Erasmus University Rotterdam

Erasmus School of Economics

Innovation Persistence of Firms and the Role of Innovative Cities: An Empirical Investigation

Master Thesis

MSc Business Economics, Strategy Economics

Emese Kamilov

Student ID: 491465

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Supervisor: Ajay Bhaskarabhatla

Second Assessor: Jolanda Hessels

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Abstract:

The purpose of the paper is to examine whether innovation is persistent on a firm level and whether industry differentiation and locational factors moderate persistency. The empirical analysis employs a new approach in this subject field, namely a negative binomial zero-inflated technique, on a sample of US company patent data between the years 1975 to 2013. The industry is specified based on whether the firm is a manufacturing or service firm, and geographical effects are measured by whether the firm is located in one of the most innovative cities. Alternative tests are also applied to check the robustness of the main model. The results indicate a significant and strong persistence of innovation of firms, as well as a higher likelihood for persistency of manufacturing firms compared to other industries. This outcome confirms that investing in innovation has increasing returns. However, locational factors are found to act as both deterrents and enablers of innovation persistence. Locations with the highest innovative atmosphere are advantageous to persistence and depict positive path dependency, while lower-ranked innovative spaces show a decrease in firms' innovation persistence. Industry differentiation does not influence the effect of innovative cities. The robustness checks overall confirm the main results with slight variations. The insight of this research contributes to innovation research, firm strategy and policy planning.

Table of contents

1. Introduction

Innovation has become a highly significant topic for academia and firm strategy over the last decades. The discipline has evolved over the years, shaped by main ideas such as Schumpeter, Solow, or Arrow (Greenacre, Gross, & Speirs, 2012). Innovating is vital for an organization to stay competitive and expand (Arroyabe & Schumann, 2022; Howitt & Aghion, 1990; Teece, Pisano, & Shuen, 1997). With today's rapidly changing market posing a challenging environment for companies to operate in, innovation strategy is increasingly relevant. As the economy shifts from the pandemic, war, and new technologies, a better understanding of the nature of innovations is important for firm success (Innovation nations, 2021, In algorithms we trust, 2018).

The subject area of persistence has received increased attention in research over recent years. The discipline has evolved, with each new paper building on the prior authors' findings. Path dependence and persistence originate from the innovation theories of Schumpeter and evolutionary theory, where innovation is viewed as a dynamic firm activity (Galende, 2006). Some initial assessments of the relationship pointed towards a low persistency on a firm level (Geroski, Van Reenen, & Walters, 1997; Malerba & Orsenigo, 1999). However, subsequent investigations revealed that firm-level persistency is strong in many cases (Duguet & Monjon, 2004; Peters, 2009; Raymond, Sybrand Schim van der Loeff, Franz Palm, & Pierre Mohnen, 2010). Furthermore, previous studies emphasized the importance of firm heterogeneity when discussing persistence.

This analysis aims to examine whether firm persistency is present in a sample of firms patenting in the U.S. between 1975 to 2013 and whether industry differences and locational factors mitigate the effects of persistence. Prior studies on the topic have mainly focused on the European context. However, the U.S. is highly relevant to the examination, as it has been one of the most innovative countries for decades (Mowery & Rosenberg, 1993; WIPO, 2022). In addition, a one-country view is suitable for patent data since having data from multiple countries' patent organizations in the sample would introduce differences in institutions and patent policy (Cabagnols, Gay, & Le Bas, 2006). Simultaneously, the U.S. is valuable for studying regional effects, as it contains various heterogeneous regions.

A negative binomial zero-inflated model is employed to examine the relationship between past patenting behavior and current patents, including firm heterogeneity and locational factors.

Contrasting to many previous works on the subject that use a binary variable for measuring innovation, this paper uses a count data model to give a precise estimate of the intensity of persistency. Furthermore, a negative binomial zero-inflated model is applied to the sample to account for overdispersion and excessive zeros in the sample (Korosteleva, 2018; Moghimbeigi, Eshraghian, Mohammad, & Mcardle, 2008).

The results indicate substantial and significant effects of innovation persistence on the firm level. Various firm-specific characteristics, as well as industry specialization, have an important influence on patenting behavior. More specifically, the analysis shows that manufacturing firms are more persistent than other industries; however, a significant difference in persistency cannot be confirmed for service firms. Furthermore, the outcome suggests that the effects of being in one of the most innovative cities can either boost persistence or restrain it, depending on the level of innovation performance of the location. This result contradicts the prediction that knowledge spaces are likely to affect the relationship overall positively. The effect of location does not vary among industries. Alternative tests are then applied to the data, confirming strong persistence but displaying some disparity in the outcome.

This research and its implications are imperative for several groups. Based on the finding that innovation is persistent, firms can benefit from making more precise strategy decisions and, in turn, gain a better competitive advantage through innovating. Moreover, the results highlight important aspects of market conditions for innovation persistence. For academia, this paper is innovative in the new type of model estimation it is using and, therefore, establishes count data models suitable for the topic of persistence. The paper also adds to the research field by focusing on the U.S. and adding locational aspects of the relationship, both of which are lacking in prior studies (Cabagnols et al., 2006; Holl, Peters, & Rammer, 2022). Additionally, the results confirm that innovation has increasing returns, which is an implication that is crucial for fundamental growth and innovation theory. Lastly, governmental bodies can also benefit from the insight of this work for policy purposes that aim at encouraging innovation.

The paper is organized as follows: First, the theoretical background behind the concept of innovation persistence is discussed, and the hypotheses are developed. Then, the data and the methodology are specified to estimate the relationship, followed by a presentation of the results of the model. The outcome is afterwards explained and compared to prior studies, next to recognizing the implications and limitations of the research. Lastly, the conclusions based on the analysis are noted.

2. Literature review

In this section, the literature review is discussed, first explaining the development of innovation theory, followed by the explanation of why innovation is argued to be persistent on a firm level. Then, the topic's relevance is expanded, and hypotheses are formed based on prior literature on persistency, the effects of firm industry, and regional factors.

2.1 Theoretical background

Innovation theories and the concept of innovation in motion

Implementing new market offerings and better practices that succeed their outdated counterparts is fundamental to achieving long economic prosperity (Greenacre, Gross, & Speirs, 2012; Holl et al., 2022). The innovation theories stem from many fields, ranging from cognitive analysis and company strategy studies to industrial systems and economic theorems (Greenacre et al., 2012).

A new array within innovation theory started with the approach by Schumpeter and Solow (J. Schumpeter, 1942; J. A. Schumpeter, 1934; Solow, 1957). A new dimension of innovation was now highlighted by Schumpeter and Solow's theory: technology (Aghion, Akcigit, & Howitt, 2015; Galende, 2006; Howitt & Aghion, 1990). Solow emphasizes that for promoting growth, enhancing technology can be more effective than gathering resources; therefore, investing in innovation creation would aid technological advancement (Howitt & Aghion, 1990). Schumpeter describes two types of the innovation process: creative destruction, where innovation is by companies who previously did not innovate, and creative accumulation, where innovation is by companies who have innovated before (Cefis & Orsenigo, 2001). Furthermore, the methodology is centered on better innovation succeeding over outdated innovations (Aghion et al., 2015; Howitt & Aghion, 1990). Schumpeter's (1934, 1942) work has set the tone for a new view of innovation, as his theories established innovation as an evolving character of a company instead of something constant (Dosi, 1991).

Built on this altered view of innovation developing over paths of transformation over time, the evolutionary theory was formed (Dosi, 1991; Galende, 2006). This theory emphasizes the importance of the past since, as an organization acquires knowledge over time, it creates its foundation for future technology and know-how (Galende, 2006; Roper & Hewitt-Dundas, 2015). Therefore, this foundation is also valuable when imitating the competition's practices (Cohen & Levinthal, 1990; Galende, 2006). As this knowledge foundation gives way for the firm's future innovation activities, each firm is theorized to be on a set trajectory, explaining the variation among firms' technologies (Galende, 2006; Metcalfe, 2009). The idea of a company's future innovation being on a set trajectory created by its past innovation is the basis for the concept of the path dependence of innovation (Galende, 2006).

The path dependence theory is built upon the previously mentioned waves of innovation studies. Innovation is shown to evolve over particular paths set in motion as a function of the firm's earlier acquired knowledge. Based on this idea, the definition of a persistent innovator is a firm that has innovated in a specific time frame and, as a result of the present innovation, will innovate in the next time frame as well (Colombelli & Von Tunzelmann, 2010; Galende, 2006; Le Bas & Latham, 2006). Firm history matters greatly for persistence (Colombelli & Von Tunzelmann, 2010; David, 2000). Colombelli & Von Tunzelmann (2010) also emphasize how path-dependent developments have several steady states, and the result of the mechanism gets determined by the firm's path, which starts from original settings and gets formed by accidental occurrences throughout the path.

Theory of innovation persistence

After explaining how innovation theory has developed over time and gave birth to the idea of innovation persistence, the arguments behind the construct need to be demonstrated. The first argument for innovation persistence is centered around essential firm operations. Companies must face fixed costs when starting to innovate in a new market, which then deters entry (Holl et al., 2022). However, when a firm does enter the market and spends on the costs that come with innovating, such as supplies and personnel to perform R&D, these expenses become sunk costs (Holl et al., 2022; Máñez et al., 2009; Peters, 2009). When experiencing sunk costs, firms have more incentives to continue their innovation projects and become persistent innovators by extending their prior R&D spending (Holl et al., 2022; Peters, 2009). On the other hand, sunk costs can also act contrary to innovation persistence (Peters, 2009). Previous spending on innovation may be satisfying enough for the firm or may even discourage the firm from continuing, depending on market conditions (Peters, 2009).

Previously it was mentioned how according to evolutionary theory, the firm builds future innovation based on the knowledge foundation they have developed. This argument is closely connected to the "success breeds success" explanation behind the persistence of innovation. This concept describes that companies earning profit beforehand can reintroduce their profits into funding future innovation (Duguet & Monjon, 2004; Raymond et al., 2010). It can also happen that the earlier described firm knowledge foundation creates a trajectory for the firm and, therefore, can facilitate a steady inflow of profits (Colombelli & Tunzelmann, 2010). However, the competitive market conditions will likely accelerate the need to innovate continually and exceed the steady state (Colombelli & Tunzelmann, 2010). This process implies that firms are compelled to persistently innovate using their knowledge base and additionally drive the “success breeds success” mechanism of persistence (Colombelli & Tunzelmann, 2010).

Similarly, another argument supporting the idea of firm-level innovation persistency is the "learning by doing" theory, derived from the concepts of evolutionary theory. Previous research has suggested that companies can benefit from better capabilities from past innovation, building up the earlier mentioned knowledge base, and can then apply their learnt expertise to future innovation projects (Duguet & Monjon, 2004; Rosenberg, 1976). This expertise can be displayed in the form of technical insight and skills in manufacturing (Duguet & Monjon, 2004). In turn, this theory proposes that companies can gain cumulative success from learning by doing and, therefore, offers a good case for why persistency is present in innovation (Duguet & Monjon, 2004).

The earlier mentioned ideas of Schumpeter are also closely connected to the process behind firm innovation persistence. More specifically, his creative accumulation theory is tied to continuous innovation behavior (Cefis & Orsenigo, 2001; Guarscio & Tamagno, 2019). Creative accumulation describes how organizations gain knowledge in an increasing manner and, in turn, set up monopolistic power in their industry and generate persistent innovation (Colombelli & Tunzelmann, 2010). In this process, innovation is predominantly by organizations with more market power; therefore, it is predicted that innovation persistence is a characteristic, especially of large companies (Le Bas & Latham, 2006).

Similarly, other firm-specific differences can also account for the reason behind persistence. These firm traits can be managerial or scientific skills, following a risk-averse or risk-seeking strategy, or creating innovation at non-variable expenditures to ensure continuous innovation production (Cefis & Orsenigo, 2001).

Another firm-specific trait to consider when examining the relationship between past and future innovation is the difference in the motivation behind innovating among companies (Arrow, 1962; Duguet & Monjon, 2004). When the industry structure where the firm operates is more competitive, that firm will be more driven to innovate compared to its counterparts in industry structures with large monopolistic control (Arrow, 1962). Additionally, incumbents also need to innovate to stay competitive compared to new entrants to the market (Aghion et al., 2015; Raymond et al., 2010). Especially when it comes to a process such as the patent races, firms that get left behind would face irreversible costs and therefore be motivated to continue their innovating process, which, in turn, would push the front-runner to keep innovating as well (Gallini, 1992; Le Bas & Latham, 2006). However, companies will have less motivation to innovate in market formations where the competitors are not innovative (Holl et al., 2022). This scenario could happen where demand does not support better goods, reducing the ambition for companies to improve their merchandise or service (Holl et al., 2022). Therefore, it is likely that specific industries characterized by more intensive rivalry and more incentive for innovation will also be described by intensified innovation persistence.

While there are many explanations behind the theory of innovation persistence, empirical studies somewhat contrast whether the hypothesis holds in real applications. Various studies have pointed out differences in the results depending on factors such as firm size, industry or measure of innovation (Duguet & Monjon, 2004; Peters, 2009; Raymond et al., 2010). Previous research has evaluated persistency based on innovation proxies for innovation input, such as R&D or output, such as patents and innovation surveys (Le Bas & Latham, 2006). Some papers have criticized using patents as a measure, as they could specify innovative superiority instead of continuous innovating (Duguet & Monjon, 2004). Despite the criticism, patents also have been established to provide benefits (Cabagnols et al., 2006). Cabagnols et al. (2006) argue that patents are a good measure of innovation as they show technological ability, since a patent is a consequence of a firm's acquired expertise and know-how.

The subject area of persistence in innovating has been extending over the last two decades. While many studies examine the relationship between past and future innovations, some analysis was also done on additional topics related to the association. For example, some papers look at the reasons behind the heterogeneity in persistence among firms or if there are components that could alter the relationship, and others measure the growth effects that being a persistent innovator might have on the firm (Bianchini & Pellegrino, 2019; Guarascio & Tamagni, 2019; Holl et al., 2022; Tavassoli & Karlsson, 2018). This paper concentrates on studying innovative locations' effects on persistence, as the firm's environment remains a largely unexplored topic in this research area (Colombelli & Von Tunzelmann, 2010; Holl et al., 2022).

2.2 Relevance of the topic

The relevance of this area of research extends to multiple perspectives. First, whether innovation is persistent is valuable for policies that aim at encouraging innovation and, in turn, economic development (Guarascio & Tamagni, 2019). Previous results show that firm persistency can impact technological innovativeness among industries and nations (Le Bas & Latham, 2006). If innovation is persistent, it implies that policies nurturing innovative businesses could significantly impact industries (Guarascio & Tamagni, 2019).

The analysis of regional effects is especially important for policy implications. Regional and national municipalities can better understand the value of an investment in improving innovative local conditions, such as absorptive capacity, that would then enhance growth in the region (Audretsch & Feldman, 2004).

Whether innovation is persistent for firms is also relevant to academic research. The topic ties to how a firm's internal growth and market structure develops (Duguet & Monjon, 2004; Howitt & Aghion, 1998; Raymond et al., 2010). If a firm is persistently innovating, it can demonstrate expansion without additional learning effects (Raymond et al., 2010). Consequently, the theme of persistence is also related to the subject of output and efficiency (Raymond et al., 2010). Furthermore, this theory is also relevant for ease of market access and competition between firms (Cefis & Orsenigo, 2001).

Innovation is vital for a company's competitive advantage in the market (Hana, 2013). More specifically, persistent innovation is a highly relevant topic for company strategy, as it is predicted to provide a robust competitive advantage for longer periods of time due to the positive feedback loops from attaining know-how (Guarascio & Tamagni, 2019). In the case that innovation is persistent and does affect future levels of innovation, investment in innovation would have an even better payoff than previously thought, as this would imply that the competitive advantage stemming from innovation has increasing returns. Therefore, companies have a higher incentive to decide to innovate, altering firm behavior. Guarascio & Tamagni (2019) also mention the usefulness of this topic for understanding market dynamics, such as the difference among organizational forms and productivity and innovation paradigms. Furthermore, the topic of locational factors, more specifically, whether firms can gain better positive feedback loops by locating in an innovative city, is vital for firm location strategy (Belderbos, Du, & Slangen, 2020).

Next to governmental bodies, adding a regional aspect to the study is also relevant for firms (Audretsch & Feldman, 2004). Having a favorable location strategy is vital for the success of organizations (Alcácer & Chung, 2007). Regional effects can play a role in the success or failure of a company (Alcácer & Chung, 2007). Therefore, gaining insight into how locations impact innovating persistence and whether firms can benefit from spillovers effects by locating in an area is highly valuable for company strategy (Audretsch & Feldman, 2004)

2.3 Hypothesis development

<u>Persistence of firm innovation</u>

After the theoretical background of innovation persistency has been laid out, it is important to discuss what previous research has found on the topic. While this subject has been receiving continuously more attention in academia over the last two decades, there is still a lack of empirical studies published (Duguet & Monjon, 2004). However, various major works have contributed to the field over the years. Even though certain studies contrast each other's results, many general themes and insights can be deducted about the relationship between a firm's past and future innovations.

Using a sample of patents from manufacturing firms within the UK, Geroski et al. (1997) have found many occasional innovators and, therefore, a low persistence in his model. They also show differences depending on firm size (Geroski et al., 1997). Malerba & Orsenigo (1999) has reinforced the idea of low persistence and several one-shot innovators when examining European patent data. Roper & Hewitt-Dundas's (2015) results reveal even a low negative path dependence between the firm's knowledge base and the innovation of the firm.

Similarly, Cefis & Orsenigo (2001) also use patents issued by the European Patent Office for manufacturing firms, but they have found confirmation for persistence. Even though their result shows little persistence overall, they did find high persistence for radical innovators as well as non-innovators (Cefis & Orsenigo, 2001). Cefis (2003) also found a corresponding effect, highlighting the variation among different industries and organization sizes. Cefis (1999) also raises the point that firms that are persistent will, in turn, earn more profits and, as a consequence, continue innovating and benefiting more.

Then another wave of later studies demonstrated strong persistence. When using innovation surveys, Lhuillery (2014), Duguet and Monjon (2004), Raymond et al. (2010), Peters (2009), Le Bas and Poussing (2014), Arroyabe and Schuman (2022) have all confirmed strong firm-level innovation persistence. Antonelli et al. (2013) also find strong persistency when employing accounting data and measuring total factor productivity as a proxy for innovation. In addition, many of these works also emphasize that industry and firm-specific heterogeneity matters for the relationship. Based on the arguments behind the theory of innovation persistence and many authors finding evidence for persistence, the following hypothesis is proposed:

Hypothesis 1.1: Innovation is persistent at the firm level.

Many previous studies have highlighted the importance of firm and industry heterogeneity when examining the relationship in question (Lhuillery, 2014). While various works have only considered manufacturing firms, Peters's (2009) and Holl et al.'s (2022) study show that it is valuable to include an analysis of the effect of the industries. For example, industries differ in patenting strategies (Dernis H. et al., 2015). Examining the impact of industry differences may also be valuable to investigate if firms in different markets act contrasting as they face heterogeneity in their types of processes, know-how and competition. Peters (2009) and Holl et al. (2022) differentiate between companies in the manufacturing and in the service spheres; therefore, the second part of hypothesis 1 also considers those two industries. Including service companies is relevant, as they have been excluded from prior research on the topic many times, even though service firms have experienced swift growth recently (Peters, 2009). They also present an interesting addition to the model, as their R&D and innovation process varies from other sectors (Peters, 2009). Therefore, the following hypothesis is formed to examine firm industry differences:

Hypothesis 1.2: Innovation persistence varies depending on whether the firm is in the manufacturing or service sector.

Geographical location as a moderator

Audretesch and Feldman (2004) have demonstrated in their model that the knowledge production function has a geographical aspect. Yet, few previous studies have discussed the importance of geographical location as a moderator of firm innovation persistence (Holl et al., 2022). Nevertheless, regional knowledge spaces are a significant factor in the relationship in question (Antonelli et al., 2013; Audretsch & Feldman, 2004; Colombelli & Von Tunzelmann, 2010; Holl et al., 2022). The surroundings of the company's location can serve as a driving force or even as a deterrent to innovation activities (Holl et al., 2022). Holl et al. (2022) discuss how a location's existing knowledge stock could lower entry expenses and sunk costs of innovation investments, making smoother access and withdrawal of innovation projects. However, regional knowledge stocks simultaneously enhance the 'success breeds success' mechanism of persistence since firms benefit from easier access to information, increasing their success chance and, therefore, innovation persistency. The proximity to an innovative location will also help a firm's external learning and, thus, its technological knowledge foundation (Galende, 2006).

Furthermore, as other organizations in the area can develop an atmosphere of innovation, the learning and motivation to innovate for firms are likely to rise. This theory is connected to the previously mentioned argument of firms having higher innovation incentives in a market with more competition. Additionally, if a firm has a good base of technological knowledge, being located near other innovative firms will also increase the chances of gaining learning from imitation or collaboration (Cohen & Levinthal, 1990; Galende, 2006). Based on literature and previous positive results, a positive moderation effect is predicted by local innovation hubs on the persistency of innovation of a firm.

Hypothesis 2.1: Having the firm location in innovative geographical areas positively moderates the innovation persistency of firms.

There is a lack of literature on the combined effects of industry variation and location. When studying location effects, industry heterogeneity is predicted to play a role in the outcome; therefore, the same differentiation of service versus manufacturing is again included in the second hypothesis as a sub point. Service firms typically rely on acquiring knowledge and collaboration in order to innovate (Holl et al., 2022). Accordingly, know-how that fuels innovation in these firms is likely more abstract and tacit than in manufacturing firms. Therefore, innovative spaces' moderation effects on the persistency relationship may be more restrained for services, which Holl et al.'s (2022) findings have also confirmed. Based on Holl et al.'s (2022) work, the following hypothesis is drawn:

Hypothesis 2.2: The effect of locating in an innovative geographical area on innovation persistency will vary whether the firm is a service or manufacturing firm.

3. Methodology

This section details the data and variables used for the analysis and then presents the descriptive statistics and estimation techniques employed.

3.1 Data

The data is a panel data set containing patents from the United States Patent and Trademark Office (USPTO) between 1975 and 2013. This set has also been used in a study by Bhaskarabhatla et al. (2021). The given USPTO data is paired with corresponding Compustat data for firm characteristics for innovators as well as non-innovators per year. Each firm in the dataset has innovated at least once during the given period. The sample is representative of all U.S. companies that innovate.

While, as previously described, using patent data is debated to be a well-fitted measure for this topic, patents are still beneficial for studying innovation persistence (Cabagnols et al., 2006). Additionally, other types of innovation proxies also have received criticism. For example, innovation surveys, such as the CIS, could reflect managers' views of innovation and not factual observations, which might lead to bias in the estimation (Le Bas & Latham, 2006). In fact, many established prior literature has used patent data, such as Geroski et al. (1997), Cabagnols et al. (2006), Cefis & Orsenigo (2001) and Latham and Le Bas (2006). This paper focuses on the U.S. patent data. Most previous papers, with the known exception of Alfranca, Rama and von Tunzelmann (2002) and Cabagnols et al. (2006), have mainly focused on the European market concerning this subject, so it is value-adding to look at the relationship in a different setting.

For the 2nd hypothesis, the geographical space is measured by dummy variables of the most innovative cities in the U.S. In literature, it is debated whether certain spaces, such as cities by nature, are more innovative compared to other places (Shearmur, 2012). However, it is inevitable that cities play a central role in innovation and, therefore, would be a well-fit proxy for innovative geographical space (Marceau, 2014). This study will focus on the most innovative cities within the U.S. based on the list of rankings of innovativeness (2THINKNOW, 2022). The ranking is compiled based on factors that indicate support for company innovation, education, and business environment (2THINKNOW, 2022). Global cities are established as attractive for companies and are center of innovative activity, and therefore a good proxy for knowledge spaces (Belderbos et al., 2020).

3.2 Variables

The two main variables of the model are the innovation in the present, proxied by patent count in time t and innovation in the past, proxied by patent count in time t-1. The past count contains the lag of one year prior to the current invention. To differentiate between service and manufacturing industries, based on Peters's (2009) and Holl et al.'s (2022) work, a dummy is created based on Standard Industrial Classification (SIC) code ranges for each sector. These then get transformed into interaction variables, first with the previous patent count and then with the previous patent count and city dummies for hypothesis 2.2. SIC codes are an established way to define industries and are also used by Raymond et al. (2010). Then multiple other measures are applied based on previous literature to control for firm characteristics. For example, firm size proxied by employees, market power measured by the Herschmann-Herfindahl index, and total R&D is included (Antonelli et al., 2013; Bianchini & Pellegrino, 2019; Duguet & Monjon, 2004; Peters, 2009; Raymond et al., 2010). These variables are all argued to be factors affecting the likelihood of innovating for firms, as they indicate resources, competence, and know-how (Raymond et al., 2010).

Furthermore, financial information is also added, such as the availability of financial resources measured by creditworthiness and firm financial leverage as a ratio of stock equity and total liabilities (Bianchini & Pellegrino, 2019). Then, productivity is also measured by the labor productivity index, which is a value-added over the number of employees as well as profitability proxied by return on sales, which is operating profit over total sales (Bianchini & Pellegrino, 2019).

In addition, it is also checked if companies are a subsidiary, along with whether they are international or domestic (Peters, 2009; Raymond et al., 2010). When firms belong to a group, they are expected to gain capital and knowledge through spillover effects (Holl et al., 2022; Raymond et al., 2010). Similarly, if a firm is present internationally, they are predicted to have better abilities, intensified rivalry, along with a larger industry magnitude, all driving them to innovate further (Holl et al., 2022).

To examine the effect of innovative cities, a global innovation index for cities is used that measures innovation based on various factors hat measure innovativeness directly or indirectly (2THINKNOW, 2022). Three categories are made for the best 5, 10 and 25 innovative cities within the US. Moreover, based on Holl et al.'s (2022) model, an interaction variable is added to previous innovations. Lastly, industry and time dummies are added to the model (Raymond et al., 2010).

Outliers are removed, and sales, firm size, market power, and R&D variables are turned into natural logarithmic functions according to previous works (Duguet & Monjon, 2004; Holl et al., 2022; Peters, 2009; Raymond et al., 2010). Firms with less than 10 employees are also eliminated based on Triguero and Córcoles (2013). In addition, firm size, market power and R&D lagged by a year to cohere with the literature and to avoid collider bias (Raymond et al., 2010).

3.3 Descriptive statistics

Table 1

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
patentcount annual	74047	1.886	3.619	0	20
Inno(t-1)	70055	1.762	3.368	0	20
Employees	74047	8.197	40.137	.01	2200
R&D	51453	44.92	323.276	-.515	14035.289
Subsidiary/LBO	74033	.034	.18	0	1
RoS	72883	-2.9	147.098	-30175.699	1.065
RoA	73960	-.026	.319	-19.451	21.789
Leverage	73865	1.329	28.976	0	6004.089
Innocity5	74047	.084	.277	0	1
Innocity10	74047	.109	.311	0	1
Innocity25	74047	.186	.389	0	1
HHI	74047	.348	.246	0	1
Labor Productivity	73964	69323.926	310673.04	-2442125	34091552
industry==manufacturing	74047	.717	.45	0	1
industry==service	74047	.111	.314	0	1
industry==other	74047	.171	.377	0	1
International	74047	.098	.297	0	1
finquality	.	.	.	.	.
A+	39656	.014	.117	0	1

A	39656	.038	.192	0	1
A-	39656	.054	.226	0	1
B+	39656	.126	.332	0	1
B	39656	.186	.389	0	1
B-	39656	.22	.414	0	1
C	39656	.292	.454	0	1
D	39656	.071	.257	0	1
LIQ	39656	0	.014	0	1

Notes: The table displays the descriptive statistics for the dependent variable, the current patent count of a company, and the main independent variables, the previous patent count of the company, whether the firm is in the manufacturing, service or other industry, and the dummies indicating whether the firm is in the top5, top10, top25 innovative cities, as well as firm-specific characteristics that act as control variables in the estimation.

The descriptive statistics are presented in Table 1. This sample is limited to firms with a maximum of 20 patents annually to normalize the values and overcome bias by outliers within the data. This way, the influence of large and monopolistic companies likely to win the patent race is reduced (Duguet & Monjon, 2004). The distribution of the dataset is seen in Appendix A. There are 74,047 observations in total in the final sample. The table shows an unbalanced set, as some variables, especially financial quality, are missing. The unobserved data points are observations presumed to be missed at random; therefore, keeping them in the sample is acceptable. Below zero values for variables such as sales and assets have also been removed. When examining the correlation matrix in Table 2 between linear independent variables, even though some variables show moderate correlation, overall, all variables pass the cut-off value of 0.7, indicating a high correlation (Ratner, 2009).

Table 2

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Inno(t-1)	1.000							
(2) ln(Employees(t~)	0.293	1.000						
(3) ln(HHI(t-1))	-0.018	0.158	1.000					
(4) ln(R&D(t-1))	0.372	0.565	-0.127	1.000				
(5) RoA	0.026	0.299	0.073	-0.007	1.000			
(6) RoS	-0.011	0.025	0.005	-0.016	0.048	1.000		
(7) Leverage	0.006	0.010	0.007	-0.005	-0.013	0.000	1.000	
(8) Labor Producti~y	0.030	0.108	-0.060	0.185	0.218	0.062	-0.006	1.000

Notes: The table shows all the linear variables in the model and the correlation between each set of them.

The mean of patent counts every year is around two patents, implying that the average company's patenting activities are more gradual after taking out the outliers. The sample still contains companies of significant size, as the average of firm employees is 8,197, with considerable variations. The dataset is composed mainly of firms with high leverage ratios and low profitability and creditworthiness. A large portion of the sample comprises manufacturing firms, precisely 71.7%, whereas 11.1% are service. This is representative of the industry characteristics, as service relies on more tacit knowledge for innovating (Holl et al., 2022). For the location variables, it is revealed that 8.4% reside in one of the 5 most innovative cities, 10.9% in the 10 most innovative cities and 18.6% in the 25 most innovative cities. Furthermore, only 9.8% of the companies are international, and only 3.4% are subsidiaries. The HHI index displays that the average of the sample does not have monopolistic or oligopolistic power within their industry.

3.4 Estimation model

To present the economic paradigm behind innovation persistence, it is useful to show the production function integrated with innovation based on literature (Audretsch & Feldman, 2004). The specification for basic innovation function is as seen here:

$$Inno_i = \alpha RD_i^{\beta} HK_i^{\gamma} \varepsilon_i$$

The equation shows the knowledge production function, where Inno is innovation, R.D. is R&D, and H.K. is human capital (Audretsch & Feldman, 2004).

The fundamental model behind persistence is based on Holl et al.'s (2022) description, which gets later modified to fit the estimation technique. According to Holl et al. (2022), profit-maximizing agents will innovate when the anticipated current value of earnings from spending on innovation is above zero. In section 2.1, the theoretical background is established behind why firm innovation in the past is predicted to influence innovation in the present. Therefore, the equation that shows the probability of innovation based on the hypothesis is as follows:

$$Inno_{it} = \theta Inno_{it-1} + \beta x_{it} + \varphi_i + \varepsilon_{it}$$

Here, θ shows the actual state dependency, defined as the impact of prior innovation on present innovation (Holl et al., 2022). To achieve actual state dependency, it is necessary to control for company traits x_{it} and unobserved variables φ_i (Holl et al., 2022). ε_{it} shows the idiosyncratic shocks.

For hypothesis 1.2, interaction terms are added to measure the combined effect of industry specification, each for service and manufacturing together previous patent count. For simplification, in this equation, one variable of industry indicates the two specifications in the model:

$$Inno_{it} = \theta Inno_{it-1} + \beta_1 Industry + \beta_2 (Inno_{it-1} * Industry) + \beta x_{it} + \varphi_i + \varepsilon_{it}$$

For the second hypothesis, this equation needs to include the locational factor. Therefore, when considering the effect of top innovative cities, the variable InnoCity is added, representing the three variables of most innovative cites, along with the relevant interaction variables and the following equation is proposed for hypothesis 2.1:

$$Inno_{it} = \theta Inno_{it-1} + \beta_1 InnoCity_{it} + \beta_2 (InnoCity_{it} * Inno_{it-1}) + \beta x_{it} + \varphi_i + \varepsilon_{it}$$

Similarly, the following equation is created for hypothesis 2.2:

$$Inno_{it} = \theta Inno_{it-1} + \beta_1 InnoCity_{it} + \beta_2 Industry + \beta_3 (Inno_{it-1} * Industry) + \beta_4 (InnoCity_{it} * Inno_{it-1}) + \beta_5 (InnoCity_{it} * Inno_{it-1} * Industry) + \beta x_{it} + \varphi_i + \varepsilon_{it}$$

The model estimation of this paper differs from those of previous literature. While the aim is also to predict the probability of innovation, as in Holl et al. (2022), Raymond et al. (2010) and Guarascio (2019), the method here differs. The regression in this analysis is on count data, using zero-inflated negative binomial models (ZINB). Count data provides a more precise estimate of the intensity of the persistence compared to binary measures. Count data models have been used before for examining persistence, but it is scarcely employed in literature (Blundell, Griffith, & Reenen, 1995; Crépon, Duguet, Crepona, & Duguetb, 1996). A negative binomial is a beneficial technique to estimate probability when there is overdispersion (Cameron & Trivedi, 2005). The data shows overdispersion in this case; therefore, the negative binomial model is predicted to have a better-fitted method over Poisson.

The motivation behind using a zero-inflated model estimation is that many zeros are still observed after normalizing the data in the histogram in Appendix A. This technique is also used in the work of Huang & Cheng (2015) on the firm propensity to patent and Fontana (2006) on university R&D, as they both use zero-inflated models; however, the technique is regarded as new to the topic of persistence. Employing zero-inflated models is useful because this count data may be subject to a disproportionate number of zeros in the sample (Huang & Cheng, 2015; Korosteleva, 2018; Moghimbeigi et al., 2008). In the context of patenting behavior, the zeros are assumed to be structural zeros compared to chance zeros since firms tend to follow either the rare or always patenting strategy (Huang & Cheng, 2015; Korosteleva, 2018; Swycher & Harris, 2019).

Therefore, the previous equation for the simplified first model is transformed to be in a negative binomial zero-inflated form based on Korosteleva (2018), and the expected probability function for hypothesis 1.1 is as follows:

$$Inno_{it} = \begin{cases} \pi + (1-\pi)\left(\frac{r}{r+\lambda}\right)^{r}, & y = 0 \\ (1-\pi)\left(\frac{r}{r+\lambda}\right)^{r}\frac{\Gamma(r+y)}{y!\,\Gamma(r)}\left(\frac{\lambda}{r+\lambda}\right)^{y}, & y > 0 \end{cases}$$

$$\pi = \frac{exp\{\beta_0+\beta_1 Inno_{it-1} + \beta x_{it} + \varphi_i + \varepsilon_{it}\}}{1 + exp\{\beta_0+\beta_1 Inno_{it-1} + \beta x_{it} + \varphi_i + \varepsilon_{it}\}}$$

$$\lambda = exp\{\gamma_0+\gamma_1 Inno_{it-1} + \gamma x_{it} + \varphi_i + \varepsilon_{it}\}$$

The model aims to distinguish structural zeros from chance zeros, so it makes current innovation ($Inno_{it}$) estimate the amount zero with odds of π if the value is a structural zero and with odds of $1-\pi$ if not, which acts as a count variable and is part of the negative binomial distribution with a rate λ (Korosteleva, 2018).

4. Results

This section presents the results obtained by the ZINB estimation for all four hypotheses, followed by a description of the statistical interpretation of the output. Then, alternative tests are displayed to check the robustness of the main results.

The output of the regression is seen in the below table:

Table 3

Main results: Marginal effects of ZINB estimation

	(1)	(2)	(3)	(4)
VARIABLES	Inno (t)	Inno (t)	Inno (t)	Inno (t)
Inno(t-1)	0.712***	0.624***	0.710***	0.674***
	(0.00963)	(0.0514)	(0.0111)	(0.0648)
	0	0	0	0

ln(Employees(t-1))	0.0336**	0.0339**	0.0375**	0.0381***
	(0.0146)	(0.0146)	(0.0147)	(0.0147)
	0.0219	0.0206	0.0107	0.00961
ln(R&D(t-1))	0.284***	0.293***	0.283***	0.292***
	(0.0159)	(0.0159)	(0.0159)	(0.0160)
	0	0	0	0
Financial Quality = 1, A	-0.257	-0.225	-0.240	-0.215
	(0.192)	(0.191)	(0.190)	(0.189)
	0.179	0.237	0.206	0.256
Financial Quality = 2, A-	-0.0945	-0.0922	-0.0552	-0.0709
	(0.185)	(0.183)	(0.183)	(0.182)
	0.609	0.615	0.763	0.697
Financial Quality = 3, B+	-0.104	-0.0790	-0.0550	-0.0416
	(0.172)	(0.170)	(0.170)	(0.169)
	0.545	0.643	0.747	0.806
Financial Quality = 4, B	-0.315*	-0.297*	-0.277*	-0.267
	(0.169)	(0.168)	(0.167)	(0.166)
	0.0622	0.0765	0.0973	0.108
Financial Quality = 5, B-	-0.410**	-0.380**	-0.369**	-0.349**
	(0.170)	(0.168)	(0.168)	(0.167)
	0.0157	0.0238	0.0279	0.0363
Financial Quality = 6, C	-0.403**	-0.378**	-0.360**	-0.343**
	(0.170)	(0.169)	(0.169)	(0.168)
	0.0181	0.0252	0.0326	0.0408
Financial Quality = 7, D	-0.456**	-0.436**	-0.410**	-0.397**
	(0.182)	(0.181)	(0.180)	(0.180)
	0.0122	0.0158	0.0231	0.0271
Financial Quality = 8, LIQ	-0.197	-0.0127	-0.158	-0.0533
	(1.126)	(1.213)	(1.126)	(1.180)
	0.861	0.992	0.889	0.964
Subsidiary/LBO = 1, Subsidiary/LBO	-2.192***	-2.201***	-2.208***	-2.214***
	(0.347)	(0.338)	(0.341)	(0.338)

	2.52e-10	7.85e-11	8.97e-11	5.50e-11
RoS	8.33e-05	8.30e-05	8.13e-05	8.17e-05
	(7.10e-05)	(7.06e-05)	(7.16e-05)	(7.06e-05)
	0.240	0.239	0.256	0.247
RoA	0.332***	0.302***	0.331***	0.302***
	(0.0734)	(0.0733)	(0.0734)	(0.0734)
	6.21e-06	3.85e-05	6.48e-06	3.77e-05
Leverage	-0.000445	-0.000490	-0.000400	-0.000436
	(0.000795)	(0.000794)	(0.000798)	(0.000794)
	0.576	0.537	0.616	0.583
ln(HHI(t-1))	-0.203***	-0.237***	-0.203***	-0.242***
	(0.0259)	(0.0268)	(0.0260)	(0.0269)
	0	0	0	0
International	-0.0129	0.0115	-0.00728	0.0114
	(0.0602)	(0.0604)	(0.0603)	(0.0608)
	0.831	0.849	0.904	0.851
Labor Productivity	-9.77e-07***	-8.74e-07***	-9.66e-07***	-8.61e-07***
	(1.47e-07)	(1.48e-07)	(1.47e-07)	(1.48e-07)
	0	3.23e-09	0	6.07e-09
indd = 1, manufacturing		0.152		0.178
		(0.147)		(0.149)
		0.299		0.230
indd = 2, service		-0.327**		-0.313*
		(0.165)		(0.166)
		0.0474		0.0594
Inno(t-1)*Manufacturing		0.0957*		0.0350
		(0.0543)		(0.0672)
		0.0777		0.602
Inno(t-1)*Service		0.0235		-0.000234
		(0.0624)		(0.0765)
		0.707		0.998
Innocity5			-0.335	-0.412

	(0.260)	(0.254)
	0.198	0.105
Innocity10	-0.0490	0.0601
	(0.246)	(0.242)
	0.842	0.804
Innocity25	0.170	0.168
	(0.115)	(0.115)
	0.140	0.144
Inno(t-1)*Innocity10	-0.175*	-0.146
	(0.0918)	(0.236)
	0.0572	0.536
Inno(t-1)*Innocity5	0.281**	0.427*
	(0.110)	(0.248)
	0.0105	0.0846
Inno(t-1)*Innocity25	0.00473	-0.113
	(0.0516)	(0.226)
	0.927	0.618
Inno(t-1)*Manufacturing*Innocity10		0.224
		(0.292)
		0.443
Inno(t-1)*Service*Innocity10		0.0440
		(0.251)
		0.861
Inno(t-1)*Service*Innocity5		-0.224
		(0.268)
		0.404
Inno(t-1)*Service*Innocity25		-0.00744
		(0.237)
		0.975
Inno(t-1)*Manufacturing*Innocity5		-0.355
		(0.309)
		0.251

Inno(t-1)*Manufacturing*Innocity25				0.143
				(0.228)
				0.531
Observations	24,199	24,199	24,199	24,199

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The outputs for the four hypotheses are presented in the form of marginal effects on the ZINB regression. Due to the missing variables in the sample, a significant number of observations were dropped. First, the current patent count is regressed against the previous patent count and firm-specific variables. Second, industry differences are added, namely, whether the firm is manufacturing, services or other. Third, measures are added to measure whether the firm is in the most innovative areas within the US. Fourth, industry differentiation is added once again and interacts with locational measures.

4.1 Hypothesis 1

The values based on the regression for hypothesis 1.1 show a highly significant effect, at the 1% significance level, of the previous patent count in t-1 on the current patent count in t within the sample. When looking at marginal effects, it is revealed that having one patent in a year will increase the patent number in the next year by 0.712 units, keeping all other variables constant. Therefore, hypothesis 1.1 is not rejected. Many control variables significantly affect the current patent count, such as size, R&D expenses, sales volume, return on assets, being part of a group, market power, and labor productivity. Interestingly, some of these measures, for instance, being a subsidiary, market power, firm sales and labor productivity, negatively affect the current patent count. Similarly, all ranges of financial quality negatively affect the patent count; however, only worse quality ratings have a significant impact.

When running the model with the inclusion of industry differences, the effect of previous patents increases, to a unit of 0.624, while remaining highly significant. A lower marginal effects estimate indicates removing upward bias in the model specification. The slight change already signals that industry differences matter for persistence. First, we can observe that parenting behavior differs between industries, as firms in the service fields influence the current patent count significantly at the 1% level and negatively. In contrast, manufacturing ones have a positive, yet not significant effect. In fact, if the firm is in the service industry, its patent count is 0.327 units less when compared to other sectors, ceteris paribus. While the interaction variable between industry and previous patent count reflects the predicted industry heterogeneity, as manufacturing and service have positive persistency effects, however, the result is only significant for manufacturing. The average marginal effects show that for a manufacturing firm, compared to firms in other industries, the previous patent count will increase the current patent count by 0.096 units, having all other variables constant. Therefore hypothesis 1.2 does not get rejected.

4.2 Hypothesis 2

For examining whether geographic location makes a difference, three dummies are added to the model controlling for whether the firm is located in one of the 5, 10 or 25 most innovative cities. The previous patent count continues to significantly and positively affect the current patents. More specifically, the effect remains 0.710 units before controlling for industry differences and becomes 0.674 units after the industry differentiation, ceteris paribus. Contrary to previous studies, being in a top 5 or 10 innovative city decreases the current patent count, but the effect is insignificant for both cases. However, the top 25 indicates a positive but again insignificant result.

When discussing the main variables of interest, again, some uncommon associations are observed. First, the interaction variable of being in the 5 most innovative cities and the past patent count is positive and significant at the 5% significance level, corresponding to the hypothesis. More specifically, being located in the most 5 innovative cities increase the innovation persistence of firms by 0.281 units, ceteris paribus. However, when a firm is in the 10 most innovative cities, the relationship turns negative, contradicting the hypothesis, and is significant at the 10% level. Therefore, the model predicts that locating in the 10 most innovative cities decreases persistence by 0.175 units, keeping other factors constant. Then, the interaction variable of the 25 most innovative cities shows an insignificant effect. These variating results fail to find robust evidence for overall positive moderation by location. Therefore, hypothesis 2.1 is rejected.

When adding the industry aspect to the equation, the effect of the previously discussed city interaction variables only stays significant for the top 5 cities. Furthermore, even though certain location and industry effects remain significant on current patenting, none of the industry effects gets significant results for persistency. Therefore hypothesis 2.2 also gets rejected.

4.3 Robustness checks

Method 1 – Alternative count estimation techniques

The first robustness check compares estimation techniques close to the one in the primary model, namely the estimations as Negative Binomial, Poisson Pseudo Maximum Likelihood (PML), and Poisson Zero-Inflated (ZIP). When testing which model is better fitted for the sample (found in Appendix B), the analysis reveals that ZINB is closest to the observed values compared to the other count model alternatives. However, checking the output of these models still provides a valuable way to strengthen or question the prior results.

The marginal effects presented by these models are found in Appendix C. The alternative assessments do not match previous results fully. Persistency is established as positive and significant in all four estimation outputs; therefore, it verifies the prior results of hypothesis 1.1. However, the magnitude of the effects differs across the methods. The negative binomial and Poisson PML estimate for past patents are lower than those of the zero-inflated models, likely due to the influence of many zeros. For hypothesis 1.2, all three models show a significantly different persistence for manufacturing, compared to other industries, while only ZIP predicts a positive relationship as in the main results. Nevertheless, whether the effects are negative or positive, the results show a slight difference in persistence, just as in the main results. Another difference is the effect of service firms becoming significant in the Negative Binomial model and displaying a small but negative impact.

Locational effects again show some deviations. The effect of the top 5 and 10 innovative cities is similar to the main model in the Negative Binomial estimation but varies in the other two estimations. The effect of the top 10 is also similar in the ZIP model but insignificant again in the Poisson PML technique. Additionally, the industry differences are insignificant in all three alternative approaches, agreeing with the main results.

Method 2 – Probit model with a binary measure

The second check offers another alternate model estimation. In this method, the main variables of interest are converged to binary variables instead of counts, followed by running the model with a probit technique. This differentiation allows a new insight into the view of persistency, as it measures patenting activity in a more general way instead of the count form. The outcome is found in Appendix D. While the probit results reinforce the earlier effects in hypotheses 1.1, 1.2 and 2.1, they provide a contrasting outcome for 2.2. Persistence is highly significant in all four versions, showing that if a firm has patented in the past year, its likelihood of patenting is estimated to be increased by 40.9% in the current year. This effect is lowered when controlling for the industry heterogeneity, showing an increase of 36.6%. Manufacturing firms are still proved to be more persistent since because of patenting in the prior year, their probability of patenting in the current year increases by 5%.

When city effects are added, the probit estimates are alike the count ones, as the effect of locating in one of the 5 most innovative cities is observed as significant and positive, confirming the prior positive effects. Similarly, the 10 most innovative cities are significant and negative again. However, the top 25 remain insignificant. Contrary to the main model, when adding industry differences, the probit technique shows a significant and negative result for manufacturing firms located in the top 5 innovative cities. Therefore, this model predicts that being located in the most 5 innovative cities for manufacturing firms will decrease their persistence by 24.3%, ceteris paribus.

Method 3 – Small and Medium Enterprises (SMEs)

In our model, we have restricted the sample to companies with less than 20 patents within a year not to cause bias in the model by large companies less representative of the sample. This is closer to the mean value of patents annually found by a study of U.S. patenting behavior (Shackelford, 2013). However, the median found by the same research is 2 patents annually (Shackelford, 2013). As a robustness check, the sample is limited to firms with less than 5 patent counts per year. Larger companies are likely to win the patent races due to their vast knowledge, market power and capital (Duguet & Monjon, 2004; Raymond et al., 2010). This limit is an interesting robustness check because companies with 20 patents annually can still be considered more prominent players in the market. Restricting these larger companies can shed light on the process of SMEs, who play a meaningful part in innovation and patenting activity despite their smaller size (European Patent Office, 2017). Furthermore, the size of the firms within the sample also gets more restricted, as the SME definition is limited to a maximum of 250 employees (European Commission, 2003). The histogram in Appendix E shows that the distribution within the sample is more normalized as a result.

The model's output (found in Appendix E) confirms that highly innovative companies likely to win the patent race contribute to the previously large effect of persistence. While the relationship is still highly significant between past and present, confirming hypothesis 1.1, having one patent in the past year has dropped in this sample to increase the patent count in the current year by 0.420 units in the first model and 0.349 units after controlling for industry differences. For this sample, manufacturing firms do not exert a significantly different effect as before compared to other industries. The effects of location and industry differences remain as in the original model. Even though most effects by the main variables lowered in their strengths, interestingly, the magnitude of the effects of location in 5 and 10 most innovative cities is slightly higher for SMEs compared to the main model.

Method 4 – Alternative ranking of cities

The fourth and final robustness check focuses on Hypothesis 2, shown in Appendix F. Here, an alternative measure for the locational factors is employed. A new ranking is added to the sample, containing a different list of innovative cities complied by another methodology (FINOM, 2021). While the cities included in both lists have many overlaps, the ranks of cities differ in the two lists. The outcome of the analysis deviates from the original model, as the new city factors reveal no significant effects on persistence. However, the effect of industry differences shows one significant outcome for manufacturing firms located in the 10 most innovative cities. The model predicts that the effect of the previous patent count increases by 0.348 units for manufacturing firms if located in one of the 10 most innovative cities, ceteris paribus.

5. Discussion of results

The following part of the paper compares, interprets, and applies the previously shown statistical results to a broader perspective. Afterwards, implications are drawn based on the discussion and certain limitations of the analysis get highlighted.

5.1 Innovation persistence and firm heterogeneity

The main results along with the robustness checks all indicate strong and significant firm-level innovation persistency. This confirms the findings of several prior studies (Antonelli et al., 2013; Arroyabe & Schumann, 2022; Duguet & Monjon, 2004; Le Bas & Poussing, 2014; Lhuillery, 2014; Peters, 2009; Raymond et al., 2010). Contrasting to other studies that have used different estimation models, using a count data method gives better insight into how the predictor variables determine the number of patents. The finding that if a firm has one patent in the past year, that will increase their number of patents in the current year by 0.7 units reveals that innovating has strong positive feedback loops and therefore increases returns of innovation.

Heterogeneity among firms is also proved to be an important factor in persistence, as many specifications of firm characteristics also have shown significant effects. The firm's lagged size, R&D expenses, and return on assets all impact the current patenting behavior positively, cohering to that firms rely on their resources and know-how to innovate (Raymond et al., 2010). Labor productivity negatively influences patenting activities, which could be because this analysis focuses more on the product view of innovation over process innovation, which has been proved to have less patenting from firms (Arundel & Kabla, 1998). Creating a more efficient system is likely to reduce the resources for developing new products and, in turn, likely to increase labor productivity. Furthermore, being a subsidiary does not benefit the firm patenting, as predicted. This phenomenon can be explained by the group structure that might discourage self-initiated innovations of the subsidiary (Johnson & Medcof, 2007).

Two additional characteristics show an interesting view relating to the theoretical background of persistency described earlier. First, financial quality indicators only show a significant and negative impact on patenting when the creditworthiness is below adequate. This result is related to the "success breeds success" idea of persistence but in the reverse manner. A lower creditworthiness score means non-success; therefore, it can indicate a process of non-success breeding non-success. Second, the negative effect of the HHI index is connected to the previously described Schumpeterian theory, where having more market power or being in a less competitive environment will discourage the firm from innovating (Holl et al., 2022; Raymond et al., 2010). Additionally, further innovation can also pose the threat of cannibalizing profits from existing innovations (Holl et al., 2022; Raymond et al., 2010).

Industry specifications display an essential part of the association. This result also mainly confirms previous findings (Holl et al., 2022; Peters, 2009). More specifically, corresponding to prediction, the output indicated that service firms patent significantly less than firms from other industries, and manufacturing firms are more likely to be persistent innovators. The industry-specific innovation behavior is in line with the characteristics of their market structure. As service relies on more intangible knowledge to innovate, they are expected to patent less (Holl et al., 2022). The subject area lacks research focused on service firms, but the lack of significance in persistence contrasts with the results of papers that include this factor, such as Peters (2009). Nevertheless, persistence for manufacturing companies is significant, even though it shows a modest influence.

Since manufacturing is more centered around product innovation, the finding that persistence is present only in manufacturing can be explained by the fact that patenting is a proxy more for product innovation than process innovation (Triguero et al., 2013).

5.2 Location and innovation persistence

The second part of the analysis indicates that being located in a highly innovative space does not necessarily influence innovation persistence on a firm level positively. This contrasts previous works, which have found an overall positive effect of regional knowledge space on persistence (Holl et al., 2022; Tavassoli & Karlsson, 2018). While the influence is contradictory, the results imply an association between geographical location and persistence and reveal a potential new insight into the relationship.

The finding that being in the 5 most innovative cities influences persistence positively partly demonstrates the hypothesis. Innovative locations, therefore, can act as enablers of innovation persistence on the firm level, confirming earlier research on the topic (Holl et al., 2022; Tavassoli & Karlsson, 2018). The increase in persistence for companies is likely due to increased access to information, better learning from counterparts and an efficient atmosphere of innovation that drives firms to innovate more (Holl et al., 2022). These underlying mechanisms increase firms' returns when innovating, so the analysis validates that firms can benefit from locating in the most innovative and capable environments.

On the other hand, when expanding the selection of cities to a firm located in the 10 most innovative cities, geographical location shows that it can also discourage persistence. This result is surprising, yet some theories can explain the negative impact. Locations with high knowledge stocks can restrain innovation, as being in these cities can lower a firm's sunk costs and oppose the drive behind persistence (Holl et al., 2022). Being able to imitate easier when being closer to innovative firms can also reduce the need for patenting. Alternatively, due to high competition in these locations, companies might focus more significantly on guarding their patents instead of advancing or leveraging the profitability of patents (Roper & Hewitt-Dundas, 2015). Furthermore, a pattern of negative path dependency can also appear, where previous innovation becomes a restraint for companies instead of a driving force for more innovation (Thrane, Blaabjerg, & Møller, 2010). The previously mentioned positive factors present in the highest innovative cities are likely to diminish as the location is less innovative, and the negative effects of an innovative location become dominant. Therefore, the impact on innovation is expected to increase returns only for the most innovative places, and as the level of innovativeness decreases in an area, the effect shows a diminishing return. Even though we cannot establish a significant result for the list containing the 25 most innovative cities, it can also be hypothesized that the diminishing return later disappears as the locations are not as highly innovative due to lower competition.

The lack of success in identifying an overall strong positive result may be supported by prior research that found a higher persistence among companies in worse business environments but not within competent environments (Nam & Bao Tram, 2021). The failure to establish a relationship could also be due to limiting the view to cities only, as this measure does not account for knowledge spillover effects within a whole region (Christensen & Drejer, 2005).

Similarly, industry specialization has shown no significant variation of persistency for different locations, meaning that, compared to other industries, being a manufacturing or service firm makes no difference in location's effect on innovation persistence. This correlates to Holl et al.'s (2022) findings on manufacturing firms; however, their work establishes an impact on service firms. Interestingly, the robustness checks overall confirm the insignificant outcome, except for the model with probit estimation and the alternative ranking of cities. The assessment using a binary measure of innovation shows a negative influence on persistence for manufacturing firms located in the 5 most innovative locations. This result implies that manufacturing firms could be at a disadvantage if located in the most innovative spaces. However, the robustness check for the location shows the opposite direction for manufacturing firms located in the 10 most innovative areas.

This result would imply that locating in a most innovative city may discourage the advancement of tangible knowledge stocks and technical capabilities that are more relevant for manufacturing. However, as the level of innovativeness decreases in the city, locational factors may act as an enabler of this type of knowledge and increase persistence for manufacturing firms. Additionally, the same negative path dependency patterns mentioned earlier could become more significant for manufacturing firms than firms in other industries when the location has the highest innovation environment but become less relevant with less competitive spaces.

5.3 Implications

This research's implications relate to the topic's relevance for various essential groups. First, companies can gain insight into how innovation benefits an organization with increasing returns, making investments in innovation more profitable than previously thought. This finding has implications for firm strategy, cost-benefit analysis and investment decisions. Furthermore, the results highlight the relevance of company-level differences, such as market conditions, firm location, and industry specialization. Therefore, firms are suggested to consider the macroeconomic environment and firm-specific traits when following a continuous innovative strategy. Finally, based on the results of the empirical investigation, firms are also advised in to locate those innovative spaces where they can benefit from increased information and cooperation without the threat of cannibalizing their innovation activities and experiencing negative path dependence in the progress.

Second, in an academic view, the paper has focused on a region previously less covered by the research, along with applying a method beforehand not commonly used, displaying the applicability of the subject to both the U.S. and to count model estimations. While locational factors did not confirm the predicted relationship in this model, this paper highlighted the importance of including geographical spaces in this research area and their potential effect on persistence, which was previously lacking. Lastly, this investigation has contributed to a better understanding of the relevance of innovation persistence in growth theories, mainly by proving positive feedback loops by innovating.

Third, similarly to firms, decision-making bodies can make better strategic choices in investing in innovation. Projects aiming to boost economic growth ought to emphasise encouraging innovation since innovation offers long-term value. In addition, the paper highlighted that investment payoffs might vary among industries, as some, such as manufacturing, are more prone to persistence than others. Moreover, locational influences have pointed out that policies centered around cities may have an effect that lasts many times over the initial investment period, either in a negative or positive direction, depending on the location. Lastly, governmental bodies can also play a role in facilitating whether a location acts as a deterrent or enabler of persistence by limiting the risks that lead to a adverse innovation behavior.

5.4 Limitations

Even though the analysis presents various vital implications, it also has multiple limitations as well as suggestions for future research. First, there are limitations related to the model and its estimation. One disadvantage is the result of employing patent data. Patenting is argued to measure market leadership over innovation activities, therefore skewing the results (Duguet & Monjon, 2004; Raymond et al., 2010). Furthermore, the patenting behavior of companies can show high levels of variation, both in magnitude and frequency (Cabagnols et al., 2006). We overcome these problems due to patent data to a certain degree by taking out large monopolistic companies of the sample, controlling for many firm differences and using a zero-inflated model. Furthermore, the patenting count is yearly. While this is according to prior studies, innovative behavior is expected to take a prolonged period to have effects (Duguet & Monjon, 2004; Geroski et al., 1997). However, annual data adds more strictness to the sampling and gives a more distinct measurement of the association. Nevertheless, future studies are recommended to test the results by extending the lag period.

Moreover, this research is not extended to study whether the theoretical reasons behind the persistency mentioned previously hold when applied to this sample. This absence is similar to other studies on the topic; therefore, the following studies are advised to aim to reach the gap in research. In addition, based on Le Bas & Latham (2006), there is an alternative definition of persistence, a more in-depth view: innovation needs to be persistent within the same field as the prior one. This paper does not focus on this alternative definition of persistence; therefore, the coming analysis is suggested considering this measurement form.

Another limitation is the way locational space is proxied in this study. First, due to the lack of city rankings in innovation, the measure is not time-varying or averaged over the course of the years in the study. Therefore, future research should consider creating a better-fitted ranking based on its own measures of innovation. Furthermore, cities offer a limited outlook on the relationship between knowledge spaces and innovation. Instead of ranking cities, subsequent explorations into the topic should consider alternate proxies. Still, more attention needs to be paid to locational factors in this subject area.

Lastly, other recommendations for future research are the inclusion of differentiation between product and process innovation and testing the path dependence of nonpersistent innovators. In addition, the outcome for locational factors suggests the possibility of negative persistence. However, in this study, the investigation does not concentrate on examining adverse firm innovation trajectories and their mechanisms. Therefore, future studies should further evaluate the occurrence of negative path dependence for companies.

6. Conclusion

This study aims to study whether innovation is persistent on the firm level and whether industry differences and locational factors moderate the association. The empirical investigation employs a negative binomial zero-inflated technique on patent count data from 1975 to 2013 to overcome overdispersion and excessive presence of structural zeros (Korosteleva, 2018). In addition, the estimation includes various measures of firm heterogeneity, such as size, productivity, and financial health of the companies. The main analysis is later complimented by additional checks for robustness that employ alternating techniques, measures and parameters.

Contrasting to multiple previous studies using patent data, this analysis has confirmed persistency for the sample of US companies, demonstrating that patents are relevant measures of innovation regardless of their limitations. Furthermore, differences based on the industry are also detected, as manufacturing firms are predicted to be slightly more persistent than other industries. These results point out that innovation has increasing returns, a highly valuable finding for firm strategy, economic theory, and policy design.

Contradicting expectation, locational components, assessed by top innovative cities, show no robust positive results on the persistence of firms, nor do locational effects show variation for different industries. However, the model does point out that geographic knowledge spaces are nevertheless influential in the persistency relationship, in line with other works. Interestingly, firms located in the 5 most innovative cities show increased innovation persistence while the 10 most innovative cities negatively affect persistence. Therefore, it is concluded that locational factors can act both as a deterrent and an enabler of innovation persistence on the firm level because of multiple conflicting mechanisms that knowledge spaces stimulate on innovation. The role of governmental policies is highly relevant to help locations to encourage innovation and protect from developing a negative innovation trajectory for firms. Furthermore, it is suggested that future studies within the innovation persistency theme need to be more attentive to including locational effects.

Even though the analysis presents certain limitations, it nonetheless adds various new and meaningful aspects to the research in innovation persistence, namely, the focus on the U.S. setting instead of European countries, the application of count data estimation instead of a binary measure of innovation, along with zero-inflated technique, as well as the differentiation of industries, with the inclusion of service firms, and lastly, the addition of locational features. These mentioned features have previously been lacking in the literature on the topic, and future research is recommended to investigate them further.

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8. Appendix

Appendix A

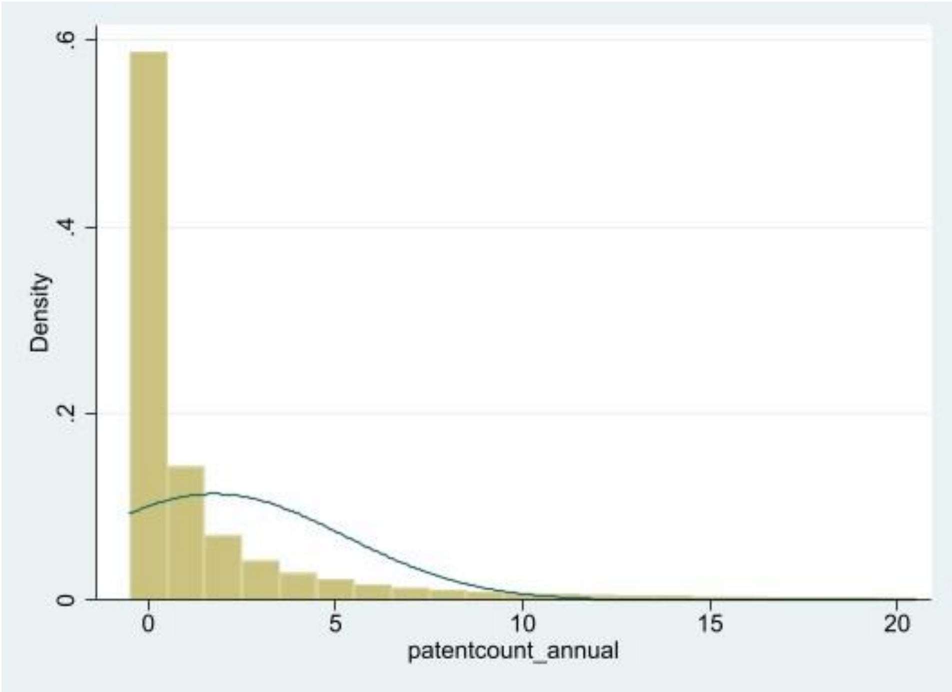

Figure A1. Histogram of the data distribution

Appendix B

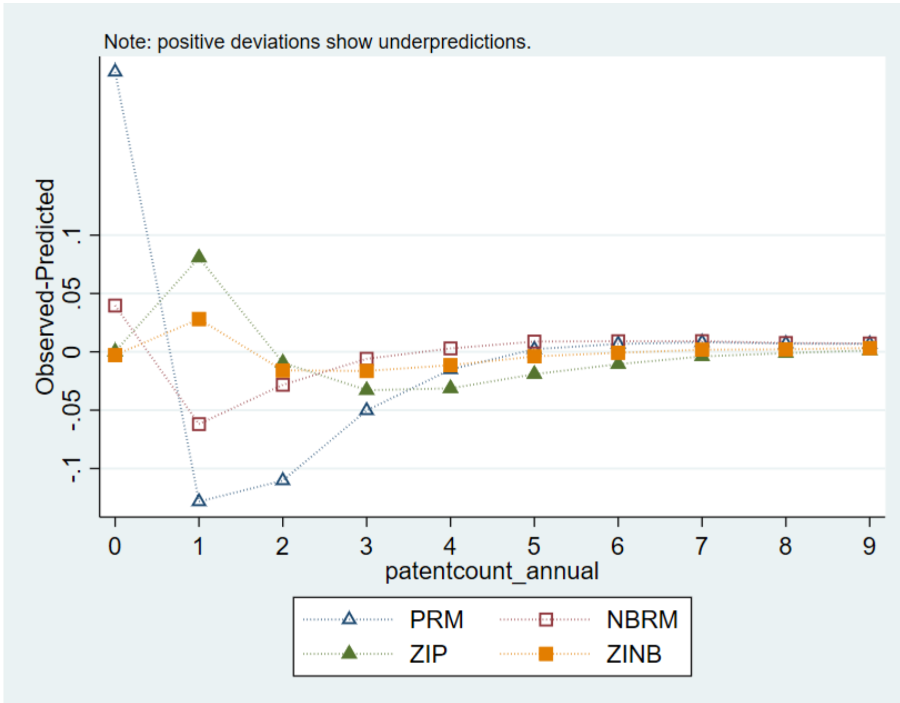

Figure B1. Model fit for Hypothesis 1.1

Note. The graph shows the model fit check for the four considered count models, Negative Binomal Zero Inflated (ZINB), Negative Binomial (NBRM), Poisson Pseudo Maximum Likelihood (PRM) and Poisson Zero Inflated (ZIP)

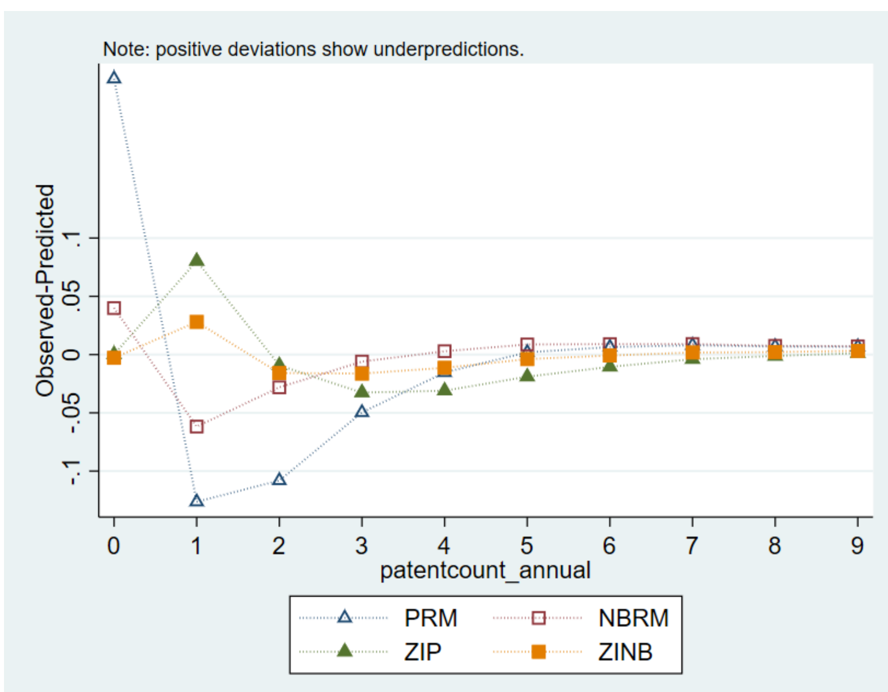

Figure B2. Model fit for Hypothesis 1.2

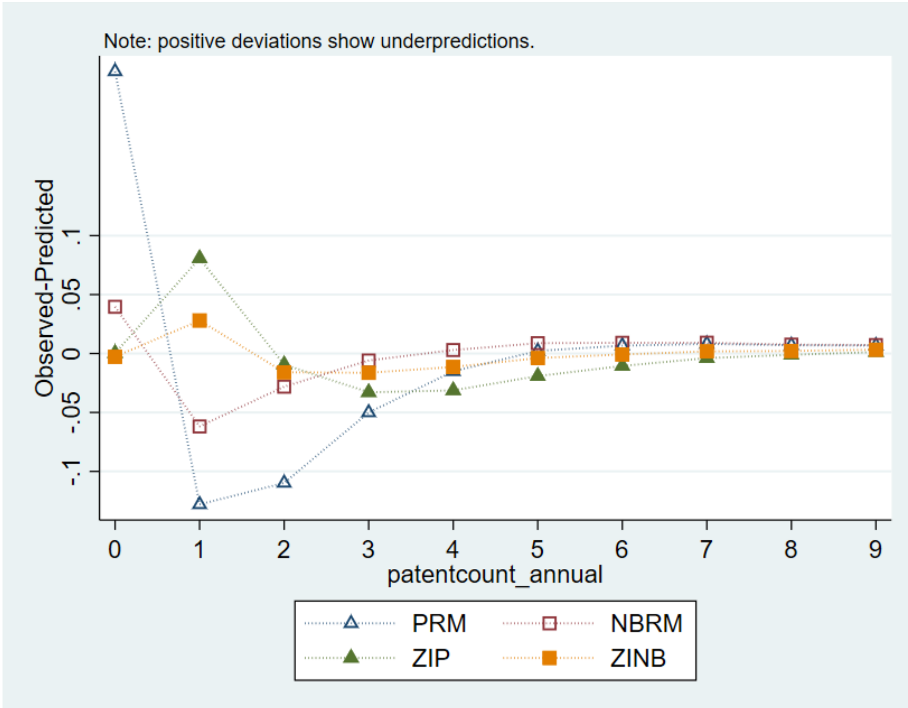

Figure B3. Model fit for Hypothesis 2.1

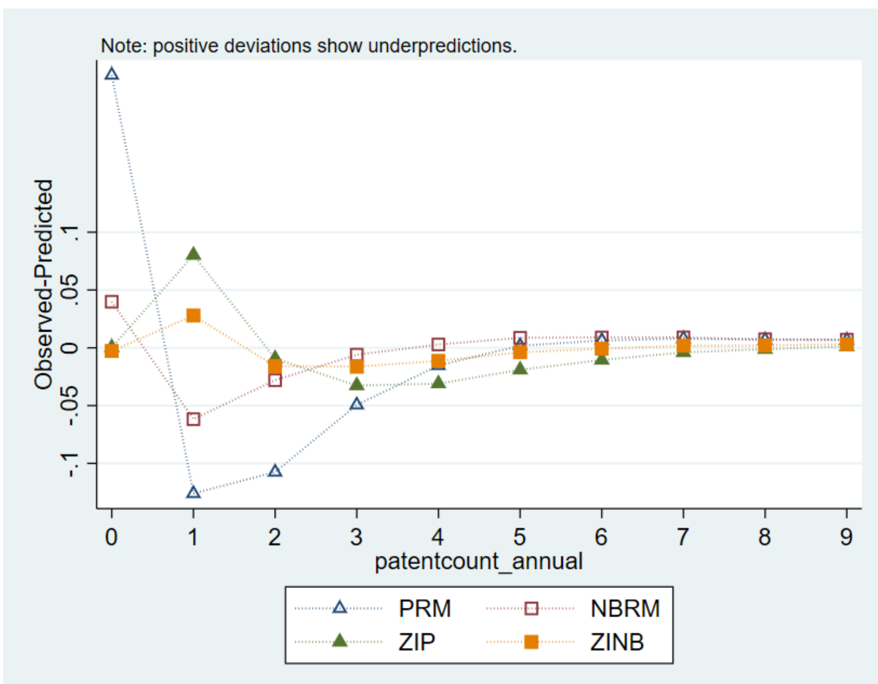

Figure B4. Model fit for Hypothesis 2.2

Appendix C

Table C1

Marginal effects of the Negative Binomial robustness check estimation

VARIABLES	(1) y1	(2) y1	(3) y1	(4) y1
Inno(t-1)	0.694***	0.833***	0.695***	0.868***
	(0.0203)	(0.0480)	(0.0206)	(0.0548)
	0	0	0	0
ln(Employees(t-1))	-0.00421	-0.00391	0.00531	0.00526
	(0.0218)	(0.0216)	(0.0218)	(0.0216)
	0.847	0.856	0.808	0.808
ln(R&D(t-1))	0.495***	0.503***	0.494***	0.501***
	(0.0234)	(0.0233)	(0.0234)	(0.0233)
	0	0	0	0
Financial Quality = 1, A	-0.271	-0.266	-0.260	-0.266
	(0.300)	(0.297)	(0.294)	(0.292)
	0.365	0.370	0.376	0.362
Financial Quality = 2, A-	0.0208	-0.0237	0.0841	0.0228
	(0.292)	(0.289)	(0.288)	(0.284)
	0.943	0.935	0.770	0.936
Financial Quality = 3, B+	0.0687	0.0652	0.165	0.148
	(0.272)	(0.269)	(0.267)	(0.265)
	0.800	0.809	0.537	0.578
Financial Quality = 4, B	-0.310	-0.329	-0.251	-0.285
	(0.265)	(0.263)	(0.260)	(0.258)
	0.243	0.210	0.334	0.271
Financial Quality = 5, B-	-0.641**	-0.626**	-0.579**	-0.579**
	(0.264)	(0.262)	(0.259)	(0.258)
	0.0154	0.0170	0.0257	0.0248
Financial Quality = 6, C	-0.610**	-0.612**	-0.539**	-0.555**
	(0.266)	(0.264)	(0.261)	(0.259)
	0.0216	0.0202	0.0386	0.0324
Financial Quality = 7, D	-0.552*	-0.545*	-0.471*	-0.480*
	(0.283)	(0.281)	(0.279)	(0.277)
	0.0512	0.0521	0.0907	0.0829
Financial Quality = 8, LIQ	0.0683	0.450	0.118	0.390
	(1.781)	(1.971)	(1.769)	(1.922)
	0.969	0.819	0.947	0.839
Subsidiary/LBO = 1, Subsidiary/LBO	-2.667***	-2.679***	-2.667***	-2.676***
	(0.336)	(0.316)	(0.333)	(0.314)
	0	0	0	0
RoS	0.000167*	0.000165*	0.000165	0.000162
	(0.000101)	(9.97e-05)	(0.000102)	(9.99e-05)
	0.0989	0.0975	0.104	0.106
RoA	0.397***	0.336***	0.395***	0.342***
	(0.107)	(0.106)	(0.107)	(0.106)
	0.000207	0.00155	0.000217	0.00128
Leverage	-0.000594	-0.000606	-0.000580	-0.000592

	(0.000911)	(0.000897)	(0.000915)	(0.000899)
	0.515	0.499	0.526	0.510
ln(HHI(t-1))	-0.357***	-0.410***	-0.355***	-0.415***
	(0.0389)	(0.0400)	(0.0388)	(0.0401)
	0	0	0	0
International	-0.172*	-0.115	-0.168*	-0.118
	(0.0933)	(0.0928)	(0.0933)	(0.0930)
	0.0659	0.215	0.0715	0.206
Labor Productivity	-1.76e-06***	-1.53e-06***	-1.72e-06***	-1.49e-06***
	(2.22e-07)	(2.20e-07)	(2.22e-07)	(2.20e-07)
	0	0	0	0
Innocity5			-1.094***	-1.270***
			(0.327)	(0.327)
			0.000822	0.000101
Innocity10			0.0541	0.405
			(0.313)	(0.315)
			0.863	0.199
Innocity25			0.372**	0.361**
			(0.151)	(0.149)
			0.0137	0.0156
Inno(t-1)*Innocity10			-0.0942*	-0.380
			(0.0564)	(0.357)
			0.0948	0.287
Inno(t-1)*Innocity5			0.116**	0.131
			(0.0571)	(0.148)
			0.0419	0.375
Inno(t-1)*Innocity25			-0.0180	0.175
			(0.0305)	(0.334)
			0.555	0.601
indd = 1, manufacturing		0.843***		0.850***
		(0.142)		(0.144)
		2.98e-09		3.97e-09
indd = 2, service		-0.136		-0.152
		(0.162)		(0.163)
		0.402		0.349
Inno(t-1)*Manufacturing*Innocity10				0.267
				(0.356)
				0.454
Inno(t-1)*Service*Innocity10				0.225
				(0.368)
				0.540
Inno(t-1)*Service*Innocity5				-0.0634
				(0.168)
				0.705
Inno(t-1)*Service*Innocity25				-0.208
				(0.343)
				0.545
Inno(t-1)*Manufacturing*Innocity5				-0.000876
				(0.149)
				0.995
Inno(t-1)*Manufacturing*Innocity25				-0.190
				(0.333)
				0.568
Inno(t-1)*Manufacturing		-0.167***		-0.202***

		(0.0432)		(0.0502)
		0.000107		5.56e-05
Inno(t-1)*Service		-0.0819*		-0.0910
		(0.0496)		(0.0570)
		0.0987		0.110
Observations	24,199	24,199	24,199	24,199

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C2

Marginal effects of the Poisson PML robustness check estimation

	(1)	(2)	(3)	(4)
VARIABLES	y1	y1	y1	y1
Inno(t-1)	0.348***	0.405***	0.349***	0.421***
	(0.00467)	(0.0173)	(0.00485)	(0.0209)
	0	0	0	0
ln(Employees(t-1))	0.0254*	0.0258*	0.0318**	0.0320**
	(0.0153)	(0.0153)	(0.0153)	(0.0154)
	0.0974	0.0926	0.0384	0.0372
ln(R&D(t-1))	0.285***	0.294***	0.284***	0.293***
	(0.0153)	(0.0154)	(0.0153)	(0.0154)
	0	0	0	0
Financial Quality = 1, A	-0.276	-0.299	-0.271	-0.303*
	(0.184)	(0.182)	(0.181)	(0.180)
	0.134	0.101	0.135	0.0921
Financial Quality = 2, A-	-0.140	-0.175	-0.116	-0.169
	(0.183)	(0.181)	(0.182)	(0.180)
	0.445	0.332	0.526	0.351
Financial Quality = 3, B+	-0.147	-0.161	-0.107	-0.137
	(0.165)	(0.163)	(0.165)	(0.163)
	0.374	0.325	0.515	0.403
Financial Quality = 4, B	-0.372**	-0.400**	-0.342**	-0.386**
	(0.163)	(0.161)	(0.162)	(0.161)
	0.0225	0.0130	0.0344	0.0165

Financial Quality = 5, B-	-0.517***	-0.527***	-0.481***	-0.508***
	(0.163)	(0.161)	(0.162)	(0.161)
	0.00151	0.00108	0.00298	0.00161
Financial Quality = 6, C	-0.504***	-0.528***	-0.467***	-0.503***
	(0.165)	(0.163)	(0.164)	(0.163)
	0.00222	0.00120	0.00435	0.00198
Financial Quality = 7, D	-0.479***	-0.503***	-0.442**	-0.479***
	(0.178)	(0.176)	(0.178)	(0.176)
	0.00719	0.00434	0.0128	0.00665
Financial Quality = 8, LIQ	-0.143	0.347	-0.116	0.307
	(0.919)	(1.094)	(0.917)	(1.075)
	0.876	0.751	0.900	0.775
Subsidiary/LBO = 1, Subsidiary/LBO	-2.090***	-2.109***	-2.090***	-2.108***
	(0.186)	(0.177)	(0.186)	(0.177)
	0	0	0	0
RoS	7.23e-05***	7.38e-05***	7.20e-05***	7.26e-05***
	(1.19e-05)	(1.16e-05)	(1.19e-05)	(1.16e-05)
	1.16e-09	2.11e-10	1.45e-09	4.30e-10
RoA	0.318***	0.280***	0.314***	0.275***
	(0.100)	(0.102)	(0.100)	(0.102)
	0.00154	0.00621	0.00171	0.00680
Leverage	0.000198	0.000164	0.000203*	0.000168
	(0.000124)	(0.000126)	(0.000115)	(0.000120)
	0.111	0.192	0.0783	0.160
ln(HHI(t-1))	-0.208***	-0.254***	-0.209***	-0.260***
	(0.0277)	(0.0299)	(0.0277)	(0.0300)
	0	0	0	0
International	-0.146**	-0.122*	-0.140**	-0.127*
	(0.0641)	(0.0645)	(0.0646)	(0.0656)
	0.0224	0.0587	0.0309	0.0527
Labor Productivity	-1.18e-06***	-1.07e-06***	-1.16e-06***	-1.04e-06***

	(1.49e-07)	(1.48e-07)	(1.48e-07)	(1.48e-07)
	0	0	0	0
Innocity5			-0.523**	-0.687***
			(0.239)	(0.241)
			0.0289	0.00443
Innocity10			-0.199	0.0772
			(0.225)	(0.227)
			0.378	0.734
Innocity25			0.287***	0.288***
			(0.100)	(0.100)
			0.00415	0.00411
Inno(t-1)*Innocity10			0.00893	-0.157
			(0.0245)	(0.153)
			0.715	0.305
Inno(t-1)*Innocity5			0.0242	0.0136
			(0.0239)	(0.0677)
			0.312	0.840
Inno(t-1)*Innocity25			-0.0199	0.116
			(0.0130)	(0.141)
			0.127	0.411
indd = 1, manufacturing		0.683***		0.690***
		(0.108)		(0.110)
		2.60e-10		3.60e-10
indd = 2, service		-0.0530		-0.0643
		(0.127)		(0.128)
		0.677		0.617
Inno(t-1)*Manufacturing*Innocity10				0.149
				(0.152)
				0.328
Inno(t-1)*Service*Innocity10				0.160
				(0.160)

				0.319
Inno(t-1)*Service*Innocity5				-0.0195
				(0.0756)
				0.796
Inno(t-1)*Service*Innocity25				-0.150
				(0.148)
				0.310
Inno(t-1)*Manufacturing*Innocity5				0.0283
				(0.0673)
				0.674
Inno(t-1)*Manufacturing*Innocity25				-0.135
				(0.140)
				0.337
Inno(t-1)*Manufacturing		-0.0668***		-0.0825***
		(0.0172)		(0.0207)
		9.92e-05		6.85e-05
Inno(t-1)*Service		-0.0252		-0.0307
		(0.0209)		(0.0247)
		0.228		0.214
Observations	24,199	24,199	24,199	24,199

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C3

Marginal effects of the Poisson zero inflated robustness check estimation

	(1)	(2)	(3)	(4)
VARIABLES	y1	y1	y1	y1
Inno(t-1)	0.563***	0.513***	0.564***	0.549***
	(0.00540)	(0.0264)	(0.00627)	(0.0342)
	0	0	0	0
ln(Employees(t-1))	0.0259***	0.0261***	0.0285***	0.0292***
	(0.00948)	(0.00948)	(0.00953)	(0.00953)
	0.00638	0.00586	0.00278	0.00219

ln(R&D(t-1))	0.228***	0.235***	0.228***	0.236***
	(0.00974)	(0.00979)	(0.00977)	(0.00984)
	0	0	0	0
Financial Quality = 1, A	-0.245*	-0.222*	-0.217*	-0.196
	(0.129)	(0.129)	(0.129)	(0.129)
	0.0580	0.0851	0.0927	0.130
Financial Quality = 2, A-	-0.100	-0.101	-0.0683	-0.0808
	(0.126)	(0.125)	(0.125)	(0.125)
	0.425	0.418	0.584	0.517
Financial Quality = 3, B+	-0.126	-0.103	-0.0866	-0.0715
	(0.117)	(0.117)	(0.117)	(0.117)
	0.283	0.377	0.459	0.541
Financial Quality = 4, B	-0.331***	-0.314***	-0.299***	-0.285**
	(0.116)	(0.116)	(0.115)	(0.115)
	0.00417	0.00663	0.00945	0.0134
Financial Quality = 5, B-	-0.405***	-0.379***	-0.372***	-0.352***
	(0.116)	(0.116)	(0.115)	(0.116)
	0.000470	0.00105	0.00127	0.00232
Financial Quality = 6, C	-0.392***	-0.370***	-0.356***	-0.335***
	(0.117)	(0.116)	(0.116)	(0.116)
	0.000767	0.00147	0.00217	0.00392
Financial Quality = 7, D	-0.403***	-0.385***	-0.362***	-0.351***
	(0.125)	(0.124)	(0.124)	(0.124)
	0.00123	0.00198	0.00351	0.00480
Financial Quality = 8, LIQ	-0.395	-0.184	-0.364	-0.225
	(0.729)	(0.768)	(0.727)	(0.755)
	0.588	0.811	0.617	0.766
Subsidiary/LBO = 1, Subsidiary/LBO	-1.992***	-2.006***	-1.997***	-2.002***
	(0.491)	(0.489)	(0.496)	(0.496)
	5.03e-05	4.09e-05	5.72e-05	5.32e-05
RoS	3.68e-05	3.73e-05	3.50e-05	3.58e-05
	(6.61e-05)	(6.52e-05)	(6.64e-05)	(6.53e-05)
	0.578	0.568	0.598	0.584
RoA	0.316***	0.291***	0.312***	0.287***
	(0.0522)	(0.0522)	(0.0521)	(0.0522)
	1.39e-09	2.61e-08	2.15e-09	3.83e-08
Leverage	-0.000335	-0.000387	-0.000317	-0.000366
	(0.000655)	(0.000653)	(0.000678)	(0.000667)
	0.609	0.554	0.640	0.584
ln(HHI(t-1))	-0.166***	-0.195***	-0.165***	-0.198***
	(0.0164)	(0.0172)	(0.0164)	(0.0172)
	0	0	0	0
International	-0.0254	-0.00358	-0.0255	-0.0108
	(0.0391)	(0.0391)	(0.0392)	(0.0395)

	0.516	0.927	0.516	0.784
Labor Productivity	-8.55e-07***	-7.57e-07***	-8.37e-07***	-7.43e-07***
	(9.23e-08)	(9.17e-08)	(9.18e-08)	(9.18e-08)
	0	0	0	0
Innocity5			-0.148	-0.223
			(0.158)	(0.160)
			0.348	0.164
Innocity10			-0.0731	0.0470
			(0.151)	(0.154)
			0.628	0.760
Innocity25			0.115	0.105
			(0.0743)	(0.0743)
			0.120	0.156
Inno(t-1)*Innocity10			-0.142***	-0.116
			(0.0526)	(0.180)
			0.00684	0.521
Inno(t-1)*Innocity5			0.0555	0.0536
			(0.0453)	(0.0805)
			0.220	0.505
Inno(t-1)*Innocity25			0.0421	-0.0421
			(0.0389)	(0.169)
			0.279	0.803
indd = 1, manufacturing		0.195**		0.200**
		(0.0868)		(0.0892)
		0.0246		0.0253
indd = 2, service		-0.199**		-0.209**
		(0.0993)		(0.101)
		0.0447		0.0385
Inno(t-1)*Manufacturing*Innocity10				-0.00283
				(0.188)
				0.988
Inno(t-1)*Service*Innocity10				0.0565
				(0.189)
				0.765
Inno(t-1)*Service*Innocity5				0.116
				(0.120)
				0.333
Inno(t-1)*Service*Innocity25				-0.0166
				(0.175)
				0.925
Inno(t-1)*Manufacturing*Innocity5				-0.0418
				(0.0970)
				0.666
Inno(t-1)*Manufacturing*Innocity25				0.112

				(0.171)
				0.512
Inno(t-1)*Manufacturing		0.0544*		0.0152
		(0.0279)		(0.0355)
		0.0511		0.668
Inno(t-1)*Service		-0.00327		-0.0274
		(0.0325)		(0.0401)
		0.920		0.494
Observations	24,199	24,199	24,199	24,199

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix D

Table D

Marginal effects of probit model

VARIABLES	(1) y1	(2) y1	(3) y1	(4) y1
d.Inno(t-1)	0.409***	0.366***	0.405***	0.369***
	(0.00327)	(0.0221)	(0.00394)	(0.0243)
	0	0	0	0
Innocity5			-0.143***	-0.152***
			(0.0344)	(0.0345)
			3.42e-05	1.01e-05
Innocity10			0.0509	0.0630*
			(0.0333)	(0.0336)
			0.127	0.0612
Innocity25			0.0122	0.0129
			(0.0159)	(0.0159)
			0.445	0.417
d.Inno(t-1)*Innocity10			0.170***	0.329***
			(0.0464)	(0.0822)
			0.000244	6.38e-05
d.Inno(t-1)*Innocity5			-0.123***	-0.150
			(0.0444)	(0.107)
			0.00543	0.162
d.Inno(t-1)*Innocity25			0.0210	-0.0660
			(0.0212)	(0.0874)
			0.322	0.450
indd = 1, manufacturing		0.0260		0.0238
		(0.0161)		(0.0164)
		0.107		0.149
indd = 2, service		0.00105		-0.00418
		(0.0194)		(0.0195)
		0.957		0.830
d.Inno(t-1)*Manufacturing		0.0500**		0.0400
		(0.0232)		(0.0252)
		0.0307		0.113
d.Inno(t-1)*Service		-0.0247		-0.0220
		(0.0272)		(0.0294)
		0.365		0.453
d.Inno(t-1)*Manufacturing*Innocity10				0.106
				(0.110)
				0.333
d.Inno(t-1)*Service*Innocity10				0.0622
				(0.121)
				0.608
d.Inno(t-1)*Manufacturing*Innocity5				-0.243***
				(0.0863)
				0.00494
d.Inno(t-1)*Service*Innocity5				-0.136
				(0.0997)
				0.173
d.Inno(t-1)*Manufacturing*Innocity25				0.0947
				(0.0873)

				0.278
d.Inno(t-1)*Service*Innocity25				0.0185
				(0.0967)
				0.848
ln(Employees(t-1))	0.00261	0.00242	0.00339*	0.00313
	(0.00204)	(0.00204)	(0.00205)	(0.00205)
	0.201	0.235	0.0977	0.126
ln(R&D(t-1))	0.0270***	0.0274***	0.0271***	0.0274***
	(0.00185)	(0.00185)	(0.00185)	(0.00185)
	0	0	0	0
Financial Quality = 1, A	-0.0419	-0.0393	-0.0395	-0.0400
	(0.0291)	(0.0293)	(0.0291)	(0.0293)
	0.150	0.180	0.175	0.172
Financial Quality = 2, A-	-0.0152	-0.0165	-0.00992	-0.0146
	(0.0281)	(0.0283)	(0.0281)	(0.0283)
	0.590	0.560	0.724	0.605
Financial Quality = 3, B+	-0.00432	-0.000173	0.00263	0.00536
	(0.0262)	(0.0264)	(0.0263)	(0.0265)
	0.869	0.995	0.920	0.839
Financial Quality = 4, B	-0.0452*	-0.0419	-0.0388	-0.0372
	(0.0258)	(0.0260)	(0.0258)	(0.0260)
	0.0801	0.107	0.133	0.153
Financial Quality = 5, B-	-0.0678***	-0.0623**	-0.0608**	-0.0576**
	(0.0259)	(0.0261)	(0.0259)	(0.0261)
	0.00872	0.0169	0.0187	0.0272
Financial Quality = 6, C	-0.0639**	-0.0592**	-0.0569**	-0.0543**
	(0.0260)	(0.0262)	(0.0260)	(0.0262)
	0.0139	0.0240	0.0287	0.0383
Financial Quality = 7, D	-0.0528*	-0.0488*	-0.0443	-0.0430
	(0.0276)	(0.0279)	(0.0277)	(0.0279)
	0.0562	0.0797	0.110	0.123
Financial Quality = 8, LIQ	-0.0671	-0.0181	-0.0618	-0.0208
	(0.157)	(0.154)	(0.157)	(0.154)
	0.670	0.906	0.694	0.893
Subsidiary/LBO = 1, Subsidiary/LBO	-0.187**	-0.193**	-0.188**	-0.194**
	(0.0816)	(0.0808)	(0.0814)	(0.0805)
	0.0218	0.0169	0.0209	0.0159
RoS	-7.16e-06	-7.02e-06	-7.77e-06	-7.59e-06
	(1.66e-05)	(1.67e-05)	(1.70e-05)	(1.70e-05)
	0.667	0.675	0.647	0.655
RoA	0.00967	0.00544	0.00954	0.00545
	(0.00960)	(0.00952)	(0.00958)	(0.00951)
	0.313	0.567	0.319	0.566
Leverage	1.65e-05	7.07e-06	2.40e-05	1.50e-05
	(0.000157)	(0.000154)	(0.000162)	(0.000159)
	0.916	0.963	0.882	0.925
ln(HHI(t-1))	-0.0200***	-0.0238***	-0.0199***	-0.0242***
	(0.00352)	(0.00366)	(0.00352)	(0.00366)
	1.42e-08	8.34e-11	1.58e-08	0
International	-0.0140	-0.00901	-0.0128	-0.00736
	(0.00938)	(0.00939)	(0.00940)	(0.00943)
	0.137	0.337	0.173	0.435
Labor Productivity	-1.12e-07***	-9.63e-08***	-1.09e-07***	-9.31e-08***
	(1.91e-08)	(1.91e-08)	(1.91e-08)	(1.91e-08)
	3.97e-09	4.51e-07	9.78e-09	1.12e-06

Observations	24,199	24,199	24,199	24,199

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E

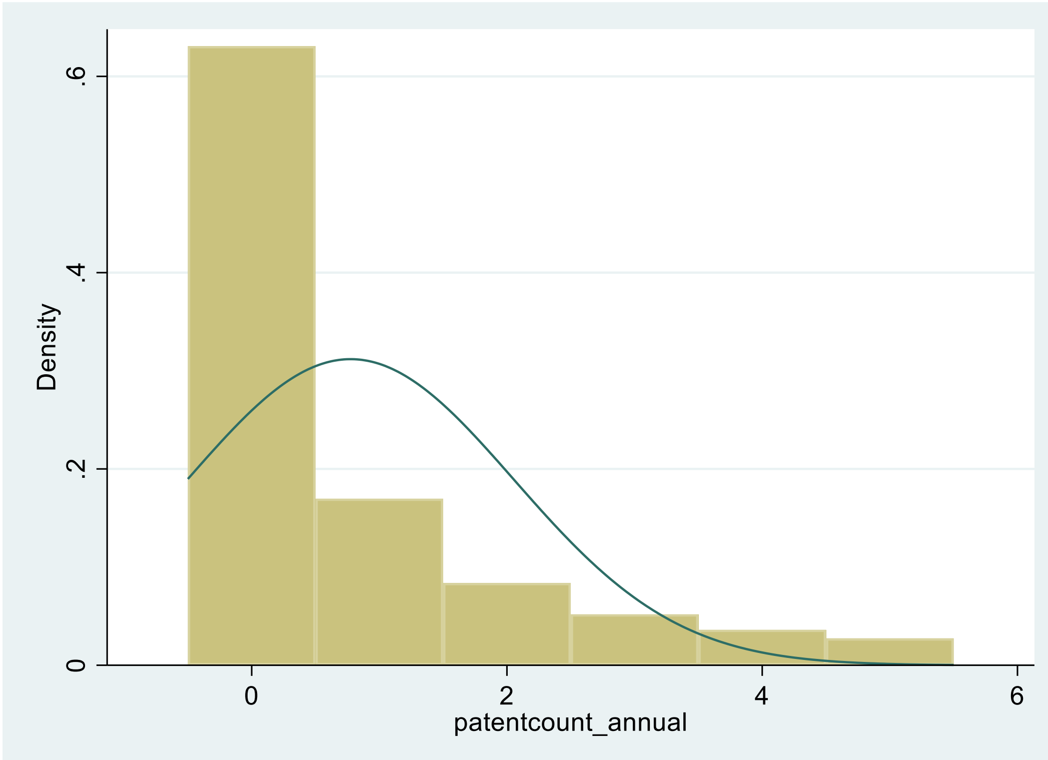

Figure E. Histogram of the distribution for SMEs

Note. The distribution shows the model after limiting the employee size to less than 250 and the patent count to less than 5 per year to proxy for the persistence effects for SMEs

Table E

Marginal effects of robustness check with more limited patent sample

VARIABLES	(1) y1	(2) y1	(3) y1	(4) y1
Inno(t-1)	0.420***	0.349***	0.418***	0.397***
	(0.00782)	(0.0474)	(0.00912)	(0.0631)
	0	0	0	3.13e-10
ln(Employees(t-1))	0.00231	0.00228	0.00406	0.00387
	(0.00658)	(0.00657)	(0.00659)	(0.00659)
	0.725	0.728	0.539	0.557
ln(R&D(t-1))	0.0481***	0.0517***	0.0480***	0.0511***
	(0.00632)	(0.00635)	(0.00633)	(0.00635)
	0	0	0	0
Financial Quality = 1, A	-0.0553	-0.0450	-0.0377	-0.0299
	(0.104)	(0.104)	(0.102)	(0.102)
	0.596	0.664	0.712	0.770
Financial Quality = 2, A-	-0.0553	-0.0557	-0.0299	-0.0437
	(0.102)	(0.101)	(0.0998)	(0.0993)
	0.586	0.580	0.764	0.660
Financial Quality = 3, B+	-0.0183	-0.00596	0.0121	0.0192

	(0.0963)	(0.0955)	(0.0946)	(0.0943)
	0.849	0.950	0.898	0.838
Financial Quality = 4, B	-0.100	-0.0909	-0.0728	-0.0688
	(0.0946)	(0.0939)	(0.0928)	(0.0925)
	0.290	0.333	0.432	0.457
Financial Quality = 5, B-	-0.165*	-0.149	-0.137	-0.127
	(0.0948)	(0.0940)	(0.0929)	(0.0926)
	0.0812	0.113	0.139	0.169
Financial Quality = 6, C	-0.168*	-0.157*	-0.139	-0.134
	(0.0952)	(0.0945)	(0.0933)	(0.0930)
	0.0770	0.0972	0.136	0.151
Financial Quality = 7, D	-0.132	-0.122	-0.0978	-0.0961
	(0.0998)	(0.0991)	(0.0982)	(0.0980)
	0.187	0.220	0.319	0.327
Financial Quality = 8, LIQ	-0.204	-0.114	-0.178	-0.0967
	(0.508)	(0.565)	(0.506)	(0.549)
	0.687	0.841	0.725	0.860
Subsidiary/LBO = 1, Subsidiary/LBO	-0.800***	-0.805***	-0.801***	-0.806***
	(0.0880)	(0.0858)	(0.0878)	(0.0854)
	0	0	0	0
RoS	-7.09e-06	-7.53e-06	-9.16e-06	-7.96e-06
	(5.06e-05)	(5.02e-05)	(5.12e-05)	(5.00e-05)
	0.889	0.881	0.858	0.873
RoA	0.0390	0.0278	0.0376	0.0253
	(0.0307)	(0.0306)	(0.0307)	(0.0306)
	0.203	0.362	0.220	0.408
Leverage	-0.000850	-0.000897	-0.000745	-0.000892
	(0.00111)	(0.00111)	(0.00111)	(0.00112)
	0.442	0.420	0.501	0.427
ln(HHI(t-1))	-0.0632***	-0.0790***	-0.0625***	-0.0811***
	(0.0114)	(0.0120)	(0.0114)	(0.0120)
	3.18e-08	0	4.66e-08	0
International	-0.0800***	-0.0714**	-0.0762**	-0.0697**
	(0.0307)	(0.0307)	(0.0308)	(0.0309)
	0.00925	0.0201	0.0133	0.0239
Labor Productivity	-3.36e-07***	-2.95e-07***	-3.28e-07***	-2.83e-07***
	(6.05e-08)	(6.03e-08)	(6.06e-08)	(6.04e-08)
	2.83e-08	1.01e-06	6.20e-08	2.85e-06
Innocity5			-0.280**	-0.328***
			(0.109)	(0.107)
			0.0103	0.00210
Innocity10			0.0522	0.0979
			(0.102)	(0.0995)
			0.609	0.325
Innocity25			0.0767*	0.0701
			(0.0462)	(0.0459)
			0.0966	0.127
Inno(t-1)*Innocity10			-0.165**	-0.199
			(0.0768)	(0.141)
			0.0318	0.160
Inno(t-1)*Innocity5			0.304***	0.415*
			(0.0992)	(0.246)
			0.00219	0.0913
Inno(t-1)*Innocity25			-0.00221	-0.0199
			(0.0427)	(0.143)
			0.959	0.889

indd = 1, manufacturing		0.0705		0.0893
		(0.0581)		(0.0583)
		0.225		0.125
indd = 2, service		-0.0985		-0.0864
		(0.0661)		(0.0659)
		0.136		0.190
Inno(t-1)*Manufacturing*Innocity10				0.298
				(0.229)
				0.194
Inno(t-1)*Service*Innocity10				0.0901
				(0.177)
				0.610
Inno(t-1)*Service*Innocity5				-0.173
				(0.276)
				0.530
Inno(t-1)*Service*Innocity25				-0.0998
				(0.155)
				0.519
Inno(t-1)*Manufacturing*Innocity5				-0.335
				(0.310)
				0.281
Inno(t-1)*Manufacturing*Innocity25				0.0431
				(0.147)
				0.770
Inno(t-1)*Manufacturing		0.0798		0.0205
		(0.0500)		(0.0653)
		0.111		0.753
Inno(t-1)*Service		0.00134		-0.0250
		(0.0571)		(0.0731)
		0.981		0.732
Observations	20,405	20,405	20,405	20,405

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix F

Table F

ZINB marginal effects of alternative city rankings by FINOM

	(1)	(2)
VARIABLES	y1	y1
Inno(t-1)	0.419***	0.388***
	(0.00895)	(0.0635)
	0	9.43e-10
ln(Employees(t-1))	0.00349	0.00344
	(0.00671)	(0.00671)
	0.603	0.608
ln(R&D(t-1))	0.0485***	0.0515***
	(0.00645)	(0.00648)
	0	0
Financial Quality = 1, A	-0.0225	-0.00879
	(0.106)	(0.105)
	0.831	0.934
Financial Quality = 2, A-	-0.0357	-0.0365
	(0.103)	(0.102)
	0.729	0.721
Financial Quality = 3, B+	-0.0114	0.00367
	(0.0975)	(0.0972)
	0.907	0.970
Financial Quality = 4, B	-0.0751	-0.0641
	(0.0959)	(0.0956)
	0.434	0.503
Financial Quality = 5, B-	-0.139	-0.120
	(0.0961)	(0.0957)
	0.149	0.211
Financial Quality = 6, C	-0.149	-0.136

	(0.0965)	(0.0962)
	0.124	0.157
Financial Quality = 7, D	-0.112	-0.0999
	(0.101)	(0.101)
	0.267	0.323
Financial Quality = 8, LIQ	-0.185	-0.101
	(0.509)	(0.554)
	0.716	0.855
Subsidiary/LBO = 1, Subsidiary/LBO	-0.803***	-0.808***
	(0.0892)	(0.0868)
	0	0
RoS	-6.57e-06	-6.76e-06
	(5.04e-05)	(4.98e-05)
	0.896	0.892
RoA	0.0320	0.0230
	(0.0311)	(0.0310)
	0.303	0.460
Leverage	-0.000691	-0.000714
	(0.00110)	(0.00110)
	0.530	0.517
ln(HHI(t-1))	-0.0628***	-0.0805***
	(0.0116)	(0.0122)
	6.62e-08	5.04e-11
International	-0.0658**	-0.0602*
	(0.0313)	(0.0314)
	0.0357	0.0553
Labor Productivity	-3.27e-07***	-2.88e-07***
	(6.13e-08)	(6.11e-08)
	1.02e-07	2.53e-06
top5_robust	-0.185*	-0.171
	(0.107)	(0.107)

	0.0829	0.109
top10_robust	-0.0777	-0.0765
	(0.0938)	(0.0916)
	0.407	0.404
top25_robust	0.110**	0.107**
	(0.0470)	(0.0467)
	0.0196	0.0221
Inno(t-1)*RobustInnocity10	0.0847	-0.142
	(0.101)	(0.155)
	0.401	0.361
Inno(t-1)*RobustInnocity5	-0.0888	0.0399
	(0.0995)	(0.151)
	0.372	0.792
Inno(t-1)*RobustInnocity25	-0.00231	-0.0321
	(0.0470)	(0.155)
	0.961	0.836
indd = 1, manufacturing		0.0755
		(0.0636)
		0.235
indd = 2, service		-0.0902
		(0.0717)
		0.209
Inno(t-1)*Manufacturing*RobustInnocity10		0.348*
		(0.198)
		0.0785
Inno(t-1)*Service*RobustInnocity10		0.168
		(0.201)
		0.404
Inno(t-1)*Service*RobustInnocity5		-0.0820
		(0.202)
		0.685

Inno(t-1)*Service*RobustInnocity25		-0.114
		(0.165)
		0.490
Inno(t-1)*Manufacturing*RobustInnocity5		-0.156
		(0.184)
		0.397
Inno(t-1)*Manufacturing*RobustInnocity25		0.0542
		(0.160)
		0.734
Inno(t-1)*Manufacturing		0.0334
		(0.0657)
		0.611
Inno(t-1)*Service		-0.0194
		(0.0734)
		0.792
Observations	19,875	19,875

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1