DO PATENTS PAY OFF?

A STUDY OF THE PATENT–PERFORMANCE RELATIONSHIP IN SWEDEN

OM SAXENA

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Abstract:

We build on the study of Taglialatela & Barontini (2024) by analyzing how the different stages of the patenting process – filing and granting – affect firm performance in Sweden. Using firm-level data, we test the external validity of their findings on Italian SMEs and extend their study by examining heterogeneous effects across firm sizes. Applying staggered difference-in-differences (DiD) and triple-difference (DDD) estimators, we find that filing without securing a grant is associated with reduced turnover growth across all firm groups. In contrast, obtaining a patent grant yields significant revenue gains for SMEs, while large firms experience no such gains and exhibit lower profitability post-grant. We challenge the assumption that larger firms capture greater patent returns, and instead suggest that SMEs are better positioned to leverage grants through external signaling. We further highlight the role of policy and capital markets in shaping performance outcomes across the patenting stages. Our findings suggest that the economic value of intellectual property is not uniform, but contingent on firm-level characteristics and the broader institutional context.

Keywords:

Patents, Firm Performance, Firm Size Heterogeneity, Intellectual Property

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1 Introduction

Over 3.5 million patent applications were filed worldwide in 2023. This trend, reflecting an increase of 2.7% over the prior year, highlights the growing importance of intellectual property (IP) in today's knowledge economy (World Intellectual Property Organization, 2024). Among the various types of IP, patents play a pivotal role by granting inventors temporary monopoly rights to protect R&D investments, incentivize innovation, and signal firm quality to the market. Despite their intended purpose, however, the true economic impact of patenting on firm performance remains widely debated by policy and academic circles alike.

The existing research highlights the empirical challenges of connecting patent activity to firm performance beyond correlation. Scholars point to issues ranging from endogeneity and unobserved heterogeneity, to the inherent ambiguity and quality limitations of patent data itself. Prior studies have tackled these challenges using distinct causal identifcation strategies. Balasubramanian and Sivadasan (2011) and Taglialatela and Barontini (2024), for example, apply difference-in-differences (DiD) frameworks with careful control group construction to infer causality; the former finding that labour productivity increased by 3.5%-10.5% after patenting. Other studies, such as Kogan, Papanikolaou, Seru, and Stoffman (2017) and Farre-Mensa, Hegde, and Ljungqvist (2020), adopt instrumental variable approaches using exogenous variations from R&D tax credits and examiner leniency respectively, with Farre-Mensa et al. (2020) reporting that patents granted can increase startup sales growth by as much as 79.5%.

Building on this growing body of literature, we extend the work of Taglialatela and Barontini (2024), who uniquely distinguish between the two stages of the patenting process: (1) filing a patent and (2) being granted a patent. From their staggered DiD approach on Italian small and medium-sized enterprises (SMEs), they find that filing alone leads to positive sales increases of 3-4% due to gains in knowledge stocks, whereas granted patents have no measurable additional benefit. Using firm-level data from Sweden's Retriever Business, we test the external validity of the authors' findings in a different institutional and economic context. Our main contribution is to assess whether the effects of patenting vary systematically by firm size – an underexplored dimension as prior studies focus exclusively on startups, SMEs, or large firms, or do not distinguish by firm size at all (Balasubramanian & Sivadasan, 2011; Conti, Thursby, & Thursby, 2013; Farre-Mensa et al., 2020; Taglialatela & Barontini, 2024). In particular, Taglialatela and Barontini (2024) suggest that SMEs may not benefit from granted patents due to limited resources to enforce their protection rights – implicitly assuming that large firms with greater resources should benefit more. We make this assumption explicit and test it directly by incorporating both SMEs and large firms into our empirical framework. Specifically, we estimate staggered DiD models overall and by firm size, and introduce a triple-difference (DDD) specification to examine how filing and granting effects vary both within and across firm sizes. Furthermore, we incorporate methodological improvements drawing from prior studies (Balasubramanian & Sivadasan, 2011; Farre-Mensa et al., 2020; Kogan et al., 2017), including the use of text-matching algorithms to link patent records to firm identifiers and implementing a stricter sample construction process to improve causal inference.

For our study, we follow the classifications of Taglialatela and Barontini (2024) and Balasubramanian and Sivadasan (2011), grouping firms into three categories:

- **Granted filers**: Firms that filed for and successfully obtained a patent.
- **Non-granted filers**: Firms that filed for a patent but were rejected, withdrew their application, or remained pending for more than five years.
- **Non-filers**: Firms that did not file for any patents during the sample period.

We structure our empirical analysis into two parts. To evaluate the *filing effect*, we compare non-granted filers (treatment group) to non-filers (control group). To assess the *granting effect*, we compare granted filers (treatment group) to non-granted filers (control group). These comparisons allow us to estimate the effects of filing and granting of a patent separately.

A key part of our study is our data collection and identification strategy. We source patent data from PATSTAT and match it to firm identifiers via PAtLink and Serrano databases using text-matching algorithms, which is then linked to firm-level data from Retriever Business. Following the approach of Taglialatela and Barontini (2024), we employ a ±4–year event window to analyze the effects of filing and granting of patents. As Retriever Business covers the period 2005-2024, we thus restrict the sample to patents filed between 2010 and 2019. Furthermore, we only include patents filed at least three years apart to isolate the effect of each patenting event. For both the filing and granting analyses, we match control firms to treatment firms through a two-step selection process: first, we select up to 30 controls

based on industry, age, and revenue; and second, we apply one-to-one nearest neighbour matching on key financial covariates. We notably extend the methodology of Taglialatela and Barontini (2024) by requiring granted patents, in addition to filed patents, to be at least three years apart to reduce further confounding effects. Moreover, we consolidate firm structures at the group level to mitigate double-counting patent applications, and categorize companies into SMEs and large firms using the European Commission's definition (European Commission, 2020).

As the first notable step of the patenting process is filing, we evaluate this treatment effect by applying a ±4–year event window centered around the filing year following Taglialatela and Barontini (2024). We find that filing a patent – without securing a grant – has a negative impact on firm turnover growth: firms experience a decline in turnover growth of around 10 percentage points (pp) in the year following filing. Using a triple-difference model to distinguish by firm size, we further observe that both SMEs and large firms experience similar negative effects. Overall, these findings contradict Taglialatela and Barontini (2024), who report positive post-filing performance effects for Italian SMEs, which they attribute to knowledge gains derived from the patenting process. We find that in Sweden, firms regardless of size, appear to not benefit from such knowledge gains. For a possible explanation, we explore differences in institutional contexts as per Kogan et al. (2017). Compared to Italy, we suggest that Sweden's less generous R&D tax regime may have made filing more burdensome than beneficial for firms.

To examine the impact of obtaining a granted patent, we appply a similar staggered DiD framework centered around the granting year. Overall, we find no significant post-granting effect when pooling all firms. However, our triple-difference estimates show that SMEs outperform large firms in terms of profitability, with ROE higher by 26 pp two years post-grant. This is driven primarily by large firms underperforming rather than SMEs attaining significant profitability gains. When analyzing absolute turnover, on the other hand, we find that granted SMEs earn 6–11 MSEK more in revenue relative to non-granted SMEs, while large firms show no significant effects. These findings again contradict Taglialatela and Barontini (2024), who argue that SMEs lack the resources to enforce granted patents. We instead align with Farre-Mensa et al. (2020), who show that patent grants can improve financing access and firm signaling for smaller companies. Differences in capital market conditions thus offer one possible explanation for why granted patents are more financially impactful for Swedish SMEs than their Italian counterparts. Meanwhile, large firms underperform in relation to SMEs post-grant as they often use patents defensively rather than commercially, in line with Lemley and Shapiro (2005), and may even face negative returns in relation to other non-granted large firms.

Our findings reinforce the idea that the economic value of patenting is not uniform across firms and depends critically on firm characteristics, institutional context, and the stage of the patenting process. We suggest that filing, in and of itself, offers little benefit in the Swedish context, and that firms, especially SMEs, should aim to pursue patents with the goal of securing enforceable rights. The absence of positive outcomes for large firms may reflect strategic misalignment in how patents are used — whether defensively, bureaucratically, or as portfolio padding — rather than as tools for commercial exploitation. We also acknowledge a possible sample bias, as our identification strategy excludes frequent patent filers. Overall, we highlight the importance of firm-specific factors, institutional conditions, and the stage of the patenting process when evaluating the returns to innovation. The economic impact of patenting, and IP more broadly, is suggested to be more nuanced than often assumed.

The rest of the paper is organized as follows. Section 2 reviews the background and existing literature on the patent-performance relationship. Section 3 details our empirical methodology, including the econometric models used, sample construction process, and descriptive statistics. Section 4 presents the results for our study. We discuss our findings and their implications in Section 5, and conclude the paper in Section 6.

2 Literature Review

This paper contributes to the extensive and growing literature on patents' impact on firm performance (Balasubramanian & Sivadasan, 2011; Budish, Roin, & Williams, 2016; Conti et al., 2013; Farre-Mensa et al., 2020; Galasso & Schankerman, 2015; Hochberg, Serrano, & Ziedonis, 2018; Kogan et al., 2017; Lemley & Shapiro, 2005; Shu, Tian, & Zhan, 2022; Taglialatela & Barontini, 2024).

More specifically, by employing a staggered DiD approach comparing patentees with non-patentees, Taglialatela and Barontini (2024) find that Italian SMEs between 2005 and 2010 experienced a significant increase in turnover immediately after filing, which they attribute to knowledge gains triggered during the patenting process. Other studies similarly investigate the causal impact of patents, but report different findings based on their methodologies. Farre-Mensa et al. (2020) exploit examiner leniency

as an instrumental variable in U.S. startups and find that receiving a granted patent led to 55% higher employment growth and 80% higher sales growth, largely driven by startups' improved access to external financing. Conti et al. (2013) support this conclusion in their study using exogenous variation in venture capital (VC) activity, showing that Israeli startups filed for more patents after their first funding rounds to signal firm quality to new external investors; filing more patents was positively associated with attracting more VC backing. Similarly, Balasubramanian and Sivadasan (2011) focus on established U.S. manufacturing firms rather than startups, yet still find that first-time patent grants led to substantial firm growth, with around 2.7 new product introductions and up to $4.4 million in additional sales relative to non-patentees. However, Lemley and Shapiro (2005) are among the scholars that remain skeptical of the economic value of patents, highlighting that in the U.S. only 1–2% of patents are litigated, just 0.1% proceed to trial, and about 46% of litigated patents are invalidated. The authors suggest that the legal and economic benefits of patents are probabilistic and often strategic.

Given the differences in findings across studies, probably due to varying data, methodology, and outcome variables, our paper contributes to the literature by providing evidence on the impact of patents on firm performance in another context. First, unlike prior studies conducted in the U.S., Japan, or Italy, we study Sweden – one of the most innovative economies according to the Global Innovation Index (Dutta, Lanvin, Rivera León, & Wunsch-Vincent, 2024). Compared to continental Europe and the U.S., Sweden offers a distinct legal environment and capital market structure that provides an opportunity to explore whether prior conclusions hold in a different context (Andersson & Lööf, 2012; Dutta et al., 2024; La Porta, Lopez-De-Silanes, Shleifer, & Vishny, 1997). Second, we introduce firm size as a moderating factor. Whereas earlier work tends to focus on either startups, SMEs, or large firms — or does not distinguish firm size at all — we explicitly examine how patent effects differ across firm groups using a triple-difference framework. This approach is motivated by existing research showing that SMEs and large firms exhibit distinct patenting behavior and outcomes: SMEs patent less frequently but often derive greater commercial benefits through licensing and access to external financing (Acs & Audretsch, 1988; European Patent Office, 2017; Hughes, 2010). Furthermore, Taglialatela and Barontini (2024) suggest that SMEs may not benefit from granted patents due to limited resource capacity, thus implicitly assuming that larger firms should benefit more. We design our empirical framework to explicitly test how patent filing and patent granting vary both within and across firm groups. Lastly, we improve the identification strategy for causal inference across patenting stages. Compared to Taglialatela and Barontini (2024), we implement stricter sample restrictions when comparing non-granted filers to non-filers and granted filers to non-granted filers. These refinements are informed by best practices from earlier work (Balasubramanian & Sivadasan, 2011; Farre-Mensa et al., 2020; Kogan et al., 2017), and include text-matching algorithms to link patent records to firms, along with stricter timing constraints to better isolate treatment effects.

Ultimately, we provide evidence on how firm performance varies across the different stages of the patenting process, and the factors that influence this relationship.

3 Data and Methodology

3.1 Methodology

Ideally, two experimental conditions are required to investigate the causal relationship between patents and performance:

1. To assess the impact of filing, we would need two groups of firms with the exact same inventions, where one group files for a patent and the other does not.

2. To assess the impact of granting, we would need two groups of firms that filed the exact same patent applications, where one group is granted their patent applications and the other is not.

In a perfect scenario, these treatment decisions would be made randomly. However, since we rely on observational data in practice, we adopt the framework of Taglialatela and Barontini (2024) to address potential simultaneity and heterogeneity issues related to studying the causal link between patents and performance, as addressed by previous studies (Balasubramanian & Sivadasan, 2011; Farre-Mensa et al., 2020; Kogan et al., 2017). To mitigate potential bias, we carefully construct our sample using a time-bound window, applying a rule to select only patents filed at least 3 years apart to isolate the impact of individual patenting events. This rule excludes most high-frequency patenting firms in Sweden,

such as Ericsson and AstraZeneca as seen in Table 2, but we consider this trade-off essential for reducing confounding effects and ensuring a robust identification strategy as per Taglialatela and Barontini (2024).

Moreover, firms that file for or are granted patents may differ systematically from those that do not (Kannebley, Sekkel, & Araújo, 2010). We address this by using propensity score matching (PSM) to create comparable treatment and control groups, aligning with the approach of Taglialatela and Barontini (2024). The PSM approach allows us to estimate the probability of filing or being granted a patent for each firm based on observable characteristics – firms with similar probabilities are then matched across treatment and control groups using nearest neighbour matching with caliper distance 0.2. While this strict matching reduces the sample size, we consider it a necessary trade-off to construct balanced control groups and ensure the validity of our design. The treatment and control group definitions for both the filing and granting analyses are summarized in Table 1. Section 3.3 provides a detailed explanation of the two-step control group selection process.

A key addition to Taglialatela and Barontini's (2024) methodology is our more conservative approach to corporate group structure. Since financial metrics are often reported and allocated at the group level (IFRS Foundation, 2024), we consolidate subsidiaries under their parent firm. For example, Volvo Trucks and Volvo Energy are treated as a single unit under Volvo AB to reduce double-counting. We also make methodological adjustments, such as an additional criterion to select patents that are granted at least 3 years apart to further reduce confounding effects. Lastly, to examine heterogeneous treatment effects by firm size, we classify firms according to the European Commission's SME definition, i.e. firms with fewer than 250 employees and either an annual turnover of less than €50 million or total assets below €43 million (European Commission, 2020).

Table 1: Firm group classification and corresponding empirical comparisons.
This table defines the three firm groups used in the study, following Taglialatela and Barontini (2024) and Balasubramanian and Sivadasan (2011). Distinct treatment and control group assignments are applied to separately identify the effect of filing a patent from the additional effect of obtaining a grant.

Firm Group	**Definition**
Granted filers	Firms that filed for and successfully obtained a patent.
Non-granted filers	Firms that filed for a patent but were rejected, withdrew their application, or remained pending for more than five years.
Non-filers	Firms that did not file for any patents.

Empirical Comparison	**Treatment Group**	**Control Group**
Filing effect	Non-granted filers	Non-filers
Granting effect	Granted filers	Non-granted filers

3.2 Econometric Model

Even after matching treatment and control firms based on strict observable factors as outlined in Section 3.1, it is reasonable to assume that matched firms may still differ in unobservable characteristics. To address this, we exploit the longitudinal dimension of our data and apply a staggered difference-in-differences (DiD) estimator with firm fixed effects, as per Taglialatela and Barontini (2024). This method complements our matching methodology by controlling for time-invariant unobservable firm characteristics that matching alone cannot account for – thereby strengthening causal identification in both the filing effect (comparing non-granted filers with non-filers) and the granting effect (comparing granted filers with non-granted filers).

We estimate our model on the matched dataset in three main ways. First, to estimate the overall impact of patenting events across all firms – without distinguishing between large firms and SMEs – we run the following pooled regression using a ±4–year event window:

$$Y_{ik} = \alpha_i + \sum_{\substack{k=-4 \\ k\neq -1}}^{4} \beta_k \cdot (\text{treatment}_i \cdot \text{year}_k) + \mathbf{X}'_{ik}\theta + \varepsilon_{ik} \tag{1}$$

where Y_{ik} is our firm performance indicator, α_i are firm fixed effects, treatment_i is a binary variable

for whether firm i is in the treatment group, year_k are event-time dummies for years relative to the treatment (excluding year -1 as the reference year), X'_{ik} is a vector of time-varying controls described below, and ε_{ik} is the error term. Unlike a standard DiD model that uses a single post-treatment dummy, we use a full set of relative-year dummies. This allows us to observe dynamic treatment effects over multiple periods before and after the patenting events. The coefficients β_k represent the year-specific treatment effects and are thus the actual DiD estimators adjusted for multiple periods.

As we extend the literature by examining whether treatment effects vary by firm size, we further distinguish between SMEs and large firms using the European Commission's definition (European Commission, 2020). We then run the following triple-difference regression:

$$Y_{ik} = \alpha_i + \sum_{\substack{k=-4 \\ k\neq -1}}^{4} \beta_k \cdot (\text{treatment}_i \cdot \text{year}_k) + \sum_{\substack{k=-4 \\ k\neq -1}}^{4} \gamma_k \cdot (\text{treatment}_i \cdot \text{year}_k \cdot \text{SME}_i) + \mathbf{X}'_{ik}\theta + \varepsilon_{ik} \quad (2)$$

where SME_i is a binary variable equal to 1 if firm i is classified as an SME, β_k captures the treatment effect for large firms (non-SMEs), and γ_k captures the additional effect for SMEs in comparison to large firms. Since the total treatment effect for SMEs is not directly reported in the regression output, we compute it separately by summing the baseline effect and the interaction term: $\beta_k + \gamma_k$. This step is important for interpreting whether observed differences are driven by SMEs' performance or by large firms' performance. For example, a negative interaction effect (γ_k) can result from SMEs underperforming or from large firms overperforming. Standard errors (SE) for SME treatment effects are calculated separately using the following formula:

$$\text{SE}(\beta_k + \gamma_k) = \sqrt{\text{Var}(\beta_k) + \text{Var}(\gamma_k) + 2 \cdot \text{Cov}(\beta_k, \gamma_k)} \quad (3)$$

Following Taglialatela and Barontini (2024), we focus on the following four firm performance indicators: turnover, turnover growth, ROE, and ROE growth, as defined in Table 11 (see Appendix). However, to maintain comparability between SMEs and large firms, we exclude absolute turnover from both of our regressions above. It is reasonable to assume that absolute turnover is heavily skewed by firm size, leading to pooled estimates being biased and meaningful comparisons difficult. Prior studies like Taglialatela and Barontini (2024) and Balasubramanian and Sivadasan (2011) used turnover as an outcome variable only within more homogenous firm samples, such as SMEs or large firms in isolation.

To still examine how patent filing and patent granting affect absolute turnover, we estimate separate regressions for SMEs and large firms:

$$\text{Turnover}_{ik}^{\text{SME}} = \alpha_i + \sum_{\substack{k=-4 \\ k\neq -1}}^{4} \beta_k^{\text{SME}} \cdot (\text{treatment}_i \cdot \text{year}_k) + \mathbf{X}'_{ik}\theta + \varepsilon_{ik} \quad (4a)$$

$$\text{Turnover}_{ik}^{\text{Large}} = \alpha_i + \sum_{\substack{k=-4 \\ k\neq -1}}^{4} \beta_k^{\text{Large}} \cdot (\text{treatment}_i \cdot \text{year}_k) + \mathbf{X}'_{ik}\theta + \varepsilon_{ik} \quad (4b)$$

In all regressions, we control for cash flow, age, size, and leverage, as defined in Table 11 (see Appendix). Although these covariates were included in the matching procedure, we include them again in the regressions to account for longitudinal variation, as recommended by Taglialatela and Barontini (2024). Additionally, we cluster standard errors at the firm level and apply winsorization to address outliers, which is further discussed in Section 3.4.

3.3 Sample Construction

3.3.1 Data Collection

We collect our data according to the methodology specified above. We begin by obtaining patent data through PATSTAT, selecting all applications filed by Swedish applicants between 2000-2024 for our initial dataset. This includes information such as filing year, application status, grant date, totalling 616,625 observations. To link patents to financial data, we need each applicant's Swedish organisation number. Due to inconsistencies in PATSTAT data (e.g. missing characters, typos), we use a combination

of PAtLink and Serrano to match applicant names to organisation numbers through application IDs, exact and fuzzy name matching with 95% confidence, and manual verification, as inspired by prior studies (Balasubramanian & Sivadasan, 2011; Farre-Mensa et al., 2020; Kogan et al., 2017). We cluster subsidiaries under their parent companies using Serrano data. Following this firm ID mapping, we clean the dataset by removing duplicates and individual applicants, and retain only organisation numbers starting with "5" (limited companies), which leaves us with 414,079 observations across 8,964 unique firms.

As Retriever Business has available financial data for Swedish firms from 2005-2024, we limit our patents to those filed between 2010 and 2019 to ensure full coverage for our ±4-year analysis window. Importantly, we select only patents filed at least three years apart. These filters remove 353,727 applications and 4,842 firms, including mostly high-frequency filers such as Ericsson and AstraZeneca as seen in Table 2. For granted patents, we apply a separate 3-year separation rule for grant dates in addition to the filing-year criterion. Firms with both granted and non-granted applications are excluded, resulting in a sample of 3,224 applications across 3,090 unique firms.

Table 2: Top 5 firms removed by 3-year separation rule.
This table shows the five largest patent applicants excluded due to the 3-year separation rule, which filters out patents filed within three years of each other. The table lists each firm's organization number, number of applications removed, and the share of total applications in the mapped dataset that these exclusions represent.

Org. nr	Company Name	Applications	% of Total Applications
5560160680	ERICSSON AB	113,536	27.42%
5560117482	ASTRAZENECA AB	26,233	6.34%
5560125790	VOLVO AB	14,077	3.40%
5560840976	SCANIA CV AB	12,011	2.90%
5560003468	SANDVIK AB	10,792	2.61%
Combined share of top 5 removed companies			42.67%

We collect firm-level financial data and construct control variables following Taglialatela and Barontini (2024), which are defined in Table 11 (see Appendix). Finally, we select treatment firms with full data coverage for all covariates over ±4 years from their treatment year, which result in 379 non-granted filers for analyzing filing effect (339 SMEs, 40 large firms), and 746 granted filers for analyzing granting effect (682 SMEs, 64 large firms). Figure 1 provides a detailed visual summary of the data collection process in sequential steps.

3.3.2 Control Group Selection Process

For the first part of our empirical analysis – filing effect – we use non-patenting firms as the control group. We start by identifying all Swedish firms through Serrano and exclude those with patent filings between 2010 and 2019. After filtering for valid financial data, we retain 239,187 non-patenting firms as potential controls pre-matching.

In the second part of our empirical analysis – granting effect – we use our existing non-granted filers as the control group. Unlike the filing analysis, which requires non-granted filers to have at least a three-year gap between patent filings to isolate events, the granting analysis focuses specifically on the timing of patent grants. We therefore include only non-granted filers who have not received a granted patent within three years prior to their filing. For example, a firm that filed for patents in both 2011 and 2012 but was never granted a patent, would qualify as a control in the granting analysis, but not as a treated firm in the filing analysis. The same non-granted filer can thus qualify in one part of the study but not the other, based on which type of patenting effect we aim to isolate.

Having compiled raw datasets for both control groups, we follow a two-step matching process based on the approach by Taglialatela and Barontini (2024). In the first step, we select up to 30 comparable control firms for each treatment firm using three key criteria: industry (SNI digits 2-4), firm age, and revenue, as defined in Table 11 (see Appendix). For example, if a manufacturing firm filed for a patent in 2008, we compare it to a non-filing manufacturing firm with data from the exact same year. In our granting analysis, while we match firms based on available data on the granting year, we add an additional condition to ensure that both firms filed for patents around the same time. These filters result

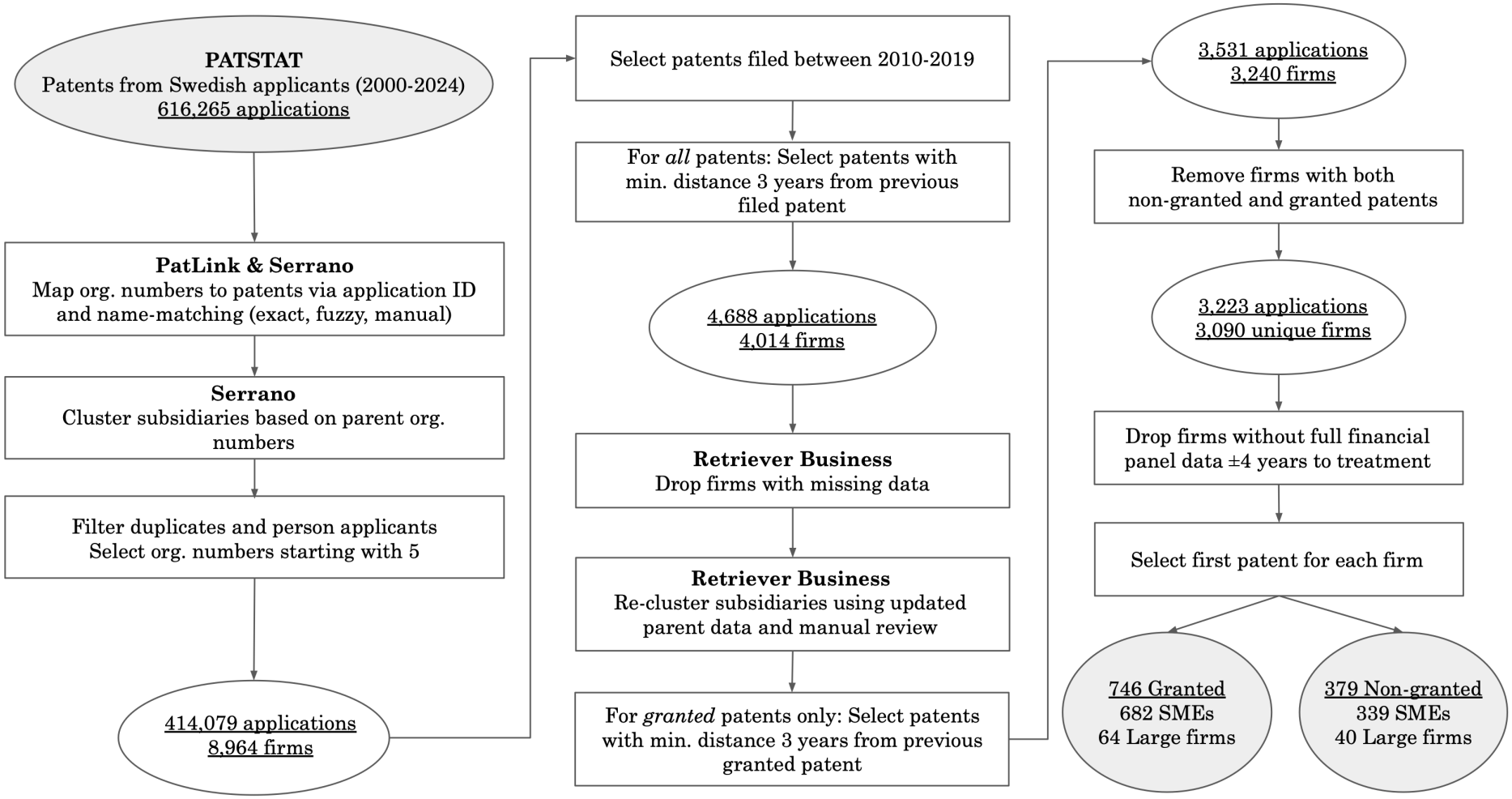


Figure 1: Overview of the data collection process.
This figure outlines the sequential data pipeline used in our study, starting from the initial extraction of 616,625 patent applications from PATSTAT. Key steps include mapping applicants to firm IDs, clustering subsidiaries under parent firms, applying separation rules, and filtering for full panel data. The final filtered samples serve as the treatment groups used in the subsequent two-step control group selection process.

in 7,506 control candidates for the non-granted filer treatment group, and 396 control candidates for the granted filer treatment group. Treatment firms without eligible matches are dropped, reducing the sample from 379 to 376 for the filing effect and from 746 to 498 for the granting effect.

The second step of the matching process involves one-to-one nearest neighbour matching with a caliper distance of 0.2. Treatment and control firms are matched based on age, size, capital intensity, cash flow, and leverage, per Table 11 (see Appendix). A single control firm can be matched to multiple treatment firms. This results in 293 final treatment firms for the filing effect analysis, and 277 final treatment firms for the granting effect analysis – reflecting a further reduction of 83 and 221 treatment firms, respectively. Overall, these reductions in sample size stem from our use of strict matching criteria to ensure covariate balance. We consider this a justified trade-off, as it strengthens causal identification and aligns with the rigorous methodology of Taglialatela and Barontini (2024). A detailed visualization of the selection and matching process can be found in Figure 2.

The overall matching quality between treatment and control firms is assessed through Table 3, which shows that the matching is satisfactory. In the granting analysis, no significant differences are found between treatment and control firms across covariates. In the filing analysis, age and capital intensity show small but statistically significant differences; however, given their limited magnitude of 0.109 and 0.069 respectively, we consider the matching sufficiently robust for causal analysis.

Table 3: Post-matching differences in characteristics between treatment and control groups. This table presents mean values for treatment and control groups after propensity score matching, used to assess matching quality in the filing and granting analyses defined in Table 1. The top panel compares non-granted filers (treatment) and non-filers (control) for the filing effect study. The bottom panel compares granted filers (treatment) and non-granted filers (control) for the granting effect study. P-values from two-sided t-tests are used to asses whether differences are significant. Variable definitions are provided in Table 11.

Filing Effect: Non-Granted Filers vs Non-Filers					
Covariate	Overall	Filing	Non-filing	Difference	p-value
Age	3.076	3.022	3.131	0.109 **	0.023
Cash Flow	0.070	0.084	0.056	–0.028 *	0.093
Size	9.926	9.882	9.969	0.087	0.648
Capital Intensity	0.360	0.326	0.395	0.069 ***	0.004
Leverage	0.573	0.586	0.560	–0.026	0.212
Granting Effect: Granted Filers vs Non-Granted Filers					
Covariate	Overall	Granted	Non-Granted	Difference	p-value
Age	2.953	2.951	2.955	0.004	0.929
Cash Flow	0.055	0.043	0.066	0.023	0.324
Size	9.839	9.879	9.799	–0.080	0.619
Capital Intensity	0.289	0.281	0.297	0.017	0.426
Leverage	0.588	0.571	0.604	0.033	0.176

Note: * p<0.10; ** p<0.05; *** p<0.01.

3.4 Descriptive Statistics

Table 4 reports summary statistics for our two treatment groups after matching. The summary data is presented over a "years-to-treatment" window of ±4 years as opposed to calendar years, reflecting our staggered DiD design.

We observe notable differences in certain firm characteristics between non-granted and granted filers. For instance, at the year of treatment, non-granted filers report an average total asset value of 464.5 MSEK, which is 323.5 MSEK more in total assets than their granted counterparts. A similar gap is evident in absolute turnover: at the year of treatment, non-granted filers report an average turnover of 261.2 MSEK, compared to 177.4 MSEK for granted filers. These differences in both assets and turnover persist across the ±4-year event window. A likely explanation is the larger representation of large firms in the non-granted sample (33 large firms) compared to the granted sample (12 large firms), which skews the group-level averages upward. Given that larger firms typically exhibit higher turnover and

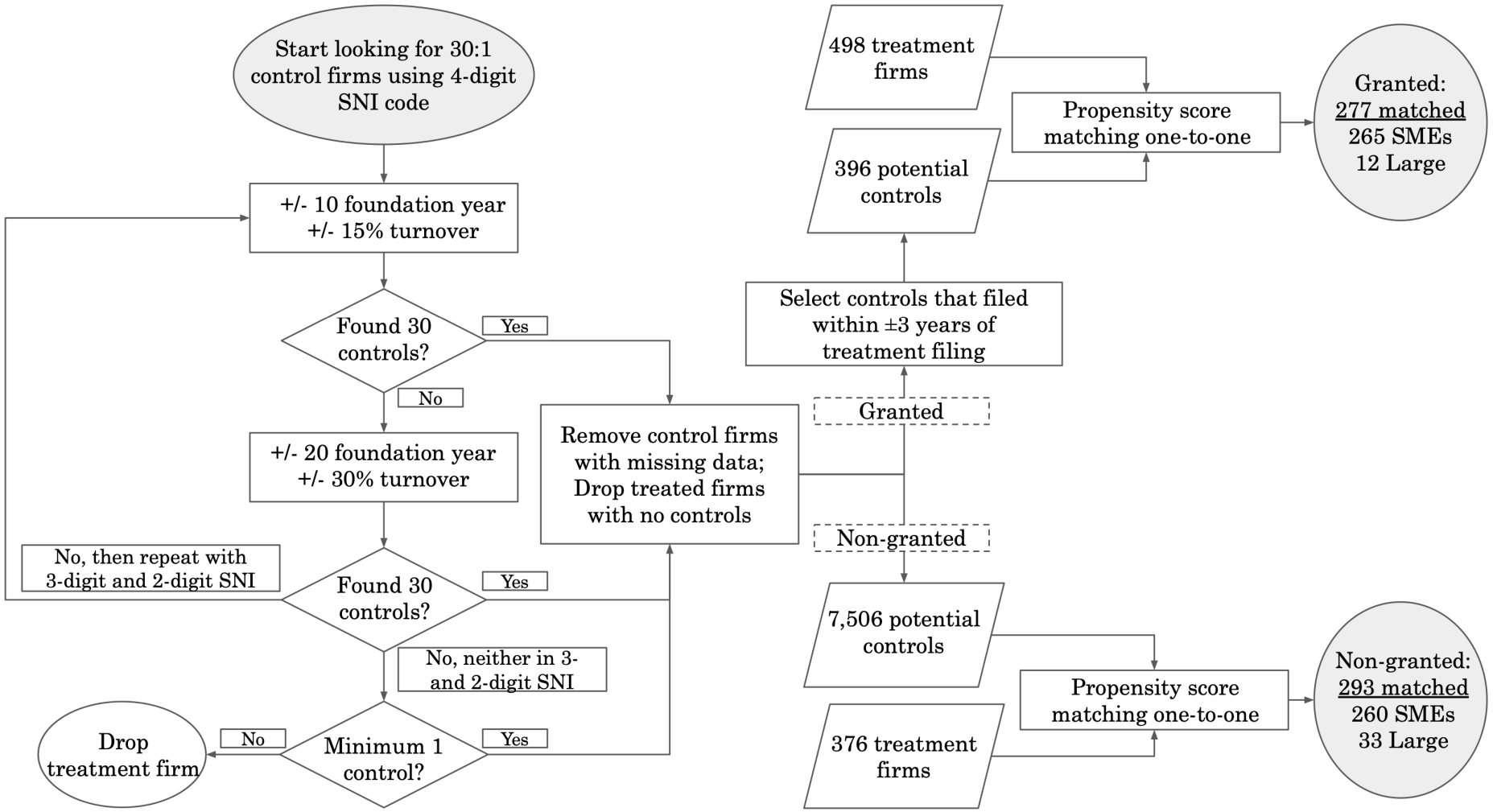


Figure 2: Overview of the two-step control selection process.
Step 1 (left) selects up to 30 candidates per treatment firm based on industry, age, and turnover. Step 2 (right) separates treatment groups and applies nearest-neighbour PSM on key financial covariates. The final matched samples represent treatment firms used in the subsequent regressions. Variable definitions are provided in Table 11.

asset levels, these variables are also used as proxies for firm size in our two-step matching procedure, as described in Section 3.3. In contrast, profitability metrics such as ROE and ROE growth display no clear pattern and fluctuate substantially across both groups. Meanwhile, control variables — including cash flow, capital intensity, leverage, and firm age— remain broadly comparable, supporting the validity of our identification strategy despite differences in firm size composition.

An important aspect of the data is the presence of extreme values. We observe that both treatment groups exhibit extreme outcome values, especially in the pre-treatment years. Non-granted filers post an abnormally high mean ROE of 107.37% two years before filing, as well as an abnormally high mean ROE growth of 138.45 pp during the same year. Granted filers follow a similar pattern, with an abnormal turnover growth of 195% four years prior to granting, and an abnormally low ROE of -74.39% two years before granting. While the control variables remain relatively stable throughout the time frame, the magnitude of the outcome variables underscore the need to address extreme values before our econometric estimation. Figure 7 (see Appendix) displays the distribution of all four outcome variables for both samples in our empirical analysis, including their respective control groups. Since thresholds at the 1st percentile and 99th percentile capture most outliers, we conclude that winsorizing at those levels is sufficient without overly distorting the original dataset.

Table 4: Summary statistics for treatment groups.
This table reports yearly average values for outcome and control variables, from year –4 to +4 relative to the treatment year. Panel A presents data for non-granted filers used in the filing analysis, while Panel B presents data for granted filers used in the granting analysis. Variable definitions are provided in Table 11. Assets and Turnover are reported in Thousands of SEK.

Panel A: Non-Granted Filers

Years To Treatment	Turnover	Turnover Growth	ROE	ROE Growth	Age	Assets	Cash Flow	Capital Intensity	Leverage
Year –4	214,432.38	57.05	7.22	7.09	21.00	452,926.73	0.08	0.32	0.61
Year –3	213,778.11	54.52	–31.08	–38.30	22.00	448,686.04	0.07	0.30	0.60
Year –2	232,511.21	89.09	107.37	138.45	23.00	449,148.35	0.07	0.31	0.59
Year –1	253,210.18	22.90	–26.67	–134.04	24.00	449,425.95	0.09	0.31	0.58
Year 0	261,248.43	37.86	–2.83	23.84	25.00	464,522.50	0.08	0.33	0.59
Year 1	281,547.17	37.06	–44.34	–41.52	26.00	538,603.67	0.06	0.34	0.58
Year 2	286,709.04	19.86	18.00	62.34	27.00	480,698.53	0.04	0.33	0.57
Year 3	325,356.65	18.97	17.07	–0.93	28.00	498,448.76	0.08	0.33	0.56
Year 4	364,288.72	6.92	13.41	–3.66	29.00	523,720.02	0.33	0.33	0.58

Panel B: Granted Filers

Years To Treatment	Turnover	Turnover Growth	ROE	ROE Growth	Age	Assets	Cash Flow	Capital Intensity	Leverage
Year –4	127,870.13	195.04	0.73	–33.82	18.61	133,623.05	0.07	0.30	0.55
Year –3	133,035.87	46.40	–2.20	–2.92	19.61	150,273.56	0.06	0.31	0.55
Year –2	147,361.10	44.37	–74.39	–72.19	20.61	142,686.50	0.05	0.29	0.56
Year –1	158,425.03	27.08	1.90	76.29	21.61	153,442.14	0.06	0.28	0.56
Year 0	177,373.95	19.44	–0.52	–2.42	22.61	150,610.93	0.04	0.28	0.57
Year 1	194,324.45	94.38	1.54	2.06	23.61	150,074.59	0.05	0.28	0.56
Year 2	188,126.09	8.89	58.72	57.18	24.61	151,152.46	0.10	0.27	0.59
Year 3	202,234.74	33.67	–15.01	–73.72	25.61	171,563.33	0.07	0.26	0.56
Year 4	217,539.14	21.46	–12.53	2.48	26.61	182,637.85	0.51	0.26	0.54

Additional summary statistics disaggregated by firm size – for both the filing and granting analyses – are provided in Table 12 (see Appendix). We present separate tables for SMEs and large firms, without further distinguishing between treatment and control groups. At the year of treatment, SMEs overall report an average absolute sales of 63 MSEK, whereas large firms report an average of 2,137 MSEK. These statistics further confirm the substantial differences in absolute turnover by firm size, making direct comparisons based on absolute turnover challenging. This is addressed in our econometric estimations outlined in Section 3.2 by accounting for firm size when using absolute turnover as an outcome variable. We furthermore observe that outcome variables display different distributions across firm sizes, including size-specific outliers. For example, SMEs displayed on average an abnormal turnover growth of 1562% two years before obtaining a granted patent. To account for this, we apply winsorization separately for

SMEs and large firms at the 1st and 99th percentiles, ensuring that outlier treatment is tailored to each group's distribution while preserving comparability across size categories.

4 Results

4.1 Patent Filing and Firm Performance

Filing for a patent marks the first step in the patenting process, and we begin our empirical analysis by evaluating its effects. Using the staggered DiD framework described in Section 3.2, we estimate three specifications with non-granted filers as the treatment group and non-filers as the control group.

The validity of the DiD methodology relies on the parallel trends assumption that, in the absence of treatment, the outcome variables in the treatment and control groups would have followed similar trajectories (Roth, Sant'Anna, Bilinski, & Poe, 2023). Since this assumption cannot be formally tested, we adopt the visual inspection approach used by Taglialatela and Barontini (2024), where Figure 3 presents the trends of the four outcome variables over time. We observe relatively parallel pre-treatment trends for turnover, turnover growth, and ROE, supporting our assumption. While ROE growth trends are slightly less aligned, we argue that our two-step matching procedure outlined in Section 3.3 mitigates concerns about pre-existing differences between groups. Overall, we find sufficient evidence to justify the DiD approach in this context.

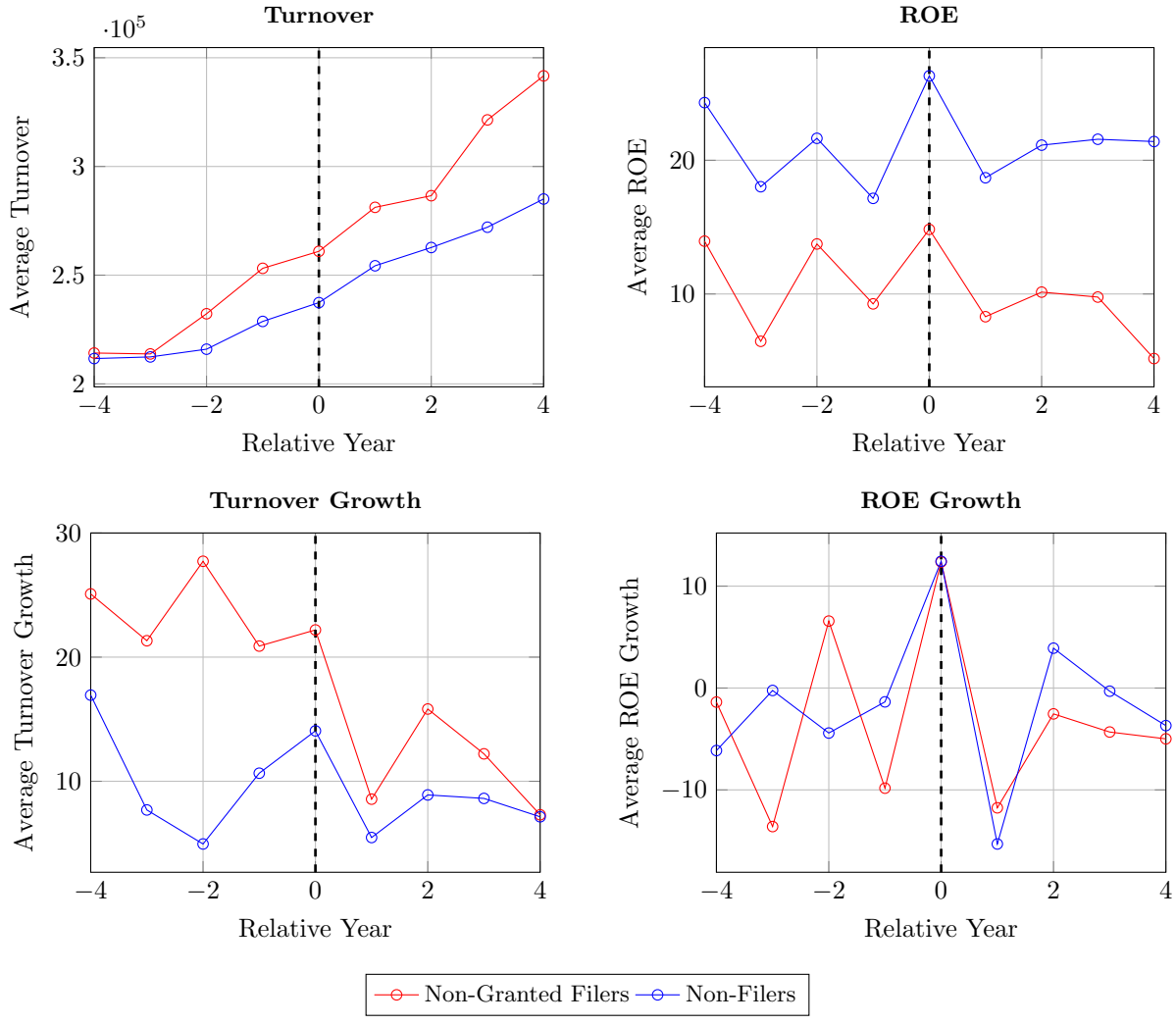


Figure 3: Pre- and post-filing outcome trends for treatment and control groups.
This figure shows average yearly values of firm outcomes between ±4 years to treatment. Trends are compared between non-granted filers (treatment) and non-filers (control). Visual inspection suggests the parallel trends assumption is reasonably satisfied. Variable definitions are provided in Table 11.

Table 5 presents the average effect of patent filing on firm performance across all firms (per Equation 1). The results show a significant drop in turnover growth for filing firms compared to non-filers. Specifically, filing firms experience a 10.66 percentage point (pp) decrease in turnover growth in the year following the filing. This effect is statistically significant only in the first post-filing year and applies only to turnover growth. For the other two performance measures – ROE and ROE growth – no statistically significant effects are observed, indicating that filing for a patent has no meaningful impact on firm profitability at the aggregate level.

Table 5: DiD estimates of post-filing performance on all firms.
This table reports DiD regressions estimating the effect of patent filing on firm performance, per Equation 1. Coefficients represent differences between non-granted filers (treatment) and non-filers (control) with year -1 as the reference year. Estimates are reported for years 0 to 4 post-filing. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. All variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Table 11.

	Dependent variable:		
	Turnover Growth	ROE	ROE Growth
	(1)	(2)	(3)
Filing : Year 0	2.068	5.349	22.235
	(6.739)	(5.855)	(14.026)
Filing : Year 1	-10.656**	-1.567	-2.391
	(5.254)	(6.925)	(16.275)
Filing : Year 2	-2.073	-0.578	5.655
	(5.459)	(6.868)	(14.802)
Filing : Year 3	-4.534	-1.505	3.592
	(5.973)	(7.047)	(13.841)
Filing : Year 4	-7.430	-2.606	7.229
	(5.923)	(6.378)	(11.167)
Cash Flow/Assets	-0.100	-0.343	-9.800***
	(0.274)	(0.887)	(2.833)
log(Age)	-42.990***	-31.847***	-5.037
	(7.974)	(10.816)	(13.312)
log(Assets)	17.900***	24.203***	4.540
	(3.422)	(4.457)	(4.744)
Debt/Assets	-5.626	-107.711***	-81.261***
	(7.851)	(20.057)	(28.287)
Observations	5,274	5,274	5,274
N. of groups	583	583	583
R^2	0.023	0.064	0.015
Residual Std. Error	10.451 (df=4,679)	19.892 (df=4,679)	19.611 (df=4,679)
F Statistic	9.019*** (df=595; 4679)	26.557*** (df=595; 4679)	6.062*** (df=595; 4679)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6 examines the heterogeneous effects of patent filing by firm size, including a triple-difference specification that distinguishes between SMEs and large firms (per Equation 2). Separate outcome trends for both groups are shown in Figure 8 (see Appendix) to further support the parallel trends assumption. The findings suggest that both SMEs and large firms experienced declines in turnover growth after filing for a patent. SMEs report an 11.54 pp lower turnover growth one year after filing, while large firms exhibit a 8.38 pp decline in the year of filing and a 11.03 pp decline two years later. In contrast, the interaction terms between firm size and treatment are statistically insignificant, indicating no meaningful difference in filing effects between SMEs and large firms. Consistent with the aggregated analysis, ROE and ROE growth remain unaffected by patent filing for both firm groups, as all estimates are statistically insignificant both within and across firm types throughout the period.

Table 6: Triple-difference (DDD) estimates of post-filing performance by firm size.
This table reports DDD regressions estimating the effect of patent filing on firm performance by firm size, per Equation 2. Baseline coefficients represent the filing effect for large firms, measured as differences between non-granted filers (treatment) and non-filers (control), with year -1 as the reference year. Interaction terms capture the additional effect for SMEs; the total SME effect is computed separately by summing baseline and interaction terms per Section 3.2. Estimates are reported for years 0 to 4 post-filing. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. All variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Table 11.

	Dependent variable:		
	Turnover Growth	ROE	ROE Growth
	(1)	(2)	(3)
Filing Effect for Large Firms (Baseline)			
Large Filing : Year 0	-8.378**	-4.716	7.937
	(3.665)	(6.668)	(18.355)
Large Filing : Year 1	-4.206	-3.942	15.516
	(4.979)	(10.261)	(15.818)
Large Filing : Year 2	-11.031*	-14.335	-0.868
	(5.820)	(9.393)	(19.843)
Large Filing : Year 3	1.109	-11.169	12.530
	(5.902)	(9.415)	(14.945)
Large Filing : Year 4	-2.837	-11.681	0.925
	(5.798)	(9.938)	(15.920)
Additional Filing Effect for SMEs (Interaction)			
Interaction : Year 0	11.739	11.353	16.130
	(8.404)	(9.270)	(24.055)
Interaction : Year 1	-7.333	2.697	-20.145
	(7.608)	(12.678)	(24.031)
Interaction : Year 2	10.000	15.529	7.405
	(8.317)	(12.049)	(25.725)
Interaction : Year 3	-6.482	10.924	-10.001
	(8.649)	(12.083)	(21.106)
Interaction : Year 4	-5.325	10.267	7.191
	(8.467)	(12.145)	(20.107)
Total Filing Effect for SMEs (Baseline + Interaction)			
SME Filing : Year 0	3.361	6.637	24.067
	(7.581)	(6.532)	(15.633)
SME Filing : Year 1	-11.540**	-1.245	-4.629
	(5.878)	(7.684)	(18.228)
SME Filing : Year 2	-1.031	1.195	6.537
	(6.100)	(7.670)	(16.501)
SME Filing : Year 3	-5.373	-0.245	2.529
	(6.667)	(7.870)	(15.435)
SME Filing : Year 4	-8.162	-1.414	8.115
	(6.607)	(7.125)	(12.446)
Control Variables			
Cash Flow/Assets	-0.098	-0.345	-9.806***
	(0.273)	(0.889)	(2.828)
log(Age)	-42.488***	-31.941***	-5.351
	(8.001)	(10.829)	(13.380)
log(Assets)	17.897***	24.166***	4.567
	(3.432)	(4.461)	(4.763)
Debt/Assets	-5.659	-107.803***	-81.115***
	(7.861)	(20.113)	(28.348)
Observations	5,274	5,274	5,274
N. of groups	583	583	583
R^2	0.023	0.064	0.016
Residual Std. Error	10.575 (df=4,671)	19.993 (df=4,671)	19.930 (df=4,671)
F Statistic	5.525***	16.051***	3.745***
Note:			*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 7 presents the effect of filing on absolute turnover, regressed separately for SMEs and large firms (per Equation 4a and 4b). Firm groups are thus split prior to regression. The results show mixed but statistically insignificant effects, indicating that filing for a patent has no meaningful impact on sales levels for either firm group in themselves. For example, in the fourth year after filing, large firms show an average increase in turnover of around 285.27 MSEK, while SMEs report a smaller gain of 3.54 MSEK, relative to their non-filing counterparts. However, as both estimates are accompanied by substantial standard errors, they are rendered insignificant. We thus do not find evidence that filing improves firm-level turnover for either firm group.

All regressions include firm fixed effects and standard errors clustered at the firm level. Additionally, outcome variables are winsorized at the 1st and 99th percentiles in order to reduce the influence of extreme values that may distort regression estimates, as discussed in Section 3.4. In order to test the robustness of our results to outlier treatment – motivated by the presence of extreme observations addressed in Section 3.4 – we re-estimate all models using a more conservative winsorization at the 5th and 95th percentiles. The additional robustness tests are reported in Tables 13, 14, 15 (see Appendix), and remain consistent across all three model specifications. We conclude that our findings are robust to alternative methods of handling outliers.

Table 7: Separate DiD estimates of post-filing turnover by firm size.
This table reports DiD regressions estimating the effect of patent filing on firm turnover per Equations 4a and 4b. SMEs and large firms are split into separate samples prior to estimation. Coefficients represent differences between non-granted filers (treatment) and non-filers (control) with year -1 as the reference year. Estimates are reported for years 0 to 4 post-filing. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. All variables are winsorized at the 1st and 99th percentiles. Turnover is reported in Thousands of SEK. Variable definitions are provided in Table 11.

	Dependent variable: Turnover	
	Large	SME
	(1)	(2)
Filing : Year 0	-25,358.20	-115.02
	(36,297.82)	(1,323.81)
Filing : Year 1	41,932.39	-424.74
	(67,567.75)	(1,783.51)
Filing : Year 2	-6,630.08	-533.03
	(90,551.77)	(2,627.96)
Filing : Year 3	225,257.50	512.99
	(208,779.52)	(3,014.27)
Filing : Year 4	285,267.45	3,541.66
	(225,205.58)	(3,508.41)
Cash Flow/Assets	-82,917.53	231.72
	(141,109.25)	(274.06)
Debt/Assets	-213,351.29	690.07***
	(288,420.51)	(108.23)
log(Assets)	641,985.78***	22,154.28***
	(154,611.91)	(3,539.48)
log(Age)	529,097.63	17,223.77***
	(418,062.71)	(6,070.70)
Observations	612	4,698
N. of groups	67	520
R^2	0.31	0.17
Residual Std. Error	323,089.12 (df=533)	11,973.80 (df=4166)
F Statistic	19.84*** (df=79; 533)	71.88*** (df=532; 4166)
Note:		*p<0.1; **p<0.05; ***p<0.01

4.2 Patent Granting and Firm Performance

To assess the impact of granting, we define the treatment group as granted filers and the control group as non-granted filers. Similar to Section 4.1, we visually inspect the parallel trends assumption using Figure 4. In the pre-treatment period, we find the trends to be reasonably aligned for turnover and turnover growth, supporting the validity of the DiD methodology. Although the alignment is weaker for ROE and ROE growth, the pre-treatment trajectories are not substantially divergent from two years prior to treatment onward, suggesting an acceptable level of comparability. Combined with our two-step control selection process outlined in Section 3.3, we suggest that the treated and control groups are sufficiently similar in the pre-treatment period to justify the DiD approach in this context.

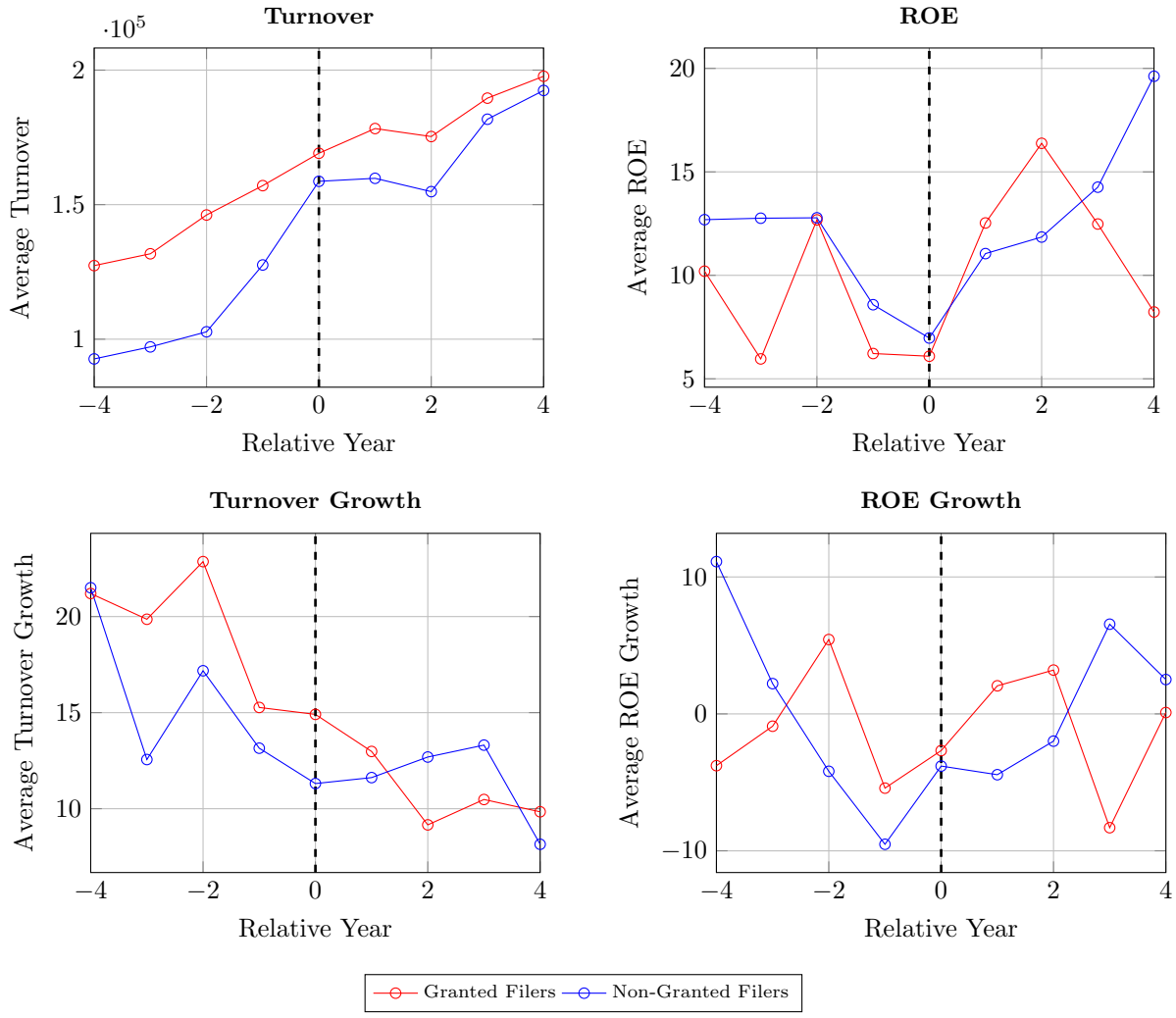


Figure 4: Pre- and post-granting outcome trends for treatment and control groups. This figure shows average yearly values of firm outcomes between ±4 years to treatment. Trends are compared between granted filers (treatment) and non-granted filers (control). Visual inspection suggests the parallel trends assumption is reasonably satisfied. Variable definitions are provided in Table 11.

Table 8 reports the average effect of patent granting on firm performance aggregated across all firms (per Equation 1). The results show mixed but statistically insignificant effects across all three performance proxies. For instance, in the second year following patent grant, firms exhibit an increase in ROE of 10.46 pp compared to non-granted firms, while turnover growth declined by 5.09 pp. Although these signals point in opposite directions, both estimates are statistically insignificant given their standard errors. Overall, these findings suggest that patent granting has no meaningful impact on firm performance at the aggregate level.

Table 8: DiD estimates of post-granting performance on all firms.
This table reports DiD regressions estimating the effect of patent granting on firm performance, per Equation 1. Coefficients represent differences between granted filers (treatment) and non-granted filers (control) with year -1 as the reference year. Estimates are reported for years 0 to 4 post-granting. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. All variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Table 11.

	Dependent variable:		
	Turnover Growth	ROE	ROE Growth
	(1)	(2)	(3)
Granting: Year 0	2.262	–3.735	–2.645
	(6.061)	(7.109)	(14.293)
Granting: Year 1	–0.096	0.415	2.520
	(5.100)	(9.502)	(14.604)
Granting: Year 2	–5.077	10.456	7.413
	(5.414)	(7.875)	(14.317)
Granting: Year 3	0.103	–0.736	–21.373
	(6.263)	(8.922)	(14.384)
Granting: Year 4	2.676	–7.145	–3.781
	(6.504)	(8.817)	(14.024)
Cash Flow/Assets	0.235	2.653***	1.157
	(0.328)	(1.679)	(0.773)
log(Age)	–48.231***	8.429	0.932
	(8.786)	(15.924)	(20.065)
log(Assets)	17.268***	19.820***	15.258***
	(5.566)	(5.874)	(5.864)
Debt/Assets	0.476	8.267***	9.127*
	(0.782)	(2.576)	(5.203)
Observations	4,986	4,986	4,986
N. of groups	453	453	453
R^2	0.022	0.018	0.004
Residual Std. Error	10.947 (df = 4,521)	14.000 (df = 4,521)	13.009 (df = 4,521)
F Statistic	8.602*** (df = 465; 4521)	6.799*** (df = 465; 4521)	1.669* (df = 465; 4521)
Note:			*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 9 presents the results of the triple-difference regression (per Equation 2), showing the heterogeneous impact of granted patents by firm size. Separate outcome trends for both SMEs and large firms are shown in Figure 9 (see Appendix) to further support the parallel trends assumption. While SMEs show no significant effects following patent granting on any performance measure, large firms exhibit clear signs of negative profitability effects. Specifically, ROE for large firms decrease significantly by 15.79 pp, 14.29 pp, 16.11 pp, and 33.61 pp from year 1 to year 4 after granting, with year 1 and 4 effects being strongly significant at the 1% level. Similarly, ROE growth declines by 30.13 pp and 29.22 pp in years 1 and 4, respectively, compared to non-granted large firms. Interestingly, we find that SMEs significantly outperform large firms post-granting. Two years after granting, SMEs report an average ROE 25.89 pp higher than large firms, and a weakly significant but positive difference of 27.71 pp in year 4. Furthermore, in terms of ROE growth, granted SMEs outperform granted large firms by 34.17 pp in year 1. All three interaction estimates are statistically significant. These findings indicate that while SMEs may not benefit significantly on their own, according to the three performance proxies, they still perform relatively better than large firms in terms of profitability after obtaining a patent grant.

Table 9: Triple-difference (DDD) estimates of post-granting performance by firm size. This table reports DDD regressions estimating the effect of patent granting on firm performance by firm size, per Equation 2. Baseline coefficients represent the granting effect for large firms, measured as differences between non-granted filers (treatment) and non-filers (control), with year -1 as the reference year. Interaction terms capture the additional effect for SMEs; the total SME effect is computed separately by summing baseline and interaction terms per Section 3.2. Estimates are reported for years 0 to 4 post-granting. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. All variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Table 11.

	Dependent variable:		
	Turnover Growth (1)	ROE (2)	ROE Growth (3)
Granting Effect for Large Firms (Baseline)			
Large Granting: Year 0	67.679	8.349	7.202
	(62.087)	(9.749)	(12.826)
Large Granting: Year 1	−1.258	−15.701**	−30.133***
	(9.854)	(6.200)	(10.846)
Large Granting: Year 2	−9.139	−14.291*	−6.065
	(12.432)	(7.780)	(7.226)
Large Granting: Year 3	−1.139	−16.112*	−9.222
	(14.760)	(9.040)	(9.680)
Large Granting: Year 4	−11.032	−33.613***	−29.219**
	(16.298)	(12.111)	(12.226)
Additional Granting Effect for SMEs (Interaction)			
Interaction: Year 0	−68.335	−12.621	−10.270
	(62.321)	(12.267)	(19.699)
Interaction: Year 1	1.289	16.862	34.174*
	(11.035)	(11.434)	(18.554)
Interaction: Year 2	4.358	25.894**	14.151
	(13.374)	(10.759)	(16.151)
Interaction: Year 3	1.443	16.107	−12.621
	(15.739)	(12.221)	(17.219)
Interaction: Year 4	14.521	27.712*	26.692
	(17.189)	(14.227)	(17.867)
Total Granting Effect for SMEs (Baseline + Interaction)			
SME Granting: Year 0	−0.656	−4.272	−3.068
	(5.607)	(7.424)	(14.946)
SME Granting: Year 1	0.031	1.162	4.041
	(5.307)	(9.923)	(15.260)
SME Granting: Year 2	−4.781	11.602	8.085
	(6.100)	(7.670)	(16.501)
SME Granting: Year 3	0.304	−0.006	−21.843
	(6.483)	(9.290)	(15.017)
SME Granting: Year 4	3.489	−5.900	−2.527
	(6.717)	(9.146)	(14.604)
Control Variables			
Cash Flow/Assets	0.232	2.651	1.152***
	(0.328)	(1.682)	(0.775)
log(Age)	−49.116***	8.196	0.557
	(8.705)	(15.982)	(20.138)
log(Assets)	17.513***	19.901***	15.293***
	(5.532)	(5.892)	(5.875)
Debt/Assets	0.508	8.279***	9.143*
	(0.779)	(2.574)	(5.201)
Observations	5,274	5,274	5,274
N. of groups	583	583	583
R^2	0.028	0.018	0.005
Residual Std. Error	12.233 (df=4,512)	14.135 (df=4,512)	13.237 (df=4,512)
F Statistic	6.148***	3.946***	0.984
Note:			*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 10 evaluates the impact of patent granting on absolute turnover, estimated separately for SMEs and large firms (per Equation 4a and 4b). We find a positive effect for SMEs, with an increase of 6 MSEK one year post-granting, and a strongly significant increase of 11.6 MSEK four years after granting. While the increase of 6 MSEK is only marginally significant at the 10% level, the overall results suggest a lagged but economically meaningful sales improvement for SMEs post-grant. For large firms, while the coefficients are positive and larger in magnitude than for SMEs, none of the estimates are statistically significant when compared to non-granted large firms.

All regressions include firm fixed effects and firm-level clustered standard errors. Outcome variables are winsorized at the 1st and 99th percentiles. Furthermore, we conduct a robustness check on our results by re-estimating all models using a more conservative winsorization at the 5th and 95th percentiles. These results are reported in Tables 16, 17, 18 (see Appendix) and remain consistent with our findings. Notably, Table 18 reports an additional sales increase of 4.41 MSEK for SMEs three years after the patent grant, which — despite being slightly smaller than the 6–11 MSEK observed in our main model — further supporting the interpretation of a sustained and positive effect of patent granting on SME turnover. Overall, we conclude that our results are robust to alternative treatments of outliers across all three model specifications.

Table 10: Separate DiD estimates of post-granting turnover by firm size.
This table reports DiD regressions estimating the effect of patent granting on firm revenue per Equations 4a and 4b. SMEs and large firms are split into separate samples prior to estimation. Coefficients represent differences between granted filers (treatment) and non-granted filers (control) with year -1 as the reference year. Estimates are reported for years 0 to 4 post-granting. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. All variables are winsorized at the 1st and 99th percentiles. Turnover is reported in Thousands of SEK. Variable definitions are provided in Table 11.

	Dependent variable: Turnover	
	Large	SME
	(1)	(2)
Granting : Year 0	347,613.04	1,456.27
	(223,101.13)	(1,423.77)
Granting : Year 1	280,586.78	6,006.01*
	(266,264.00)	(3,184.48)
Granting : Year 2	17,086.19	5,704.57
	(137,383.00)	(3,832.38)
Granting : Year 3	221,761.66	6,735.33
	(217,463.30)	(4,101.88)
Granting : Year 4	340,807.30	11,601.84**
	(349,690.81)	(4,616.56)
Cash Flow/Assets	253,294.11	1,055.30***
	(392,147.01)	(394.38)
Debt/Assets	1,041,642.27**	2,640.11***
	(477,007.89)	(911.77)
log(Assets)	-135,841.29	44,145.86***
	(442,560.91)	(7,603.87)
log(Age)	1,949,548.15*	-6,433.87
	(1,175,578.87)	(8,651.28)
Observations	216	4,770
N. of groups	24	431
R^2	0.078	0.286
Residual Std. Error	420,735.23 (df=180)	23,411.93 (df=4327)
F Statistic	1.27 (df=36; 180)	144.71*** (df=443; 4327)
Note:		*p<0.1; **p<0.05; ***p<0.01

5 Discussion

The findings from our analyses of patent filing and patent granting shed light on how different stages of the patenting process affect firm performance in the Swedish context. Overall, our results diverge significantly from those of Taglialatela and Barontini (2024), both in terms of direction and magnitude of the observed effects.

Tables 5, 6, and 7 examine the effects of patent filing on Swedish firms, both in aggregate and by firm size. As shown in Table 5, filing is associated with a significant decline in turnover growth at the aggregate level. When disaggregated by firm size using the DDD estimates in Table 6, we observe that this negative effect persists for both SMEs and large firms, with declines in turnover growth observed up to two years post-filing. These results contradict those of Taglialatela and Barontini (2024), who report that Italian SMEs experienced moderate gains in turnover growth following patent filing — 3.5 percentage points in the first year and 2.8 percentage points in the second — attributing the effect to knowledge stock gains triggered by the filing process as seen in Figure 5. While both studies find no significant impact on profitability measures such as ROE or ROE growth, our findings suggest that Swedish firms do not benefit from the filing stage in the same way as Italian firms, pointing to potential contextual differences in how firms derive value from early-stage patent activity.

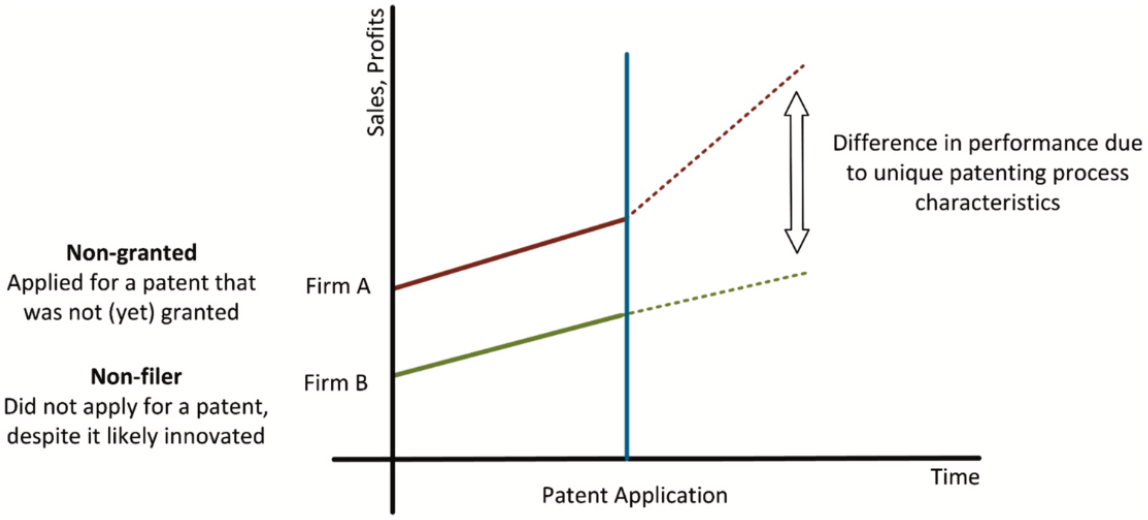


Figure 5: Hypothesis A outlined by Taglialatela and Barontini (2024).
The authors propose that patent filing – without a subsequent grant – has a positive effect on SME firm performance. They find statistically significant evidence in support, attributed to knowledge stock gains. In contrast, our results for Swedish firms show negative post-filing effects for both SMEs and large firms.

Table 8, 9, and 10 show how firms respond after being granted a patent. Our results also diverge from those of Taglialatela and Barontini (2024), albeit in a different direction. While the authors hypothesize a positive impact from granting, as illustrated in Figure 6, their results show no significant performance effect for Italian SMEs. They attribute this to SMEs' limited resources to commercialize patent rights. Implicit in this reasoning is thus the assumption that larger firms, with greater resources, should benefit more from being granted a patent.

At the aggregate level, Table 8 shows no significant post-granting effects for Swedish firms, which is consistent with the findings of Taglialatela and Barontini (2024). However, as this aggregated approach may mask firm-level differences, we use DDD estimates in Table 9 to distinguish between SMEs and large firms. The disaggregated results show a notable pattern: large firms experience significantly negative profitability effects, with substantially lower ROE growth than non-granted large firms in year one through four. Meanwhile, the interaction terms show that SMEs outperform large firms in relative terms. However, these relative differences are mainly driven by the under performance of large firms post-granting, as SMEs themselves exhibit no statistically significant profitability gains. Taglialatela and Barontini (2024) also report no meaningful benefits for SMEs, with ROE increases of 0.9 pp in year two being statistically insignificant. In terms of absolute turnover, however, Table 10 shows that granted SMEs did experience significant gains of 6 MSEK in year one and 11.6 MSEK in year four, relative to non-granted SMEs. Large firms, in contrast, experience no significant effects. These findings

further contradict those of Taglialatela and Barontini (2024), who argue that SMEs lack the resources to benefit from patent grants. Our results suggest that Swedish SMEs achieve tangible revenue gains in the short to medium term, consistent with prior evidence from studies such as Farre-Mensa et al. (2020). Meanwhile, large firms – despite having greater resources – fail to convert grants into financial returns, which challenges the assumption that greater firm size is linked to greater appropriation of patent returns.

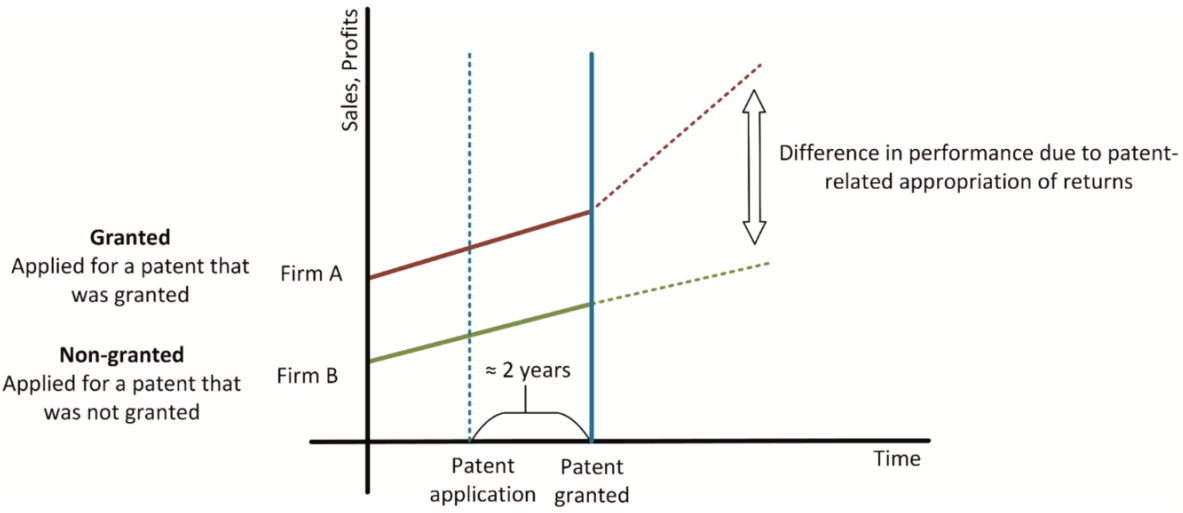


Figure 6: Hypothesis B outlined by Taglialatela and Barontini (2024).
The authors propose that patent granting has a positive effect on SME firm performance. However, they find no statistically significant evidence in support, attributed to SMEs' lack of resources. In contrast, our results for Swedish firms show positive post-granting effects for SMEs and negative effects for large firms.

A key divergence between our findings and those of Taglialatela and Barontini (2024) lies in the effect of filing a patent without securing a grant. While their study – focused on Italian SMEs between 2005-2010 – suggests that the patenting process itself strengthens firms' knowledge stocks through learning activities that translate into financial returns, we do not observe similar benefits among Swedish firms. A possible explanation for this divergence lies in differences in institutional R&D support, with prior work by Kogan et al. (2017) underscoring the importance of R&D tax credit regimes in shaping firm-level innovation outcomes. In Italy, profitable SMEs during 2005-2010 received an average implied R&D tax subsidy of 4.7%, while Swedish firms during 2010-2019 operated under a flatter and less generous R&D support system, with an average implied tax subsidy of 2.6% (Organisation for Economic Co-operation and Development, 2024). Given that the patenting process can be costly – with filing and search fees alone amounting to at least €1,655 (European Patent Office, 2024) – such institutional support plays a critical role in shaping whether filing in itself leads to knowledge gains or instead imposes a financial burden on the firm. Policy differences point to the fact that Italian SMEs were better positioned to absorb costs and derive internal benefits from the act of filing a patent, as proposed by Taglialatela and Barontini (2024). In Sweden, however, lesser fiscal support likely rendered the filing process – without the corresponding benefit of granted monopoly rights – more burdensome and less conducive to positive firm outcomes. The negative effects we observe are largely short-term, concentrated within the first two years post-filing and limited to turnover growth. We suggest that in the absence of sufficient policy support, the initial costs of filing may strain firm resources without generating immediate returns, whereas stronger incentives — such as those in Italy — can help firms better absorb these costs and potentially translate filing efforts into future performance gains.

A second key contrast in our findings concerns the effect of patent granting on SMEs. While Taglialatela and Barontini (2024) find no significant benefits for Italian SMEs from granted patents – arguing that SMEs lack resources to enforce patent rights – we observe the opposite for Swedish SMEs. Specifically, SMEs in Sweden with granted patents earn 6 MSEK more in revenue one year post-granting, and 11 MSEK more by year four, compared to non-granted SMEs. Unlike filing, patent grants confer enforceable legal rights that open channels such as licensing, collateralization, and external signaling — mechanisms that extend beyond the internal knowledge gains associated with filing. To explore a possible

explanation, we thus draw on Farre-Mensa et al. (2020), who show that granted patents can serve as valuable signals to investors and improve access to external capital, particularly for smaller firms. While our study does not directly examine external financing, we suggest that such a signaling and financing channel may be stronger in Sweden than in Italy. The European Central Bank (2025) highlights Sweden's capital market as one of the most developed in Europe, marked by strong IPO and VC activity, while Swedish Intellectual Property Office (2025) undescores the nation's robust legal framework for leveraging IP through collateral, licensing, and other financial channels. Although Sweden's flatter R&D tax credit regime may reduce the internal benefits associated with filing, the broader financial ecosystem appears more conducive to translating granted patents into external value. By contrast, data from the Bank of Italy (2025) indicate that Italy's VC ecosystem remains significantly underdeveloped. Between 2021 and 2023, total VC investment in Italy was only 20% of that in comparable EU countries, and just 3% of VC exits occurred via IPOs. Institutional investor participation is limited, and major public support initiatives for VC only began in 2019 – well after Taglialatela and Barontini's (2024) study period. These structural differences constitute one plausible explanation for why granted patents may carry greater signaling value in Swedish capital markets, making them more financially consequential for Swedish SMEs compared to their Italian counterparts. We suggest that the more developed markets in Sweden may explain the lagged revenue effects observed among SMEs — with the larger and more statistically significant gains in year four pointing to medium-term impacts likely driven by commercialization and financing opportunities that materialize over time, rather than immediate signaling alone.

However, while the aforementioned factors help explain why Swedish SMEs may benefit more from granted patents than Italian SMEs, they do not account for an additional finding: that large firms in Sweden not only underperform relative to SMEs after receiving a patent grant, but also underperform relative to other non-granted large firms. Firstly, we challenge Taglialatela and Barontini's (2024) implicit assumption that firm size and greater resources lead to greater appropriation of patent-related returns. A possible explanation is that a majority of large firms pursue patenting for primarily defensive and commercially vague purposes, such as litigation deterrence or portfolio expansion, which may not translate directly into commercial performance gains (Lemley & Shapiro, 2005). Such strategies can even introduce additional costs and legal burdens post-grant. This may furthermore explain why large firms show negative effects on ROE measures rather than on turnover — as administrative costs tied to patent maintenance can depress profit margins without affecting top-line revenue. In contrast, SMEs have been found to patent less frequently than large firms but derive relatively higher commercial value through licensing, external financing, or signaling to investors (Acs & Audretsch, 1988; European Patent Office, 2017; Hughes, 2010). To further understand why granted patents appear detrimental for large firms, we also consider potential sample biases. For example, our 3-year separation rule excludes frequent filers like Ericsson and AstraZeneca as outlined in Table 2. It is reasonable to assume this exclusion skews the large-firm sample toward potentially less innovative firms who are less experienced with leveraging granted patents. This issue is less pronounced for innovative SMEs, however, who file fewer patents and are thus less affected by the 3-year separation rule in relation to their larger counterparts. Additionally, the granted large-firm treatment group is small (n = 12), which limits statistical power and increases the risk of estimation noise. Although the limited sample size reflects our decision to uphold a strict identification strategy in line with Taglialatela and Barontini (2024), it may introduce sampling bias. While the internal validity of our methodology is robust, these limitations should be kept in mind when interpreting the granting effect for large firms.

6 Conclusion

In conclusion, we find that the economic impact of patenting varies by both firm size and the stage of the patenting process. Our results show that filing a patent — without securing a grant— is associated with short-term negative effects on turnover growth among Swedish firms. In contrast, granted patents are linked to significant revenue gains for Swedish SMEs, while large firms experience no such benefit and in some cases exhibit negative effects on profitability.

Building on the work of Taglialatela and Barontini (2024), we replicate and extend their identification strategy by applying it to a new context: Swedish firms with patent applications filed between 2010 and 2019. Using a staggered difference-in-differences approach extended into a triple-difference model, we go beyond the original study by comparing effects both within and across SMEs and large firms, while implementing a stricter control group selection process to improve causal inference. This enables us to evaluate not only the original hypotheses regarding SMEs and patenting, but also the broader implicit assumption that larger firms are more likely to benefit from patent protection.

Our results challenge both claims. Swedish SMEs show no benefit from filing alone, but do benefit significantly from granted patents. Meanwhile, larger firms neither gain from grants nor filings, and may even experience adverse profitability effects. Ultimately, our findings highlight the importance of firm-specific characteristics in determining innovation outcomes, and emphasize how institutional and financial contexts — such as R&D policy and capital market conditions — shape the returns to intellectual property.

Appendix A: Additional Results

Table 11: Variable definitions.
This table defines the variables used in the treatment-control matching processes and econometric estimations, in line with Taglialatela and Barontini (2024).

Variable	Description
First Step Matching Variables	
Industry	Based on SNI classification at 4-digit, 3-digit, and 2-digit levels.
Turnover	Annual sales for the corresponding year.
Age	Company age, determined by year of foundation.
Second Step Matching Variables (PSM)	
Size	Logarithm of total assets, proxy for firm size.
Cash Flow	Proxied by (EBIT + Depreciation – ΔWorking Capital) divided by total assets.
Capital Intensity	Fixed assets divided by total assets.
Leverage	Total debt divided by total assets.
Age	Logarithm of firm age.
Outcome Variables	
Turnover	Annual sales in SEK thousands.
Turnover Growth	Percentage change in turnover compared to previous year.
Return on Equity (ROE)	Net income divided by previous year's equity.
ROE Growth	Absolute percentage-point change in ROE compared to previous year.

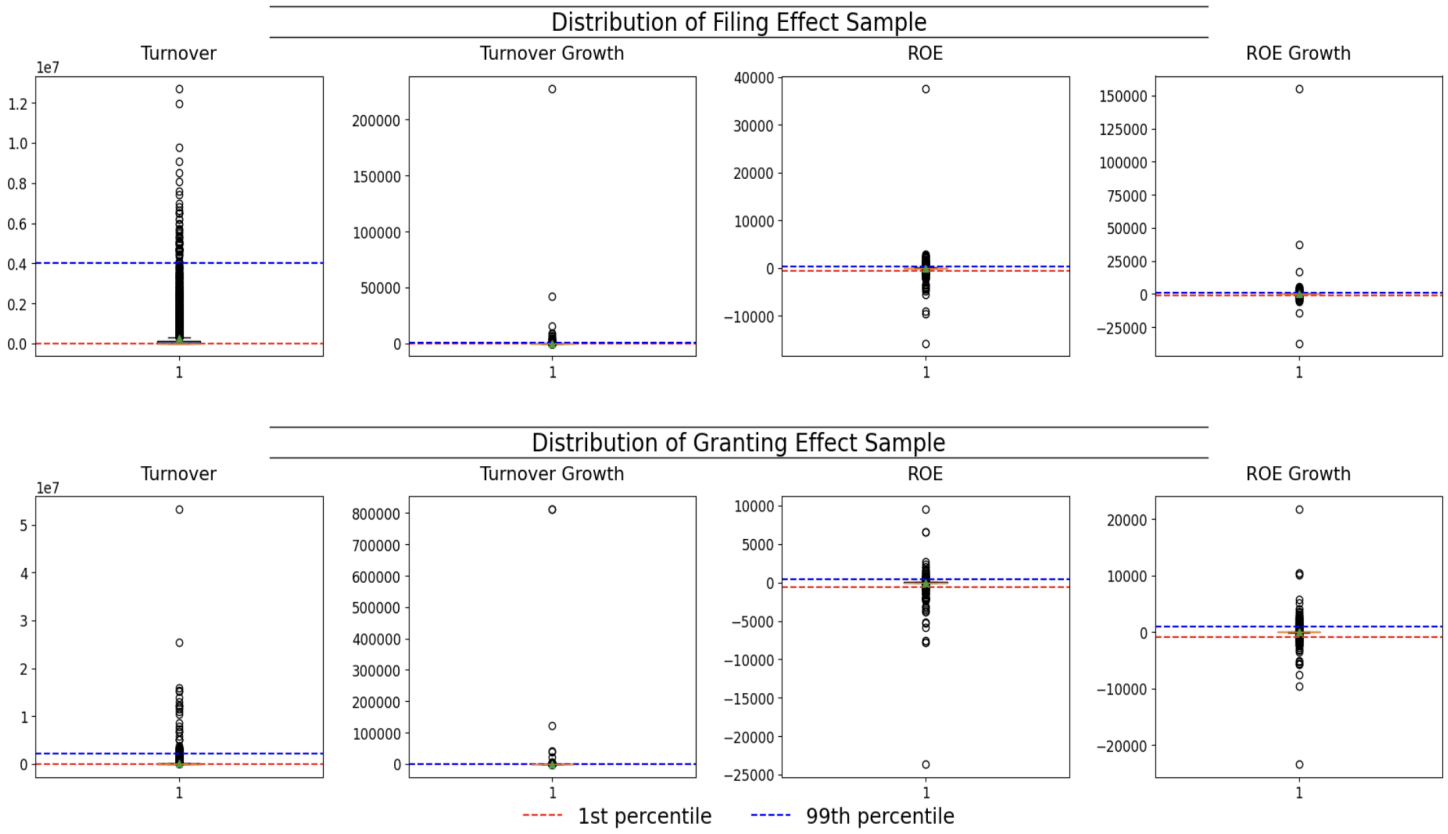


Figure 7: Distributions of outcome variables.
This figure show the box plot distributions of outcome variables across the filing and granting analyses. The samples include both treatment and control firms. Horizontal lines in each box represent the 1st and 99th percentile thresholds used for winsorization.

Table 12: Summary statistics by firm size.
This table reports yearly average values for outcome and control variables from year –4 to +4 relative to the treatment year, disaggregated by firm size. Panels A and B present firms used in the filing analysis split into SMEs and large firms, respectively. Panels C and D present firms used in the granting analysis split into SMEs and large firms, respectively. Variable definitions are provided in Table 11. Turnover and Assets are measured in SEK thousands.

(a) Filing Effect: All SMEs

Years To Treatment	Turnover	Turnover Growth	ROE	ROE Growth	Age	Assets	CF/Assets	FA/Assets	Debt/Assets
Year –4	51,191.81	430.47	0.68	–17.77	17.62	36,206.45	0.05	0.29	0.60
Year –3	54,717.05	1,564.08	–8.49	–9.18	18.62	39,315.10	0.06	0.29	0.60
Year –2	58,842.39	1,562.11	–41.34	–32.85	19.62	42,728.70	0.07	0.29	0.59
Year –1	62,113.48	22.02	–12.75	28.59	20.62	45,132.08	0.05	0.28	0.59
Year 0	64,526.40	16.04	–1.82	10.94	21.62	47,954.56	0.05	0.28	0.59
Year 1	72,896.42	56.80	–0.12	1.70	22.62	56,729.57	0.06	0.28	0.58
Year 2	83,967.78	19.84	8.25	8.37	23.62	75,378.56	0.09	0.28	0.59
Year 3	98,760.95	34.03	–10.46	–18.71	24.62	95,796.01	0.07	0.26	0.57
Year 4	117,829.66	19.78	31.65	42.12	25.62	107,913.97	0.35	0.27	0.68

(b) Filing Effect: All Large Firms

Years To Treatment	Turnover	Turnover Growth	ROE	ROE Growth	Age	Assets	CF/Assets	FA/Assets	Debt/Assets
Year –4	1,414,858.33	3.92	11.84	–0.20	35.46	4,191,165.54	0.05	0.46	0.58
Year –3	1,448,214.58	61.60	14.60	2.76	36.46	4,976,996.38	0.10	0.46	0.58
Year –2	1,587,349.04	114.13	18.41	3.81	37.46	3,938,620.46	0.09	0.44	0.62
Year –1	1,941,133.29	32.32	21.81	3.40	38.46	3,884,418.08	0.03	0.41	0.59
Year 0	2,470,154.83	84.33	42.94	21.13	39.46	4,020,867.50	0.06	0.39	0.58
Year 1	2,504,225.88	4.73	15.10	–27.83	40.46	3,769,853.25	0.12	0.41	0.61
Year 2	2,237,793.50	–1.82	13.91	–1.19	41.46	3,572,584.04	0.05	0.41	0.60
Year 3	3,145,430.75	22.00	9.57	–4.34	42.46	4,054,850.83	0.10	0.42	0.61
Year 4	4,487,701.46	9.34	5.75	–3.82	43.46	4,302,489.42	0.09	0.43	0.62

(c) Granting Effect: All SMEs

Years To Treatment	Turnover	Turnover Growth	ROE	ROE Growth	Age	Assets	CF/Assets	FA/Assets	Debt/Assets
Year –4	53,328.76	129.61	13.10	–8.01	19.48	55,439.02	0.09	0.34	0.60
Year –3	54,724.09	34.49	–5.28	–18.39	20.48	57,222.41	0.08	0.33	0.59
Year –2	56,745.08	50.64	65.28	70.56	21.48	55,852.74	0.08	0.34	0.58
Year –1	60,486.43	28.45	–14.90	–80.18	22.48	58,696.07	0.10	0.35	0.58
Year 0	63,423.23	469.69	19.64	34.54	23.48	69,726.85	0.07	0.35	0.57
Year 1	64,897.56	23.72	–17.16	–36.80	24.48	76,358.40	0.09	0.35	0.57
Year 2	67,962.00	15.84	20.94	38.10	25.48	82,926.16	0.06	0.35	0.55
Year 3	73,199.27	22.57	20.49	–0.45	26.48	99,037.46	0.23	0.34	0.54
Year 4	80,836.03	8.73	14.28	–6.22	27.48	110,780.20	0.23	0.33	0.54

(d) Granting Effect: All Large Firms

Years To Treatment	Turnover	Turnover Growth	ROE	ROE Growth	Age	Assets	CF/Assets	FA/Assets	Debt/Assets
Year –4	1,471,869.68	8.97	48.47	2,391.99	40.17	2,352,933.41	0.08	0.45	0.61
Year –3	1,462,476.39	4.32	14.48	–33.99	41.17	2,365,080.65	0.08	0.45	0.63
Year –2	1,544,418.73	18.39	29.73	15.25	42.17	2,390,913.76	0.07	0.44	0.63
Year –1	1,664,820.64	244.87	59.51	29.78	43.17	2,491,523.85	0.08	0.44	0.63
Year 0	1,716,969.68	5.65	15.00	–44.52	44.17	2,499,684.50	0.11	0.44	0.63
Year 1	1,871,409.74	9.65	19.22	4.23	45.17	2,800,910.74	0.09	0.45	0.61
Year 2	1,916,196.32	2.53	18.26	–0.96	46.17	2,564,841.26	0.07	0.44	0.61
Year 3	2,121,983.50	16.05	15.21	–3.04	47.17	2,564,737.20	0.15	0.46	0.62
Year 4	2,352,590.53	8.09	10.71	–4.50	48.17	2,715,851.41	0.12	0.44	0.65

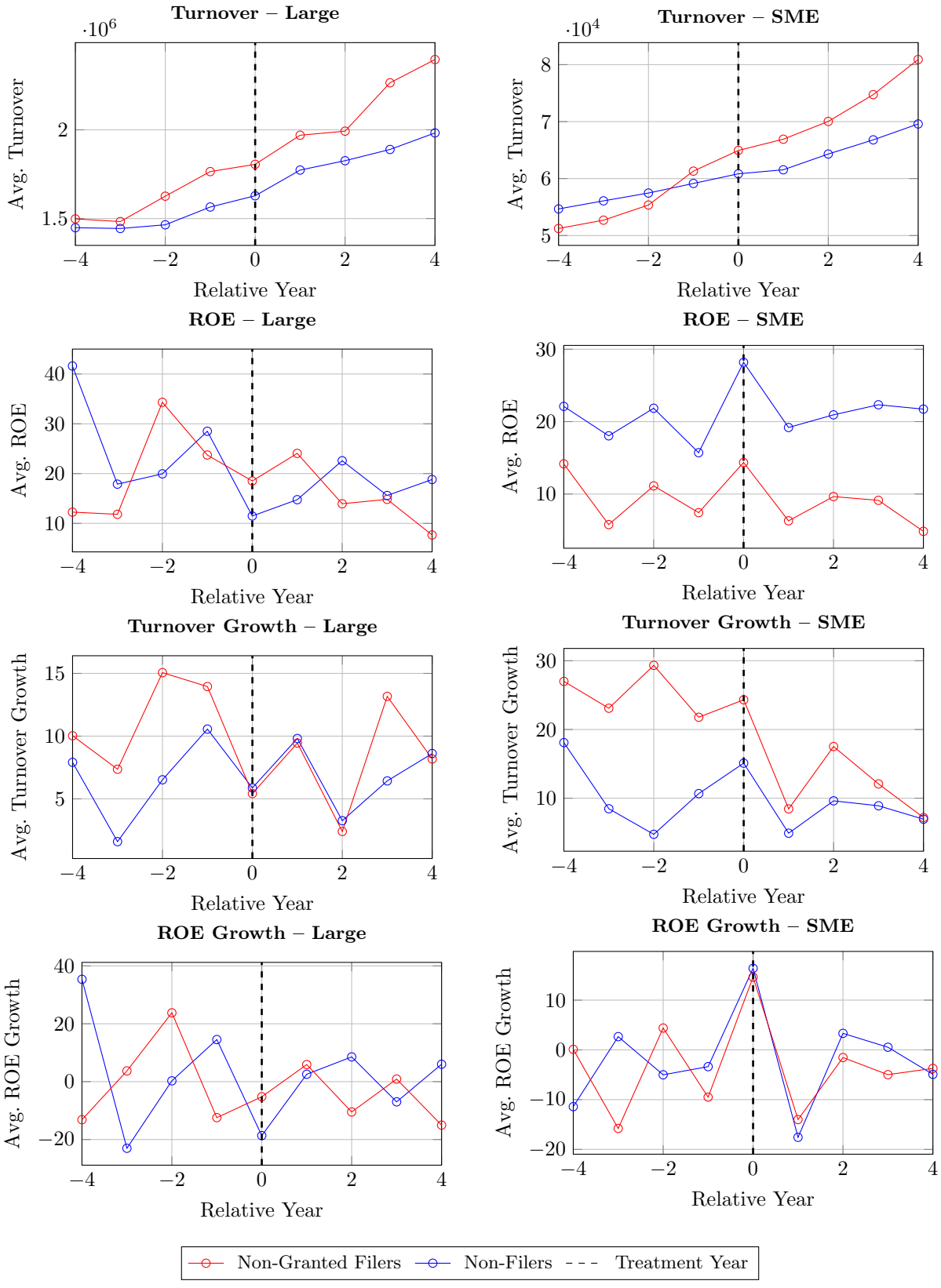


Figure 8: Pre- and post-filing outcome trends by firm size.
This figure shows average yearly values of firm outcomes between ±4 years to treatment, separately for SMEs and large firms. Trends are compared between non-granted filers (treatment) and non-filers (control). Visual inspection suggests the parallel trends assumption is reasonably satisfied. Variable definitions are provided in Table 11.

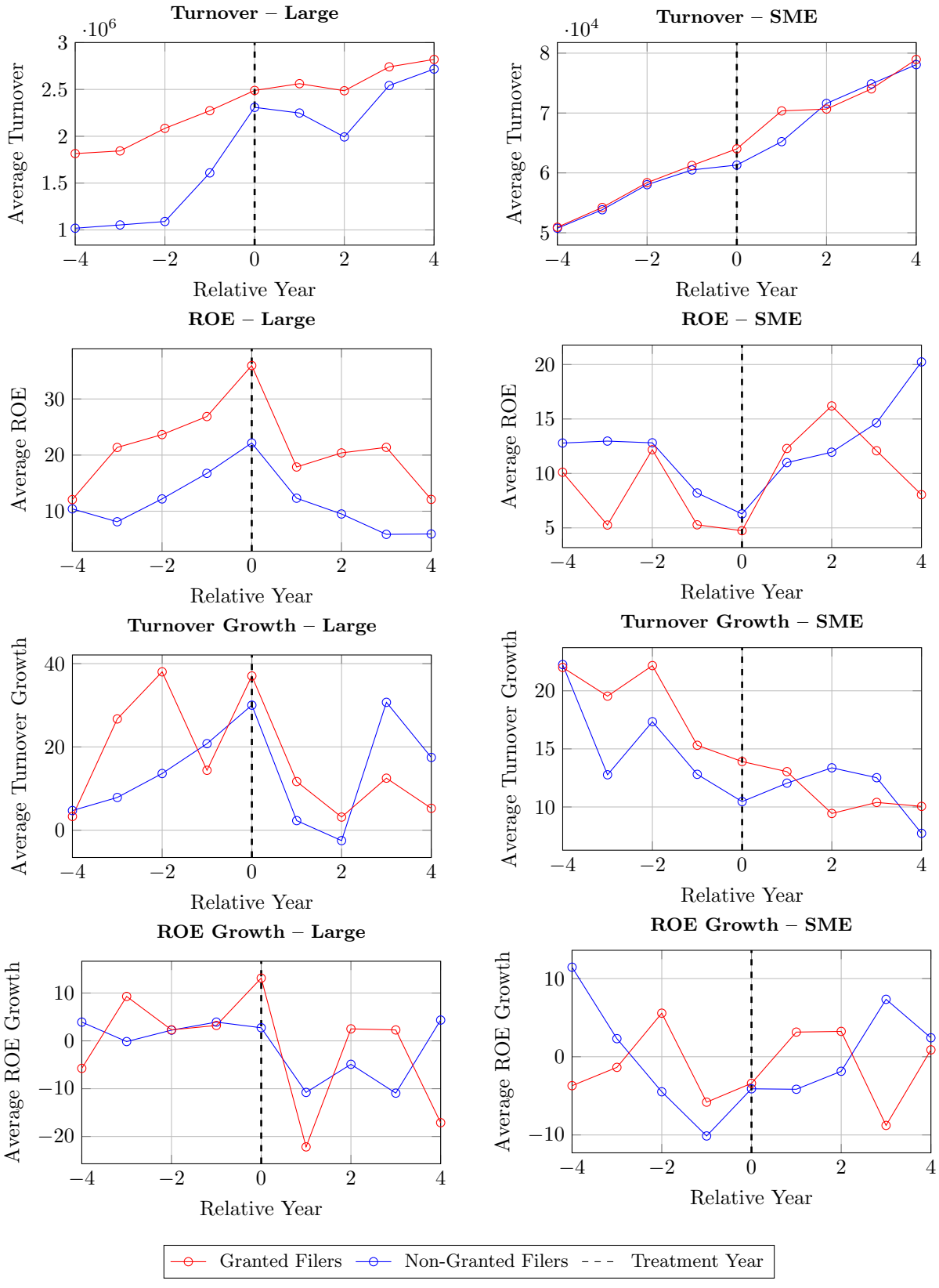


Figure 9: Pre- and post-granting outcome trends by firm size.
This figure shows average yearly values of firm outcomes between ±4 years to treatment, separately for SMEs and large firms. Trends are compared between granted filers (treatment) and non-granted filers (control). Visual inspection suggests the parallel trends assumption is reasonably satisfied. Variable definitions are provided in Table 11.

Table 13: Robustness test on DiD estimates of post-filing performance on all firms.
This table reports DiD regressions estimating the effect of patent filing on firm performance, per Equation 1. As a robustness check, all variables are winsorized at the 5th and 95th percentiles instead of the 1st and 99th percentiles. Coefficients represent differences between non-granted filers (treatment) and non-filers (control) with year -1 as the reference year. Estimates are reported for years 0 to 4 post-filing. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. Variable definitions are provided in Table 11.

	Dependent variable:		
	Turnover Growth	ROE	ROE Growth
	(1)	(2)	(3)
Filing : Year 0	–4.771	–0.517	6.436
	(3.042)	(2.667)	(5.711)
Filing : Year 1	–8.234***	–3.255	–0.320
	(3.097)	(2.960)	(4.945)
Filing : Year 2	–4.381	–3.718	2.824
	(2.805)	(2.932)	(4.881)
Filing : Year 3	–4.930	–3.016	2.414
	(3.083)	(3.151)	(5.064)
Filing : Year 4	–6.026*	–0.041	5.316
	(3.137)	(3.216)	(4.593)
Cash Flow/Assets	–0.003	–0.391	–2.282***
	(0.144)	(0.268)	(0.177)
log(Age)	–24.547***	–20.849***	–1.195
	(3.852)	(5.646)	(5.146)
log(Assets)	11.030***	12.586***	3.343**
	(1.512)	(1.839)	(1.648)
Debt/Assets	1.977	–38.653***	–30.091***
	(4.127)	(6.860)	(7.249)
Observations	5,274	5,274	5,274
N. of groups	583	583	583
R^2	0.031	0.063	0.013
Residual Std. Error	6.041 (df=4,679)	8.451 (df=4,679)	6.380 (df=4,679)
F Statistic	12.504*** (df=595; 4679)	26.061*** (df=595; 4679)	5.192*** (df=595; 4679)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 14: Robustness test on triple-differences (DDD) estimates of post-filing performance by firm size.

This table reports DDD regressions estimating the effect of patent filing on firm performance by firm size, per Equation 2. As a robustness check, all variables are winsorized at the 5th and 95th percentiles instead of the 1st and 99th percentiles. Baseline coefficients represent the filing effect for large firms, measured as differences between non-granted filers (treatment) and non-filers (control), with year -1 as the reference year. Interaction terms capture the additional effect for SMEs; the total SME effect is computed separately by summing baseline and interaction terms per Section 3.2. Estimates are reported for years 0 to 4 post-filing. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. Variable definitions are provided in Table 11.

	Dependent variable:		
	Turnover Growth (1)	ROE (2)	ROE Growth (3)
Filing Effect for Large Firms (Baseline)			
Large Filing : Year 0	-7.057**	-1.319	2.513
	(3.140)	(3.165)	(9.199)
Large Filing : Year 1	-5.827	-1.044	3.803
	(3.582)	(5.722)	(8.215)
Large Filing : Year 2	-9.943***	-6.915	-2.038
	(3.853)	(5.707)	(9.505)
Large Filing : Year 3	-3.233	-3.347	3.888
	(3.348)	(6.700)	(8.361)
Large Filing : Year 4	-3.051	-5.866	-2.753
	(4.114)	(6.589)	(7.800)
Additional Filing Effect for SMEs (Interaction)			
Interaction : Year 0	2.573	0.894	4.424
	(4.616)	(4.323)	(11.149)
Interaction : Year 1	-2.718	-2.511	-4.640
	(4.942)	(6.527)	(9.836)
Interaction : Year 2	6.258	3.574	5.489
	(4.899)	(6.474)	(10.873)
Interaction : Year 3	-1.924	0.337	-1.649
	(4.694)	(7.414)	(9.947)
Interaction : Year 4	-3.367	6.519	9.109
	(5.284)	(7.383)	(9.196)
Total Filing Effect for SMEs (Baseline + Interaction)			
SME Filing : Year 0	-4.484	-0.425	6.937
	(3.405)	(2.979)	(6.329)
SME Filing : Year 1	-8.545**	-3.555	-0.837
	(3.458)	(3.252)	(5.470)
SME Filing : Year 2	-3.685	-3.341	3.451
	(3.114)	(3.216)	(5.359)
SME Filing : Year 3	-5.157	-3.010	2.239
	(3.439)	(3.430)	(5.584)
SME Filing : Year 4	-6.418*	0.653	6.356
	(3.491)	(3.523)	(5.065)
Control Variables			
Cash Flow/Assets	-0.000	-0.397	-2.289***
	(0.143)	(0.270)	(0.180)
log(Age)	-24.515***	-20.663***	-1.229
	(3.883)	(5.695)	(5.173)
log(Assets)	11.041***	12.560***	3.332**
	(1.515)	(1.842)	(1.654)
Debt/Assets	1.951	-38.629***	-30.041***
	(4.126)	(6.881)	(7.269)
Observations	5,274	5,274	5,274
N. of groups	583	583	583
R^2	0.031	0.063	0.014
Residual Std. Error	6.082 (df=4,671)	8.490 (df=4,671)	6.515 (df=4,671)
F Statistic	7.584***	15.736***	3.239***
Note:			$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 15: Robustness test on separate DiD estimates of post-filing turnover by firm size. This table reports DiD regressions estimating the effect of patent filing on firm turnover per Equations 4a and 4b. As a robustness check, all variables are winsorized at the 5th and 95th percentiles instead of the 1st and 99th percentiles. SMEs and large firms are split into separate samples prior to estimation. Coefficients represent differences between non-granted filers (treatment) and non-filers (control) with year -1 as the reference year. Estimates are reported for years 0 to 4 post-filing. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. Turnover is reported in Thousands of SEK. Variable definitions are provided in Table 11.

	Dependent variable: Turnover	
	Large	SME
	(1)	(2)
Filing : Year 0	-12,268.89	-124.61
	(33,843.17)	(1,088.48)
Filing : Year 1	54,919.45	-173.10
	(74,189.75)	(1,467.59)
Filing : Year 2	17,729.12	693.41
	(96,579.23)	(2,146.59)
Filing : Year 3	211,588.89	884.64
	(183,650.24)	(2,431.75)
Filing : Year 4	254,818.19	2,394.73
	(195,870.27)	(2,787.92)
Cash Flow/Assets	-35,997.59	606.06***
	(135,819.01)	(167.64)
Debt/Assets	-206,405.27	1,868.99
	(238,583.03)	(4,421.14)
log(Assets)	389,014.54**	20,049.43***
	(154,925.15)	(3,022.84)
log(Age)	669,624.52*	10,780.33**
	(392,776.00)	(4,735.31)
Observations	594	4,680
N. of groups	65	518
R^2	0.26	0.18
Residual Std. Error	270,936.62 (df=517)	10,409.15 (df=4150)
F Statistic	15.46*** (df=77; 517)	74.91*** (df=530; 4150)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 16: Robustness test on DiD estimates of post-granting performance on all firms. This table reports DiD regressions estimating the effect of patent granting on firm performance, per Equation 1. As a robustness check, all variables are winsorized at the 5th and 95th percentiles instead of the 1st and 99th percentiles. Coefficients represent differences between granted filers (treatment) and non-granted filers (control) with year -1 as the reference year. Estimates are reported for years 0 to 4 post-granting. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. Variable definitions are provided in Table 11.

	Dependent variable:		
	Turnover Growth	ROE	ROE Growth
	(1)	(2)	(3)
Granting : Year 0	0.998	0.253	4.422
	(3.123)	(2.788)	(6.236)
Granting : Year 1	–0.032	4.792	4.965
	(2.899)	(3.471)	(5.270)
Granting : Year 2	–1.293	4.804	2.174
	(2.885)	(3.662)	(5.689)
Granting : Year 3	0.017	2.951	–0.649
	(3.094)	(3.660)	(5.280)
Granting : Year 4	–0.601	–0.263	2.315
	(3.193)	(3.741)	(5.834)
Cash Flow/Assets	0.209*	1.123**	0.294
	(0.124)	(0.571)	(0.269)
log(Age)	–24.557***	–8.138	1.101
	(4.289)	(6.470)	(7.144)
log(Assets)	9.559***	11.461***	2.878
	(1.609)	(2.456)	(2.383)
Debt/Assets	0.190	2.740***	0.790
	(0.449)	(0.891)	(1.387)
Observations	4,986	4,986	4,986
N. of groups	453	453	453
R^2	0.025	0.022	0.001
Residual Std. Error	5.725 (df=4,521)	6.159 (df=4,521)	2.382 (df=4,521)
F Statistic	9.598*** (df=465; 4521)	8.484*** (df=465; 4521)	0.432 (df=465; 4521)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 17: Robustness test on triple-differences (DDD) estimates of post-granting performance by firm size.

This table reports DDD regressions estimating the effect of patent granting on firm performance by firm size, per Equation 2. As a robustness check, all variables are winsorized at the 5th and 95th percentiles instead of the 1st and 99th percentiles. Baseline coefficients represent the granting effect for large firms, measured as differences between granted filers (treatment) and non-granted filers (control), with year -1 as the reference year. Interaction terms capture the additional effect for SMEs; the total SME effect is computed separately by summing baseline and interaction terms per Section 3.2. Estimates are reported for years 0 to 4 post-granting. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. Variable definitions are provided in Table 11.

	Dependent variable:		
	Turnover Growth (1)	ROE (2)	ROE Growth (3)
Granting Effect for Large Firms (Baseline)			
Large Granting : Year 0	15.064	3.629	5.034
	(12.247)	(7.294)	(11.135)
Large Granting : Year 1	−1.378	−11.674**	−24.513***
	(5.588)	(5.140)	(9.452)
Large Granting : Year 2	−9.634	−9.431	−1.805
	(7.976)	(6.985)	(6.545)
Large Granting : Year 3	−1.109	−11.555*	−3.093
	(9.480)	(5.948)	(7.635)
Large Granting : Year 4	−6.403	−16.754**	−20.454**
	(10.540)	(6.698)	(10.424)
Additional Granting Effect for SMEs (Interaction)			
Interaction : Year 0	−14.700	−3.523	−0.622
	(12.650)	(7.831)	(12.888)
Interaction : Year 1	1.412	17.219***	30.845***
	(6.313)	(6.171)	(10.867)
Interaction : Year 2	8.727	14.892*	4.208
	(8.453)	(7.834)	(8.708)
Interaction : Year 3	1.187	15.178**	2.618
	(9.906)	(6.807)	(9.222)
Interaction : Year 4	6.079	17.259**	23.880**
	(10.932)	(7.406)	(11.800)
Total Granting Effect for SMEs (Baseline + Interaction)			
SME Granting : Year 0	0.364	0.106	4.412
	(3.213)	(2.896)	(6.505)
SME Granting : Year 1	0.034	5.545	6.332
	(3.020)	(3.611)	(5.478)
SME Granting : Year 2	−0.907	5.461	2.402
	(2.987)	(3.807)	(5.936)
SME Granting : Year 3	0.078	3.623	−0.476
	(3.197)	(3.800)	(5.502)
SME Granting : Year 4	−0.324	0.505	3.425
	(3.294)	(3.873)	(6.059)
Control Variables			
Cash Flow/Assets	0.208*	1.123**	0.291
	(0.124)	(0.572)	(0.271)
log(Age)	−24.633***	−8.257	0.790
	(4.295)	(6.501)	(7.172)
log(Assets)	9.590***	11.509***	2.924
	(1.611)	(2.462)	(2.390)
Debt/Assets	0.194	2.747***	0.804
	(0.449)	(0.890)	(1.381)
Observations	4,986	4,986	4,986
N. of groups	453	453	453
R^2	0.026	0.023	0.002
Residual Std. Error	5.861 (df=4,512)	6.271 (df=4,512)	2.955 (df=4,512)
F Statistic	5.733***	5.009***	0.378
Note:			*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 18: Robustness test on separate DiD estimates of post-granting turnover by firm size.

This table reports DiD regressions estimating the effect of patent granting on firm turnover per Equations 4a and 4b. As a robustness check, all variables are winsorized at the 5th and 95th percentiles instead of the 1st and 99th percentiles. SMEs and large firms are split into separate samples prior to estimation. Coefficients represent differences between granted filers (treatment) and non-granted filers (control) with year -1 as the reference year. Estimates are reported for years 0 to 4 post-granting. The model includes firm fixed effects and controls for cash flow, age, size, and leverage. Standard errors are clustered at the firm level and reported in parentheses. Turnover is reported in Thousands of SEK. Variable definitions are provided in Table 11.

	Dependent variable: Turnover	
	Large	SME
	(1)	(2)
Granting : Year 0	73,124.31	820.80
	(67,214.07)	(974.32)
Granting : Year 1	10,269.17	3,997.78**
	(117,900.02)	(1,853.45)
Granting : Year 2	2,549.71	3,539.15
	(121,322.97)	(2,314.40)
Granting : Year 3	28,117.66	4,413.06*
	(167,229.52)	(2,593.96)
Granting : Year 4	48,968.15	8,788.24***
	(224,507.40)	(2,982.96)
Cash Flow/Assets	185,195.73	387.28**
	(348,697.95)	(192.03)
Debt/Assets	241,396.25	1,777.37***
	(387,615.36)	(510.72)
log(Assets)	187,622.31	28,832.90***
	(298,582.97)	(3,426.71)
log(Age)	1,785,227.01	-5,422.06
	(1,082,159.34)	(5,142.68)
Observations	216	4,770
N. of groups	24	431
R^2	0.10	0.32
Residual Std. Error	367,021.60 (df=180)	15,444.11 (df=4327)
F Statistic	1.65* (df=36; 180)	168.30*** (df=443; 4327)
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix B: AI Disclosure

We have used OpenAI's ChatGPT to assist us with specific coding tasks.

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