The small business contribution to productivity growth: macro evidence from corporate patenting in Europe

Jan-Bart Vervenne[1] and Bart Van Looy[2]

jan-bart.vervenne@kuleuven.be
KU Leuven, faculty of business and economics, department of managerial economics, strategy and innovation, Naamsestraat 69, B-3000 Leuven (Belgium)

[2] *bart.vanlooy@kuleuven.be*
KU Leuven, faculty of business and economics, department of managerial economics, strategy and innovation, Naamsestraat 69, B-3000 Leuven (Belgium)

Abstract
By the end of the past century, the endogenization of knowledge capital in macroeconomic performance models has become widely accepted in the economic literature. More recent growth accounting research advanced entrepreneurship capital as one of the final pieces explaining the residual that remains. The revival of small business activity in the developed world from the 70s onwards has emphasized the need to obtain a better understanding of its wealth-implications. The current paper aims at contributing to this line of research. Relying on a 12 year panel of post-millennial observations for 23 European countries, proof was found suggesting that the nature of the firm size distribution funnelling general economic and innovative activities matters for national productivity. Coefficient estimates suggest that the manufacturing industry in Europe as a whole continues to thrive on the potential static efficiency gains attached to more smallness. Only a core of European knowledge economies on the contrary appears to benefit from the dynamic efficiency effects associated with their prevalence. The disambiguation of the patent stock used to test the latter in a young small and mature small component suggest this finding to be attributable to start-ups. Start-up impact on dynamic efficiency is contingent on the quality of the local innovation system. The consistent contribution to dynamic efficiency by mature small firms in core and periphery countries on the other hand signals a lower dependence on systemic factors on their behalf. Supported by complementary descriptive statistics we advance the view that the focus of mature small firms on more mature technologies potentially explains their capability to innovate in less knowledge-intensive environments.

Introduction
Substantial agreement exists among economists and policymakers that technological innovation is a key driver of economic growth. Technological innovation implies the implementation of inventions in the production of final goods or services and as such yields productivity gains for the innovating economy. Using knowledge capital to transform existing knowledge into such inventions, the amount of research and development (R&D) efforts is an important determinant of the pace of technological innovation.

Over the past century, a large body of research has been devoted to the quest for growth models with maximal explanatory power. Neoclassical growth theorists restricted attention to the wealth enhancing effects of increased levels of labour and physical capital. In their view technological progress was an exogenous phenomenon and was to be left out of the growth equation (Solow, 1956). Both theoretically (Romer, 1986; Romer, 1990; Lucas, 1988; Aghion & Howitt, 1992) as well as empirically (Nadiri, 1993), endogenous growth scholars showed that technological innovation is an endogenous component of the process of long-term economic growth. Profit-maximising firms purposely allocate resources towards R&D and are confident they will be capable to appropriate the gains from it. Or at least a share of the gains from it: given its non-rival nature, investment in knowledge is very likely to be associated with large and persistent spill-overs to other actors. The capacity of the latter to exploit it productively forms an equally important driver of economic expansion in the endogenous growth framework (Braunerhjelm et al., 2010; Audretsch et al., 2006).

In the past decades a complementary line of research has emerged investigating the extent to which entrepreneurship can account for the part of economic growth left unexplained by the endogenous growth theorists that pulled knowledge into the equation.[1] Entrepreneurship implies the recognition of opportunities – potentially resulting from such knowledge spillovers – and the willingness to grasp those opportunities. (Wennekers & Thurik, 1999; Thurik & Wennekers, 2004; Stevenson & Gumpert, 1991). Entrepreneurial behaviour involves or eventually can result in the introduction of new activity to the marketplace. New activity can refer to new entry and newness. Wennekers and Thurik (1999) point at these 2 major roles of entrepreneurship when relating it to economic growth. The former refers to entrepreneurs as introducing new economic activity, whether that activity is innovative or imitative. In its most formal expression, this implies the foundation of a new business. The latter perceives the entrepreneur as the innovator, transforming inventions and ideas into viable commercial activity, whether or not this implies the creation of a new firm.

This renewed interest in entrepreneurship is among other factors rooted in scholarly attempts to explain how economic recovery in the late 70s and 80s has been supported by a surge in small business activity in the Western world (Wennekers & Thurik, 1999; Thurik & Wennekers, 2004). Entrepreneurial behaviour can happen in any type of organizational structure but is often associated with small firms. Indeed, small organizations are a vehicle in which entrepreneurship tends to thrive and one can assume that the size class structure of an industry and the proportion of entrepreneurs in its working force are strongly related (Wennekers & Thurik, 1999; Carree and Thurik, 1998). Not surprisingly, a large overlap exists between the streams of literature investigating the economic impact of small venture activity and entrepreneurship.

The aim of the current paper is to contribute to both lines of research. More specifically we aim to shed light on the relationship between small business incidence and national productivity. In previous studies assessing their conjunction, traditionally business incorporation statistics or information resulting from the annual reporting requirements attached to business incorporation were plugged in models set up to quantify the economic effects of more smallness. Whether it is eventually the share of small businesses in employment, the rate of self-employment or start-up counts that were relied upon, measures derived from aggregated business register or annual account information fail to differentiate between the multiple growth-enhancing mechanisms associated with the proliferation of small business. Whilst enjoying the merit of being easily accessible, they pick up both the effects of static and dynamic mechanisms without distinguishing between them. The latter mechanism can be associated with small ventures' suitability to introduce new technologies. The former implies the more efficient exploitation of existing technologies that can be the result from an increasing small business prevalence e.g. due to their larger flexibility or the increased competition that results from their entry. Assumptions have to be taken up when solely relying on the abovementioned indicators to measure one of these effects exclusively (e.g. Callejon & Segarra, 1999).

In the empirical section of this paper, we propose the use of information on firms' patenting activity to isolate the effects that can be associated with dynamic mechanisms in the framework of a production function. The assignment over time of patents to cohorts of firms of equivalent size and age yields an explicit account of the involvement of entrepreneurial ventures in attempts to commercialize new knowledge. The inclusion of a more traditional variable capturing the small business footprint in general is then expected to control for the potential existence of static effects. Based on a large scale mapping of patent applications to European

[1] Schmitz (1989) pioneered this complementary branch of research by introducing entrepreneurship as a determinant of the allocation of knowledge in an endogenous growth framework.

firms, a novel dataset covering the manufacturing industries of 23 European countries in the first decade of the new millennium was developed to test underlying research hypotheses. The panel data estimators that were relied upon to conduct this analysis reveal the existence of different patterns for a core of countries classified as innovation leaders and a periphery of followers.

The remainder of this paper is organized as follows. Section 2 describes and explains why the footprint of small businesses in developed economies has gradually increased in the past decades. Section 3 lists a range of theoretical motivations for associating smallness and productivity. Section 4 provides an overview of prior empirical literature explaining macro-economic performance using measures of entrepreneurship. Section 5 subsequently presents the research hypotheses and is followed by a methodological section, results, caveats and some concluding notes.

The shift towards smallness

Accounts of how and why economists' and policymakers' have gradually reasserted the role of small businesses in economic policy are provided in Brock and Evans (1989), Wennekers and Thurik (1999) and Thurik and Wennekers (2004). Interest for the effects of small firm activity on economic growth grew in the course of the 1970s and 1980s. The first oil crisis had set in motion a period of slow growth, inflation and high unemployment. In search for ways to overcome stagflation, the quest for alternative explanations of economic growth was reopened. In the 1960s and 1970s the perception had grown that economic progress was mainly driven by large enterprises' exploitation of all sorts of economies of scale and scope in distribution, marketing, production and R&D. The continuous growth and year-by-year increasing average firm size observed in those years were assumed to be intertwined phenomena. Small business was expected to fade away as a consequence of its own inefficiencies. Preservation of the small-enterprise sector was assumed to only serve social and political purposes (Thurik & Wennekers, 2004; Robbins et al., 2000). The upward trend in industrial activity accounted for by large firms however reversed by the late 1970s (Brock & Evans, 1989). The contribution of small firms to employment and added value in the US and Europe started augmenting year by year. It became clear that firms of different size continued to coexist in each industry. The economy achieved recovery based on economic activity relatively more underpinned by small firms; an observation that was seen as proof that smallness was not a disadvantage per se (Wennekers & Thurik, 1999).

Several scholars have provided explanations for the return towards smallness witnessed in the Western economies' manufacturing industries (Brock & Evans, 1989; Carlsson, 1992; Loveman & Sengenberger, 1991; Audretsch & Thurik, 1998). Wennekers and Thurik (1999) and Carree and Thurik (1998) list the majority of them and – to the extent they can lead to a permanent change in the size distribution of an industry – label them 'diseconomies of scale'. A few of these factors identified in earlier research have affected the firm size distribution of industries more or less independently but the majority cannot be interpreted in isolation from the rest. In the first place, recent technological changes, such as the permanent decrease in computer costs and the lowered fixed cost of automating certain processes, have reduced the optimal firm size and the minimum scale of entry (Brock & Evans, 1989; Acs et al., 1991; Carlsson, 1992). Furthermore, declining transaction costs have lowered the need for centralization and vertical integration. In a number of cases, large firms have been replaced by new types of business communities with intermediate forms of market coordination i.e. clusters of small firms operating in geographic proximity among others of peers in the same or complementary businesses (Loveman & Sengenberger, 1991). On top of that in the 80s and

90s, together with a wave of deregulation and privatisation, one could witness the relaxation of entry barriers in some industries e.g. telecommunication, facilitating the emergence of new start-up activity (Brock & Evans, 1989; Carree & Thurik, 2002). Changes in consumer tastes induced by increasing incomes and wealth have resulted in increases in the demand for specialty products at the expense of mass-produced goods. Boutique firms have the opportunity to reign in niche industries with markets too small to exploit for large firms (Brock & Evans, 1989; Carlsson, 1992; Carree & Thurik, 2002). Next, globalisation has set in motion a wave of corporate downsizing. More foreign competition in general, together with unstable exchange rates, has led to an increase in competitive risks and a greater variability in sales. This has increased the benefits of being flexible, a characteristic that better suits the description of a small firm than of a more inert large firm seeking efficiency gains in scale (Brock & Evans, 1989; Piore & Sabel, 1984; Jackson, 1984; Acs et al., 1991). In addition, the advent in competition from emerging countries with considerably lower labour costs in the aftermath of the Cold War has forced Western manufacturers to substitute labour by equipment and technology and to shift production from high- to low-cost countries. The latter was facilitated by the communications revolution that rendered the cost of transferring information in geographic space to virtually nothing. Not coincidentally, mainly production facilities in traditional industries with standardized processes, products and organizational methods have been transferred to low-cost locations (Audretsch & Thurik, 1998; Carlsson, 1992; Thurik & Wennekers, 2004). Aiginger and Tichy (1991) provide an additional explanation in attributing this downsizing tendency to the opportunistic conglomerate merger wave of the late 1960s. Lacks of synergies induced large firms to re-concentrate on core competences and divest uncomplimentary businesses (Carree & Thurik, 2002; Carlsson, 1989). At the same time, small firms have equally benefited from quantitative and qualitative changes in the available pool of labour. Robbins et al. (2000) underline the greater presence of small businesses in general in the ‘secondary labour market’ consisting of long-term unemployed, individuals at low educational levels, part-time employees, women, certain minorities, immigrants and previously self-employed. Brock & Evans (1989) refer to the positive shock in the labour supply, fuelled by increased labour force participation of women and the entry of baby-boomers into the labour market, that refrained wage growth in the course of the 80s. Relatively more labour-intensive small businesses were in a better position to profit from that evolution than more capital-intensive large firms. Furthermore, the available labour force has not only relatively grown, it has gotten more educated (Brock & Evans, 1989) and seemingly more educated in topics with employability-perspectives in businesses characterized by a lot of start-up activity e.g. ICT. Finally, with less advanced economies attracting more and more traditional industrial activity, the comparative advantage of the ‘high labour cost’, advanced economies has shifted towards knowledge-intensive activity. Hotspots of creative, idea-driven activity that have gradually emerged in advanced economies cannot just be moved to low-cost countries ‘overnight’. Neither can the knowledge stocks that fuel economic activity in such clusters be duplicated by non-local competitors. Essential to the dynamism of these innovative clusters is the occurrence of knowledge spill-overs between members from different sectors: universities and other public institutions, large incumbent firms, start-ups etc. The non-rival nature of knowledge allows these actors to tap from knowledge stocks external to their organization whereas its tacit nature – implying the need for face-to-face contact to transmit it – explains the localized reach of this externality. Spill-overs between cluster members are facilitated by a shared pool of human capital and formal and less formal interfaces maintaining and expanding the clusters’ social capital. The knowledge-based economies that remain as a result of this shift are bound to be characterized by a larger footprint of small firms. The inherent uncertainty surrounding activities based on new knowledge lies at the source of this ‘entrepreneurialization’. Asymmetries in the valuation of some new ideas – not rarely the ones intending the disruption of existing or the creation of new businesses – induce workers to chase them outside of existing organizations. New, small firms with more straightforward incentive structures and less biased than hierarchic incumbents by information asymmetries between inventors and managers have been shown to be more suited as a platform for such ventures. As such, the agent of change role of small firms in economies competing on innovation rather than scale is the final rationale explaining the observed shift towards smallness (Audretsch & Thurik, 1998; Carlsson, 1992; Thurik & Wennekers, 2004; Wennekers & Thurik, 1999).

Smallness vs. productivity

The abovementioned research provides a number of rationales to associate the firm size distribution with economic expansion in terms of employment or output. In the current study we aim to investigate to what extent countries gain in terms of productivity from a larger footprint of small business. The link with research addressing effects on output and employment is obvious since growth in productivity, output and employment should correlate in the longer run: increasing productivity improves competitiveness, leads to higher demand for the goods and services produced which in its turn boosts demand for labour inputs (Boschma et al., 2011; Krugman, 1994). Studies relating growth in productivity or output per capita to the firm size distribution concur in advancing the entrepreneurial nature of small firms as one of the potential drivers (Beck et al., 2005; Robbins et al., 2000). As such, they are complemented theoretically by a larger body of research relating other, more 'direct' measures of entrepreneurship – rates of entry, exit, net entry, self-employment and business ownership – to measures of regional or national economic performance.

The association between the firm size distribution and productivity is orchestrated by a range of mechanisms. Carree et al. (2002) classify them as enhancing 'static' or 'dynamic' efficiency. The former is the result of factors pushing existing technology endowments closer towards the optimal allocation, the latter implies the development of new technology to address equivalent or new business opportunities (Ghemawhat & Ricart I Costa, 1993). The mechanisms we discuss in the next paragraphs are respectively classified as increasing either static or dynamic efficiency. Note however that the delineation at times can be perceived as arbitrary.

One can expect static efficiency to be affected by the levels of competition, flexibility and scale economies that characterize an economy. Ceteris paribus, an increase in the relative footprint of small firms, e.g. in terms of employment, is likely to imply that more firms are active in the economy. The presence of more firms can be expected to augment competition in the product market. More competition has been shown to increase the efficiency at which existing resources are being used. Nickell (1996), Nickell et al. (1997) and Lever and Nieuwenhuijsen (1999) provide evidence that an increased number of competitors boosts total factor productivity (Carree & Thurik, 2002). A relative lack of flexibility as opposed to their small counterparts makes large firms less suited to cope with the increased volatility of current day markets (cf. supra). Their more rigid nature is among other factors fed by the larger regulatory burdens they have to comply with. They are for instance more likely to be unionized, which increases the odds that a part of their labour force is left idle in times of lower demand. The latter exerts a downward pressure on firm level labour productivity (Acs & Audretsch, 1989). In the form of forgone scale economies, Carree and Thurik (2008) and Braunerhjelm and Borgman (2004) attribute potential negative productivity-effects to larger shares of smallness. Technological progress may have lowered size thresholds at which firms can reach maximal efficiency but it has not abolished them.

The productivity-effects of an increasing allocation of resources towards small businesses mainly focussed upon in this study emerge from the suitability of the latter as vehicle for entrepreneurship. When surfacing in the form of imitative entry, entrepreneurship affects the degree of competition in the sense referred to above: increasing what Carree and Thurik (2002) identify as 'static efficiency' by optimally exploiting existing production techniques. The three mechanisms Audretsch and Keilbach (2004) underline to motivate the productivity-enhancing capability of entrepreneurship, depart from a more narrow definition of it in which its role in the process of change is emphasised. These mechanisms described in the next 2 paragraphs are expected to fuel increases in what Carree and Thurik (2002) refer to as 'dynamic efficiency'.

Audretsch and Keilbach (2004) equally embrace the idea that the expansion of the firm population fuelled by new entry is beneficial for the degree of competition in the economy. Hereby however they refer to the competition between entrepreneurs for new ideas rather than the product market competition improving static efficiency. Furman et al. (2002) suggest that the rivalry among local ventures to develop an idea into the best possible commercial application has a beneficial effect on a country's capacity to innovate. Audretsch and Keilbach (2004) furthermore emphasize the emergence of opportunities in other parts of the value chain when more firms become active in the same niche: the demand for complementary inputs and services can increase to a point where it becomes interesting enough for other small niche firms to specialize in it. Next, Audretsch and Keilbach (2004) advance the diversity-increasing potential of entrepreneurship. When one assumes that each new organization represents a unique approach, more entrepreneurship not only increases the number of enterprises, but also the variety of enterprises in a location. A larger variety of approaches, resulting from distinctive mixes of knowledge pieces, positively affects the odds that a winner will emerge from the selection process of which entrepreneurship is the engine (Jovanovic, 1982; Audretsch & Keilbach, 2004; Boschma et al., 2011). The performance-increasing effect of diversity is based on the existence of Jacobian externalities (Jacobs, 1969): economically-relevant knowledge is more likely the result from the exchange of knowledge across economic agents with diverse but complementary knowledge bases than from peers sharing the same knowledge base (Audretsch & Keilbach, 2004).

Pivotal in both abovementioned mechanisms according to which entrepreneurship is expected to enhance dynamic efficiency – by spurring competition over the same ideas and inducing variety through the pursuit of different mixes of knowledge pieces – is its suitability for knowledge transmission. It is this knowledge transfer function *an sich* that Audretsch and Keilbach (2004) identify as 3rd and core mechanism by which entrepreneurship contributes to dynamic efficiency and thus long-term economic growth. A body of theoretical and empirical research (e.g. Audretsch et al., 2008; Baumol, 2004; Audretsch & Keilbach, 2004; Braunerhjelm et al., 2010; Acs et al., 1994; see Braunerhjelm, 2007 for an overview) has been devoted in the past decades to this aspect of the economics of knowledge that initially was left underexposed by pioneers of endogenous growth theory like Romer (1986; 1990), Aghion and Howitt (1992) and Lucas (1988) (Wennekers & Thurik, 1999). Audretsch and Keilbach (2004) refer to this function of entrepreneurship as the 2nd of 2 major channels along which knowledge can spill over.[2] Inherent uncertainty regarding the economic value of new knowledge created by public and private R&D, with large incumbent firms accounting for the bulk of the latter, withholds R&D investors purposely or unknowingly from fully exploiting it. Unknowingly because of knowledge asymmetries between scientists, engineers or knowledge workers active

[2] Cohen and Levinthal (1989) framed the first one by suggesting that performing in-house R&D as a firm not only generates new knowledge, but also increases the firm's 'absorptive capacity': its ability to assimilate and exploit knowledge created externally.

in an incumbent firm and the decision-making bureaucracy. When the former place greater value on their ideas than the latter, they might choose to appropriate the value of their new knowledge in a start-up or a small firm less biased by these asymmetries (Audretsch & Keilbach, 2004). Purposely because of the uncertain outcomes of and thus the risky investment involved with transforming new knowledge into new products and processes. According to Audretsch et al. (2008) incumbents will only engage in knowledge capital investments to the extent these risks remain calculable. At a certain point the uncertainty surrounding an idea becomes too large for an incumbent and it will take the commitment and focus of 1 or more entrepreneurs recognizing the opportunity and willing to 'bet' on it to achieve actual innovation. Baumol (2004) attributes the larger share of breakthrough innovations accounted for by small firms to this dichotomy.[3] He explicitly assigns different but complementary roles to small – entrepreneurial ventures – and large firms – incumbents – in innovation systems. Oligopolistic competition between a relatively limited amount of very large firms, particularly in high-tech industries, forces incumbents to keep innovating but in a very risk-free and path-dependent way. Interests in existing products and markets biases their assessment of new ideas, especially when they bear the capacity to disrupt their current business model. Routinized innovation management processes are implemented in order to address this competition in a seemingly manageable way. The result is an ever-increasing stream of incremental improvements to existing products and processes, multiplying capacity and speed and increasing reliability and user-friendliness originating from incumbents. Whether they spilled over from larger organizations or not, the development of more experimental ideas encompassing an abundance of unknown parameters is more likely to be left to the judgment and guts of 1 or multiple entrepreneurial ventures. The selection process driven by the market mechanism allocating finance and product market share eventually determines which of these ventures translate in commercial success stories (cf. Jovanovic, 1982). The ideas preceding radical innovations tend to comply with this description and are therefore more likely to last in the pipeline of the small business economy (Dahlin & Behrens, 2005).

The lack of organizational complexity blurring a fair assessment of a new idea's potential is assumed to be one of the key factors for smaller firms' larger receptiveness towards them. Contributing to this receptiveness is the more straightforward incentive structure associated with the organizational simplicity of small firms. This incentive structure can be expected to be not only conducive to dynamic efficiency, but also to its static variant. According to Van Stel et al. (2005) self-employed business owners, and thus small businesses, may be inclined to work longer hours and more efficiently as their income is directly linked to their working effort. Acs et al. (1999) underline the hampering effects of agency problems and blurred property rights on employees' incentives to innovate, and in a broader sense to act entrepreneurial, in large corporations. Inventive employees only get partially rewarded for their successful innovations whereas other employees get the possibility to free-ride on their efforts. Incentive contracts may mitigate the agency-incentive problem, but they create other problems. Linking job compensation to earnings from intrapreneurship will lead to inevitable disputes over who has made what contribution (Acs et al., 1999). We believe that this holds a fortiori for projects involving the commercialization of new ideas which can be expected to involve more uncertainty than projects implying imitative entry. Given the unpredictable nature of the R&D process and the lack of precedents in attempts to commercialize them, mapping the contribution by various stakeholders and identifying the decisive steps can be assumed to be less obvious in

[3] A range of empirical studies have explored the proposition that small firms are more suited for breakthrough or rather 'actual' innovation. Whereas Block and Keller (2009), CHI Research (2001), Prusa & Schmitz (1991), US Small Business Administration (1995) find evidence for this proposition, Frietsch et al. (2013) prove that large firm patents receive more citations.

the former type of projects. In addition, incentive contracts can lead to bureaucratic inertia by creating interests for employees to protect cash flows generated by their old innovations (Acs et al., 1999). In summary, in line with Rothwell (1984) and Sull et al (1997), Acs et al. (1999) we assign the innovation advantage to small firms. Less attached to complex corporate hierarchies, their key human capital can be expected to be more capable to reap the full benefits of their innovation.

By advancing a number of conditions under which more smallness can also be detrimental for the innovative capacity of an economy Acs et al. (1999) equally provide arguments against the above-elaborated plea in favor of the small firm contribution to dynamic efficiency. Information asymmetry between innovators and outsiders evokes adverse selection and moral-hazard problems, both limiting and increasing the costliness of outside financing options. On top of that, breaking down market entry barriers hampering the adoption and commercialization of innovations equally tends to require deep pockets. An abundance of internal financial resources can signal the determined nature of attempts to bridge these barriers. As they dispose of more internal financial resources and collateral assets to raise external funds than their small counterparts, both rationales pledge in favor of a substantial large firm impact on the innovative capacity of a country. The latter would especially hold to the extent large firms are capable to overcome the above-described bias towards incremental innovation. Balasubramanian and Lee (2008) refer to organizational learning as an argument to explain a potential positive association between firm age and innovativeness. Rather than becoming inert and path dependent, with age comes experience and absorptive capacity (cf. Cohen & Levinthal, 1989). Assuming it takes time, even for high-growth ventures, to reach the stage of incumbency, this rationale provides an additional argument attributing the innovative edge to large firms.

Empirical literature review

A number of studies using countries as the unit of analysis have empirically addressed the relation between productivity or output per capita and the distribution of employment across firms of different sizes. For a set of 45 countries highly varying in terms of economic development, Beck et al (2005) find evidence of a strong, positive association between the importance of SMEs (1990-2000) and, simultaneously, the average growth of GDP per capita.[4] They fail however to confirm this finding confidently for a lagged version of the SME footprint, thus rejecting the hypothesis that SMEs exert a causal impact on growth. For a panel (1986-1995) of 48 contiguous states in the US, Robbins et al. (2000) find proof that the share of employment accounted for by firms staffed with less than 20 FTEs positively correlates with simultaneous growth in labour productivity. They fail to confirm these results for the share accounted for by firms employing less than 500 FTEs.

A larger amount of comparable studies have relied on more focussed measures of entrepreneurship. Within the spectrum of proxies relied upon in prior research, the creation of new ventures presents itself as the most straightforward expression of entrepreneurship. A range of within-country studies have examined the association between firm births and productivity at the regional level. Audretsch and Keilbach, (2004) assess for a cross-section of 327 West German Kreise the degree to which cross-regional start-up rates can help to explain variation in the gross regional product. Controlling for the amount of labour inputs in the framework of a production function, they confirmed that entrepreneurship capital is a key factor in explaining differences in regional output. For a more recent sample of German regions, Audretsch et al. (2008) prove that the start-up rate in a number of high-tech manufacturing sectors and IT

[4] SME threshold: < 250 FTEs

positively affects subsequent manufacturing productivity. For a set of Spanish regions, Callejon and Segarra (1999) identify a productivity-enhancing effect of increased rates of entry and exit in the manufacturing sector. Boschma et al. (2011) obtain comparable results for the Dutch service sector but fail to do so for the manufacturing sector.[5]

Data issues have refrained scholars from assessing the validity of equivalent research questions at the national level. Gaps in the availability of data on new firm formation or a lack of consistency in the measures provided by countries that did keep track of it lie at the origin of this vacuum. In an attempt to address this lacuna, at the end of the 90s the Global Entrepreneurship Monitor (GEM) was set up by a number of entrepreneurship scholars, ordering the assembly of firm entry indicators across 37 developed and emerging countries in a consistent manner. The sustained efforts of GEM participants resulting in a multi-year dataset of harmonized firm entry measures have greatly facilitated cross-country analysis of the impact of new firm formation on national economic performance. Among the empirical studies exploiting this novel source of data, Wong et al. (2005) are (and remain) the first to have addressed the productivity implications of new business creation.[6] An augmented Cobb-Douglas production function is used to explore firm formation and technological innovation as separate determinants of growth. Only the creation of businesses with high potential – implying compliance with 4 criteria regarding expected growth, expected market coverage/impact and novelty of the used technology – is found to have a positive impact on simultaneous productivity growth. None of the other GEM indicators, new business creation overall – irrespective of such criteria –, businesses creation out of opportunity or out of necessity, can be positively associated with productivity growth.

Finally, another often casted candidate to proxy entrepreneurial behaviour has been the number of self-employed. To a certain extent this construct suffers from comparable flaws as the rate of small business employment when it comes to proxying the degree of entrepreneurship. As opposed to the formation of new businesses it has the advantage of being available across countries on a more widespread basis in time. Effects on productivity or per capita output are empirically analysed in Carree et al. (2002), Carree and Thurik (2008) and Braunerhjelm and Borgman (2004).[7] For a panel of 23 OECD countries, Carree et al. (2002) find that deviations between the actual and equilibrium share of business owners in the labour force have a negative effect on GDP per capita growth in the next 4 years. Using the same dataset, Carree and Thurik (2008) devote particular attention to the lag structure of the effects of changes in the number of businesses but fail to observe a significant effect on productivity over any of the included lags. Braunerhjelm and Borgman (2004) model productivity in a range of industries in 70 Swedish regions using self-employment amongst a selection of other predictors. Whereas a clear positive effect can be witnessed for the service sector, results are less conclusive for manufacturing.

Research hypotheses

In the empirical part of this paper we aim to contribute to the abovementioned literature investigating the productivity implications for a country of increasingly becoming a small

[5] Comparable studies departing from the region as unit of analysis have focussed on the association between new firm formation rates and output, e. g. Dejardin (2011), or employment, e. g. Van Stel and Suddle (2008), Van Stel and Storey (2004), Fritsch and Mueller (2007) and Acs and Armington (2004).

[6] Van Stel et al. (2005) and Hessels and Van Stel (2011) assess the relation between new firm formation and GDP growth.

[7] Again, comparable studies departing from the region as unit of analysis have focussed on the association between self-employment rates and output, e. g. Braunerhjelm et al. (2010), Blanchflower (2000) and Carree and Thurik (2008), or employment, e. g. Blanchflower (2000), Audretsch & Thurik (1998; 2000), Carree and Thurik (2008).

business economy. The first research hypothesis adheres the closest to the abovementioned prior research by investigating the effects of industrial restructuring on growth, with industrial structure proxied for by the firm size distribution of employment (Beck et al., 2005; Robbins et al., 2000; Carree, 2002; Carree & Thurik, 1998; Audretsch et al., 2002). The remaining 2 research hypotheses exploit the availability of patent data mapped according to firm size and age.

Hypothesis 1: an increasing weight of small business employment in national employment has a positive impact on subsequent national productivity.

The footprint of small businesses in the industrial structure is proxied by the firm size distribution of employment. By relying on the small business stake in employment we aim to assess the impact of its prevalence in the 'overall' economy as opposed to the 'knowledge' economy (cf. infra). We assume it to pick up the effects of more activity accounted for by the 'average' small firm rather than the small firm operating at the frontier of new knowledge. Especially when compared with labour productivity in the short run, we expect the 'broad' economy measure to be well suited to pick up the effects of more smallness on static efficiency (cf. supra).

Hypothesis 2a: an increasing weight of small businesses in a country's knowledge capital stock has a positive impact on subsequent national productivity.

The 2nd research hypothesis zooms in on the subpopulation of firms that contribute to renewing the national stock of knowledge capital by deploying inventive activities. An increased share of smallness in knowledge-intensive activity can be expected to increase dynamic efficiency. Theoretically this hypothesis mainly builds on Baumol's (2004) allocation of different roles towards large and small firms in the innovation process with the latter being more likely to introduce breakthrough innovation (cf. supra). To the extent a linear relation exists between the quantity of small firm inventions and the odds that an actual quality innovation emerges from that pool of inventions, one can assume that a larger share of smallness in national inventive activities and thus in the resulting stock of knowledge capital positively affects productivity. Assuming that more smallness is often a reflection of the presence of more firms, a larger share of innovative activity accounted for by small firms should also boost productivity in fiercening the competition for ideas and increasing the variety of approaches by which these ideas are developed (cf. supra).

Hypothesis 2b: it is the increasing weight of young small businesses rather than mature small businesses in a country's knowledge capital stock that can be associated with subsequent national productivity growth.

An obvious extension of research hypothesis 2 is the question whether it is the young, the mature or both types of small firms that have an edge over large firms in taking up the agent of change role. One might expect the 1st scenario to be the case as one could interpret Baumol's (2004) role description of small innovators to be mainly embodied by start-ups. Developing innovation of higher technical quality often requires the development of capabilities that are new to the industry. Having invested in their current capabilities already, existing firms will not find it economically optimal to engage in large adjustments to them (Balasubramanian & Lee, 2008). Start-ups are not burdened by these capability adjustment costs at all and that could lead us to suggest that it is their contribution to innovative activity that explains the small firm edge over large firms in impact innovation. Not coincidently, the more recent body of research linking entrepreneurship to growth has favored the use of start-ups as unit of analysis over firm size distribution indicators that fail to distinguish seasoned family firms from actual entrepreneurial ventures.

Methodology

The validity of these research hypotheses is tested using the framework of a neo-classical growth model (Nadiri, 1993; Audretsch & Keilbach, 2004; Wong et al., 2005) derived from an augmented Cobb-Douglas production function:

$$Y = A^{O} K^{\propto} L^{\beta}$$

Where Y = output, A^{O}= disembodied factor productivity, K = stock of physical capital and L = labour employed. Assuming constant returns to scale, $\alpha + \beta = 1$, both sides of the equation are then divided by labour. Taking natural logs results in the following model to estimate labour productivity:

$$\ln\left(\frac{Y}{L}\right) = lnA^{o} + \propto ln\left(\frac{K}{L}\right)$$

Following the approach by Wong et al. (2005), we assume that disembodied factor productivity A^{O} is determined by the normalized stock of knowledge capital and 3 focal measures capturing the footprint of (young) small businesses in the stock of knowledge capital and the overall industrial structure. The knowledge capital based constructs are derived from patent data. Due to their codified nature, patents yield a paper trail of inventive activity, providing detailed information among others regarding its inventors, applicants, their institutional affiliations and geographic origins. Patent counts have traditionally been used as a measure of innovative output. Obviously, not every innovation gets patented, but at an aggregate level, in our case the country level and over time, it is deemed to have informative value as a proxy for the evolution of overall inventive activity (Porter & Stern, 2000; Furman et al., 2002; Ulku, 2004). The stock of knowledge capital (*KNOWL_CAP_ST*) is measured departing from annual, per-country patent counts. Patents from all sectors – the small business sector, the incumbent sector, universities, individuals, government and non-profit institutions etc. – are incorporated in this indicator to capture the full breadth of national inventive capacity in the model. Yearly stock values were obtained by aggregating counts from the current and previous application years. More specifically, patent counts for the current year were added to the stock value from the previous year, depreciated at the rate of 20% advanced by Pakes and Schankerman (1984). One can assume that the effects of investment in knowledge bear the potential to transcend the short run.[8] The stock of knowledge capital was normalized by employment (per 1000 FTEs) to capture its intensity and to avoid overweighing the impact of a number of large countries in the obtained coefficient estimates (cf. Audretsch et al., 2008; Ulku, 2004).

As suggested in the previous section, the general stock of knowledge capital measure is complemented by 2 indicators measuring the degree of small firm engagement in innovative

[8] All patent statistics were extracted from EPO's Worldwide Patent Statistical Database 'PATSTAT' (Autumn version 2014). Depreciation of the patent stock at a rate of 20% per year is based on the perpetual inventory method described in Ulku (2004; 2007). The patent stock variable incorporates annual EPO patent counts from 1970 onwards. The restriction of our attention to EPO patents can be easily justified given the geographical reach of our dataset and their costliness which among other factors is a consequence of their supra-national character. Counts of them at the macro-level bear the potential to be good signals of R&D input and output levels per country over time, assuming that the propensity to patent remains fairly constant across firms from all sizes and ages.

activity and an equivalent employment-based indicator controlling for overall small firm activity. Apart from providing a test for the validity of research hypothesis 1, incorporation of the latter indicator should assure that increased innovative activity of small firms is not simply capturing the potential productivity effects of an increase in small business activity in general.

Determining the degree to which national innovation systems have been fuelled by small business is based on the assignment of patents to small and large firms. For the large majority of European countries we had access to such data. The methodology that was adopted to allocate patents to European firm data on a large scale is presented in Eurostat (2014).[9] Due to shortcomings in the matching methodology and data gaps in the financial database – among others the result of country-specific disclosure exemptions rewarded to certain company types – only for approximately 76.5% of the corporate applicants in Europe, firm size could be determined (see Table 1 for per-country matching rates). We assume however that these country-level constraints equally hold for all years of the sample and as such are captured by estimating coefficients using empirical techniques that account for country fixed effects (cf. infra). Equivalently we expect the fixed effect components of the model proposed below to absorb country differences in industrial composition and their underlying propensity to patent (Porter & Stern 2000). Whereas applicant address information was used to match corporate patents to firms in the financial database, in line with previous research efforts (e.g. Ulku, 2004; Ulku, 2007; Wong et al., 2005) the mapping of innovative activity to countries was based on inventor address information. Finally, the footprint of small businesses in the stock of knowledge capital (*%_SMALL_in_KNOWL_CAP*) was measured by computing the share of small firms in the stock of patents assigned to firms with identified size. Conform the computation of the knowledge capital variable, underlying small firm and large firm patent stocks were expected to depreciate at an annual rate of 20%.[10]

_ Insert Table 1 here _

Note that the effects of small and large firm engagement in innovative activity could not just be measured separately by plugging their respective patent stocks normalized by the amount of people they employ into the equation: underlying factors, e.g. knowledge spill-overs, appear to evoke high rates of correlation amongst both constructs – more than 0.92 even when using mean-centered versions to account for country effects – and with the stocks of knowledge capital registered for by the national innovation system as a whole. Coefficient estimates resulting from testing such a model would be biased by multicollinearity. In addition, retaining

[9] The lack of dynamic shareholder data in BvD's Amadeus (a database gathering annual account information) withheld us from determining firm size at the business group level for the allocation used in this paper. Following the suggestion by Acs et al. (1999) that larger firms usually have more large scale establishments, we assume that establishment-based firm size distributions are sufficiently reflective of the tendencies occurring at the consolidated level. The latter especially when one accounts for the potential bias induced by tax havens attracting so called special purpose entities (cf. infra). In contrast with the matching exercise presented in Eurostat (2014), firm size was determined dynamically by linking patents to financial information from the financial years that corresponded with the patent application filing year. In addition financial account data from Amadeus 2012 was enriched with equivalent information from earlier versions (2004 and 2007) to dispose of financial information in the earliest years of the matched sample (1999-2011) and to account for the BvD rule to discard companies not filing accounts for 5 years in a row. The firm size – or rather entity size – classification for patenting companies from 1999 onwards was based on the European Commission SME definition (2005): enterprises that employ fewer than 250 employees and which have an annual turnover not exceeding 50 million euro, and/or an annual balance sheet total not exceeding 43 million euro.

[10] Whereas annual counts of corporate patents were available before 1999, mappings of them to small and large firms were not. The computation of backward looking patent stocks per firm size was therefore based on the assumption that the 1999 firm size distribution of patents also applied to pre-1999 annual corporate patent counts.

the undivided stock of knowledge capital for these economies as a whole as variable in the core model enhances comparability with prior tests of endogenous growth models. The within variance of the share value that is used instead captures to what extent small firms have shown relative over- or underactivity in R&D in comparison with their large counterparts. Hereby we maintain the reasonable assumption that small and large firm innovative activities do not have an opposite effect on economic productivity which would hamper interpretation of coefficient estimates for *%_SMALL_in_KNOWL_CAP*. At most, one of them can have a relatively larger impact on productivity which would be supported empirically by proving that the overactivity of that side across time significantly correlates with dynamic changes in labour productivity. In line with research hypothesis 2a elaborated above we expect that to be the small innovators.

To explore the validity of research hypothesis 2b, *%_SMALL_in_KNOWL_CAP* is replaced in the model by the combination of 2 measures that are calculated in an equivalent manner: *%_YOUNG_SMALL_in_KNOWL_CAP* and *%_MATURE_SMALL_in_KNOWL_CAP*. They represent the share of young and mature small firms in the stock of patents assigned to companies with identified size. The stock of patents filed by small firms before or during the 10^{th} year of their incorporation comprise the denominator of the former, the stock of remaining small firm patents the denominator of the latter.

Given that the large majority of patents in Europe can be assigned to the manufacturing industry (Fraunhofer, 2003), downloads of observations for the non-patent based variables of country *c* in year *t* were restricted to that sector.[11] [12] Indicators for value added at factor cost (*VALUE ADDED*), the number of persons employees (*EMPL*), the stock of investment in physical capital (*PHYS_CAP_ST*) and the share of small firms in corporate employment (*%_SMALL_in_EMPL*)

[11] Note that a more fine-grained investigation per subsector (2-digit NACE class) in the manufacturing industry was not feasible. In the first place subindustry-level numbers were more fragmented than the data for the manufacturing industry as a whole. An update of the NACE classification scheme in the course of the 2000s equally withheld us from digging deeper. The lack of correspondence between a share of the old and new NACE classes and the absence of an update of historical data conform the new scheme obstructed subindustry analysis as presented for instance in Ulku (2007). Comparison of overlapping NACE rev. 1.1 and NACE rev. 2 observations for the manufacturing industry as a whole (available for the years 2005-2007) suggested that both schemes were consistent enough at the industry-level to extend the NACE rev. 1.1 time series available up to 2007 with NACE rev. 2 observations until 2010. Note that nevertheless a correction was applied to the latter observations using factors computed by comparing 2005-2007 observations that were available for both NACE schemes. Sensitivity analysis confirmed the robustness of the regression results to the use of the minimum, maximum and average values obtained for these factors.
[12] To maximize the manufacturing focus on both sides of the model equation, a minority of patents (less than 2% of the full population of corporate patents) that was mapped to the only sub-industry not classified as part of the manufacturing sector, ‘computer and related activities’ (NACE rev. 1.1 class 72), were not taken into consideration for the calculation of the patent indicators.

were extracted from Eurostat.[13] [14] The limited number of observations does not allow for many competing explanatory variables. Preferably time dummies are included to control for Europe-wide business-cycle effects but using a functional form, in this case a quadratic trend allowing for one up and one down trend, can be an alternative in order to preserve degrees of freedom.[15] By the same logic we refrained from adding additional controls listed in studies such as Sala-I-Martin (1997). We assume that the fixed effects approach we adopt in the analysis absorbs cross-country variance determined by structural determinants of economic performance that change more gradually over time (Van Stel et al., 2005).[16] Conform previous research all knowledge capital related indicators are lagged since it is assumed that it takes a while for the first effects of innovative activity on economic performance to surface. Given the limited time-window at our disposition in which patents were mapped according to firm size and conform a number of other studies (Ulku, 2004; Porter & Stern, 2000) we applied relatively short lags i.e. 2 years.[17] Expressing independent variables in lags also helps safeguarding results from the potential bias caused by endogeneity. Accordingly, the small business employment variable capturing the 'broad' economy implications of more smallness and the stock of physical capital normalized by labour were also lagged.

A full version of the resulting equation to be estimated using panel data techniques is:[18]

$$log\left(\frac{VALUE\ ADDED}{EMPL}\right)_{c,t} = \alpha + \beta_1 log\left(\frac{PHYS\ CAP\ ST}{EMPL}\right)_{c,t-1} + \beta_2\left(\frac{KNOWL\ CAP\ ST}{EMPL}\right)_{c,t-2}$$

$$+\beta_3 \%\ SMALL\ in\ EMPL_{c,t-1} + \beta_4 \%\ SMALL\ in\ KNOWL\ CAP_{c,t-2}$$

$$+\beta_5\ year\ trend + \beta_6\ year\ trend^2 + u_c + \varepsilon_{ct}$$

---

[13] The resulting set of 23 countries consists of: Austria, Belgium, Germany, Denmark, Finland, France, United Kingdom, the Netherlands, Norway, Slovenia, Sweden (INNOVATION LEADERS cf. infra), Bulgaria, Czech Republic, Estonia, Greece, Hungary, Italy, Latvia, Poland, Portugal, Romania, Slovakia and Spain (INNOVATION FOLLOWERS cf. infra). Other European countries were discarded for multiple reasons: a lack of employment, investment or gross added value statistics available to the public or a too low rate of patenting companies matched to companies in the financial database, as such hampering a representative image of the distribution of patents between incumbents and small businesses. Following the example of Carree and Thurik (2008), 2 countries, in our case Ireland and Luxemburg, were discarded from the sample due to the nature of their economies. We assume the variation in productivity over time for these countries to have been affected too much by fiscal optimization strategies of multinationals involving local subsidiaries rather than being evoked by entrepreneurship and technological innovation dynamics. For other countries maintaining multinational-friendly tax schemes (e.g. Belgium, the Netherlands) we expect the effect of these latter, more structural determinants of economic performance to remain dominant. 3 observations for the United Kingdom (2008-2010) were removed based on outlying labour productivity values.

[14] All currency-based series – expressed in Euro – were deflated using per country GDP price deflators (World Bank WDI website). A stock variant of the investment in physical capital was not directly available on the Eurostat website or on any publicly available, related source of data. To account for this deficiency we computed one ourselves departing from the yearly observations of 'gross investment in tangible goods' provided on the Eurostat website to which we applied a yearly depreciation rate of 5.8%. Available only from 1995 onwards, we assumed that gross investment in tangible goods grew at an annual rate of 4.5% beforehand. Both rates were taken from Boschma et al. (2011). Finally note that the allocation of employment to large and small firms was based exclusively on the staff count criterion (250 FTEs) as the Eurostat website only reports the distributions of employment accordingly.

[15] The results are consistent with the outcomes of a dummy-based variant (cf. Table 7 in appendix).

[16] E.g. schooling, climate, institutional quality and quality of property rights etc.

[17] Results are robust for a variant of the model adopting 3-year lags (cf. Table 8 in appendix).

[18] Note that all knowledge capital based variables exploiting the distribution across small and large firms in their computation are replaced by their young small and mature small variant jointly in the model variants used to test hypothesis 2b and 3b.

Results

The panel dataset finally subjected to empirical analysis comprised 10 years of post-millennial observations (2001-2010) for 23 European countries. To shed some light on the evolution of the economic texture over time, Table 2 reports per country observations for the main variables at the beginning and the end of the investigated time window. Countries are presented consecutively according to their rank in the Innovation Union Scoreboard (IUS) (2015) (cf. infra). Small business participation shares in employment suggest that the shift towards smallness in the Europe witnessed from the 70s onwards has not ceased in the 2000s: for 19 out of the 23 countries its stake continues to increase. Absolute employment numbers for the manufacturing industry confirm that the manufacturing industry is in decline in Europe, although comparison with 2007 observations suggests that trend to be amplified by the financial crisis that struck Europe from the second half of 2008 onwards.

_Insert Table 2 here _

The pairwise correlations between the variables comprising the model are presented in Table 3. Note that country-specific differences are accounted for by reporting correlation values based on mean-centered variants of the variables.[19] Taking a look at bivariate associations between the prevalence of smallness and labour productivity across 3 subsets of data already hints at the different dynamics that are potentially at play in the core of Europe and in more peripheral member states.

_ Insert Table 3 here _

Table 4 and Table 5 report estimates, including robust standard errors, for the basic model and the variant optimized to test hypotheses 2b. This implies that a lagged version of the dependent variable is included among the predictors. We expect it to pick up the effects of non-modelled factors causing shifts in productivity spreading out over multiple years (Frietsch et al., 2014). The estimators reported here were obtained using fixed effects regression. By conducting OLS on mean-centered variants of the variable it controls for the country specific factors. Thus it yields consistent estimators in the presence of country fixed effects provided that the regressors are not correlated with the error term.[20]

_ Insert Table 4 here _

[19] Note that correlation values trespassing the absolute value of 0.6 raise the multicollinearity warning flag for one of our core independent variables (% MATURE SMALL in KNOWL CAP (2y lag)) in the second data subset. Analysis of the obtained coefficient estimators by computing their variance inflation factors and robustness checks removing both of the correlated control variables (PHYS CAP ST / EMPL (1y lag); KNOWL CAP ST / EMPL (2y lag)) from the model suggested it not to be of concern for the outcomes of the multivariate analysis we present below.

[20] Given that the OLS regression models bear the potential to suffer from omitted variables, the assumption that the regressors are not correlated with the error term might not hold. Inclusion of lagged dependent variable can be expected to account for this by picking up effects of non-modelled factors causing shifts in productivity spreading out over multiple years. For dynamic panel data models, estimates obtained using the GMM methodology introduced by Arellano and Bond (1991) can be deemed to be more consistent than the ones the more traditional OLS fixed effects technique would yield. In addition, GMM further maximizes consistence by incorporating lagged endogenous variables as their own instruments (Roodman, 2009). The latter is of concern here since physical capital investment, the share of SMEs in employment and the patent based variables cannot be expected to be strictly exogenous when equated against labour productivity. Results turned out to be robust for a variant of the model adopting difference GMM (cf. Table 9 in appendix).

Results for the most comprehensive model reported in Table 4 provide evidence for the validity of research hypothesis 1 for the full set of countries. To the extent that effects of the mechanisms enhancing dynamic efficiency are captured by the patent based variables and given the 1-year lag, one could expect the positive effect to be mainly fed by the static efficiency gains attached to more smallness. As a potential explanation we advance the rationale that the small firm presence in the average European country has not reached a steady state or equilibrium value yet (Carree et al., 2002). Sufficient opportunities for (imitative) entry potentially remain, leaving room for competition to fiercen and productivity to increase. We fail to confirm the validity of research hypothesis 2a: no dynamic efficiency effects appear to be attached to the engagement in knowledge-intensive activities by small firms in general. 1 of the 2 separately analysed subpopulations of small firms does appear to support dynamic efficiency though. In contrast to our expectations expressed in hypothesis 2b, that subpopulation consists of mature small firms rather than their young small counterparts.

In general results suggest that European innovation systems suffer from 'a start-up deficit'. Inventive activity by start-ups does not seem to support dynamic efficiency in general. To get a better understanding of underlying drivers, in the second part of this result section we explore to what extent the validity of the developed hypotheses regarding the role of smallness is contingent on systemic factors beyond the reach of company-level decision making. Results could suggest that small firms take up different roles in the north-western core of Europe and the peripheral countries in the east and the south. Whereas the Global Competitiveness Report (2015) classifies the economies constituting the core consistently as having reached an advanced status, it perceives the majority of peripheral countries as emerging economies. Among the factors Porter et al. (2002) rely on to distinguish between advanced and emerging economies is whether government, institutions, private companies, universities and other stakeholders contribute to and interact in the context of something that qualifies as a national innovation system (Porter et al., 2002; Acs et al., 2008). The fact that the lion's share of innovations shaping modern times originate from firms residing in advanced economies is by no means a coincidence. A lot of current day innovations have not unfolded in isolation: in those cases a firm's capability to innovate was influenced by the breadth and depth of the innovation eco-system in which it operates. To explore the potential role of the latter, in Table 5 the analysis conducted above is replicated for the countries scoring above and below the median on an innovation system quality index drawn from the Innovation Union Scoreboard (2015).[21] Henceforth these 2 non-overlapping subsets of countries will be labelled as innovation leaders and followers. Not surprisingly, large differences can be observed in the patent stock per employee rates between the countries at the head and in the tail of a ranking based on this index (see Table 2). This dichotomy is mainly fed by the presence of a number of large private and public R&D investors in the innovation leading countries. Together these players maintain a vast pool of knowledge from which spill-overs towards other firms can originate.

_ Insert Table 5 here _

In general split dataset results for the subset of innovation following countries confirm the patterns observed for the full set of countries. Accordingly, the validity of Hypothesis 1 is only confirmed by estimators of the most comprehensive model whereas in innovation leading countries estimates for all models provide unanimous support. Conform findings for the full set of European countries, hypothesis 2a remains unvalidated for the innovation follower countries. In the more mature European knowledge economies on the contrary, dynamic efficiency gains

[21] The split data approach is also adopted in Van Stel et al. (2005) and Hessels and Van Stel (2011).

do appear to be attached to an increasing stake of small firms in general in national knowledge capital development. On top of a mature small firm impact that is reported for all subsets of countries, the significant positive impact of young small firm engagement in knowledge-intensive activity in these innovation leader countries seems to explain why.

In sum, results for the models disambiguating the knowledge capital footprint of small firms into a young and mature small firm component seem to confirm the view that the truly innovative start-ups comprise a cog in a broader innovation system. This finding fits the pattern predicted by the knowledge spill-over theory of entrepreneurship (Acs et al., 2013): knowledge-intensive start-up activity with economic impact does not happen in isolation, it is contingent on the presence of critical knowledge capital mass. The latter is embodied in the innovation leader countries by the clustering of knowledge-intensive firms around large, established R&D investors. Equally, findings underline the plausibility of Baumol's (2004) assignment of separate but complementary roles towards small and large firms in the innovation process. Knowledge spill-overs from the latter potentially provide a constant supply of opportunities for knowledge-intensive entrepreneurship that can be expected to be less intense in the follower countries.

More striking maybe is the consistent observation for each subset of countries, albeit less significant for the leading countries, that mature small innovator activity matters. Delineating one or more rationales explaining this observation forms a challenge. Their smallness by itself can be expected to be conducive to entrepreneurial initiative as organizational structures tend to be less complex and incentives for owner-managers more straightforward. In addition, their age implies experience and absorptive capacity (Balasubramanian and Lee, 2008). Both factors, referred to already earlier on in this paper, can be expected to be conducive to innovativeness, however by themselves do not explain why small mature innovators would outperform large ones in terms of productivity impact. Other potential grounds explaining the mature small innovator impact might be sought in the relative prevalence of the family business sector in Europe, especially among SMEs (Austrian Institute for SME Research, 2008). Being established for more than 10 years, we can expect business transfer to be a more important concern in mature small businesses.[22] Counting a large share of SMEs with ownership in the hands of 1 individual or family among them, for a potentially important share within this segment succession by a family member is a real option. At that point one can expect the firm's focus to have shifted from the realisation of short-term profits towards the long-term sustainability of its business (Block & Spiegel, 2013; Hsu et al., 2014; Berlemann & Jahn, 2015). Remaining truly innovative forms an important key to the latter. The local roots and a strong embeddedness of family firms in their direct environment help to identify valuable sources of knowledge and strengthen the regional innovation system they pertain to (Block & Spiegel, 2013).[23]

We assume the nature of the technology these mature small firms develop potentially explains why their weight in the stock of national knowledge capital matters independent of whether these entities operate in a knowledge-intensive environment or not. From a theoretical point of view one can assume that mature small firms are more likely to be operating in industries

[22] The average age of the identified small mature companies filing patents in the time window under investigation is approximately 32 years.

[23] Note that a too large degree of local embeddedness can be detrimental for regional innovation performance. Conform Block and Spiegel (2013) we expect these negative effects resulting from a too strong inward orientation to be outweighed by the positive ones.

exploiting more mature technologies.[24] Knowledge of technologies perceived as emerging at the time of their incorporation might have lied at the origin of their emergence, but along with the firm this technological basis is likely to have matured as well. In addition the financial constraints attached to smallness increase the relative costs for these firms to venture into other, newer technologies. A potential explanation for the observation that mature small firm impact is reported consistently across all country subsets could then be that making valuable contributions to the mature technologies we expect them to master depends less on interactions with the surrounding innovation system. Rather it is their experience that comes with age that they are able to translate in valuable technological advances. To demonstrate more concretely how this translates to the European economy, again we look in the direction of the core of established SMEs characterized by family ownership. Due to their central role in the economies of the German speaking countries, at times they are referred to as a separate economic sector: the *Mittelstand*. Often serving in niche industries in which more mature technologies prevail they might be less dependent on interaction with the local innovation system than start-ups. Interpreted in that sense the evidence would suggest that they seem to be capable of rejuvenating themselves sufficiently to persist at the frontier of knowledge in their field. We withhold ourselves from making claims regarding the actual existence of family business externalities in Europe though: that would require additional research incorporating management and shareholder information.

Caveats

The potential contingent effect of firm size and age on the extent to which a firm's engagement in innovative activities is reflected by patent counts forms the main caveat to the above-elaborated interpretation. This concern mainly holds for coefficient estimators obtained for the variables measuring the weight of small, young small and mature small firms in the national stock of knowledge capital. A number of mechanisms favour the reliance of small firms on IP rights to protect their innovations. SMEs have a greater need for strategic alliances in production and marketing. Therefore more of their transactions occur through the external market rather than within the firm. Lower levels of trust between transacting parties make legal contracts more attractive (Jensen & Webster, 2006). Moreover, SMEs face information asymmetries various markets they come in touch with. Patents can be used as signal for the quality of the firm to rebalance the distribution of information with potential investors and customers (Blind et al., 2006). Other rationales favour a larger propensity of large firms to seek patent protection: they are less financially constrained, maintain in-house IP departments with experience in the patenting process and are more capable to enforce their patents when facing litigation (Holgersson 2006; Blind et al., 2006). The latter mechanisms have been perceived as and proven to be dominant in prior research (Blind et al., 2006; De Rassenfosse, 2012). To the

[24] Table 6 in the appendix provides potential support for this view. Scholars have advanced scientific discoveries as an important source of opportunity for new technologies to emerge from (Scherer, 1965; Klevorick et al., 1995; Leten et al., 2016). Patents have been an important source of information in the research exploring the role of science in the emergence of technologies. Prior arts lists attached to patent applications provide an account of prior (patented) technology and (published) science that is perceived by the patent examiner to have inspired the inventor (Van Looy et al., 2007). One can assume that patents citing science are more likely to embody truly novel technology comprising more uncertainty regarding potential future commercial applicability. Confirming the above-stated conjecture, statistics in Table 6 show that young small firms are consistently more active in emerging fields than their mature counterparts. In fact Table 6 shows that young small firms in innovation leading countries overall showcase the largest propensity to create technology citing science and thus involving more uncertain parameters. As such, the distinctive economic impact of young small firms in innovation leading regions could be explained by their larger focus on fields where the combination of commitment, enthusiasm and focus only witnessed in start-ups from time to time potentially makes the difference. Not unoften these young small firms are the result from spill-overs of experimental knowledge created by large R&D investors – large firms, but also universities and public research centers – of which advanced knowledge economies showcase larger endowments.

extent that strategic patenting behaviour by large firms blurs the correlation between changes in their patent stock over time and their engagement towards innovation, the positive coefficient reported for *%_SMALL_in_KNOWL_CAP* might simply reflect the larger suitability of small firm patent portfolios to proxy evolutions in national innovative activity over time.[25] Another caveat is mainly of concern for the follower country findings: the relatively low patent volumes that are used to proxy characteristics of their knowledge capital endowments bear the capacity to introduce measurement error (Dejardin, 2011). Finally, evolutions in patent intensive industries bear the potential to be overweighed in our analysis.

Conclusion

Previous research has suggested that the prevalence of small firms in Europe has been on the rise since the 1970s (Wennekers & Thurik, 1999). Post-millennial observations of the employment share accounted for by small business confirms that this evolution has not ceased to stop. In the current paper an attempt has been provided to explain the implications of more smallness for the productivity of these economies, both theoretically as well as empirically. In doing so we aim at contributing to a recent route of inquiry in growth accounting research explaining the residual remaining in endogenous growth theory by referring to entrepreneurship capital. Small firm activity in general has been a frequently casted candidate proxying entrepreneurship in prior empirical contributions. In explaining productivity, most but not all of the effects associated with the prevalence of smallness relate to their suitability as vehicle of entrepreneurship. We present a classification dividing underlying mechanisms associating smallness with national labour productivity in 2 categories: a first one affecting the static efficiency and a second one the dynamic efficiency of an economy. Static efficiency gains result from optimization of the production factor allocation taking endowments of existing technologies for granted. At play in the relatively short run, they can be the result of increased product market competition, augmented flexibility and the more straightforward incentive structure associated with more smallness. Foregone scale economies in turn deteriorate it. Dynamic efficiency gains, at play in the longer run, originate from the reconsideration of existing technological conditions. Contingent effects of more smallness on the pool of ideas available within a knowledge economy are expected to be conducive to it. These contingencies present themselves in the form of potential fiercer competition over the development of ideas, the larger diversity of approaches adopted to exploit these ideas business-wise and the higher odds that an effective breakthrough emerges from the selection process fed by both phenomena.

The empirical analysis presented in this paper exploits the availability of firm size distribution information for annual employment and knowledge capital statistics covering 23 European countries. Dynamic panel data techniques are applied to estimate the productivity-implications of changes in the allocation of both production factors towards small businesses. Findings for the aggregate set of European countries reveal that the prevalence of smallness in employment positively correlates with productivity in the manufacturing sector on the aggregate European level. No additional effects appear to stem from small firm footprint changes in the stock of knowledge capital that is proxied using patent statistics. This aggregate pattern however disguises differential dynamics unfolding in different parts of Europe. The above-reported association between the employment distribution and productivity remains confirmed for

[25] Note that the outcomes of an attempt to account for this larger patent propensity in large firms is presented in Table 10 in the appendix. We do so by counting patents pertaining to the same broad INPADOC level only once. One can assume that large firms are more likely to use multiple patents to protect variants of what is essentially the same invention for strategic purposes. Those patents are likely to share the same priority directly or indirectly according to the INPADOC family definition. Coefficient estimates resulting from INPADOC family-corrected patent variables turned out to be robust.

countries with larger ('innovation leaders') and smaller knowledge capital endowments ('innovation followers'). The lack of association between the knowledge capital distribution and productivity however is no longer consistent across both country subsets. For knowledge capital-abundant economies ('innovation leaders'), results do signal a positive relationship between the footprint of SMEs in the stock of knowledge capital and productivity.

A young-mature firm disambiguation of the small firm footprint in knowledge capital does reveal a consistent positive association between productivity and innovative activity originating from mature small firms across all 3 country samples. The young small firm contribution on the other hand only appears to matter accordingly in innovation leading countries. In sum, our findings suggest that start-up success should be perceived as a component of a broader local innovation eco-system. Their potential impact seems to be contingent on the quality of the innovation system that is among other factors endorsed by the presence of large R&D investors. System interaction can take the form of ideas spilling over from the vast pool of knowledge the latter maintain to one or multiple start-ups that try to develop it into a commercial application. Often it is the ideas that are deemed too risky by large firms that are recognized by these entrepreneurial ventures as opportunities. We advance that start-up impact surfaces at the macro-level when the system allows them to focus on their strength: the development of technologies in an early, experimental stage, still encompassing a sufficient amount of uncertain parameters. They derive the potential added value they can introduce in doing so from their start-up nature. If some of these firms are able to combine all characteristics associated with that nature – a.o. focus, commitment, enthusiasm – one or more solutions can emerge addressing these uncertainties. The market selection mechanism is then expected to do the rest.

A specific role appears to be reserved for mature small firms in supporting dynamic efficiency across Europe as a whole. Potential rationales distinctively explaining the impact of mature small innovators were sought in the local embeddedness and relatively stronger directedness towards the long run of the family-owned business economy that prevails in Europe. To confirm the validity of the latter claim additional research remains to be conducted though. The observation that this impact was observed irrespective of the environment in which these mature small firms operate is attributed to the nature of the technology they focus upon: more mature and as such potentially less dependent on eco-system interaction. The 'Mittelstand', typically championing a number of niche industries in German-speaking countries, was referred to as an example of how smallness and mature technology development should not be perceived as incompatible by definition. Taken together, the above-described mechanisms captured by employment- and knowledge capital-based firm size distributions seem to complement the views expressed by Porter et al. (2002) on what separates innovation-driven, advanced economies from efficiency-driven, emerging economies. The former evolving towards innovation eco-systems in which emerging technologies can bolster under guidance of multiple start-ups; both however supported by a body of established small firms thriving on more mature technologies. Policymakers should account for this and refrain from overemphasizing Young Innovative Companies (so called 'YICs') in SME directed innovation policies and this holds a fortiori for countries of the latter type. The main caveat that could undermine the validity of our knowledge capital derived results lies in the potential disjunction between patent counts and innovativeness as firms grow larger and the tendency to overweigh effects from evolutions in patent-intensive industries that is embedded in our approach.

Future research is necessary to further delineate the mechanisms that are potentially responsible for the observed patterns. The incorporation of shareholder and management information in company typologization could allow for a more fine-grained mapping of innovative activity.

Accordingly we could not only assess the impact of family businesses directly but also remove large firm subsidiaries from our small firm population. Furthermore, mind an all too normative treatment of the interpretation of our results as a start-up sector that is more efficient at developing emerging technologies and a mature small firm sector capable of improving mature technologies. A more precise classification of patents across mature or emerging technological fields would be a good starting point for this, at the minimum followed by actual multivariate analysis of such data. Per industry analysis could reveal whether patterns differ for low- and high-tech industries. An extended time window would facilitate an investigation of the term structure of innovation effects that are also likely to differ across industries. Patent citation data could be used to measure the localized knowledge spill-over intensity between large R&D investors and small or young small innovators. A comparison with results of an equivalent analysis for the US might be enlightening given the so called entrepreneurial innovation deficit Europe shows as opposed to its transatlantic partner (Veugelers, 2009).

Appendix

Table 1: applicant and patent matching success rates.

Country (applt.)	# corporate applicants	Applicant match rate	# corporate patents	Patent match rate
AT	2,175	75.5%	14,051	91.5%
BE	1,594	80.1%	13,631	94.0%
BG	33	36.4%	50	50.0%
CY	105	24.8%	260	46.2%
CZ	291	77.3%	798	87.5%
DE	19,843	77.3%	256,536	94.6%
DK	2,079	81.7%	11,930	93.7%
EE	46	91.3%	70	92.9%
ES	2,872	66.3%	8,634	78.7%
FI	1,747	82.8%	18,228	96.3%
FR	7,411	71.5%	81,223	88.1%
GB	9,569	92.0%	46,056	96.1%
GR	140	40.0%	336	55.1%
HU	236	51.7%	645	73.0%
IE	774	82.4%	3,210	90.8%
IS	57	52.6%	301	58.1%
IT	10,235	79.2%	41,006	86.4%
LI	203	14.3%	3,139	75.3%
LT	8	100.0%	14	100.0%
LU	410	33.7%	3,013	59.8%
LV	32	46.9%	73	68.5%
MT	57	64.9%	187	82.9%
NL	4,447	82.4%	47,255	95.9%
NO	1,287	78.8%	4,434	89.1%
PL	268	69.0%	646	77.6%
PT	218	69.7%	529	75.0%
RO	22	68.2%	29	75.9%
SE	3,623	80.4%	31,048	94.4%
SI	152	65.1%	745	83.8%
SK	77	74.0%	149	83.2%
Total	**74,750**	**76.5%**	**642,425**	**91.8%**

Table 2: summary statistics for the European countries retained in the final sample.

Country	labour productivity (in EUR)		# employees (in FTEs)		% small firms in employment		Patent stock per 1000 employees		% small firms in patent stock		% young small firms in patent stock	
	2000	2009	2000	2009	2000	2009	2000	2009	2000	2009	2000	2009
SE	59,892	62,881	791,764	657,720	47.1%	53.3%	11.36	20.09	35.0%	38.9%	20.1%	19.1%
DK	56,386	74,887	488,000	309,792	53.3%	56.7%	6.94	19.52	41.9%	46.4%	26.6%	29.5%
FI	74,909	56,790	435,780	380,972	46.4%	49.5%	10.81	18.03	25.2%	25.3%	19.0%	16.6%
DE	56,732	54,939	7,551,269	6,877,330	45.0%	46.4%	10.97	16.99	25.3%	30.7%	14.4%	12.8%
NL	71,413	69,335	904,778	749,929	63.8%*	67.2%	12.94	25.09	31.6%	33.2%	14.7%	14.9%
GB	59,413	102,766	4,100,152	2,319,583	54.0%	55.2%	5.15	11.46	49.7%	49.2%	31.1%	30.6%
BE	72,821	74,562	676,973	572,433	54.5%	56.2%	7.40	13.88	27.5%	33.8%	16.7%	19.8%
FR	57,409	53,417	4,026,591	3,385,278	53.5%	55.2%	7.57	13.15	29.2%	27.0%	16.8%	13.1%
AT	61,629	62,822	628,754	619,769	56.0%	54.1%	7.58	13.98	43.2%	45.0%	28.6%	25.9%
SI	19,280*	22,321	257,164*	214,495	59.6%*	59.5%	0.78*	2.53	27.2%	17.5%	20.9%	9.5%
NO	78,056	76,002	283,955	260,931	57.8%	62.3%	5.21	9.21	62.0%	60.5%	51.2%	42.2%
EE	9,248	12,247	119,379	101,826	64.9%	75.3%	0.21	1.25	75.5%	63.1%	69.4%	48.2%
CZ	13,158	17,523	1,377,896	1,228,893	55.3%	59.4%	0.17	0.65	42.2%	48.4%	27.5%	25.1%
IT	48,585	39,177	4,821,489	4,337,681	77.0%	77.0%	3.03	5.23	48.8%	50.3%	18.8%	18.4%
PT	22,869	20,936	937,553	746,304	76.3%	82.1%	0.15	0.70	52.3%	53.6%	21.2%	30.9%
ES	47,178	44,051	2,594,842	2,128,109	73.6%	72.4%	1.03	3.13	54.6%	47.0%	28.2%	23.4%
HU	17,766	22,134	756,003	679,548	46.0%	57.8%	0.54	1.26	28.7%	31.5%	21.3%	15.2%
GR	46,299	38,846	223,393	405,279	60.5%	80.7%	1.05	1.27	64.9%	59.5%	41.6%	32.7%
SK	9,278	16,017	411,256	385,598	39.6%	47.5%	0.17	0.55	78.6%	52.4%	75.1%	34.2%
PL	16,637*	17,811	2,402,050*	2,544,669	55.7%	60.0%	0.10*	0.35	71.9%	57.0%	64.5%	34.1%
LV	8,952	7,553	153,516	113,383	61.4%	77.1%	0.10	0.82	79.6%	44.8%	18.4%	38.3%
BG	3,322*	5,113	615,305*	586,806	59.2%*	69.2%	0.09*	0.19	50.7%	29.4%	50.7%	14.3%
RO	5,180	7,512	1,835,416	1,220,984	36.8%	57.3%	0.02	0.12	93.7%	54.2%	93.7%	23.1%

Note: countries are sorted according to their IUS rank / Sources: Eurostat, EPO PATSTAT & BvDEP / *: 2002 value since value for 2000 not available.

Table 3: pairwise correlation analysis.

	VALUE ADDED (log)	PHYS CAP ST / EMPL (1y lag; log)	KNOWL CAP ST / EMPL (2y lag)	%_SMALL _in_EMPL (1y lag)	% SMALL in KNOWL CAP (2y lag)	% YOUNG SMALL in KNOWL CAP (2y lag)
ALL COUNTRIES						
PHYS CAP ST / EMPL (1y lag)	**-0.115**					
KNOWL CAP ST / EMPL (2y lag)	**0.266**	**-0.459**				
%_SMALL_in_EMPL (1y lag)	**0.467**	-0.052	**0.242**			
% SMALL in KNOWL CAP (2y lag)	**-0.158**	-0.100	0.098	**-0.557**		
% YOUNG SMALL in KNOWL CAP (2y lag)	**-0.307**	0.014	-0.017	-0.082	**0.450**	
% MATURE SMALL in KNOWL CAP (2y lag)	**0.133**	-0.110	0.111	**-0.465**	**0.554**	**-0.495**
INNOVATION LEADING COUNTRIES						
PHYS CAP ST / EMPL (1y lag)	**-0.306**					
KNOWL CAP ST / EMPL (2y lag)	**0.533**	**-0.722**				
%_SMALL_in_EMPL (1y lag)	**0.389**	**-0.373**	**0.572**			
% SMALL in KNOWL CAP (2y lag)	**0.386**	**-0.453**	**0.427**	0.067		
% YOUNG SMALL in KNOWL CAP (2y lag)	0.079	0.118	-0.100	**-0.270**	**0.688**	
% MATURE SMALL in KNOWL CAP (2y lag)	**0.381**	**-0.718**	**0.661**	**0.430**	**0.368**	**-0.422**
INNOVATION FOLLOWING COUNTRIES						
PHYS CAP ST / EMPL (1y lag)	-0.035					
KNOWL CAP ST / EMPL (2y lag)	0.133	-0.077				
%_SMALL_in_EMPL (1y lag)	**-0.238**	-0.039	-0.054			
% SMALL in KNOWL CAP (2y lag)	**-0.375**	-0.005	0.035	**0.433**		
% YOUNG SMALL in KNOWL CAP (2y lag)	0.115	-0.033	-0.083	**0.564**	**-0.500**	
% MATURE SMALL in KNOWL CAP (2y lag)	**0.488**	0.053	**0.200**	**-0.630**	-0.061	**-0.549**

Sources: Eurostat, EPO PATSTAT & BvDEP / values in bold = p-value < 0.05

Table 4: OLS fixed effects estimators for full set of countries (main estimation results using 2-year lagged patent-based variables and a quadratic year trend).

	ALL		
PHYS CAP ST / EMPL (1y lag)	0.068 (.50)	0.055 (.36)	0.093 (1.00)
KNOWL CAP ST / EMPL (2y lag)	-0.006 (.55)	-0.004 (.39)	-0.006 (.59)
%_SMALL_in_EMPL (1y lag)		1.225 (1.64)	1.942 (4.13)***
% SMALL in KNOWL CAP (2y lag)		0.188 (1.30)	
% YOUNG SMALL in KNOWL CAP (2y lag)			-0.078 (.88)
% MATURE SMALL in KNOWL CAP (2y lag)			0.712 (4.81)***
year trend	0.029 (1.73)*	0.035 (1.49)	0.047 (2.76)**
year trend²	-0.001 (1.01)	-0.002 (1.24)	-0.003 (3.03)***
constant	9.592 (6.58)***	8.89 (4.51)***	8.035 (7.27)***
# observations	229	212	212
# groups	23	23	23
F statistic	4.25	4.15	10.4
R-squared Within	0.25	0.3	0.44
Adjusted R-squared	0.24	0.28	0.43
R-Squared Between	0.01	0.02	0
R-squared Overall	0.01	0.01	0

Dependent variable: VALUE ADDED / EMPL; t-statistics between parentheses; * *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table 5: OLS fixed effects estimators for split sets of innovation leading and following countries (main estimation results using 2-year lagged patent-based variables and a quadratic year trend).

	FOLLOWERS			LEADERS		
PHYS CAP ST / EMPL (1y lag)	0.005	-0.002	0.047	0.196	0.301	0.348
	(.03)	(.01)	(.40)	(1.79)	(3.42)***	(3.62)***
KNOWL CAP ST / EMPL (2y lag)	-0.174	-0.154	-0.115	0.016	0.012	0.016
	(3.49)***	(2.53)**	(2.27)**	(2.38)**	(2.24)**	(2.42)**
%_SMALL_in_EMPL (1y lag)		0.558	1.655		0.813	0.803
		(.52)	(2.38)**		(2.89)**	(2.89)**
% SMALL in KNOWL CAP (2y lag)		0.129			1.068	
		(.73)			(3.03)**	
% YOUNG SMALL in KNOWL CAP (2y lag)			-0.113			1.005
			(1.20)			(4.59)***
% MATURE SMALL in KNOWL CAP (2y lag)			0.736			1.918
			(4.96)***			(2.27)**
year trend	0.033	0.042	0.064	0.024	0.046	0.042
	(1.24)	(1.07)	(2.19)*	(2.63)**	(3.49)***	(3.12)**
year trend²	0	-0.001	-0.004	-0.002	-0.003	-0.004
	(.02)	(.35)	(1.86)*	(3.29)***	(3.34)***	(3.30)***
constant	9.666	9.279	7.965	8.691	6.713	6.081
	(5.09)***	(3.64)***	(5.87)***	(7.16)***	(5.84)***	(4.71)***
# observations	117	110	110	112	102	102
# groups	12	12	12	11	11	11
F statistic	3.5	2.4	41.43	37.91	27.36	41.01
R-squared Within	0.35	0.35	0.54	0.38	0.47	0.49
Adjusted R-squared	0.33	0.31	0.51	0.35	0.44	0.45
R-Squared Between	0.47	0.29	0.07	0.69	0.75	0.79
R-squared Overall	0.38	0.22	0.08	0.58	0.69	0.73

Table 6: % of patents including 1 or more scientific non-patent references.

Country group	all companies	large companies	small companies	mature small companies	young small companies
Innovation leading countries	20.1%	19.9%	21.4%	15.3%	27.7%
Innovation following countries	17.5%	20.8%	14.8%	10.4%	21.5%

Table 7: OLS fixed effects estimators (robustness checks using 2-year lagged patent variables and year dummies).

	ALL			LEADERS			FOLLOWERS		
PHYS CAP ST / EMPL (1y lag)	0.063	0.046	0.081	0.202	0.308	0.375	-0.005	-0.022	0.028
	(.45)	(.30)	(.84)	(1.70)	(3.63)***	(4.33)***	(.03)	(.10)	(.22)
KNOWL CAP ST / EMPL (2y lag)	-0.007	-0.006	-0.007	0.011	0.006	0.012	-0.167	-0.142	-0.11
	(.68)	(.55)	(.73)	(1.65)	(2.07)*	(3.13)**	(3.28)***	(2.39)**	(2.13)*
%_SMALL_in_EMPL (1y lag)		1.102	1.773		0.351	0.316		0.669	1.643
		(1.42)	(3.61)***		(.66)	(.58)		(.64)	(2.42)**
% SMALL in KNOWL CAP (2y lag)		0.182			1.185			0.139	
		(1.25)			(2.78)**			(.80)	
% YOUNG SMALL in KNOWL CAP (2y lag)			-0.066			1.108			-0.092
			(.71)			(5.02)***			(1.14)
% MATURE SMALL in KNOWL CAP (2y lag)			0.665			2.357			0.701
			(4.42)***			(2.82)**			(4.52)***
year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
constant	9.683	9.143	8.351	8.685	6.936	6.054	9.8	9.513	8.289
	(6.48)***	(4.64)***	(7.44)***	(6.56)***	(6.00)***	(5.02)***	(4.96)***	(3.66)***	(5.91)***
# observations	229	212	212	112	102	102	117	110	110
# groups	23	23	23	11	11	11	12	12	12
R-squared Within	0.41	0.44	0.57	0.64	0.73	0.76	0.48	0.48	0.64
Adjusted R-squared	0.37	0.41	0.53	0.6	0.69	0.72	0.42	0.41	0.58
R-Squared Between	0.04	0.05	0.01	0.75	0.7	0.77	0.48	0.26	0.06
R-squared Overall	0	0.03	0.01	0.59	0.66	0.73	0.35	0.16	0.07

Dependent variable: VALUE ADDED / EMPL; t-statistics between parentheses; * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 8: OLS fixed effects estimators (robustness checks using 3-year lagged patent variables and a quadratic year trend).

	ALL			LEADERS			FOLLOWERS		
PHYS CAP ST / EMPL (1y lag)	0.039	0.081	0.099	0.221	0.38	0.41	-0.021	0.029	0.044
	(.29)	(.60)	(.97)	(1.56)	(3.38)***	(3.69)***	(.11)	(.18)	(.34)
KNOWL CAP ST / EMPL (3y lag)	-0.008	-0.006	-0.007	0.007	0.006	0.011	-0.158	-0.117	-0.094
	(.69)	(.73)	(.85)	(1.15)	(1.32)	(1.85)*	(2.97)**	(2.16)*	(1.84)*
%_SMALL_in_EMPL (1y lag)		1.222	1.699		0.596	0.576		0.844	1.659
		(1.65)	(3.15)***		(2.34)**	(2.03)*		(.73)	(1.89)*
% SMALL in KNOWL CAP (3y lag)		0.068			1.132			0.021	
		(.48)			(3.45)***			(.11)	
% YOUNG SMALL in KNOWL CAP (3y lag)			-0.016			1.07			-0.03
			(.13)			(4.94)***			(.20)
% MATURE SMALL in KNOWL CAP (3y lag)			0.346			1.762			0.376
			(3.20)***			(3.13)**			(2.66)**
year trend	0.026	0.058	0.065	0.032	0.073	0.069	0.028	0.061	0.074
	(1.63)	(2.79)**	(3.49)***	(3.38)***	(3.97)***	(3.84)***	(1.05)	(1.99)*	(2.45)**
year trend²	-0.001	-0.004	-0.004	-0.002	-0.005	-0.005	0	-0.003	-0.004
	(.85)	(2.75)**	(3.78)***	(3.60)***	(3.44)***	(3.54)***	(.08)	(1.49)	(2.41)**
constant	9.927	8.62	8.109	8.474	5.916	5.508	9.955	8.77	7.993
	(6.73)***	(4.97)***	(6.78)***	(5.40)***	(4.40)***	(4.05)***	(5.12)***	(4.17)***	(5.64)***
# observations	221	192	192	109	92	92	112	100	100
# groups	23	23	23	11	11	11	12	12	12
F statistic	3.18	15.21	11.18	23.1	51.62	55.85	2.62	5.29	9.79
R-squared Within	0.22	0.36	0.4	0.33	0.45	0.46	0.31	0.42	0.48
Adjusted R-squared	0.21	0.34	0.37	0.3	0.41	0.42	0.28	0.39	0.44
R-Squared Between	0.32	0.01	0.01	0.75	0.7	0.78	0.52	0.06	0.07
R-squared Overall	0.09	0.01	0.01	0.58	0.64	0.71	0.42	0.03	0.08

Dependent variable: VALUE ADDED / EMPL; t-statistics between parentheses; * p<0.1; ** p<0.05; *** p<0.01

Table 9: robustness checks using 1-step difference GMM dynamic panel data estimators (2-year lagged patent variables and year dummies).

	ALL			LEADERS			FOLLOWERS		
VALUE ADDED / EMPL (1y lag)	0.054	0.032	0.02	0.303	0.116	0.122	0.217	0.157	0.118
	(.18)	(.10)	(.07)	(3.20)***	(1.09)	(1.18)	(1.00)	(.52)	(.39)
PHYS CAP ST / EMPL (1y lag)	0.105	0.113	0.042	0.186	0.354	0.402	-0.004	0.02	0.004
	(.69)	(.81)	(.26)	(1.44)	(3.27)***	(3.27)***	(.04)	(.18)	(.03)
KNOWL CAP ST / EMPL (2y lag)	0.017	0.016	0.01	-0.001	0.01	0.012	-0.111	-0.108	-0.096
	(1.09)	(.95)	(.97)	(.13)	(2.98)***	(3.39)***	(2.79)***	(2.16)**	(1.45)
%_SMALL_in_EMPL (1y lag)	2.841	2.932	3.278	-1.054	-0.723	-0.613	1.227	1.174	1.58
	(3.52)***	(3.02)***	(3.00)***	(1.87)*	(1.32)	(.97)	(3.15)***	(2.40)**	(3.49)***
% SMALL in KNOWL CAP (2y lag)		0.059			1.017			-0.043	
		(.37)			(1.91)*			(.29)	
% YOUNG SMALL in KNOWL CAP (2y lag)			-0.161			0.981			-0.234
			(1.10)			(2.29)**			(1.45)
% MATURE SMALL in KNOWL CAP (2y lag)			0.484			1.648			0.365
			(2.09)**			(1.88)*			(1.92)*
year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
# observations	201	189	189	99	91	91	102	98	98
# groups	23	23	23	11	11	11	12	12	12
# instruments	59	56	57	59	56	57	59	56	57
p-value of Hansen statistic	0.86	0.51	0.78	1	1	1	1	1	1
p-value of AB test for AR(1)	0.09	0.59	0.11	0.05	0.13	0.11	0.02	0.31	0.02
p-value of AB test for AR(2)	0.72	0.92	0.5	0.38	0.46	0.56	0.3	0.72	0.76

Dependent variable: VALUE ADDED / EMPL; t-statistics between parentheses; * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 10: OLS fixed effects estimators (robustness checks using 2-year lagged, INPADOC-family corrected patent variables and a quadratic year trend).

	ALL			LEADERS			FOLLOWERS		
PHYS CAP ST / EMPL (1y lag)	0.067	0.056	0.096	0.196	0.312	0.351	0.005	-0.001	0.053
	(.50)	(.36)	(1.04)	(1.73)	(3.42)***	(3.49)***	(.03)	.0	(.45)
KNOWL CAP ST / EMPL (2y lag)	-0.006	-0.005	-0.006	0.015	0.011	0.016	-0.177	-0.157	-0.117
	(.57)	(.41)	(.60)	(2.36)**	(2.30)**	(2.35)**	(3.45)***	(2.50)**	(2.28)**
%_SMALL_in_EMPL (1y lag)		0.192			1.119			0.129	
		(1.28)			(2.94)**			(.72)	
% SMALL in KNOWL CAP (2y lag)		1.222	1.912		0.865	0.858		0.555	1.611
		(1.64)	(4.07)***		(2.89)**	(2.78)**		(.52)	(2.36)**
% YOUNG SMALL in KNOWL CAP (2y lag)			-0.096			1.059			-0.139
			(1.03)			(4.09)***			(1.38)
% MATURE SMALL in KNOWL CAP (2y lag)			0.697			1.843			0.712
			(4.62)***			(2.12)*			(4.58)***
year	0.029	0.036	0.047	0.025	0.047	0.043	0.033	0.042	0.063
	(1.74)*	(1.50)	(2.72)**	(2.72)**	(3.54)***	(3.20)***	(1.24)	(1.07)	(2.12)*
$year^2$	-0.001	-0.002	-0.003	-0.002	-0.003	-0.004	0	-0.001	-0.003
	(1.01)	(1.25)	(2.96)***	(3.24)***	(3.32)***	(3.23)***	(.02)	(.35)	(1.79)
constant	9.599	8.887	8.03	8.693	6.546	6.022	9.665	9.271	7.947
	(6.58)***	(4.50)***	(7.38)***	(6.93)***	(5.41)***	(4.41)***	(5.09)***	(3.64)***	(5.98)***
# observations	229	212	212	112	102	102	117	110	110
# groups	23	23	23	11	11	11	12	12	12
F statistic	4.19	4.11	9.85	39.09	27.95	42.53	3.45	2.3	39.09
R-squared Within	0.25	0.3	0.44	0.37	0.47	0.48	0.35	0.35	0.54
Adjusted R-squared	0.24	0.28	0.43	0.35	0.44	0.44	0.33	0.31	0.51
R-Squared Between	0	0.02	0	0.7	0.74	0.78	0.47	0.29	0.07
R-squared Overall	0	0.02	0	0.58	0.68	0.72	0.38	0.22	0.08

Dependent variable: VALUE ADDED / EMPL; t-statistics between parentheses; * $p<0.1$; ** $p<0.05$; *** $p<0.01$

References

Acs, Z. J., and Armington, C. (2004). Employment growth and entrepreneurial activity in cities, Regional Studies 38: pp. 911–927.

Acs, Z. J., and Audretsch, D. B. (1989). Small-firm entry in US manufacturing, Economica 56 (222): pp. 255-265.

Acs, Z. J., Audretsch, D. B., and Feldman, M. (1994). R&D spillovers and recipient firm size, Review of Economics and Statistics 76: pp. 336–340.

Acs, Z. J., Audretsch, D. B., and Lehmann, E. E. (2013). The knowledge spillover theory of entrepreneurship. Small Business Economics 41: pp. 757-774.

Acs, Z. J., Audretsch, D., and Carlsson, B. (1991). Flexible technology and firm size, Small Business Economics 3 (4): pp. 307-319.

Acs, Z. J., Desai, S., and Hessels, J. (2008). Entrepreneurship, economic development and institutions, Small Business Economics 31: pp. 219-234.

Acs, Z. J., Morck, R. and Yeung, B. (1999), Productivity Growth and Firm Size Distribution, in Z. J. Acs, B. Carlsson and C. Karlsson (eds.), Entrepreneurship, Small and Medium-sized Enterprises and the Macroeconomy, Cambrige University Press, Cambridge.

Aghion, P., and Howitt, P. (1992). A model of growth through creative destruction, Econometrica 60: pp.323-351.

Aiginger, K., and Tichy, G. (1991). Small firms and the merger mania, Small Business Economics 3: pp. 83–101.

Arellano, M., and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, The Review of Economic Studies 58: pp. 277–297.

Arrow, K. J. (1962). The economic implications of learning by doing. Review of Economic Studies 29: pp. 155-173.

Audretsch, D. B. (2001). The dynamic role of small firms: evidence from the US, Small Business Economics 18 (1/3): pp. 13-40.

Audretsch, D. B., and Keilbach, M. (2004). Entrepreneurship capital and economic performance. Regional Studies 38 (8): pp. 949-959.

Audretsch, D. B., and Thurik, A. R. (1998). The knowledge society, entrepreneurship and unemployment, Research Report 9801/E, EIM: Zoetermeer.

Audretsch, D. B., and Thurik, A. R. (2001). What's new about the new economy? From the managed to the entrepreneurial economy. Industrial and Corporate Change 10 (1): pp. 267-315.

Audretsch, D. B., and Thurik, R. A. (2000). Capitalism and democracy in the 21st century: from the managed to the entrepreneurial economy, Journal of Evolutionary Economics 10: pp. 17-34.

Audretsch, D. B., Bönte, W., and Keilbach, M. (2008). Entrepreneurship capital and its impact on knowledge diffusion and economic performance, Journal of Business Venturing 23: pp. 687-698.

Audretsch, D. B., Carree, M. A., Van Stel, A. J., and Thurik, A. R. (2002). Impeded industrial restructuring: the growth penalty, Kyklos 55 (1): pp. 81-97.

Austrian Institute for SME Research (2008). Overview of family business relevant issues, Final report of study conducted on behalf of the European Commission, DG Enterprise and Industry (contract no. 30-CE-0164021/00-51).

Balasubramanian, N., and Lee, J. (2008). Firm age and innovation, Industrial and Corporate Change 17 (5): pp. 1019-1047.

Baumol, W. J. (2004). Entrepreneurial enterprises, large established firms and other components of the free-market growth machine, Small Business Economics 23: pp. 9-21.

Beck, T., Demirguc-Kunt, A., and Levine, R. (2005). SMEs, growth, and poverty: cross-country evidence. Journal of Economic Growth 10: pp. 199–229.

Berlemann, M., and Jahn, V. (2015). Regional importance of mittelstand firms and innovation performance, Regional Studies 2015.

Blind, K., Edler, J., Frietsch, R., and Schmoch, U. (2006). Motives to patent: empirical evidence from Germany. Research Policy 35: pp. 655-672.

Block, F., and Keller, M. R. (2009). Where do innovations come from? Transformations in the US economy 1970-2006, Socio-Economic Review 7: pp. 459-483.

Block, J. H., and Spiegel, F. (2013). Family firm density and regional innovation output: an exploratory analysis, Journal of Family Business Strategy 4: pp. 270-280.
Boschma, N., Stam, E., and Schutjens, V. (2011). Creative destruction and regional productivity growth: evidence from the Dutch manufacturing and services industries, Small Business Economics 36: pp. 401-418.
Braunerhjelm, P. (2007). Entrepreneurship, knowledge and economic growth, Cesis Electronic Working Paper Series, Paper 102.
Braunerhjelm, P., Acs, Z. J., Audretsch, D. B., and Carlsson, B. (2010). The missing link: knowledge diffusion and entrepreneurship in endogenous growth, Small Business Economics 34: pp. 105-125.
Braunerhjelm, P., and Borgman, B. (2004). Geographical concentration, entrepreneurship and regional growth: evidence from regional data in Sweden, 1975-1999, Regional Studies 38 (8): pp. 929-947.
Brock, W. A., and Evans, D. S. (1989). Small business economics, Small Business Economics 1 (1): pp. 7-20.
Callejón, M., and Segarra, A. (1999). Business dynamics and efficiency in industries and regions: the case of Spain, Small Business Economics 13: pp. 253–271.
Carlsson, B. (1989). The evolution of manufacturing technology and its impact on industrial structure: an international study, Small Business Economics 1: pp. 21–37.
Carlsson, B. (1992). The rise of small business: causes and consequences, in W. J. Adams (ed.), Singular Europe, Economy and Policy of the European Community after 1992, University of Michigan Press: Ann Arbor, MI.
Carlsson, B., Acs, Z. J., Audretsch, D. B., and Braunerhjelm, P. (2009). Knowledge creation, entrepreneurship and economic growth : a historical review, Industrial and Corporate Change 18 (6): pp. 1193-1229.
Carree, M. .A., and Thurik, A. R . (2008). The lag structure of the impact of business ownership on economic performance in OECD countries, Small Business Economics 50 (1): pp. 101-110.
Carree, M. A., and Thurik, A. R. (1998). Small firms and economic growth in Europe, Atlantic Economic Journal 26 (2): pp. 137-146.
Carree, M., Van Stel, A., Thurik, R., and Wennekers, S. (2002). Economic development and business ownership: an analysis using data on 23 OECD countries in the period 1976-1996, Small Business Economics 19: pp. 271-290.
Cohen, W., and Levinthal, D. (1989). Innovation and learning: the two faces of R&D, Economic Journal 99: pp. 569-596.
Dahlin, K. B., and Behrens, D. B. (2005). When is an invention really radical? Defining and measuring technological radicalness. Research Policy 34: pp. 717-737.
De Rassenfosse, G. (2012). How SMEs exploit their intellectual property assets: evidence from survey data, Small Business Economics 39: pp. 437-452.
Dejardin, M. (2011). Linking net entry to regional economic growth, Small Business Economics 36 (4): pp. 443-460.
European Commission (2005). The new SME definition: user guide and model declaration, Enterprise and industry publications, European Commission.
European Commission (2015). Innovation Union Scoreboard 2015.
Eurostat (2014). Patent statistics at Eurostat: mapping the contribution of SMEs in EU patenting.
Fraunhofer Institute, Systems and Innovation Research (2003). Patents in the service industries. Final report European Commission Contract No. ERBHPV2-CT-1999-06.
Frietsch, R., Neuhäusler, P., and Rothengatter, O. (2003). SME patenting: an empirical analysis in nine countries. Fraunhofer ISI Discussion Papers Innovation Systems and Policy Analysis, No. 36.
Frietsch, R., Neuhäusler, P., Jung, T., and Van Looy, B. (2014). Patent indicators for macroeconomic growth: the value of patents estimated by export volume, Technovation 34: pp. 546-558.
Fritsch, M., and Mueller, P. (2008). The effect of new business formation on regional development over time: the case of Germany, Small Business Economics 30: pp. 15-29.
Furman, J. L., Porter, M.E., and Stern, S. (2002). The determinants of national innovative capacity, Research Policy 31: pp. 899-933.
Ghemawat, P., and Ricart I Costa, J. E. (1993). The organizational tension between static and dynamic efficiency, Strategic Management Journal 14: pp. 59-73.

Hessels, J., and Van Stel, A. (2011). Entrepreneurship, export orientation and economic growth, Small Business Economics 37 (2): pp. 255-268.
Holgersson, M. (2006). Patent management in entrepreneurial SMEs: a literature review and an empirical study of innovation, appropriation, patent propensity and motives. R&D Management 43 (1): pp. 21-36.
Hsu, P. H., Huang, S., Massa, M., and Zhang, H. (2014). The new lyrics of the old folks: the role of family ownership in corporate innovation, INSEAD Faculty & Research Working Paper 2014/51/FIN.
Jackson, L. F. (1984). Hierarchic demand and the Engle curve for variety, Review of Economics and Statistics 66: pp. 8–15.
Jensen, P. H., and Webster, E. (2006). Firm size and the use of intellectual property rights. The Economic Record 82: pp.44-55.
Jovanovic, B. (1982). Selection and the evolution of industry. Econometrica 50: pp. 649-670.
Klevorick, A., Levin, R., Nelson, R. and Winter, S. (1995). On the sources and significance of inter-industry differences in technological opportunities. Research Policy 24: pp. 185-205.
Krugman, P. (1994). The age of diminished expectations. MIT Press: Cambridge, MA.
Leten, B., Belderbos, R., and Van Looy, B. (2016). Entry and technological performance in new technology domains: technological opportunities, technology competition and technological relatedness. Journal of Management Studies (forthcoming).
Lever, M. H. C., and Nieuwenhuijsen, H. R. (1999). The impact of competition on productivity in Dutch manufacturing, in D. B. Audretsch and A. R. Thurik (eds.), Innovation, Industry Evolution and Employment, Cambridge University Press: Cambridge.
Loveman, G., and Sengenberger, W. (1991). The re-emergence of small-scale production; an international comparison. Small Business Economics 3: pp. 1-37.
Lucas, R. E (1988). On the mechanics of economic development, Journal of Monetary Economics 22: pp. 3-42.
Marshall, A. (1890). Principles of Economics. Macmillan: London.
Nadiri, I. (1993). Innovations and technological spillovers, NBERWorking Paper 423.
Nickell, S. J. (1996). Competition and corporate performance, Journal of Political Economy 104: pp. 724–746.
Nickell, S., Nicolitsas, P., and Dryden, N. (1997). What makes firms perform well? European Economic Review 41: pp. 783–796.
Pagano, P., and Schivardi, F. (2003). Firm size distribution and growth, Scandinavian Journal of Economics 102 (23): pp. 255-274.
Pakes, A., and Schankerman, M. (1984), The Rate of Obsolescence of Patents, Research Gestation Lags, and the Private Rate of Return to Research Resources, in Z. Griliches (ed.), R&D, Patents, and Productivity, University of Chicago Press, Chicago.
Piore, M., and Sabel, C. (1984). The second industrial divide: possibilities for prosperity, Basic Books: New York, NY.
Porter, M., and Stern, S. (2000). Measuring the “ideas” production function: evidence from international patent output. NBER Working Paper Series no. 7891.
Porter, M., Sachs, J., and McArthur, J. (2002). Executive summary: competitiveness and stages of economic development. In M. Porter, J. Sachs, P. K. Cornelius, J. W. McArthur, and K. Schwab (Eds.), The global competitiveness report 2001–2002 (pp. 16–25). New York: Oxford University Press.
Prusa, T. J., and Schmitz, J. A. (1991). Are new firms an important source of innovation? Evidence from the software industry, Economics Letters 35: pp. 339–342.
Romer, P. M. (1986). Increasing returns and long run growth, Journal of Political Economy 94: pp. 1002-1037.
Romer, P. M. (1990). Endogenous technical change, Journal of Political Economy 98: pp. 71-102.
Roodman, D. (2009). How to do Xtabond2:an introduction to difference and system GMM in Stata. Stata Journal 9: pp. 86–136.
Rothwell, R. (1984). The role of small firms in the emergence of new technologies, OMEGA The International Journal of Management Science 12: pp. 19–29.

Sala-i-Martin, X. (1997). I Just Ran Two Million Regressions, American Economic Review 87: pp. 178–183.
Scherer, F. M. (1965). Firm size, market structure, opportunity, and the output of patented inventions. American Economic Review 55 (5): pp. 1097-1125.
Schmitz, J. A. (1989). Imitation, entrepreneurship and long-run economic growth, Journal of Political Economy 97: pp. 721-739.
Schmoch, U., LaVille, F., Patel, P., and Frietsch, R. (2003). Linking technology areas to industrial sectors. Final report to the European Commission, DG Research.
Schwab, K., and Sala-i-Martin, X. (Eds.) (2015). The Global Competitiveness Report 2015-2016, World Economic Forum.
Solow, R. M. (1956). A contribution to the theory of economic growth, Quarterly Journal of Economics 70: pp. 65-94.
Stevenson, H. H., and Gumpert, D. E. (1991). The heart of entrepreneurship, in Sahlman, W. A., and Stevenson, H. H. (eds.), The entrepreneurial venture, McGraw-Hill: Boston, MA.
Sull, D. N., Tedlow, R. S., and Rosenbloom, R. S. (1997). Managerial commitments and technological change in the US tire industry, Industrial and Corporate Change 6 (2): pp. 461-50.
Thurik, A. R., and Wennekers, S. (2004). Entrepreneurship, small business and economic growth. Journal of Small Business and Enterprise development 11 (1): pp. 140-149.
U.S. Small Business Administration, 1995, The State of Small Business: A Report of the President, 1994, Washington, D.C.: U.S. Government Printing Office.
Ulku, H. (2004). R&D, innovation, and economic growth: an empirical analysis, IMF Working Paper 04/185.
Ulku, H. (2007). R&D, innovation, and growth: evidence from four manufacturing sectors in OECD countries, Oxford Economic Papers 59: pp. 513-535.
Van Looy, B., Magerman, T., and Debackere, K. (2007). Developing technology in the vicinity of science: An examination of the relationship between science intensity (of patents) and technological productivity within the field of biotechnology. Scientometrics 70 (2): pp. 441–458.
Van Stel, A . J., Carree, M. A., and Thurik, A. R. (2005). The effect of entrepreneurial activity on national economic growth, Small Business Economics 24 (3): pp. 301-321.
Van Stel, A. J., and Suddle, K, (2008). The impact of new firm formation on regional development in the Netherlands, Small Business Economic 50 (1): pp. 31-47.
Van Stel, A., and Storey, D. (2004). The link between firm Births and job creation: Is there a Upas tree effect? Regional Studies 38 (8): pp. 893–909.
Veugelers, R. (2009). A lifeline for Europe's young radical innovators, Bruegel Policybrief 1.
Wennekers, S., and Thurik, A. R. (1999). Linking entrepreneurship and economic growth, Small Business Economics 13: pp. 27-55.
Wong, P.K., Ho, Y.P., and Autio, E. (2005). Entrepreneurship, innovation and economic growth: evidence from GEM data, Small Business Economics 24: pp. 335-350.