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Impact of Intellectual Capital on Small-Firm Growth: A Longitudinal Study from Inc. 5000

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Abstract

We explore whether intellectual capital is a precursor to small and medium enterprise (SME) growth. We use data from Inc. 5000 of fast growing SMEs in the United States of America (US) and match companies to patent applications. We use a zero-inflated negative binomial model corrected for endogeneity to account for the large number of SMEs without intellectual capital. We find the marginal benefit from intellectual capital on SME growth, revenue, and the number of years on the Inc. 5000 list. Across industries we find a 1% increase in intellectual capital results in a 3.6% increase in revenue growth. The results change by industry: in particular, IT Services, Software, and Telecommunications are the only sectors that have a positive relationship between intellectual capital and growth. Perhaps surprisingly, SMEs in the Business Services, Engineering, and Health industry sectors experience negative growth with an increase in intellectual capital.

Keywords

SME; intellectual property; Inc. 5000; patent data; zero-inflated negative binomial model

1. Introduction

In this paper we explore whether intellectual capital is a precursor to small and medium enterprise (SME) growth. "Small-and Medium- Sized Enterprises (firms of fewer than 250 employees in Europe and fewer than 500 in the US (OECD, 2005)) are the backbone of the American…[economy]," according to the Office of the United States Trade Representative (2019). In the same publication, SMEs are said to be 30 million firms and "account for nearly two-thirds of net new private sector jobs in recent decades" (Office of the United States Trade Representative, 2019).

For an economy to grow so must its firms. However, for private SMEs, as most SMEs are privately held firms, data is difficult to find in large quantities and researchers tend to resort to survey methods. SMEs, by nature of their size may not have the resources to innovate and patent. Hence, they may look for growth through other means (competitive pricing, operational efficiencies, volume sales, niche contracting). In fact, the literature is split on the impact of financial constraints on innovation and patenting (Gibbert, Hoegl, & Valikangas, 2014). Some argue constraints foster innovation and patenting while others argue that constraints adversely restrict innovation and patenting. From an SMEs perspective after a period of growth, to free itself from economic constraints, a firm may innovate and patent to differentiate itself. Alternatively, an SME may patent early to stimulate growth and then foster new growth via other means. This is what some colloquially refer as the chicken and egg problem, i.e., which came first. The literature linking firm growth and patenting identifies that patenting leads to new product sales, though only a small fraction of firms conducting research and development (R&D) actually patent (Hall, Helmers, Rogers, & Sena, 2013). Some studies find that patents are signals for investors in software and semiconductors (Conti, Thursby, &

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Thursby, 2013; Hsu & Ziedonis, 2008; Useche, 2014). We endeavor to expand on the current literature with the inclusion of firms linked to their patent portfolios in 24 industries. Which leads to our research question: Is intellectual capital an antecedent or an outcome of SMEs' growth?

Our study uses nine years of cross-sectional time-series analysis to show long-term benefits of intellectual capital as measured by data provided by Inc. 5000 and the United States Patent and Trademark Office (USPTO). Our analysis echoes previous work in showing that intellectual capital (patenting) is a statistically significant predictor for SME growth while SMEs that patent more grow at a faster rate than those that do not (Love & Roper, 2015). We contribute to the literature in the following ways. The work by Hall et al. (2013) and Uzuegbunam et al. (2019) partially explain why we find a large disparity between industrial sectors and patent activity in our study. It seems that each industrial sector has its own relationship between patenting and growth. This also explains the inconsistent results found previously when authors tend to consider only one industry at a time. We also contribute to this stream of literature with the use of a zero-inflated binomial estimator corrected for endogeneity. To our knowledge this approach is not used in the literature to determine the relationship between patenting and SME growth.

In the subsequent section we first discuss related work in Section 2. Next, in Section 3 we present the theoretical work that motivates our expected results. In Section 4 we present our data and the econometric model used for our analysis is presented and discussed in Section 5. Section 6 presents the paper results and Section 7 concludes the paper.

2. Related Work

Our work spans two streams of literature. The first stream explores firm growth and its relationship to intellectual property. The second stream explore the use of patents as a signaling device. We now discuss each stream in greater detail and how our work relates to each stream.

The first stream, firm growth and its relationship with intellectual capital is explored from multiple angles. As a whole as late as the turn of the century there was still little evidence if there is any clear association between intellectual property activity (e.g., patenting, trademarking, copyrighting, innovation) and SME growth (Cefis & Orsenigo, 2001; Love & Roper, 2015; Rogers, Helmers, & Greenhalgh, 2007). However, that simply means that there are potentially conflicting results. There is literature that suggests patenting, regardless of the size, is positively correlated with firm growth (Love & Roper, 2015; Mann & Sager, 2007), usually measured in terms of investments. However, the relationship may be more complex than simply more patenting means more investments or growth. For example, some argue that above average patenting firms receive a positive benefit, while lower tier patentors receive a negative benefit (Jaffe, 1986). This result may be echoed in recent work showing that patents are important to only very fast-growing firms (Coad & Rao, 2008). As one may expect, the literature linking firm growth and patenting spans tangentially related concepts. For example, an established result is that patenting leads to new product sales, though only a small fraction of firms that conduct research and development (R&D) actually patent (Hall et al., 2013).

The above arguments all indicate that patents precede growth. However, it is conceivable that growth may well be the predecessor to patenting. Studies find that corporate venture capital funding influences post-funding patenting only for specific industries (Uzuegbunam et al., 2019); recently, the literature established that crowdfunding does not influence SME intellectual property, though it is strongly correlated with growth (Eldridge, Nisar, & Torchia, 2019). When considering grants, Srhoj, Škrinjarić, & Radas (2019) show that business development grants may help obtain future funding (bank loans), but has no impact on firm performance. We contribute to firm growth and patenting literature by using our dataset we can identify industry specific benefits from patenting, something not currently done in the literature. Specifically, examining all industries at once highlights industry differences, something that is left currently implied.

The second stream of literature we relate to is the use patents for signaling. In our data we do not have any indication of external funding the firms receive. However, we argue that if patents are indeed predictors of revenue growth, then a potential investor will incorporate patenting activities when making their investment decisions. The literature on signaling theory is quite vast, as such we focus on patents and their use as signals to investors. Multiple studies find that patents are indeed used as signals for investors in a variety of industries such as software and semiconductor (Conti et al., 2013; Hsu & Ziedonis, 2008; Useche, 2014). However, the benefits of these signals are not the same for all firms. For example, small firms use patents to reduce the impact of financial constraints, while larger firms are less likely to have financial constraints and thus are less likely to use patents as signals (Hottenrott, Hall, & Czarnitzki, 2016). Recently, researchers are taking a lender's perspective. Results indicate that financial institutions use high-quality patents, usually an entire IP portfolio, as collateral in financing agreements (Block, Colombo, Cumming, & Vismara, 2018; Fischer & Ringler, 2014), suggesting financial institutions are able to determine patent (or patent portfolio) quality. Another lender's perspective taken is that of lenders on crowdfunding platforms such as Kickstarter. Results indicate that a firm self-promoting patents does not help garner funding, but a third-party such as the media mentioning patents does help garner funding on the platform (Courtney, Dutta, & Li, 2017; Scheaf et al., 2018). Patents are also not the only signal source as recently pointed out government research grant are also used as signals for venture capital funding (Islam, Fremeth, & Marcus, 2018). In this paper we contributed to the patents as signals literature by identifying the relationship between past patent activity and growth. Further, having industry specific comparisons is unique and provides insights not currently found in the literature.

3. Theoretical Foundations

In a 1998 paper Mazzoleni and Nelson (1998) describe four theories regarding the motivation for patenting. The theories that they summarize include: patents motivate invention; patents induce disclosure and wide use of inventions; patents induce the development and commercialization of inventions; patents enable orderly development of broad prospects. Here we are concerned with theories explaining how patents induce the development and commercialization of inventions, as the authors say: "...the possession of a patent by the original inventor facilitates handing off the task to an organization better situated for development and commercialization." However, in the authors' brief summary, they omitted theories regarding patents as a signaling device for investors. Indeed, capital markets appraise patents as a signal for other firm attributes that are non-observable (Griliches, 1990; Hall, Jaffe, & Trajtenberg, 2005; Lev, 1999; Pakes, 1985). From the aforementioned studies, capital markets perceive more patents as a stronger indicator that the firm is investing in R&D, which is a good signal.

As Kortum & Lerner (2000) state, venture capitalists evaluate the quality and quantity of patent applications. This is particularly important during the early stages of the startups life. Furthermore, a firm's commitment to patenting serves as a signal to investors that they are willing to make verifiable and credible statements about their invention(s). It is illegal to make false statements to the USPTO and penalties range from a fine to imprisonment or both (https://www.uspto.gov/web/offices/pac/mpep/s602.html). To give the reader the essence of a patent signaling model we modify Spence's job market signaling model (Spence, 1973). We modify the model such that a venture capitalist (VC) is the 'employer' and the SME who applies for funding is the 'worker' who applies for a job. Patents here substitute for education as the signaling device to the VC. The VC's decision to fund an SME is essentially investment under uncertainty as there exists asymmetry between the SMEs knowledge of the ability of the invention(s) to generate sales versus the VC's limited knowledge of the same. We assume that the VC is risk neutral and for each signal received from an SME they will have an expected marginal revenue. The 'signaling costs' incurred by the SME include all the relevant costs of applying for and receiving a USPTO patent. The cost of applying for a patent are nontrivial. Based on complexity the costs range from a low of $5,000 to $16,000 however, internal communications with university IP officers estimate the true cost of a USPTO technology-based patent to be upwards of $40,000 (Scott Inwood, Director WatCo, personal communication). The SME will invest in a patent if the rents received from the investment schedule exceed the costs. Here we assume that not all SMEs apply for VC investment funds, rather, firms within industries that typically patent their inventions will consider patenting as a signal. We also must assume, as Spence asserts "...that a signal will not effectively distinguish one applicant from another, unless the costs of signaling are negatively correlated with productive capability". In terms of patenting, this means that it costs the low-ability firm more to patent than it does for the high-ability firm. The payoff to the firm in this case is the level of investment, where the firm's utility is a function of investment, which in turn is a function of its number of patents, $u_t(I(p), p)$. We can generate the same kind of separating equilibria with this model as with wages and education. Suffice it to say, with imperfect information, a high-ability firm will over-patent than a rival low-ability firm to send an appropriate signal to investors. From the foregoing the hypothesis is:

H1: Intellectual capital is an antecedent of SME performance.

Performance in this case is measured by three dependent variables: years on the Inc. 5000 list, revenue and growth.

4. Data

We now discuss the data sources and data processing carried out prior to our analysis. Our data came from two sources. Inc. 5000 and the United States Patent Office. We will first discuss each source in turn and then discuss how we merged the data from the two sources.

Inc. 5000 is a service run by Inc. the business magazine. According to Inc.'s help center the list has a long history:

> *In 1982, Inc. introduced the Inc. 500 list of the fastest-growing privately held companies in the United States. Since then, this prestigious list of the nation's most successful private companies has become the hallmark of entrepreneurial success and the place where future household names first make their mark. Pandora, 7 Eleven, Toys 'R' Us, Zipcar, Zappos.com and numerous other well-known brands have been honored by the Inc. 5000. In 2007, the Inc. 500 list expanded to the Inc. 5000, giving readers a deeper, richer understanding of the entrepreneurial landscape and capturing a broader spectrum of success.*

Today, the list is a distinguished editorial award, a celebration of innovation, a network of entrepreneurial leaders, and an effective public relations showcase. The Inc. 5000 ranks companies by overall revenue growth over a three-year period. All 5,000 honoree companies are individually profiled on Inc.com. The top 500 are featured in the September issue of Inc. Magazine, the leading entrepreneurial advocate for 38 years running. Inc. also ranks the fastest-growing companies by industry, metro area, revenue, and number of employees, and we also highlight women and minority run companies."

For a firm to appear on the Inc. 5000 list it must first submit an application and pay an application fee between $195 and $245, depending on the application submission date. Firms are ranked by the percentage growth of annual revenue over a three-year period (Inc., 2019). If a firm earned $1 million in 2012 and $11 million in 2015, then in 2015 the percentage growth is (11-1)/1*100% = 1000%. We collected the Inc. 5000 list from 2007 to 2015, inclusive in this study. A record of Inc. 5000 is shown in Figure 1 below, note that we also have the metropolitan area information, the number of times the firm was on the list, and number of employees.

Figure 1: Example of Inc. 5000 record, source (https://www.inc.com/inc5000/2019/top-private-companies-2019-inc5000.html, accessed 11/12/2019)

RANK ↑	COMPANY	GROWTH	INDUSTRY	REVENUE	STATE	CITY
1	Freestar	36,680%	Advertising & Marketing	$36.9 million	Arizona	Phoenix

USPTO data is collected from the publicly available bulkdata system hosted by the USPTO. The bulkdata system has available patent information on applications and issued grants dating back to 1976 (USPTO, 2019). The data was stored into a mySQL database that we use to merge the two datasets.

We matched the Inc. 5000 companies with USPTO data. We made this matching using the following method: 1) Generate a unique list of all companies across all years, 2007 to 2015 in the Inc. 5000 data. 2) Look through all USPTO data where the assignee of the patent is the company listed. The second step is not trivial for two reasons: 1) company names are not consistent in the USPTO data. For example, IBM is an example where the firm may be listed as IBM, I.B.M, International Business Machines, IBM Inc., etc. This is likely not an issue with the SMEs we consider, but there may be capitalization issues. As such, we use regular expression matching between the Inc. 5000 company name and the name listed in the USPTO patent application. We then create a list of Inc. 5000 company names and candidate USPTO company name. We then ensure that each Inc. 5000 company name is listed only once in the USPTO name database, and if a company is listed multiple times in the USPTO database with different names, then we inspect multiple entries manually. For our data, each company name listed in the Inc. 5000 data appeared only once in the USPTO database, and did not require manual intervention. One obvious shortcoming of this approach is we omit any patents that may be acquired by the Inc. 5000 company through a third party, i.e., the original patent recipient. However, this may be a non-issue as we consider SMEs and we are considering patent applications when measuring innovation, and not issued patents. Once the pairing (between Inc. 5000 and USPTO datasets) of company names is complete, then we query the USPTO database for each company name and generate a record for each patent application listing the date of patent application and date of patent issuance. Using this record, we generate our panel data by counting the total number of patent applications by each company up to and including the year in question (the company's patent applications are summed from the year it entered the list).

The initial number of observations was 44,916. By using the unique firm identifier we find that 9,621 firms are on the list for only one year. We wanted to create a panel of firms with a minimum of two years on the Inc. 5000 list, thus the one-year-only observations are dropped. Out of the 35,295 remaining observations, three industries had fewer than 25 observations: consulting (2), logistics (11) and transportation (21), furthermore we dropped firms with more than 500 employees. These observations are dropped from the analysis leaving 31,222 observations. Table 1 shows the distribution of patent applications by industry. Industries with a substantial percentage of patents include: advertising and marketing, business products and services, computer hardware, consumer products and services, energy, engineering, government services, health, IT services, manufacturing, security, software, and telecommunications. Of which the top four industries are consumer products and services with 1,105 patents, manufacturing with 533 patents, software with 475 patents and health with 454 patents. In terms of patent intensity (mean patents per firm) computer hardware averages 3.33 patents per firm, consumer products and services averages 2.68 patents per firm, security averages 1.33 patents per firm and finally telecommunications averages 1.14 patents per firm.

Table 1. Descriptive statistics by industry (after cleaning)

	Industry	N total	Number of firms	Firms with patents	Total number of patents	Percent firms with patents	Mean patents per firm
1	Advertising & Marketing	2,925	935	40	119	4.3	0.13
2	Business Products & Services	3,061	914	40	147	4.4	0.16
3	Business Services	116	57	3	8	5.3	0.14
4	Computer Hardware	308	88	17	293	19.3	3.33
5	Construction	1,488	534	8	1	1.5	0.00
6	Consumer Products & Services	1,337	412	73	1,105	17.7	2.68
7	Education	515	158	5	19	3.2	0.12
8	Energy	637	203	21	99	10.3	0.49
9	Engineering	557	169	29	145	17.2	0.86
10	Environmental Services	460	139	15	144	10.8	1.04
11	Financial Services	1,527	472	17	28	3.6	0.06
12	Food & Beverage	807	240	11	22	4.6	0.09
13	Government Services	1,699	508	22	94	4.3	0.19
14	Health	2,228	658	66	454	10.0	0.69
15	Human Resources	1,183	351	6	9	1.7	0.03
16	IT Services	4,521	1,321	34	166	2.6	0.13
17	Insurance	413	125	2	1	1.6	0.01
18	Manufacturing	1,912	598	107	533	17.9	0.89
19	Media	398	127	9	31	7.1	0.24
20	Retail	1,278	398	86	87	21.6	0.22
21	Security	433	143	32	190	22.4	1.33
22	Software	2,147	626	109	475	17.4	0.76
23	Telecommunications	1,013	291	31	333	10.7	1.14
24	Travel & Hospitality	259	78	2	18	2.6	0.23
	Total	31,222	9,545	785	4,521		

Table 2 has the summary statistics for the dependent and independent variables. Before cleaning, the sample size is 35,179. One firm (c) listed their total employment as 194,000 with revenue of $30.6 billion. But for the analysis we restricted employment to less than 500. This resulted in a loss of 3,957 observations along with eight industries containing fewer than 50 observations. We see that before and after cleaning approximately 6% of firms apply for patents (*bin_ptot*). Total number of patent applications (num_total) is the dependent variable in the first stage of the estimation procedure. We see that patent applications per firm are quite small, however, after cleaning one firm has 223 patent applications. We see from the variable *growth*, that on average, Inc. 5000 firms have a very high three-year growth rate of 174%.

Table 2. Summary statistics						
Variable		Obs	Mean	Std. Dev.	Min	Max
Before Cleaning						
bin_ptot	Patent applications? (binary)	35,179	0.0642	0.2451	0	1
emp	Number of employees	35,176	248.59	2,317.83	1	194,000
growth	3-year revenue growth rate (%)	35,179	171.42	186.12	0	999
ind_id	Industries (= 32)	35,179	12.71	7.47	1	26
list_years	Years on Inc. 5000 list	35,179	2.65	1.67	1	12
num_total	Total patent applications (count)	35,179	0.50	5.64	0	273
revenue	Annual revenue ($million)	35,178	34.80	81.50	1	995
year	Survey year	35,179	2011.10	2.43	2,007	2,015
After Cleaning						
bin_ptot	Patent applications? (binary)	31,222	0.0629	0.2428	0	1
emp	Number of employees	31,222	84.38	92.79	1	498
growth	3-year revenue growth rate (%)	31,222	174.13	187.96	0	999
ind_id	Industries (=24)	31,222	12.00	6.99	1	24
list_years	Years on Inc. 5000 list	31,222	2.60	1.61	1	12
num_total	Total patent applications (count)	31,222	0.40	4.03	0	223
revenue	Annual revenue ($million)	31,221	23.73	50.73	1	2,000
year	Survey year	31,222	2,011.07	2.43	2,007	2,015

5. Econometric Model

We begin this section by giving a broad overview of the statistical method we use. We assume that patents affect the firm's performance: revenue (in levels), and growth (revenue growth). We also hypothesize that patents may influence the firm's tendency to remain on the Inc. 5000 list. We further assume that patents are endogenous with performance, such that not considering the endogeneity will make a single equation estimator inconsistent. Taking this into consideration, we estimate a zero-inflated count model (Poisson or negative binomial) and generate predicted values from it. The predicted values serve as an instrument in the performance equations corrected for heteroskedasticity.

Here we detail the statistical method we use. Patenting within a firm can be conceptualized as a two-step decision. The firm may have an invention or inventions that should or should not be patented. For instance, it is well known that process inventions are usually held as secrets rather than patented. It is also well known that firms producing tangible goods are more likely to patent their products than service firms who invent new products that are intangible. The decision to patent is a binary choice or $Y \in \{0, 1\}$ and how many inventions to patent is a count process wherein $Y \in \{1, 2, 3 \ldots\}$. In the literature a single equation is often used to represent both steps by using a Poisson functional form (Mullahy, 1986).

With the Poisson functional form the 'X' matrix is identical for the decision to patent and how many inventions to patent. Conceivably these two processes could be separate, allowing for different matrices 'X_1' and 'X_2'. We can parameterize the two steps as either a 'hurdle model' or we can use a zero-inflated estimator (Cameron & Trivedi, 2010; Mullahy, 1986). Zero-inflated models are used when there are excess zeros in the data. It is hypothesized that the process for generating the excess zeros differs from the process generating the counts.

$Let\ X_1 \cup X_2 = X$ and $X_1 \cap X_2$ need not be empty

For a regular Poisson model we have:
$\Pr(Y = i \mid X) \sim \text{Poisson}\ \forall_i$ where $i = 0, 1, 2, 3, 4 \ldots$ (1)

For a two-step model we have:
$\Pr(Y = 0 \mid X_1)$ and $\Pr(Y \neq 0 \mid X_1)$ (2)
$\Pr(Y = i \mid X_2)$ for $\forall\ i \geq 1$ (3)

In terms of a functional form we can show that (2) and (3) can be written:

$$\Pr(Y = k) = \begin{cases} \gamma + (1-\gamma)g(Y = 0) & if\ k = 0 \quad (4) \\ (1-\gamma)g(Y) & if\ k > 0 \quad (5) \end{cases}$$

$$Z_j = \text{h}(Y^* \mid Z) \text{for industry } j \quad (6)$$

The symbol γ represents the logit link function. The function $g(\cdot)$ is the parametric log-likelihood of the estimator, in this case negative binomial, while the $h(\cdot)$ function is the parametric form of the estimator, in this case OLS (for revenue and growth), or log-likelihood of the Poisson estimator (for years on list). The two-step model shown in (2) – (3) and (4) – (5) applies to both hurdle and zero-inflated estimators. In our case we choose to use a zero-inflated negative binomial estimator, this is captured by $g(\cdot)$ in equations (4) – (5), since the standard deviation of patent applications is 10 times that of the mean (significant over dispersion). As stated above the predicted values of the zero-inflated model (Y^*) serve as an instrument in each of the performance equations as shown in (6) where Z_j is the outcome variable and j is years on the Inc. 5000 list, revenue or growth. The revenue and growth equations are both estimated using panel OLS. While the years on list equation is estimated using a panel Poisson estimator. It should be noted that the predicted patent values were converted into a growth variable as such: $\delta Y^* = (Y_t^* - Y_{t-1}^*)/Y_{t-1}^*$. This variable was used in the revenue growth equation as an independent variable. All estimator error terms are bootstrapped and heteroskedasticity corrected.

6. Results and Analysis

After estimating stage 1 for the patent equation, only ten industries remained (3, 6, 9, 12, 13, 14, 16, 18, 22, 23) as well as the regression that contains all observations (see the Appendix). Stage 2 regression results are in the Appendix, while the elasticities for patents are in Table 3. A 1% increase in patents is associated with a 152% increase in revenue in the Engineering industry, and a 119% increase in revenue in the Government Services industry. We can also see that firms self-select to be included on the Inc. 5000 list when they have patents in the same three industries.

As previously discussed, patents are used as signals to investors. This signal is positively correlated with growth in only four industry sectors: Telecommunications, IT Services and pooled industry results. In all other sectors we find no correlation between patent activity and growth. In fact, increased patenting is associated with lower growth rates in Business Services, and Health.

When it comes to negative revenue and growth effects in the Health industry, it is surprising to see that a 1% increase in patents is associated with a 98% reduction in revenue and an 8.6% reduction in growth. This might be due to the fact that FDA approval takes many years beyond the filing of a patent. Furthermore, patent costs and the expensive research and development process associated with the health sector can reach $19 million dollars just for the clinical trials (Moore, Zhang, Anderson, & Alexander, 2018), while the cost to develop an FDA approved drug approaches $2.6 billion (Sullivan, 2019). According to Kreus & Saukkonen (2018) intellectual property should be a core mission of SMEs, however poor returns to patents can be due to lack of an intellectual property strategy within the firm, and/or knowledge of lack of a knowledge management strategy. Kreus & Saukkonen (2018) also find that a lack of financial resources limits the exploitation of patents. Regardless of financial constraints, as de Rassenfosse (2012) shows, relative to large firms SMEs have a larger share of licenses from patents. Although we do not have evidence to compare our findings directly, it is most likely the case that IT services, software and telecommunications are better able to monetize their patents than other industries.

Table 3. Elasticities of patents relative to years on list, revenue, and growth by industry[ł]

Industry	Years on list	Revenue	Revenue growth
	(percent change in dependent variable relative to a 1% increase in patents)		
Pooled industry results	-15.9	.	3.6
Business Services	.	.	-13.5
Consumer Products & Services	-40.2	.	.
Engineering	53.2	151.9	-0.6
Food & Beverage	58.2	44.0	.
Government Services	22.3	119.4	.
Health	.	-98.4	-8.6
IT Services	-29.5	.	1.4
Manufacturing	-7.5	.	.
Software	-147.6	.	4.6
Telecommunications	-14.2[*]	.	6.4

[ł] All elasticities are significant at 5% or 1%. [*]Indicates significant at 10%. "." Indicates not significant.
Note: How to read the table - a 1% increase in patents is associated with a 21.9% increase in revenues for Business Services.

We contribute and relate to the preceding literature in multiple ways. First, work by Hall et al. (2013) and Uzuegbunam et al. (2019) partially explain why we find a large disparity between industrial sectors and patent activity in our study. It seems that each industrial sector has its own relationship between patenting and growth. This also explains the inconsistent results found previously when authors tend to consider only one industry at a time. Second, we contribute to this stream of literature with the use of a zero-inflated binomial estimator corrected for endogeneity. To our knowledge this approach is not used in the literature to determine the relationship between patenting and SME growth. In addition, we use unbalanced panel data for firms over a nine-year period. Our results correlate with those of Jaffe (1986) by showing that low patenting activity (when a firm only has a few patents) predicts a negative relationship between growth and intellectual property. However, as patenting increases the relationship reverses and growth increases. These results also partially echo the results by Coad & Rao (2008).

7. Conclusion

In this paper we explored the relationship between growth, revenue, and the number of years a firm is listed on the Inc. 5000 list and patent applications for all SME firms listed on the Inc. 5000 list between 2007 and 2015. Due to the fact we consider SMEs in all sectors, it is not surprising that the majority of firms did not engage in any patents. As most firms have zero patents in all years we consider we used a zero-inflated estimator in our analysis to determine the relationship between patents and key attributes listed on the Inc. 5000 list. Our main findings are listed in Table 3. We find that across all industries, a 1% increase in patent activity leads to a 3.6% increase in growth. However, this positive relationship holds only for three industry sectors, IT Services, Software, and Telecommunications (1.4%, 4.6%, and 6.4% growth respectively). Note that a growth of 1.4% grown for every 1% growth may seem low, but it is important to keep in mind that patents are quantized. Considering IT Services, there are 166 patents across 34 firms, with an average of 4.88 patents per firm. Rounding the patents to 5, one additional patent for this firm results in a 20% increase in patent activity, which suggests a 28% increase in growth. Similar analysis suggests a single patent leads to 92% and 58% increase in growth for an average Software and Telecommunications firm, respectively.

Perhaps it is not surprising that all of the industry sectors with positive relationship between patent activity and growth are generally classified as technology sectors. The only sectors that experience negative growth with patent activity are Business Services, Engineering, and Health. The case for Health is previously discussed and there is a potentially larger cost aspect with Health than the other sectors. Business services, may be an artifact of the number of firms with patents, only 3 in our data. Engineering, though having negative relationship it is -0.6% which is -12% for an average firm for each additional patent. This is likely due to the nature of the industry, long-term projects that take years to conclude, tend to have long projects and the return on innovation may be too slow for it to be captured in the available data. One thing to note is if we consider only revenue during each year, and not growth, we see that Engineering has a 151.9% increase in revenue for 1% increase in innovation, this is 3,038% increase in revenue for an additional patent. This is not surprising as due to the cost aspect of patenting, larger firms are those engaging in patenting, meaning revenue growth does not translate to percent growth. A similar argument holds for the other two sectors that experience positive revenue growth with innovation, but no relationship between innovation and percent growth.

One insight to glean from our results is that in the Engineering and Government Services industries, a firm may be well served to consider innovation earlier in the growth process. Perhaps due to the self-selection aspect of the Inc. 5000 list, not all firms with a relationship between innovation and growth have a relationship between innovation and revenue. In particular, large growth in revenue, over a three-year period, is not actually captured by realized revenue; as firms leave the Inc. 5000, perhaps through their own volition, we do not observe firms with large revenues also experiencing large revenue growth.

The paper has limitations. For instance, due to the self-selection aspect of firms on the Inc. 5000 list, it is hard to argue that the list is an unbiased sample of all companies in the US. A natural argument one may make is: like patents, being on the Inc. 5000 list is a signal to potential investors. Others argue that being on the list is a sign of a successful company and of management success for the firm (Schurenberg, 2016). In addition, we restricted our consideration for SME firms, as to be on the list a firm must be in the US and privately held, however not necessarily an SME. In looking at the list of firms on the Inc. 5000 list, most are SMEs as the list is ordered by percentage growth. It is far easier for an SME to experience triple and quadruple digit growth than for a larger firm over a three-year period.

Furthermore, our results mesh with the finding that intellectual capital has an impact on growth specifically[1], but also on financial performance and market value (Molodchik, Jardon, & Bykova, 2019; Sardo & Serrasqueiro, 2017, 2018). Though we contribute to the literature on the impact of innovation/intellectual capital on SME growth, it is worth pointing out that some in the field argue that innovation/intellectual capital, as measured by patents may not be appropriate. As pointed out in a recent article in *Forbes* (Key, 2017) patents may not be useful for protecting intellectual property (IP), however startups with patents "raise the most capital" which, as previously discussed is a precursor for growth.

In terms of future research, it would be fruitful to conduct a longitudinal study of the same set of firms over multiple years. The available data we use does not take a longitudinal approach, as such the conclusions may problematic. However, determining if the differences across different types of industries holds with a rigorous panel design will be of great interest. In addition, we did not explore the inherent differences between patenting and non-patenting firms within a single industry, let alone if there are industry specific factors that lead to patenting activity. Though the literature explores both aspects in some level of detail, it is of interest to see if, by way of instrumental variables, causal relationships may be established. Such insights will inform SME policy, education, and funding throughout the world. Though we are not able to establish these factor level causal relationships, we think we are taking the needed first steps. In particular, we think that investors may use our results to inform their decisions on investing in a private SME in the US.

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[1] Note that we operationalize 'growth' in a narrow sense as we only use 'sales growth'. There are other obvious candidates for growth such as employment growth, private funding growth (from venture capitalists), market share growth, retained capital growth.

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Appendix

Table A1. Stage 1, zero-inflated negative binomial regressions for USPTO patents by industy

	all industries	ind 1	ind 2	ind 3	ind 4	ind 5	ind 6	ind 7	ind 8	ind 9
		(not sig) coef/se	(not sig) coef/se	coef/se	(not sig) coef/se	(not sig) coef/se	coef/se	(not sig) coef/se	(not sig) coef/se	coef/se
Year	-0.064**	-0.001	-0.020	-0.358*	0.144	-0.001	-0.076	-0.199	-0.246*	0.030
	(0.027)	(0.083)	(0.136)	(0.193)	(0.088)	(0.090)	(0.057)	(0.137)	(0.133)	(0.119)
emp	0.004***	0.005	-0.000	-0.003	0.012	0.004	0.006***	0.011**	0.006	-0.012***
	(0.001)	(0.003)	(0.002)	(0.008)	(0.009)	(0.003)	(0.002)	(0.005)	(0.006)	(0.004)
revenue	-0.134***	-0.293*	-0.385**	-0.054***	-0.293***	-0.018	-0.226**	-0.713**	0.008	-0.303**
	(0.029)	(0.167)	(0.161)	(0.019)	(0.097)	(0.012)	(0.107)	(0.297)	(0.007)	(0.150)
lnalpha	2.819***	3.451***	3.834***	-0.828	2.499***	3.426**	2.414***	2.287***	2.434***	2.702***
	(0.100)	(0.285)	(0.280)	(1.700)	(0.393)	(1.392)	(0.195)	(0.838)	(0.636)	(0.310)
_cons	1.262***	0.340	39.612	720.512*	-290.032	-1.514	153.555	396.893	494.217*	-59.457
	(0.198)	(165.805)	(273.700)	(385.335)	(176.735)	(181.524)	(115.048)	(275.604)	(267.464)	(238.803)
Number of observations	31,221	2,925	3,061	116	308	1,488	1,337	515	637	557
N_clust	9,545	935	915	58	88	534	412	158	203	169
Log-Likelihood	-11,302.98	-589.79	-626.73	-26.03	-287.21	-87.78	-1211.18	-68.52	-290.78	-390.45
Chi2 model	292.00	2.64	0.03	57.53	3.99	2.49	8.20	4.40	3.53	8.71
Predicted number of events	0.00	0.27	0.98	0.00	0.14	0.29	0.02	0.11	0.17	0.01
Prob>ch2	0.00	0.27	0.98	0.00	0.14	0.29	0.02	0.11	0.17	0.01

note: .01 - ***; .05 - **; .1 - *

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Table A1. (cont'd)

	ind 10 (not sig) coef/se	ind 11 (not sig) coef/se	ind 12 coef/se	ind 13 coef/se	ind 14 coef/se	ind 15 (not sig) coef/se	ind 16 coef/se	ind 17 (not sig) coef/se	ind 18 coef/se	ind 19 (not sig) coef/se
Year	-0.031	-0.175	0.204	-0.038	-0.264***	0.000	-0.194**	-0.000	0.109*	-0.237
	(0.123)	(0.113)	(0.148)	(0.130)	(0.080)	(0.133)	(0.087)	(0.083)	(0.066)	(0.169)
emp	0.004	-0.003	-0.008***	-0.005***	0.001	-0.000	0.007***	0.000	0.010***	0.001
	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)	(0.007)	(0.003)	(0.019)	(0.003)	(0.003)
revenue	-0.176	-0.117**	-0.769	-0.043***	-0.104**	0.747***	-0.084***	2.019*	-0.562	-0.730**
	(0.148)	(0.057)	(0.802)	(0.013)	(0.051)	(0.237)	(0.029)	(1.056)	(0.444)	(0.346)
lnalpha	2.683***	3.079***	3.442***	2.323***	2.537***	4.704***	3.539***	-40.449***	2.302***	2.002***
	(0.398)	(0.636)	(0.604)	(0.577)	(0.289)	(0.773)	(0.297)	(0.351)	(0.191)	(0.478)
_cons	61.979	349.364	-411.755	78.082	531.415***	-37.949***	387.726**	-5.701	-220.269*	11.519**
	(247.330)	(228.229)	(297.263)	(260.594)	(160.206)	(12.068)	(175.031)	(166.272)	(132.568)	(4.644)
Number of observations	460	1,527	807	1,699	2,227	1,183	4,521	413	1,912	398
N_clust	139	472	240	508	658	351	1,321	125	598	127.000
Log-Likelihood	-231.46	-185.31	-162.02	-399.26	-1225.04	-103.46	-668.93	-6.70	-1472.39	-93.41
Chi2 model	1.00	3.33	8.47	20.72	11.37	0.00	8.09	0.00	12.85	2.034
Predicted number of events	0.61	0.19	0.01	0.00	0.00	0.00	0.02	1.00	0.00	0.362
Prob>ch2	0.61	0.19	0.01	0.00	0.00	1.00	0.02	1.00	0.00	0.36

note: .01 - ***; .05 - **; .1 - *

Table A1. (cont'd)

	ind 20 (not sig)	ind 21 (not sig)	ind 22	ind 23	ind 24 (not sig)
	coef/se	coef/se	coef/se	coef/se	coef/se
Year	-0.328	0.084	-0.116**	-0.137	-0.000
	(0.201)	(0.104)	(0.050)	(0.120)	(0.185)
emp	-0.008	-0.000	0.004**	0.007***	0.000
	(0.005)	(0.003)	(0.002)	(0.002)	(0.008)
revenue	-0.033***	-0.157***	-0.079***	-0.100***	-1.409*
	(0.013)	(0.053)	(0.017)	(0.033)	(0.814)
lnalpha	3.208***	1.446***	1.600***	2.240***	3.267***
	(0.996)	(0.323)	(0.249)	(0.345)	(1.127)
_cons	659.309	-167.282	232.825**	274.972	-0.912
	(403.928)	(209.640)	(100.298)	(242.132)	(372.928)
Number of observations	1,278	433	2,147	1,013	259
N_clust	398	143	626	291	78
Log-Likelihood	-125.97	-432.22	-1493.97	-533.64	-56.25
Chi2 model	4.54	0.87	9.44	12.71	0.00
Predicted number of events	0.10	0.65	0.01	0.00	1.00
Prob>ch2	0.10	0.65	0.01	0.00	1.00

note: .01 - ***; .05 - **; .1 - *

Table A2. Stage 2, panel Poisson for number of years on list

	all industries	ind 3	ind 6	ind 9	ind 12	ind 13	ind 14	ind 16	ind 18	ind 22	ind 23
	list_years	list_years	list_years	list_years	list_years	list_years	list_years	list_years	list_years	list_years	list_years
list_years											
predicted patents	-0.174***	-4.606	-0.0690**	1.425***	5.403***	1.115***	-0.939***	-1.221***	-0.0431**	-1.008***	-0.103*
	(5.05)	(1.25)	(3.27)	(3.61)	(13.37)	(4.73)	(10.28)	(6.76)	(2.73)	(7.32)	(2.01)
emp	0.00572***	0.0206***	0.00808***	0.0115***	0.00459***	0.00694***	0.00335***	0.00790***	0.00907***	0.0117***	0.00828***
	(27.13)	(5.16)	(7.11)	(4.00)	(7.13)	(18.53)	(9.42)	(15.91)	(8.77)	(11.18)	(6.46)
N	31,220.00	115.00	1,337.00	557.00	807.00	1,698.00	2,226.00	4,521.00	1,912.00	2,147.00	1,013.00
Number groups	9,544	57	412	169	240	507	657	1,321	598	626	291
Log-likelihood	-30,941.30	-58.19	-1,292.70	-538.10	-744.40	-1,631.40	-2,112.80	-4,577.70	-1,846.80	-2,094.10	-1,042.60
Chi2 model	1,189.80	74.92	55.35	15.99	283.90	343.70	168.00	366.60	85.81	204.50	77.84
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3. Stage 2, panel fixed effects OLS for firm revenue

	all industries	ind 3	ind 6	ind 9	ind 12	ind 13	ind 14	ind 16	ind 18	ind 22	ind 23
	revenue	revenue	revenue	revenue	revenue	revenue	revenue	revenue	revenue	revenue	revenue
predicted patents	14.85	28.56	14.63	28.44**	113.4***	147.7***	-42.21***	-12.53	0.326	0.659	1.705
	(1.64)	(0.32)	(1.06)	(2.96)	(5.23)	(3.68)	(3.79)	(1.43)	(0.42)	(0.19)	(0.96)
emp	0.151***	0.179*	-0.0916	0.300***	0.124***	0.149*	0.172***	0.190***	0.292***	0.137***	0.205***
	(5.14)	(2.36)	(0.21)	(3.79)	(3.96)	(2.35)	(4.91)	(5.80)	(4.99)	(5.87)	(4.49)
_cons	5.323***	-0.351	1.745	-32.34*	3.922	-20.28***	36.53***	4.349**	0.506	1.821*	7.462*
	(3.48)	(0.02)	(0.29)	(2.49)	(1.27)	(3.64)	(5.93)	(3.06)	(0.14)	(2.13)	(2.26)
N	31,221	116	1,337	557	807	1,699	2,227	4,521	1,912	2,147	1,013
N of groups	9,545	58	412	169	240	508	658	1,321	598	626	291
Panel SD	40.12	16.23	49.38	9.44	33.07	25.45	56.64	28.97	26.80	14.46	56.45
Error SD	25.63	13.67	61.26	7.04	24.77	32.82	33.80	17.50	22.01	7.54	13.49
R2 within	0.0962	0.0568	0.06	0.554	0.118	0.165	0.191	0.164	0.16	0.482	0.282
R2 between	0.216	0.635	0.238	0.649	0.163	0.484	0.0812	0.156	0.378	0.423	0.135
Chi2 model	276.1	5.768	15.74	14.58	38.59	55.83	24.23	54.65	31.7	214	47.69
P-value	0.000	0.056	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.710	0.585	0.394	0.643	0.641	0.375	0.737	0.733	0.597	0.786	0.946

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4. Stage 2, panel fixed effects OLS for firm 3-year growth

	all industries	ind 3	ind 6	ind 9	ind 12	ind 13	ind 14	ind 16	ind 18	ind 22	ind 23
	growth	growth	growth	growth	growth	growth	growth	growth	growth	growth	growth
predicted patent growth	1.012***	3.314**	0.417	-0.642**	0.0438	0.191	2.108***	0.401***	0.109	1.450***	1.147***
	(13.39)	(2.95)	(1.65)	(-3.08)	(0.78)	(0.81)	(5.41)	(3.76)	(1.22)	(4.070)	(4.620)
emp	-0.475***	1.275	-0.585*	-0.488	-0.184	-0.215	-0.233*	-0.521***	-0.444***	-0.555***	-0.811*
	(13.50)	(0.55)	(2.54)	(1.93)	(1.02)	(1.90)	(2.10)	(6.03)	(3.37)	(5.07)	(2.38)
_cons	208.0***	134	216.2***	188.9***	174.6***	231.1***	219.9***	222.7***	159.7***	241.4***	230.5***
	(61.81)	(0.68)	(12.54)	(8.79)	(9.89)	(17.64)	(14.07)	(29.09)	(15.35)	-22.85	(8.950)
N	31,222	116	1,337	557	807	1,699	2,228	4,521	1,912	2,147	1,013
N of groups	9,545	58	412	169	240	508	658	1,321	598	626	291
Panel SD	146.2	219.6	168.1	124.3	133.2	158.9	143.9	143.4	121.7	154.3	146.8
Error SD	157.4	161.9	172.8	118.3	146.1	187.9	157	156.9	111.7	173.6	162
R2 within	0.021	0.153	0.014	0.028	0.008	0.004	0.046	0.030	0.010	0.027	0.053
R2 between	0.013	0.001	0.000	0.037	0.027	0.007	0.013	0.006	0.008	0.017	0.010
Chi2 model	237.000	9.058	7.244	10.150	1.716	5.171	30.260	36.390	11.390	28.960	23.640
P-value	0.000	0.011	0.027	0.006	0.424	0.075	0.000	0.000	0.003	0.000	0.000
Rho	0.463	0.648	0.486	0.524	0.454	0.417	0.456	0.455	0.543	0.441	0.451

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$