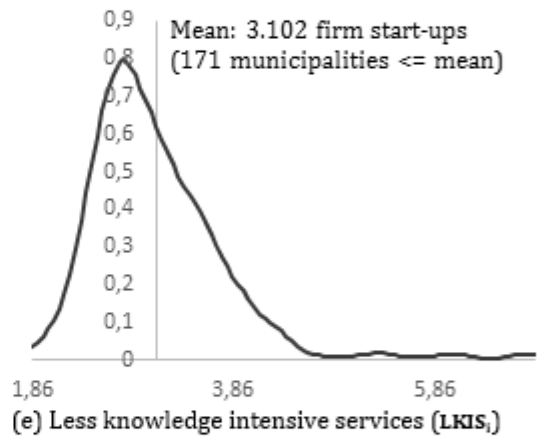
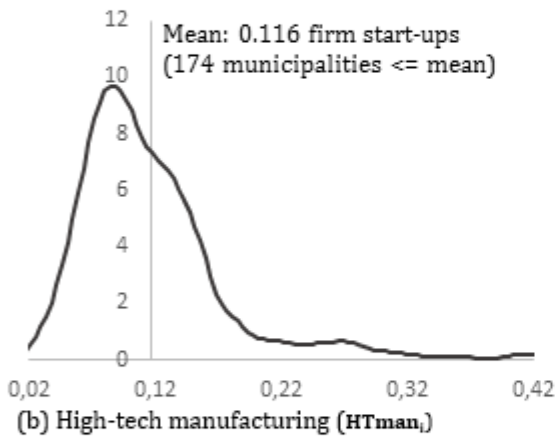
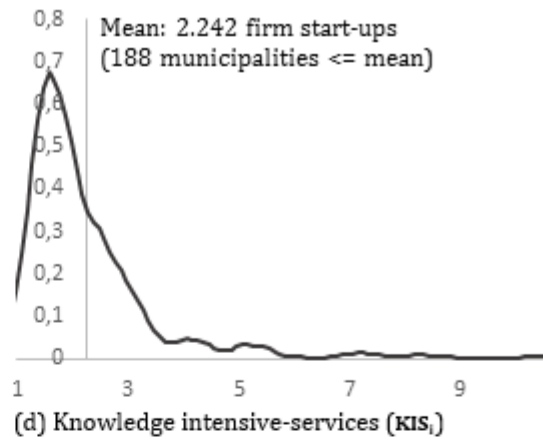
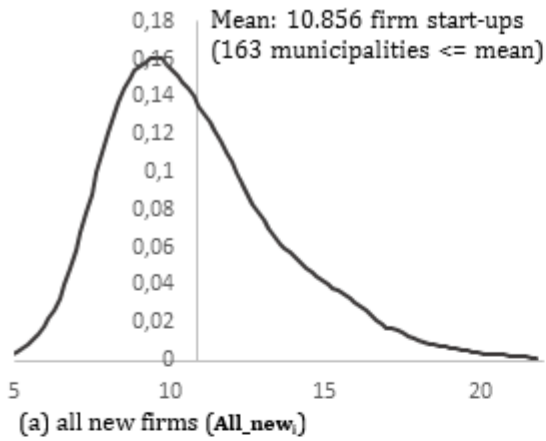


Figure 1a-f. Firm start-ups per working age individual; (a) in total and by industry (b-f).



**Figure 2a-f.** Kernel density functions of total firm start-ups (a) and by industry (b-f).

**Note:** The horizontal axis cuts the vertical axis at the average firm start-ups per 1000 individuals for each type of firm start-ups. The estimations are based on the Epanechnikov kernel function using a bandwidth selection method that minimizing the mean integrated squared error.

## 4. RESULTS

### *The overall rate of new firm formation*

Table 2 presents the estimation results for the total rate of new firm formation. All estimates are based on the 2SLS estimator in which we instrument local job growth with the Bartik-instrument (see Section 3.2). To ease comparison, the reported estimates are standardized regression coefficients; that is, for each variable, the mean is subtracted from the observation and divided with the standard deviation. This applies to all variables except dummies (**University<sub>i</sub>**, **Central<sub>i</sub>** and **LargestUrban<sub>i</sub>**). In the analysis, the four groups of supply- and demand-side factors are added successively, and we perform a joint-significance test for each group.

Column 1 presents the results when we only include basic local economic conditions, i.e. employment growth (instrumented), industry diversity, employment size, human capital, local university dummy, as well as working-age share of population. This model ‘explains’ roughly 9 percent of the variation in the rate of new-firm formation across Swedish municipalities, and the variables are jointly significant as indicated by the reported Chi-square test. Local job growth has a positive influence on the new-firm formation rate, whereas industry diversity, employment size and share of working-age populated are negatively associated with local entrepreneurship. Surprisingly, neither human capital nor the presence of a local university is statistically significant.

The positive effect of local employment growth may be explained by that the lion’s share of start-ups are in services that often depend on local demand.<sup>14</sup> The estimated influence of employment size indicates that when one controls for other characteristics, the negative effects associated with size, e.g. congestion or the cost of office space and land, appear to dominate.

Column 2 adds the industry structure variables: industry employment shares and average establishment size. As is evident, the distribution of employment across broad industries matters little in explaining local new-firm formation. Average establishment size is the only statistically significant variable. The results are coherent with previous findings that municipalities with larger average establishment sizes having lower rates of new-firm formation. Although only one industry-structure variable is significant, it is notable that the fraction of the variance in entrepreneurship across municipalities that is ‘explained’ by the model rises from about 9 percent to almost 56 percent when adding these variables (see adjusted  $R^2$ ). This illustrates the important role of average establishment size in accounting for spatial variations in new-firm formation.

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<sup>14</sup> It should be noted that the F-test for the first stage requirements as well as the test for underidentification are satisfied, as indicated by the test-statistics reported in the table.

Moreover, the positive influence of local job growth and negative influence of industry diversity, employment size and working-age population share remains after industry structure is accounted for. After controlling for industry structure, we also see that the estimated parameter associated with human capital is positive and statistically significant, consistent with previous studies (e.g. Glaeser 2009, Armington and Acs 2002).

Column 3 adds the indicators related to the municipality's position in the urban hierarchy. As Lavesson (2018), we find some evidence favoring a 'distance protection-effect' with longer distances to an urban center being associated with higher new-firm formation rates. Since the estimated coefficient represent the net of spread and backwash effects, it means that backwash effects dominate. Backwash effects, could for example, be explained by the importance of service industries in new-firm formation, which are heavily influenced by competition local effects.

**Table 2.** Determinants of the local rate of new firm formation across municipalities in Sweden, (2SLS, IV)

	<b>Dependent variable: New firms per working age individual (in 1000s)</b>			
	1	2	3	4
	Base: local	+industry	+geography	+agglomeration
Employment growth (1993-2012)	1.169*** (0.160)	0.577*** (0.176)	0.544*** (0.166)	0.582*** (0.166)
Inverted Herfindahl-index	-0.358*** (0.0880)	-0.149* (0.0794)	-0.184*** (0.0668)	-0.118** (0.0560)
Initial 1993 Population (logarithm)	-0.279*** (0.0646)	-0.138** (0.0573)	-0.0919 (0.0612)	-0.114* (0.0640)
Share of individuals in working age	-0.683*** (0.123)	-0.477*** (0.0789)	-0.330*** (0.0768)	-0.495*** (0.0866)
Share of highly educated	0.0928 (0.107)	0.355*** (0.112)	0.423*** (0.0954)	0.454*** (0.0776)
University (0/1)	-0.248 (0.238)	-0.178 (0.141)	-0.267 (0.169)	-0.101 (0.179)
High-tech manufacturing		-0.185 (0.165)	0.0969 (0.158)	0.0157 (0.165)
Low-tech manufacturing		-0.211 (0.220)	0.161 (0.215)	0.0173 (0.223)
Knowledge intensive-services		-0.201 (0.195)	0.0156 (0.202)	-0.0848 (0.211)
Less knowledge intensive-services		-0.0768 (0.165)	0.0929 (0.164)	0.0200 (0.182)
Average establishment size		-0.505*** (0.148)	-0.717*** (0.123)	-0.741*** (0.102)
Distance to nearest urban center (UC)			0.266*** (0.0655)	0.137** (0.0579)
Additional distance to medium UC			0.0219 (0.0301)	0.0393 (0.0298)

Additional distance to large UC			0.0746 (0.0770)	-0.000873 (0.0762)
Central municipality (0/1)			0.103 (0.138)	0.330** (0.147)
Largest urban municipality (0/1)			0.351 (0.340)	0.0201 (0.406)
1993 population (logarithm) (LMA)				-0.0563 (0.125)
Share of individuals in working age (LMA)				0.376*** (0.102)
Share of highly educated (LMA)				-0.460*** (0.142)
High-tech manufacturing (LMA)				-0.0454 (0.0923)
Low-tech manufacturing (LMA)				-0.0128 (0.137)
Knowledge intensive-services (LMA)				0.256* (0.138)
Less knowledge intensive-services (LMA)				0.0969 (0.0954)
Constant	0.0346 (0.0963)	0.0250 (0.0704)	0.00668 (0.0769)	-0.0726 (0.0606)
First-stage (F-stat).	101.5	94.42	119.00	88.28
Prob(F-Stat)	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk LM statistic (p-value)	0.0008	0.0017	0.0021	0.0011
Group LOCAL (chi2)	135.8	155.3	204.9	269.5
Prob(chi2)	0.0000	0.0000	0.0000	0.0000
Group INDUSTRY (chi2)		72.91	58.61	116.8
Prob(chi2)		0.0000	0.0000	0.0000
Group GEOGRAPHY (chi2)			51.41	16.16
Prob(chi2)			0.0000	0.0064
Group AGGLOMERATION (chi2)				35.52
Prob(chi2)				0.0000
Obs (N)	286	286	286	286
R-square (adj)	0.0922	0.555	0.638	0.670

**Note:** Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. The reported values are standardized regression coefficients. Dummy variables are not standardized (University 0/1, Central municipality 0/1, Largest urban municipality 0/1). **Sources:** Statistics Sweden (LISA and FAD databases 1993–2012) and own calculations.

Column 4 adds the wider-agglomeration characteristics (the local labor market), reflecting the full model in which all four variable groupings are included. This model accounts for about 67 percent of the variation in new-formation rates across Swedish municipalities. The addition of these variables does not change the sign or significance of variables in the other groups (compare e.g. column 3). One exception is the dummy for being the largest municipality in the local labor market region becomes positive.

Among the variables in the fourth group, wider agglomeration, we see that the working-age population share, and the human capital variables are statistically significant at the 5 percent level. The influence of human capital in the wider region is negative and may be explained by a competition effect for skilled labor. If the supply of skilled labor in nearby municipalities is high, then new-firm formation may be drawn to those municipalities.<sup>15</sup>

In summary, the results regarding the overall rate of new-firm formation suggests that all four variable groupings matter. We find evidence that local job growth and human capital drive entrepreneurship in municipalities and that industry diversity is negatively related to overall new-firm formation. Average establishment size has a consistent negative effect and there is evidence of a distance-protection effect in which longer distances to an urban center shelters a municipality from negative backwash effects. At the level of wider agglomeration, we find particular that especially a large supply of skilled labor in the wider local labor market regions has a negative influence, possibly indicating supply-side competition effects.

### *Results by industry*

Table 3 presents the full models that include all four variable groupings (column 4 in Table 2) for each respective industry aggregate. All models are estimated using 2SLS in which local employment growth is instrumented using the Bartik-instrument. In every model, the test statistics for the F-test of the first stage as well as the test for underidentification are satisfactory.

The results suggest sharp differences across broad industry aggregates, consistent with industry heterogeneity regarding the roles of demand- and supply-side factors for local new-firm formation rates. Local job growth drives local entrepreneurship exclusively in services. It is only positive and statistically significant at the 5 percent level for services, knowledge-intensive and less-knowledge-intensive. In quantitative terms, the effect of local growth is strongest in low-knowledge-intensive services. This supports the argument that this service group is most geared towards basic consumer services that depend on the local market. The insignificance of local growth for manufacturing is probably due to it being more reliant on external markets that are less distance-sensitive than services.

Industry diversity is only positively significant for high-tech manufacturing and knowledge-intensive services, while it is negative for the other industry group (agriculture and fishing, etc.). For low-tech manufacturing and less knowledge-intensive services, industry diversity is insignificant. This suggests that negative industrial diversity effects found for the overall new-firm formation rate is driven by the

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<sup>15</sup>A potential explanation for the positive influence of the working-age population share is that when surrounding municipalities are more self-sufficient regarding local labor supply, supply-side competition effects are reduced

residual industry category (agriculture, fishing, etc.). The fact that industry diversity only drives local entrepreneurship in high-tech and knowledge-intensive activities is consistent with the argument that diversity primarily matters for innovative industries that draw on opportunities for cross-fertilization of ideas and knowledge in diversified and urban regions (cf. Feldman and Audretsch 1999, Duranton and Puga 2001).

**Table 3.** Determinants of the local rate of new firm formation across municipalities in Sweden by industry (2SLS, IV), only models with all four groups of variables.

	<b>Dependent variable: New firms per working age individual (in 1000s)</b>				
	HT-man	LT-man	KIS	LKIS	Others
Employment growth (1993-2012)	0.0459 (0.163)	0.255 (0.176)	0.270** (0.107)	0.664*** (0.223)	0.211* (0.115)
Inverted Herfindahl-index	0.332*** (0.0964)	0.179* (0.0929)	0.363*** (0.0313)	0.0278 (0.0927)	-0.428*** (0.0401)
1993 population (log)	-0.467*** (0.103)	-0.142* (0.0792)	0.0107 (0.0412)	-0.0333 (0.0821)	-0.0404 (0.0372)
Share of individuals in working age	-0.0786 (0.127)	-0.407*** (0.0972)	-0.122** (0.0513)	-0.605*** (0.115)	-0.278*** (0.0810)
Share of highly educated	0.175** (0.0834)	0.362*** (0.0804)	0.673*** (0.156)	0.305*** (0.0701)	0.211*** (0.0400)
University (0/1)	-0.0830 (0.103)	-0.0492 (0.137)	-0.0872 (0.155)	-0.206 (0.216)	0.00145 (0.0779)
High-tech manufacturing	0.289 (0.263)	0.0248 (0.105)	0.0355 (0.177)	-0.183 (0.150)	-0.510*** (0.0962)
Low-tech manufacturing	0.00226 (0.186)	-0.0145 (0.187)	0.0885 (0.249)	-0.196 (0.204)	-0.769*** (0.135)
Knowledge intensive-services	-0.0229 (0.166)	-0.312** (0.128)	0.776* (0.452)	-0.297 (0.194)	-0.703*** (0.106)
Less knowledge intensive-services	0.0553 (0.116)	-0.0255 (0.0923)	0.0612 (0.173)	0.574** (0.283)	-0.463*** (0.0946)
Average establishment size (internal)	-0.272 (0.221)	-0.211* (0.117)	-1.159*** (0.389)	-0.632 (0.418)	-0.339*** (0.0467)
Average establishment size (external)	-0.337*** (0.122)	-0.721*** (0.139)	0.272 (0.191)	0.186 (0.304)	-0.174*** (0.0484)
Distance to nearest urban center (UC)	0.130 (0.112)	0.198*** (0.0744)	-0.0395 (0.0396)	0.196** (0.0782)	0.138*** (0.0430)
Additional distance to medium UC	0.0215 (0.0673)	0.0352 (0.0371)	0.0207 (0.0254)	0.0284 (0.0394)	0.0363 (0.0243)
Additional distance to large UC	-0.117 (0.0995)	0.273** (0.107)	-0.0859 (0.0555)	-0.126 (0.0936)	0.157*** (0.0564)
Central municipality (0/1)	0.209 (0.210)	0.345** (0.148)	0.192 (0.127)	0.206 (0.166)	0.191* (0.109)
Largest urban municipality (0/1)	0.723** (0.332)	0.0137 (0.291)	0.179 (0.199)	0.429 (0.306)	-0.404* (0.241)
1993 population (log) (LMA)	-0.164 (0.214)	0.209 (0.144)	0.0314 (0.0873)	0.203 (0.145)	-0.142 (0.0997)
Share of individuals in working age (LMA)	0.219** (0.110)	0.506*** (0.0863)	0.135** (0.0648)	0.175 (0.155)	0.293*** (0.0699)
Share of highly educated (LMA)	-0.214 (0.188)	-0.788*** (0.147)	-0.125 (0.0918)	-0.539*** (0.203)	-0.285*** (0.0945)



High-tech manufacturing (LMA)	0.226*	0.151	-0.0663	-0.0253	-0.0210
	(0.137)	(0.112)	(0.0748)	(0.108)	(0.0655)
Low-tech manufacturing (LMA)	0.141	0.243	-0.0345	-0.120	0.0103
	(0.171)	(0.174)	(0.112)	(0.161)	(0.0996)
Knowledge intensive-services (LMA)	0.295	0.403**	0.140	0.115	0.130
	(0.201)	(0.171)	(0.116)	(0.187)	(0.0919)
Less knowledge intensive-services (LMA)	0.0241	0.0957	-0.0715	0.0264	0.113*
	(0.117)	(0.0977)	(0.0766)	(0.100)	(0.0644)
Constant	-0.0509	-0.0838	-0.0399	-0.0298	-0.0460
	(0.0685)	(0.0594)	(0.0469)	(0.0735)	(0.0375)
<hr/>					
First-stage (F-stat).	88.28	85.37	78.66	83.06	74.84
Prob(F-Stat)	0.0000	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk LM statistic (p-value)	0.0011	0.0012	0.0023	0.0014	0.0006
<hr/>					
Obs (N)	286	286	286	286	286
R-square	0.299	0.616	0.794	0.506	0.876

**Note:** Standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . The reported values are standardized regression coefficients. Dummy variables are exceptions and are not standardized (University 0/1, Central municipality 0/1, Largest urban municipality 0/1). **Sources:** Statistics Sweden (LISA and FAD databases 1993–2012) and own calculations.

The role of industry structure varies substantially across industries. Services differ from manufacturing in that service new-firm formation tends to be higher in municipalities with a greater employment share in that industry category. This pattern is rather strong for low knowledge intensive services (LKIS) and positive, but weaker, in knowledge-intensive services (KIS). There are no such patterns for the two manufacturing industries, whereas all employment share coefficients are negative for the residual “other industry”. The latter can be explained by this group comprising industries that depend on spatially ‘fixed’ resources, such as agricultural land—i.e., such new-firm formation is higher in areas well-endowed with the pertinent resource.

The industry-level models make a distinction between internal and external average establishment size. The former is average establishment size in the industry and the former is average establishment size in all other industries in the municipality. In both manufacturing industries, external average establishment size is negative and statistically significant. Since employment outside manufacturing is dominated by services, one explanation for this result is that manufacturing new-firm formation is stimulated by the local presence of small-scale business service providers than supply manufacturing firms. This story is consistent with Chinitz’s (1961) arguments. Neither internal nor external average establishment size is significant in explaining new-firm formation in services with low knowledge intensity (LKIS). On the other hand, in knowledge-intensive services (KIS), internal average establishment size is negative and significant, in which the magnitude of the estimated coefficient also indicates that the effect is economically important. This effect may, for example, be explained by small firms being more likely to spawn employee spinoffs that draw on their industry experience (cf. Wagner 2004). The dominance of this effect in knowledge-intensive services may be explained by this industry have relatively low start-ups costs, and it represent a growing industry (cf. Schettkatt 2007). This industry often has activities

with intensive customer contacts such that employees acquire entrepreneurial knowledge and information that facilitate employee spinoffs.

Another finding is that the ‘distance-protection’ effect is present in all industries except high-tech manufacturing and knowledge-intensive services. One explanation is that high-tech and knowledge-intensive industries have less reliance on local markets and they also have a stronger dependence on the resources offered by large cities. Therefore, remoteness from urban centers is not an advantage for their local rate of new-firm formation. Moreover, the negative effect of skilled workers in the wider local labor market region found for the overall results (Table 2) appears to be driven by low-tech manufacturing, low knowledge-intensive services, and the other industry category (Table 3). The lack of a negative for high-tech manufacturing and knowledge-intensive services may be explained by these industries being more reliant on skilled labor, which implies that the benefits from being in a local labor market region with significant access to skilled workers outweighs possible negative supply-side competition effects.

Finally, the industry-level results also confirm the central role of human capital in local new firm formation: the only local factor that has a consistent positive effect on new firm formation across industries is the local density of skilled workers. We interpret this as industry structure, geography, and agglomeration do matter in various ways for different industries, but in the end, new firms are started by people and the main factor driving local entrepreneurship comes down to the characteristics of the local residents.

## 5. CONCLUSIONS

Our empirical analyses analyzed the relative role of four categories of factors in explaining local rates of new firm formation across municipalities in Sweden. First, for total start-ups rates, we show that human capital drive entrepreneurship in municipalities and that industry diversity is negatively related to overall new-firm formation. Average establishment size has a consistent negative effect and there is evidence of a distance-protection effect in which longer distances to an urban center shelters a municipality from negative backwash effects. At the level of wider agglomeration, we find particular that especially a large supply of skilled labor in the wider local labor market regions has a negative influence, possibly indicating supply-side competition effects. Our IV estimates also show that local growth has robust positive influence on the local rate of new-firm formation. That is, the local rate of firm formation appears to be stimulated by local job growth, even after accounting for endogeneity.

Second, we also document that the relative importance of different local factors in explaining the new-firm formation differs significantly across industries. Local job growth only supports new-firm

formation in services, and in particular low-end services like retail and wholesale trade that depend on local demand. The ‘distance-protection’ effect is present in all industries except high-tech manufacturing and knowledge-intensive services, perhaps due to less reliance on local markets, and also because they have a stronger dependence on the rich resources offered by large cities and city centers. Therefore, longer distance to urban centers is not advantageous for their rate of new firm formation. Moreover, indicators of local industry structure add explanatory power, especially for services. Services also differ from manufacturing due to a greater tendency for services to ‘cluster’. New-firm formation in services tend to be higher where services have greater local employment shares, but not manufacturing firm formation. Another clear result is that local industry diversity is only positively associated with new-firm formation in high-tech and knowledge-intensive industries, corroborating findings from several studies.

The results at the industry level also confirm the central role of human capital in local rates of new firm formation; local average educational attainment is the only local factor with a consistently positive relation to new-firm formation across all industry subgroups. The main conclusion is that industry structure, geography, and agglomeration matter in explaining local rates of new firm formation, but in the end, people start new firms and their characteristics are the main factor driving local entrepreneurship.

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## APPENDIX A, summary statistics

**Table A1.** Summary statistics ( $N=286$ )

		Mean	SD	Min	Max
New firms per working age individual	<b>All_new<sub>i</sub></b>	10.856	2.745	5.486	21.065
New HT-man firms per working age individual	<b>HTman<sub>i</sub></b>	0.116	0.059	0.025	0.416
New LT-man firms per working age individual	<b>LTman<sub>i</sub></b>	0.545	0.200	0.234	1.350
New KIS firms per working age individual	<b>KIS<sub>i</sub></b>	2.242	1.239	0.980	10.389
New LKIS firms per working age individual	<b>LKIS<sub>i</sub></b>	3.102	0.687	1.862	6.868
New Other firms per working age individual	<b>Others<sub>i</sub></b>	4.850	1.977	1.548	11.530
<b>LOCAL<sub>i</sub></b>					
Employment growth (1993-2012)	<b>EmpGr93_12<sub>i</sub></b>	0.085	0.176	-0.263	0.861
<i>BARTIK-IV</i> : Employment growth (1993-2012)	<b>IVEmpGr93_12<sub>i</sub></b>	0.176	0.054	-0.070	0.307
Inverted Herfindahl-index	<b>InvHerfindahl<sub>i</sub></b>	4.004	0.673	2.366	5.496
Initial 1993 Population (logarithm)	<b>LNDayPop<sub>i</sub></b>	8.863	0.969	6.823	13.003
Share of individuals in working age	<b>WorkShare<sub>i</sub></b>	0.425	0.028	0.319	0.493
Share of highly educated	<b>HighEDshare<sub>i</sub></b>	0.048	0.027	0.024	0.279
University (0/1)	<b>University<sub>i</sub></b>	0.140	0.347	0.000	1.000
<b>INDUSTRY<sub>i</sub></b>					
High-tech manufacturing	<b>HT_Share<sub>i</sub></b>	0.076	0.070	0.002	0.470
Low-tech manufacturing	<b>LT_Share<sub>i</sub></b>	0.146	0.097	0.013	0.516
Knowledge intensive-services	<b>KIS_Share<sub>i</sub></b>	0.401	0.074	0.180	0.707
Less knowledge intensive-services	<b>LKIS_Share<sub>i</sub></b>	0.238	0.057	0.135	0.449
Other industries	<b>Others_Share<sub>i</sub></b>	0.139	0.044	0.052	0.304
Average establishment size	<b>AvEstSize<sub>i</sub></b>	8.697	2.836	3.925	19.747
Internal average establishment size in HT-man	*	0.715	0.855	0.009	7.164
Internal average establishment size in LT-man	*	1.310	1.161	0.072	10.196
Internal average establishment size in KIS	*	3.481	1.366	1.465	10.726
Internal average establishment size in LKIS	*	2.061	0.846	0.816	6.777
Internal average establishment size in Others	*	1.131	0.318	0.396	3.662
External average establishment size in HT-man	*	7.982	2.526	3.917	19.588
External average establishment size in LT-man	*	7.387	2.533	3.629	18.260
External average establishment size in KIS	*	5.216	1.865	2.198	15.134
External average establishment size in LKIS	*	6.636	2.258	2.774	15.995
External average establishment size in Others	*	7.566	2.741	2.921	18.718
<b>GEOGRAPHY<sub>ij</sub></b>					
Distance to nearest urban center (UC)	<b>DistNearUC<sub>ij</sub></b>	50.668	40.432	0	270.969
Additional distance to medium UC	<b>AddMedium<sub>ij</sub></b>	4.148	8.203	0	42.320
Additional distance to large UC	<b>AddLarge<sub>ij</sub></b>	148.21	172.91	0	751.590
Central municipality (0/1)	<b>Central<sub>i</sub></b>	0.262	0.441	0	1

Largest urban municipality (0/1)	<b>LargestUrban<sub>i</sub></b>	0.010	0.102	0	1
<b>AGGLOMERATION<sub>LMA(-i)</sub></b>					
1993 population (logarithm) (LMA)	<b>LNDayPopLMA<sub>i</sub></b>	10.951	1.772	7.028	13.761
Share of individuals in working age (LMA)	<b>WorkShareLMA<sub>i</sub></b>	0.428	0.021	0.319	0.470
Share of highly educated (LMA)	<b>HighEDshareLMA<sub>i</sub></b>	0.066	0.022	0.029	0.110
High-tech manufacturing (LMA)	<b>HT_ShareLMA<sub>i</sub></b>	0.075	0.046	0.006	0.470
Low-tech manufacturing (LMA)	<b>LT_ShareLMA<sub>i</sub></b>	0.121	0.073	0.022	0.516
Knowledge intensive-services (LMA)	<b>KIS_ShareLMA<sub>i</sub></b>	0.431	0.057	0.180	0.531
Less knowledge intensive-services (LMA)	<b>LKIS_ShareLMA<sub>i</sub></b>	0.254	0.039	0.138	0.418
Other industries (LMA)	<b>Others_ShareLMA<sub>i</sub></b>	0.119	0.031	0.052	0.282

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**Note:** \* are not assigned any variable names; in the regressions on firm start-ups by industry these are referred to **AvEstSize\_Int<sub>i</sub>** and **AvEstSize\_Ext<sub>i</sub>** for internal and external average establishment size respectively.

## APPENDIX B, results by industry

**Table A2:** New firms in HT-manufacturing (adding group of variables)

<b>Dependent variable: New firms in HT-manufacturing per working age individual (in 1000s)</b>				
	Base: local	+industry	+geography	+agglomeration
Employment growth (1993-2012)	0.189 (0.130)	0.115 (0.152)	0.0358 (0.147)	0.0459 (0.163)
Inverted Herfindahl-index	0.185*** (0.0690)	0.304*** (0.110)	0.284*** (0.107)	0.332*** (0.0964)
Initial 1993 Population (logarithm)	-0.474*** (0.0811)	-0.400*** (0.0803)	-0.468*** (0.0964)	-0.467*** (0.103)
Share of individuals in working age	-0.0871 (0.0979)	-0.115 (0.113)	-0.0148 (0.126)	-0.0786 (0.127)
Share of highly educated	-0.0324 (0.0509)	0.0563 (0.116)	0.109 (0.0980)	0.175** (0.0834)
University (0/1)	-0.0124 (0.117)	0.0510 (0.102)	-0.0519 (0.107)	-0.0830 (0.103)
High-tech manufacturing		0.357 (0.286)	0.439 (0.306)	0.289 (0.263)
Low-tech manufacturing		-0.0163 (0.183)	0.124 (0.229)	0.00226 (0.186)
Knowledge intensive-services		-0.0418 (0.220)	0.0572 (0.233)	-0.0229 (0.166)
Less knowledge intensive-services		-0.0160 (0.115)	0.0685 (0.132)	0.0553 (0.116)
Average establishment size (internal)		-0.347 (0.215)	-0.344 (0.219)	-0.272 (0.221)
Average establishment size (external)		-0.201 (0.142)	-0.279** (0.117)	-0.337*** (0.122)
Distance to nearest urban center (UC)			0.163 (0.110)	0.130 (0.112)
Additional distance to medium UC			0.0135 (0.0669)	0.0215 (0.0673)
Additional distance to large UC			-0.0912 (0.0885)	-0.117 (0.0995)
Central municipality (0/1)			0.234* (0.141)	0.209 (0.210)
Largest urban municipality (0/1)			0.695** (0.321)	0.723** (0.332)
1993 population (logarithm) (LMA)				-0.164 (0.214)
Share of individuals in working age (LMA)				0.219** (0.110)
Share of highly educated (LMA)				-0.214 (0.188)
High-tech manufacturing (LMA)				0.226* (0.137)
Low-tech manufacturing (LMA)				0.141

				(0.171)
Knowledge intensive-services (LMA)				0.295
				(0.201)
Less knowledge intensive-services (LMA)				0.0241
				(0.117)
Constant	0.00173	-0.00713	-0.0613	-0.0509
	(0.0913)	(0.0863)	(0.0900)	(0.0685)
<hr/>				
First-stage (F-stat).	101.50	92.59	116.29	85.37
Prob(F-Stat)	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk LM statistic (p-value)	0.0008	0.0018	0.0022	0.0012
<hr/>				
Group LOCAL (chi2)	78.33	43.38	48.63	48.37
Prob(chi2)	0.0000	0.0000	0.0000	0.0000
Group INDUSTRY (chi2)		6.404	8.198	3.488
Prob(chi2)		0.171	0.0846	0.480
Group GEOGRAPHY (chi2)			10.90	9.218
Prob(chi2)			0.0533	0.101
Group AGGLOMERATION (chi2)				10
Prob(chi2)				0.189
<hr/>				
Obs (N)	286	286	286	286
R-square (adj)	0.174	0.195	0.208	0.234

*Note:* Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. The reported values are standardized regression coefficients. Dummy variables are exceptions and are not standardized (University 0/1, Central municipality 0/1, Largest urban municipality 0/1).

*Sources:* Statistics Sweden (LISA and FAD databases 1993–2012) and own calculations.

**Table A3: New firms in LT-manufacturing (adding group of variables)**

	<b>Dependent variable: New firms in LT-manufacturing per working age individual (in 1000s)</b>			
	Base: local	+industry	+geography	+agglomeration
Employment growth (1993-2012)	0.309 (0.229)	0.253 (0.241)	0.199 (0.231)	0.255 (0.176)
Inverted Herfindahl-index	-0.0937 (0.0831)	0.150 (0.131)	0.109 (0.107)	0.179* (0.0929)
1993 Population (log)	-0.329*** (0.0713)	-0.236*** (0.0688)	-0.104 (0.0895)	-0.142* (0.0792)
Share of individuals in working age	-0.378*** (0.143)	-0.417*** (0.102)	-0.217** (0.0982)	-0.407*** (0.0972)
Share of highly educated	-0.0891 (0.0903)	0.127 (0.168)	0.253** (0.128)	0.362*** (0.0804)
University (0/1)	-0.199 (0.121)	-0.0178 (0.177)	-0.0783 (0.155)	-0.0492 (0.137)
High-tech manufacturing		-0.307** (0.136)	0.101 (0.123)	0.0248 (0.105)
Low-tech manufacturing		-0.0587 (0.252)	0.295 (0.190)	-0.0145 (0.187)
Knowledge intensive-services		-0.484* (0.247)	-0.227 (0.172)	-0.312** (0.128)
Less knowledge intensive-services		-0.234* (0.123)	-0.000785 (0.106)	-0.0255 (0.0923)
Average establishment size (internal)		-0.335*** (0.106)	-0.311*** (0.107)	-0.211* (0.117)
Average establishment size (external)		-0.247 (0.173)	-0.624*** (0.136)	-0.721*** (0.139)
Distance to nearest urban center (UC)			0.297*** (0.0721)	0.198*** (0.0744)
Additional distance to medium UC			0.0150 (0.0417)	0.0352 (0.0371)
Additional distance to large UC			0.233** (0.0917)	0.273** (0.107)
Central municipality (0/1)			0.0950 (0.128)	0.345** (0.148)
Largest urban municipality (0/1)			0.214 (0.226)	0.0137 (0.291)
1993 population (logarithm) (LMA)				0.209 (0.144)
Share of individuals in working age (LMA)				0.506*** (0.0863)
Share of highly educated (LMA)				-0.788*** (0.147)
High-tech manufacturing (LMA)				0.151 (0.112)
Low-tech manufacturing (LMA)				0.243 (0.174)
Knowledge intensive-services (LMA)				0.403**

				(0.171)
Less knowledge intensive-services (LMA)				0.0957
				(0.0977)
Constant	0.0278	0.00250	-0.0162	-0.0838
	(0.0771)	(0.0836)	(0.0672)	(0.0594)
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First-stage (F-stat).	101.50	87.93	107.73	78.66
Prob(F-Stat)	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk LM statistic (p-value)	0.0008	0.0035	0.0036	0.0023
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Group LOCAL (chi2)	316.1	51.44	31.13	126.2
Prob(chi2)	0.0000	0.0000	0.0000	0.0000
Group INDUSTRY (chi2)		26.93	29.08	37.78
Prob(chi2)		0.0000	0.0000	0.0000
Group GEOGRAPHY (chi2)			40.14	18.74
Prob(chi2)			0.0000	0.0022
Group AGGLOMERATION (chi2)				36.47
Prob(chi2)				0.0000
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Obs (N)	286	286	286	286
R-square (adj)	0.284	0.366	0.519	0.581

*Note:* Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. The reported values are standardized regression coefficients. Dummy variables are exceptions and are not standardized (University 0/1, Central municipality 0/1, Largest urban municipality 0/1).

*Sources:* Statistics Sweden (LISA and FAD databases 1993–2012) and own calculations.

**Table A4: New firms in KIS (adding group of variables)**

<b>Dependent variable: New firms in KIS per working age individual (in 1000s)</b>				
	Base: local	+industry	+geography	+agglomeration
Employment growth (1993-2012)	0.988*** (0.111)	0.278*** (0.100)	0.267** (0.106)	0.270** (0.107)
Inverted Herfindahl-index	0.263*** (0.0991)	0.357*** (0.0294)	0.356*** (0.0296)	0.363*** (0.0313)
1993 Population (log)	-0.144*** (0.0444)	0.0701* (0.0420)	0.0417 (0.0431)	0.0107 (0.0412)
Share of individuals in working age	-0.288*** (0.0837)	-0.0570 (0.0435)	-0.0543 (0.0401)	-0.122** (0.0513)
Share of highly educated	0.241*** (0.0900)	0.689*** (0.140)	0.676*** (0.152)	0.673*** (0.156)
University (0/1)	-0.299 (0.261)	-0.157 (0.151)	-0.158 (0.146)	-0.0872 (0.155)
High-tech manufacturing		0.0515 (0.154)	0.0219 (0.163)	0.0355 (0.177)
Low-tech manufacturing		0.110 (0.218)	0.0698 (0.232)	0.0885 (0.249)
Knowledge intensive-services		0.872** (0.419)	0.839* (0.432)	0.776* (0.452)
Less knowledge intensive-services		0.0640 (0.153)	0.0525 (0.154)	0.0612 (0.173)
Average establishment size (internal)		-1.263*** (0.355)	-1.225*** (0.385)	-1.159*** (0.389)
Average establishment size (external)		0.347* (0.178)	0.349* (0.183)	0.272 (0.191)
Distance to nearest urban center (UC)			-0.0200 (0.0369)	-0.0395 (0.0396)
Additional distance to medium UC			0.0221 (0.0218)	0.0207 (0.0254)
Additional distance to large UC			-0.0232 (0.0450)	-0.0859 (0.0555)
Central municipality (0/1)			0.00564 (0.0900)	0.192 (0.127)
Largest urban municipality (0/1)			0.293 (0.203)	0.179 (0.199)
1993 population (logarithm) (LMA)				0.0314 (0.0873)
Share of individuals in working age (LMA)				0.135** (0.0648)
Share of highly educated (LMA)				-0.125 (0.0918)
High-tech manufacturing (LMA)				-0.0663 (0.0748)
Low-tech manufacturing (LMA)				-0.0345 (0.112)
Knowledge intensive-services (LMA)				0.140

				(0.116)
Less knowledge intensive-services (LMA)				-0.0715
				(0.0766)
Constant	0.0418	0.0219	0.0176	-0.0399
	(0.116)	(0.0652)	(0.0626)	(0.0469)
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First-stage (F-stat).	101.50	93.53	111.37	83.06
Prob(F-Stat)	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk LM statistic (p-value)	0.0008	0.0021	0.0024	0.0014
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Group LOCAL (chi2)	191.1	454.9	399	491.5
Prob(chi2)	0.0000	0.0000	0.0000	0.0000
Group INDUSTRY (chi2)		53.92	53.07	32.85
Prob(chi2)		0.0000	0.0000	0.0000
Group GEOGRAPHY (chi2)			6.823	17.16
Prob(chi2)			0.234	0.0042
Group AGGLOMERATION (chi2)				21.42
Prob(chi2)				0.0032
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Obs (N)	286	286	286	286
R-square (adj)	0.272	0.767	0.767	0.775

*Note:* Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. The reported values are standardized regression coefficients. Dummy variables are exceptions and are not standardized (University 0/1, Central municipality 0/1, Largest urban municipality 0/1).

*Sources:* Statistics Sweden (LISA and FAD databases 1993–2012) and own calculations.



**Table A5: New firms in LKIS (adding group of variables)**

	<b>Dependent variable: New firms in LKIS per working age individual (in 1000s)</b>			
	Base: local	+industry	+geography	+agglomeration
Employment growth (1993-2012)	1.158*** (0.222)	0.657*** (0.191)	0.581*** (0.203)	0.664*** (0.223)
Inverted Herfindahl-index	-0.0629 (0.0729)	0.0256 (0.0906)	0.00304 (0.0912)	0.0278 (0.0927)
1993 Population (log)	0.0106 (0.0840)	0.0116 (0.0884)	-0.0272 (0.0916)	-0.0333 (0.0821)
Share of individuals in working age	-0.819*** (0.139)	-0.659*** (0.0920)	-0.564*** (0.0815)	-0.605*** (0.115)
Share of highly educated	-0.0449 (0.129)	0.265*** (0.0827)	0.300*** (0.0675)	0.305*** (0.0701)
University (0/1)	-0.397 (0.249)	-0.186 (0.191)	-0.269 (0.196)	-0.206 (0.216)
High-tech manufacturing		-0.315** (0.135)	-0.180 (0.147)	-0.183 (0.150)
Low-tech manufacturing		-0.357* (0.185)	-0.171 (0.207)	-0.196 (0.204)
Knowledge intensive-services		-0.462*** (0.175)	-0.315 (0.196)	-0.297 (0.194)
Less knowledge intensive-services		0.583** (0.265)	0.653** (0.273)	0.574** (0.283)
Average establishment size (internal)		-0.717* (0.394)	-0.698* (0.403)	-0.632 (0.418)
Average establishment size (external)		0.330 (0.306)	0.239 (0.280)	0.186 (0.304)
Distance to nearest urban center (UC)			0.285*** (0.0851)	0.196** (0.0782)
Additional distance to medium UC			0.00505 (0.0369)	0.0284 (0.0394)
Additional distance to large UC			-0.151* (0.0853)	-0.126 (0.0936)
Central municipality (0/1)			0.0181 (0.147)	0.206 (0.166)
Largest urban municipality (0/1)			0.657** (0.300)	0.429 (0.306)
1993 population (logarithm) (LMA)				0.203 (0.145)
Share of individuals in working age (LMA)				0.175 (0.155)
Share of highly educated (LMA)				-0.539*** (0.203)
High-tech manufacturing (LMA)				-0.0253 (0.108)
Low-tech manufacturing (LMA)				-0.120 (0.161)
Knowledge intensive-services (LMA)				0.115

				(0.187)
Less knowledge intensive-services (LMA)				0.0264
				(0.100)
Constant	0.0555	0.0261	0.0259	-0.0298
	(0.0835)	(0.0606)	(0.0722)	(0.0735)

First-stage (F-stat).	101.50	85.71	100.77	83.79
Prob(F-Stat)	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk LM statistic (p-value)	0.0008	0.0028	0.0032	0.0017
Group LOCAL (chi2)	56.73	167.3	155.1	121.7
Prob(chi2)	0.0000	0.0000	0.0000	0.0000
Group INDUSTRY (chi2)		13.76	11.50	6.468
Prob(chi2)		0.008	0.0215	0.167
Group GEOGRAPHY (chi2)			15.66	14.49
Prob(chi2)			0.0079	0.0128
Group AGGLOMERATION (chi2)				17.12
Prob(chi2)				0.0166
Obs (N)	286	286	286	286
R-square (adj)	0.0222	0.407	0.478	0.460

*Note:* Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. The reported values are standardized regression coefficients. Dummy variables are exceptions and are not standardized (University 0/1, Central municipality 0/1, Largest urban municipality 0/1).

*Sources:* Statistics Sweden (LISA and FAD databases 1993–2012) and own calculations.

**Table A6: New firms in agriculture/natural resources (adding group of variables)**

	<b>Dependent variable: New firms in Agr/natural resources per working age individual (in 1000s)</b>			
	Base: local	+industry	+geography	+agglomeration
Employment growth (1993-2012)	0.564*** (0.126)	0.281* (0.153)	0.174 (0.108)	0.211* (0.115)
Inverted Herfindahl-index	-0.635*** (0.0608)	-0.503*** (0.0818)	-0.488*** (0.0508)	-0.428*** (0.0401)
1993 Population (log)	-0.253*** (0.0535)	-0.182*** (0.0526)	-0.0265 (0.0408)	-0.0404 (0.0372)
Share of individuals in working age	-0.443*** (0.0977)	-0.338*** (0.0739)	-0.140** (0.0594)	-0.278*** (0.0810)
Share of highly educated	0.00364 (0.0464)	0.112 (0.0767)	0.186*** (0.0534)	0.211*** (0.0400)
University (0/1)	0.00201 (0.111)	0.0256 (0.0733)	-0.108 (0.0760)	0.00145 (0.0779)
High-tech manufacturing		-0.325* (0.176)	-0.484*** (0.103)	-0.510*** (0.0962)
Low-tech manufacturing		-0.432* (0.243)	-0.702*** (0.142)	-0.769*** (0.135)
Knowledge intensive-services		-0.357 (0.229)	-0.674*** (0.114)	-0.703*** (0.106)
Less knowledge intensive-services		-0.243* (0.142)	-0.443*** (0.0948)	-0.463*** (0.0946)
Average establishment size (internal)		-0.0718 (0.0672)	-0.373*** (0.0474)	-0.339*** (0.0467)
Average establishment size (external)		-0.103 (0.0826)	-0.129** (0.0574)	-0.174*** (0.0484)
Distance to nearest urban center (UC)			0.254*** (0.0455)	0.138*** (0.0430)
Additional distance to medium UC			0.0223 (0.0263)	0.0363 (0.0243)
Additional distance to large UC			0.213*** (0.0540)	0.157*** (0.0564)
Central municipality (0/1)			0.139 (0.0875)	0.191* (0.109)
Largest urban municipality (0/1)			-0.204 (0.162)	-0.404* (0.241)
1993 population (logarithm) (LMA)				-0.142 (0.0997)
Share of individuals in working age (LMA)				0.293*** (0.0699)
Share of highly educated (LMA)				-0.285*** (0.0945)
High-tech manufacturing (LMA)				-0.0210 (0.0655)
Low-tech manufacturing (LMA)				0.0103 (0.0996)
Knowledge intensive-services (LMA)				0.130

				(0.0919)
Less knowledge intensive-services (LMA)				0.113*
				(0.0644)
Constant	-0.000281	-0.00357	-0.0193	-0.0460
	(0.0671)	(0.0603)	(0.0425)	(0.0375)
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First-stage (F-stat).	101.50	79.42	97.95	74.84
Prob(F-Stat)	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk LM statistic (p-value)	0.0008	0.0009	0.0010	0.0006
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Group LOCAL (chi2)	457.8	210.7	348.1	288.7
Prob(chi2)	0.0000	0.0000	0.0000	0.0000
Group INDUSTRY (chi2)		3.716	45.97	59.59
Prob(chi2)		0.446	0.0000	0.0000
Group GEOGRAPHY (chi2)			135.1	25.57
Prob(chi2)			0.0000	0.0000
Group AGGLOMERATION (chi2)				38.72
Prob(chi2)				0.0000
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Obs (N)	286	286	286	286
R-square (adj)	0.595	0.711	0.840	0.864

*Note:* Standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.10. The reported values are standardized regression coefficients. Dummy variables are exceptions and are not standardized (University 0/1, Central municipality 0/1, Largest urban municipality 0/1).

*Sources:* Statistics Sweden (LISA and FAD databases 1993–2012) and own calculations.