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TIME-TO-PATENT: DOES NPL SUPPORT ACCELERATE INNOVATION?

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ABSTRACT

The proponents of the economic theory justifying the creation of monopoly rights, through the granting of patents, claim that without patent protection, innovation would occur at a significantly reduced rate. This suggests that the timely development of new inventions strengthens the incentives for innovation. This study, therefore, focused on the extent to which R&D support provided by NPL reduces the time to a new patent among regularly supported firms compared to companies which only receive support occasionally. A probit model was estimated to identify variables that determine NPL's support, while Propensity Score Matching was utilised to create counterfactual companies, and to assess the matching. The analytical framework—based on the Resource-Based theory of the firm— was estimated with Kaplan–Meier (log rank) test and Cox proportional-hazard model. A panel of 6793 companies for 19 years, between 1999 and 2017, was used with data sourced from NPL administrative data, FAME, ORBIS, EPO PATSTAT data on granted applications, Innovate UK grants, and Eurostat R&D intensive sectors (2 digit SIC Code). The analysis showed that important variables that determine selection into NPL support are past grants, assets, and patent intensity. The time to a new patent is 26% shorter for regularly supported companies compared to companies in the occasionally supported matched control group. This study also concludes that the propensity of developing a new patent is about 23% higher for regularly supported companies compared to the matched control group, but the differences in time-to-patent between them is weakly significant.

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CONTENTS

1. INTRODUCTION

Patents are assets which provide the basis for the long-term competitive advantage for firms, increase firms' product differentiation, and enhance market penetration. It has been established that without patent protection, innovation would occur at a significantly reduced rate suggesting that timely development of new inventions strengthens the incentives for innovation. Meanwhile, time-to-patent could depend on how much external R&D support a firm could access besides the internal resources that a firm devotes to its innovative activities. This is partly because the initial fixed cost associated with innovation may be too high to make it profitable for a firm in the short term, which may disincentivise such a firm from undertaking innovation.

The Resource-Based theory of the firm argues that a firm's strategies allow for the development of specific assets to enhance its survival prospects. Based on this theory, it could be claimed that survival strategies of firms would include investment in R&D, and the timely patenting of innovations. Previous studies such as Belmana (2019), using a time frame between 2009 and 2017, showed that about 96% of the NMS's regularly supported firms survived until 2017 compared to survival rates of 88% and 66%, respectively, among businesses in the matched control group and the wider Business Structures Database (BSD)[1]. The differences in survival rates were attributed to support from the NMS laboratories, resulting in fewer businesses closing than otherwise would have been the case.

In this study, we assessed differences in time-to-patent between firms which regularly engaged with NPL and firms which only engaged occasionally. The occasionally engaged firms are used as a matched control group because many firms in the business population do not engage in patenting. Hence, a reasonable comparison can only be made between the occasionally supported firms and regularly supported firms. That is, what would have happened if the treated group had not received regular support. Specifically, the study assessed whether NPL's support to UK firms unlocks their timey innovation prospects. The central research questions this study seeks to address are:

i. Do supported companies develop new patents sooner because of NPL's support?
ii. If so, what is the average reduction in the time it takes to develop a new patent that is attributable to NPL's support?
iii. What is the probability of developing a new patent among the regularly supported companies as compared to among the occasionally support companies?

This study is unique in two major ways. Firstly, empirical studies focusing on differences in time-to-patent among groups of firms exposed to different forms of support are rare. Existing applications of survival analysis - within a time-to-event framework - have mainly focused on medical interventions and a drug's effectiveness (Lee et al, 2016; Kim, et al, 2018; In and Lee, 2018). Hence, this study fills the huge gap in empirical literature relating to firms' innovation. Secondly, this study focused on the firms which engage with NPL. This provides some insights into the impact NPL is generating in promoting timely innovation and competitiveness of UK firms.

The rest of the paper is organised as follow: Section two is on the literature review focusing on determinants of firms' time-to-patent. It also presents the framework of analysis which is broadly underpinned in the Resource-Based theory of the firm. In section 3, attention is on

1 The is a comprehensive database of UK-based companies used by the Office of National Statistics (ONS) for its statistical studies.

description of the methodology and data. Section 4 presents the main results from the estimations, while section 5 concludes the study.

2. LITERATURE REVIEW AND ANALYTICAL FRAMEWORK

2.1. LITERATURE REVIEW

Proponents of the economic theory that justifies patent protection argue that innovations occur due to patents which protect the R&D investment made by the innovator; and without such patents, innovations would occur at a significantly reduced rate (Plant, 1934; Eccleston-Turner, 2016). That is, without patents, many firms would lose profits and competitive edge due to threats posed by other firms which may want to make cheap replicas of their products. Hence, patents preserve the incentives for innovation, otherwise entrepreneurs will be reluctant to invest in an innovation which others may also acquire for purposes of setting themselves up as a competitor (Plant, 1934). However, Eccleston-Turner (2016) noted that economies of scale, complicated regulatory and licensing frameworks that are relevant to bringing some products, such as, a pandemic influenza vaccine, to market, leave manufacturers with little or no risk from generic imitators. It is important to note that, mostly, the products created by the firms that engage with NPL are not in this category. Hence, the risk of imitation by competitors cannot be ignored.

Innovative ideas need to be developed before patenting. However, the process of getting a patent is complicated because it requires overcoming some technicalities and compliance with specific standards which is unlikely to pull through without professional help[2]. This could also take several years as approvals are prioritised based on early compliance with the set standards, among other things. In the UK, specifically, the process for obtaining a new patent usually take about four years from the date of application. The timeline from patent application to approval in UK includes preparing the application, filing the initial application, searching the patent literature, publication, and substantive examination, and approval.[3.] The expectation is that a firm that accesses innovation support enhances its ability to meet technical requirements and demonstrate compliance with specific standards, and so is likely to patent faster and enjoy better survival prospects.

Previous studies within the literature on industrial organization and firm survival have identified some important factors which could motivate a firm to opt for R&D activities and take interventions that could reduce its time-to-patent. These include the need to strengthen brand and reputation, penetrate niche markets, and be the market leader in order to have a competitive edge in a particular product or service.

Determinants of time-to-patent

Literature on firm's innovation identifies several factors which determine time-to-patent among innovative firms. Firstly, it has been advanced that a shorter time-to-patent would ensure early market penetration, enhance survival and competitiveness of a firm. However, the complexity of some innovations could be a reason for longer time-to-patent. Hence, complex inventions could benefit from extending the term of patents, which grants patent holders the exclusive patent rights to exclude others from making, using, or selling an invention for a longer time to compensate for the length of the overall products development (Lexchin, 2021). This suggests that benefits that come with such an extension may create some incentives for firms to take longer in patenting highly innovative products. However, Lexchin (2021) found that patent-term extension does not appear to be justified based on changes in overall time-to-patent because the latter may not be significantly different across products (Beall, Hwang, Kesselheim, 2019).

2 https://www.gov.uk/patent-your-invention
3https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1083860/Patents-Timeline.pdf

Secondly, firm's time-to-patent could be highly dependent on its past and present R&D investments as these determine its ability to engage in innovation and collaborative R&D activities that can ease the development of new inventions. The Resource-Based Theory of the Firm suggests that the ability of a firm to develop unique capabilities, to a large extent, determines its survival prospects (Barney, 1991). However, developing the unique and distinct capacities depends on the proportion of firm's assets devoted to R&D activities, which could be within the firm, outsourced, or a combination of both.

Thirdly, a highly productive firm is assumed to be relatively efficient with higher survival rate (Ericson and Pakes, 1995; Melitz, 2003). High profitability can be an indicator of efficiency (Esteve-Pérez, and Mañez-Castillejo, 2008) and it may also provide the necessary resources to develop firm-specific R&D assets that could shorten the time-to-patent. The attributes of efficiency and profitability could be extended to affect firms' time-to-patent.

Lastly, firm's characteristics and attributes, such as, the industry within which it operates, the prevailing policy environment, age, size, patent intensity, and export intensity potentially all affect its time-to-patent. It has been acknowledged that firms in highly innovative industries are more likely to survive (Segarra and Callejón, 2002), and be more efficient and productive which helps them in efficiently dealing with complexities associated with patenting. Also, firms with desires to penetrate external markets, with innovative technologies and inventions, are more likely to patent faster because they are assumed to be more innovative, productive (Esteve-Pérez, and Mañez-Castillejo, 2008), efficient and R&D intensive. Also, large firms may have access to more resources (by raising capital from the stock market), face better R&D tax conditions and have more resources to hire better qualified staff who are needed to deal with the complexities of patenting, thereby, leading to shorter time-to-patent. More importantly, firms' size and age profiles are control variables that account for the efficiency differences arising from differences in experiences, managerial abilities, production technologies and firm organization (Pérez, and Mañez-Castillejo, 2008). Finally, it can also be argued that firms that operate in a policy environment with huge administrative bottlenecks, involved in assessing and approving patentable innovations, may take longer time-to-patent compared to firms operating in are more efficient administrative environment.

Our study fits into the literature discussed above. As detailed in the following sections, our study examined the role of firm's assets, past R&D activities, and patent intensity as important factors influencing firms' selection into NPL's innovation intervention. These factors are included in the model to reduce the influence of selection-bias on our estimate of the extent to which NPL's support speeds up the rate at which patents are produced by the supported firms.

2.2. ANALYTICAL FRAMEWORK.

This study is underpinned within the Resource-Based theory of the firm. The theory predicts that the ability of a firm to develop distinct capabilities enhances its ability to adapt to the changing competitive environment and improves its survival prospects (Esteve-Pérez, and Mañez-Castillejo, 2008). Patenting could be seen as one of these distinct capacities. However, a firm needs to survive long enough to patent. This survival likelihood function is represented as:

$$L = \prod_{i=1}^{N} \left[\left[\frac{f(T_i)}{S(\tau_i)} \right]^{ci} \left[\frac{S(T_i)}{S(\tau_i)} \right]^{1-ci} \right] = \prod_{i=1}^{N} \left[[\theta(T_i)]^{ci} \left[\frac{S(T_i)}{S(\tau_i)} \right] \right] \quad ; \theta = f/S(T_i) \qquad (1)$$

Linearising equation (1) gives:

$$LnL = \sum_{i=1}^{N} \left\{ c_i Ln\theta(T_i) + Ln \left[\frac{S(T_i)}{S(\tau_i)} \right] \right\} \qquad (2)$$

Where $S(\tau_i)$ is the probability of firm's survival from birth until assignment period (*1999)* and τ_i is the stock sampling date. The ci is the censoring indicator[4] which takes value 1 and 0 when the spell is complete and when it is censored, respectively. T_i is firm i's duration (between birth and death). $f(.), S(.) and\ \theta(.)$ are the probability density, survival, and hazard functions, respectively. The hazard function, which is the instantaneous probability that a firm patent at time t given that it has survived till time t, can be conditioned to a vector of firm's covariates Y which may include both time-varying (e.g., assets, past R&D grants, and patent intensity) and non-time varying explanatory variable (e.g., patent intensity). This condition can be expressed as:

$$\theta(t, Y) = \lim_{dt \to 0} \frac{Pr[t \le T < t + dt | T \ge t, Y]}{dt} \quad (3)$$

Where T is non-negative continuous random variable denoting time of the event (between a firm's birth and death), and t is specific firm's time-to-patent (between patent application and market approval). Equation (3) implies that as the probability that a firm patent at time t given that it has survived till time t approaches zero, the chance of not experiencing patent up to and including time t increases.

METHODOLOGY AND DATA

3.1. METHODOLOGY

In terms of sequencing, we first estimated selection model with probit regression technique to identify important variables which determine NPL R&D supports. Secondly, we utilised Propensity Score Matching (PMS) to build a group of businesses that are identical to the regularly supported businesses but have not been regularly supported by NPL (that is, counterfactual firms), and to assess the matching. Thirdly, we estimated the following proportional hazards model specification following Cox (1972):

$$\theta(t, Y_i) = \theta_0(t).\, exp(Y_i \alpha) \quad (4)$$

Where $\theta_0(t)$ is the baseline for $exp(Y_i\alpha) = 1$; hazard function when all covariates are set to 0. The impact of change in the covariates results in the parallel shift of the baseline. Cox proportional hazards model compares the risk levels of occurrence and non-occurrence influenced by a variable which could affect the outcome with the null hypothesis that the hazard ratio for the two groups is 1 (In and Lee, 2018).

There are two types of NPL supported companies: firms which received regular support between 2002 and 2008 (treated group) and other similar non-regularly supported companies (a comparator group) in the same period. We used a Cox proportional-hazards model to estimate and compare the propensity of filing a new patent for each group of firms. The Cox proportional-hazards model is like the Kaplan–Meier model[5] except that the latter enables the differences in the outcome variable for each group of firms while allowing for other factors

4 For example, suppose we are interested in measuring the impact R&D intervention on time-to-patent. It may be known that a firm's time-to-patent is at least 3 years but may be more. Such a situation could occur if the study covers only 3 years, or the firm is alive at the age of 3. Hence, censoring is a condition in which the value of an observation is only partially known.

5 This is a non-parametric statistic used to estimate the survival function. It is often used in medical research to measure the fraction of patients living for a certain amount of time after treatment. In this study, it is utilized to measure the fraction of firms surviving and patenting after the period of innovation intervention. The Kaplan-Meier estimate of the survivor function is given by $\hat{S}(t) = \prod_{j|t_j \le t} (\frac{n_j - d_j}{n_j})$,where nj is the number of businesses not closed at time tj and dj is the number of businesses closed at time t_j.

(Bewick, Cheek, and Ball, 2004). Since we worked with observational data (i.e., not from a randomised experiment), we used PMS to identify a comparator group of sometimes supported firms. The comparator group became a good counterfactual, that is, what would have happened if the treated group had not received regular support (deadweight). Also, we were faced with potential confounding effects[6] of intrinsic characteristics that influence the innovativeness of the firm. Thus, we controlled for selection bias to avoid overestimating the actual treatment effect. Selectivity is addressed by using PSM to find a suitable comparator group.

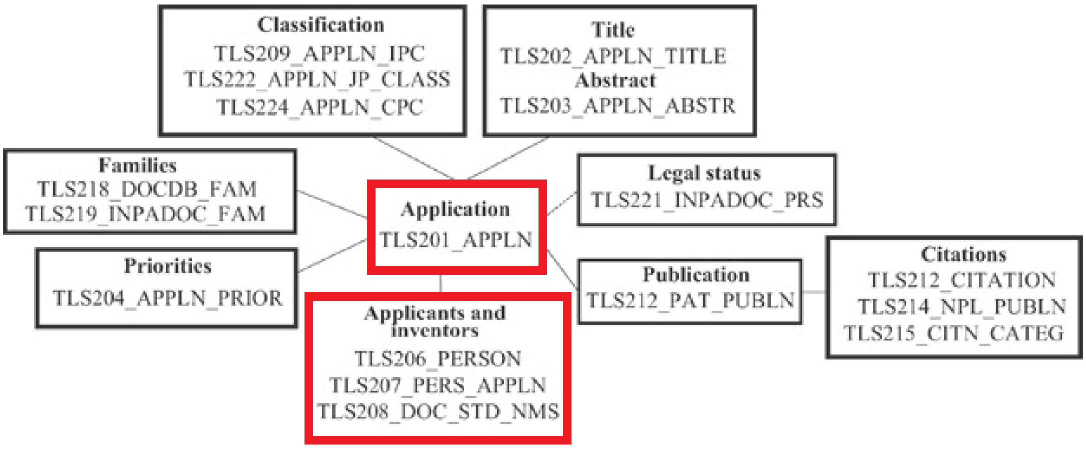
3.2. DATA

The sample frame has 6,793 firms and effectively two periods: (i) 2002-2008 where we look for (regular) support and (ii) 2009-2017 where we look for the patenting activity of the firm. We define regular support as receiving support three or more years within 2002 to 2008. Not all 6,793 observations are "valid". Some companies are set up after 2006 so did not have the chance to qualify as regularly supported. We withdrew those observations from the panel and are left with 5,454 firms.

The panel (6793 firms, 19 years) is constructed using data from several sources discussed as follows:

- NPL administrative data: This is based on invoices, income, downloads, and collaborations.
- BvD FAME data on key characteristics of a firm, such as, birth year, NUTS region, SIC code, SME indicator. BvD FAME also provides some key financials like employment, assets, turnover, and liquidity ratio.
- BvD ORBIS data on publication of new patents. This is a dummy variable that takes the value of 1 for one or more new patents each year, and is 0 otherwise
- EPO PATSTAT provides data on granted applications. PATSTAT consists of a set of tables that follow a relational database schema, where tables can be connected to each other using a relevant entry key. The central element of PATSTAT is the table on patent applications (*tls201_appln*), which contains almost 100 million records. The other tables contain information on each of the patent applications, for example, inventors and applicants, technology fields, titles and abstracts, publication instances and citations. The PATSTAT database schema is presented as follow:

6 This is effect of unmeasured variables that influences both the cause (treatment) and outcome (time-to-patent).



For this analysis, we used the tables highlighted in red in the above figure because we need information on applications (namely, the date they were filed and whether they were ultimately granted or not) and who made those applications (the company where the invertor works).

- Innovate-UK grants.
- Eurostat R&D intensive sectors (2 digit SIC Code)

It is important to note that not all variables span from 1999 to 2017. But only patent information from PATSTAT and ORBIS goes back to 1999. NPL's data goes back to 2002, FAME data to 2001, and data on Innovate-UK's grants goes back to 2003.

4. RESULTS

4.1. PSM TO IDENTIFY THE COMPARATOR GROUP

The selection variables are used to build a group of businesses that are identical to the regularly supported businesses but have been occasionally supported by the NPL. It is important for the selection model to represent variables that are significant in the selection process for regularly using NPL services. Table 1 shows that past grants, average of log of assets between 2001 and 2008, and patent intensity of the businesses are strong predictors for regular support. Past grants are a very strong predictor of regular treatment in terms of coefficient and significant level.

As previously stated, the PSM models selection by estimating a score for the likelihood of a business receiving regular support, controlling for observed firm's characteristics such as past grants, assets, and patent intensity. Businesses which have a similar history of innovation support but not securing the support being analysed provide a potential match and the use of past grants in selection modelling controls for this. A good PSM should show high confidence that comparable businesses are truly identified. The robustness of the matching should also be tested to quantify how good the match is and to estimate how sensitive results are to different modelling.

Table 1. Selection (Probit) Model and Matching Assessment

	Selection model	Matching Assessment		
		Mean		
	Coef.	Treated	Control	% Bias
Past grants	0.232 (3.33)***	0.182	0.175	1.9 (0.29)
Log assets (2001& '08)	0.058 (8.07)***	7.647	7.632	0.4 (0.07)
High patents[7]	0.277 (2.16)**	0.058	0.066	-3.9 (-0.54)
Constant	-1.602 (-29.60)***	-	-	-
LR Chi2(3)	110.87***	-	-	-
Pseudo R-square	0.03	-	-	-
Observations	4,819			

Note: In the parentheses of the selection mode and matching assessment model is Z-scores and t-test, respectively. 1% and 5% level of significance are represented by ***, and **, respectively.

A key characteristic of the matching is that it needs to produce the counterfactual group which have similar trend to the regularly treated firms in the key impact measures. If this is not the case, there is a concern that some unobserved characteristics remain, and these have put the regularly supported businesses on a different growth trajectory prior to support. If this happens, we cannot be confident that being a regularly supported firm has an influence time-to-patent compared to being sometimes supported. The robustness tests of the PSM include considering whether – after matching – the supported businesses and the matched counterfactuals are statistically similar. We assessed the matching formally with '*pstest*'.[8] This command calculates several measures of the extent of balancing of the variables between the two groups. We looked for an insignificant p-test and want biases to be less than 5%. The outcome of the test showed that any differences in time-to-patent can be attributed to regular support.

The PSM is used to construct the artificial control group by matching each of the treated group with untreated (control group) of similar characteristics. The technique generates the propensity scores which is the probability of assignment conditioned on the observed baseline characteristics. Extreme propensity scores of zero or one are indicative of never receiving treatment or almost always receiving treatment, respectively. This is an indication that causal effects cannot be established. When this occurs, there are limitations which include large weights for individual firms, and large variability in the estimated treatment effect (Fan, Laine, and Fan, 2019). One of the solutions is to use trimming methods which exclude firms with very high predicted probabilities of being in either of the treatment (firms with propensity scores close to 1) or control group (firms with propensity scores close to 0). Despite the potential benefits from trimming methods, it has the demerit of reducing the sample size. The relative performance of different approaches to trimming remains unclear, particularly in the setting of extreme propensity scores (Kang, et al, 2016).

From the Figure 1 (also indicative in the Table 2), it seems that for treated firms with a propensity score of more than 0.3 we have barely any matched firms. However, all observations are on 'pscore' support with at least two firms within a calliper of 0.01. If we decided to drop those observations, we would get similar results, but we will lose significance for the treatment variable in the subsequent survival analysis when we include more covariates.

7 About 86% of the companies did not develop a patent between 1999 and 2008. 11.5% of the companies developed less than ten patents and the remainder 2.5% developed more than 10 patents. high_patents denote those highly active firms.

8 'pstest' is a Stata command to check for the match quality.

Figure 1. Propensity Score distribution

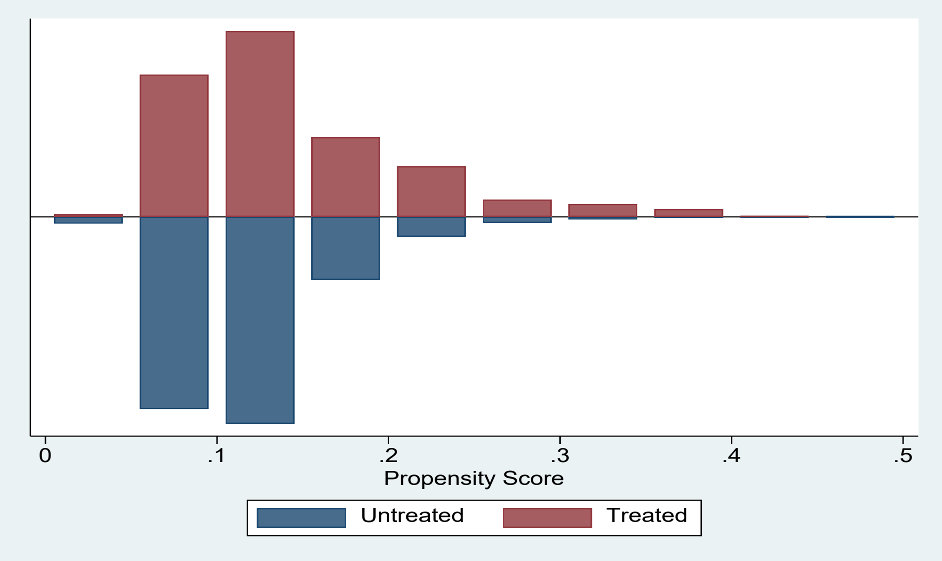


Table 2. Treatment assignment

	Pscorematch: Treatment assignment		
Pscorehigh	Untreated	Treated	Total
0	2,868	558	3,426
1	33	25	58
Total	2,901	583	3,484

4.2. TIME TO A NEW PATENT

4.2.1. Kaplan–Meier (Log Rank) Test

Table 3 shows the summary of time-to-patent between the firms in the matched control group and the regularly supported firms, utilizing the Kaplan–Meier (log rank) test. It also presents the test for equality of survival using the log rank test of equality of survival times. The log rank test is used to test whether there is a difference in time-to-patent between the matched controls and the regularly treated firms for a certain time after treatment, but it does not allow other explanatory variables to be considered.

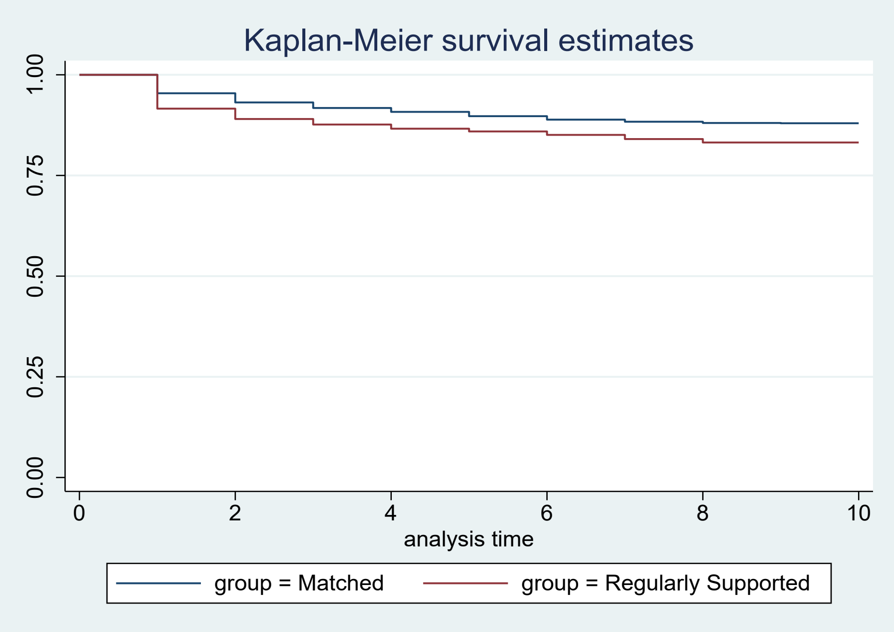
The results showed a significant difference between time-to-patent for the regularly supported firms and those in the matched control group with a shorter time-to-patent for the regularly supported firms. Hence, the hypothesis that time-to-patent for both groups of firms are the same is rejected at 1%. This is also indicated in the figure below. However, if we remove the observations with high propensity scores— the firms with high probability of treatment assignment— we cannot reject the null hypothesis at 5%. That is, time-to-patent is insignificantly different between control and regularly supported firms.

Table 3. Kaplan–Meier (log rank) test

	Time-to-patent		Log-rank test of equality of survival function	
Group of firms	Mean	Std Dev	Event observed (freq.)	Event expected
Matched control	2.857	2.079	349	373.81
Regularly supported	2.643	2.240	98	73.19
Total	2.810	2.115	447	447.0

Chi2(1)[9]	-	-	10.37***

Figure 2. Kaplan–Meier survival estimate[10]



4.2.2. Proportional Hazard (PH) Cox Model

Both log rank test and Cox's proportional hazards models assume that the hazard ratio is constant over time, but the latter enables the difference in the propensity of filling a new patent for each group of firms while allowing for other factors (Bewick, Cheek, and Ball, 2004). Table 4 presents PH Cox results, one with without and with covariates. In this model, the hazard is the propensity of filing a new patent given that a firm has survived up to a given year. That is, Table 4 presents the results of comparing the hazard function among regularly treated firms to that of occasionally treated firms.

The proportional-hazards assumption was tested using the Schoenfeld residuals of the Cox model. The Schoenfeld residuals "can essentially be thought of as the observed values minus the expected values of the covariates at each failure time". The '*estat phtest*' command tests of nonzero slope in linear regression of the Schoenfeld residuals on time. The command tests, for individual covariates and globally, the null hypothesis of zero slope, which is equivalent to testing that the log hazard-ratio function is constant over time. The rejection of the null hypothesis of a zero slope indicates deviation from the proportional-hazards assumption. A hazard ratio of 1 indicates a lack of association (i.e., equal hazard in the two groups of firms), a hazard ratio greater than 1 suggests an increased patent risk, and a hazard ratio below 1 suggests a smaller risk (Toledo, 2018).

The hazard ratios of 1.43 and 1.23 mean that the regularly treated firms had about 43% and 23% more propensity towards patenting than the occasionally treated firms (Table 4). However, the model with other covariates (such as size, industry R&D intensity, past grants, and past patents) which is a preferred mode is only significant at 10%. This implies that

9 The chi squared (Chi2(1)) tests the hypothesis of no significant difference in patenting time between the regularly supported firms and the matched controls (occasionally supported firms).
10 The Kaplan-Meier curve is used to estimate the survival function from data that are censored, truncated, or have missing values. The curve is constructed by plotting the survival function against time, and shows the probability that a firm will survive and patent up to time t.

differences in the propensity towards patenting between regularly treated and occasionally treated firms is weak. Meanwhile, we got better results for the test of the PH assumption when we control outside (i.e., stratification) the model, which is consistent with the literature on survival analysis. Specifically, trimming out those observations with a '*pscore*' higher than 0.3 we were somewhat controlling for size and innovativeness (at least, the firms we retained have a lot of similarities). The result without controlling for the rest of covariates goes down from 1.43 in Table 4 to 1.26 (significant at 10%, Table A1 in the annex), which is consistent with what we got in the model with all observations after including the rest of the variables. The conclusion from the present analysis is that the propensity towards developing a new patent is about 23% higher for the regularly supported companies compared to those in the matched control group.

The duration analysis showed that the time to a new patent is 26% shorter for regularly supported companies compared to the matched control group (table A3). This is consistent with the results of the Cox and Kaplan–Meier models.

Table 4. PH Cox Estimates

	PH Cox Model without controlling for covariates			**PH Cox Model including more covariates**		
	Cox Regression	Schoenfeld residuals Test of Proportional Hazard Assumption		Cox Regression	Schoenfeld residuals Test of Proportional Hazard Assumption	
_t	Haz. Ratio	Rho	Chi2	Haz. Ratio	Rho	Chi2
Group	1.434 (3.15) ***	-0.035	0.55 (0.55)	1.232 (1.8)*	-0.017	0.14 (0.14)
Stats						
No. of subjects (obs)	3, 484	-	-	3, 484		
No. of failures	447	-	-	447		
Time at risk	31,626	-	-	31,626		
LR Chi2 (1)	9.28**	-	-	3.13*		

Note: Z-score and global test Chi-square is the parenthesis of Cox regression and Test of Proportional Hazard Assumption's Chi-square, respectively.

5. CONCLUSION

The present study showed some evidence to believe that shorter time-to-patent among the sampled companies could be attributed to their regular usage of NPL's services and support. Specifically, the study found that time to a new patent is 26% shorter for regularly supported companies compared to companies that are occasionally supported in the matched control group. However, the result is only significant at a 10% confidence-level, which means that differences in the propensity towards patenting between regularly treated and occasionally treated firms is somewhat weak. The conclusion is that propensity of developing a new patent is about 23% higher for regularly supported companies compared to that for the matched control group, and differences in time-to-patent between them is weakly significant.

This is our first attempt at time-to-patent analysis, and the result is sufficient to indicate the contribution that NPL could make towards accelerating innovation. However, we have reached the limitations of what can be found using the present dataset, and so would need to build a larger dataset that incorporates more recent data. Moreover, in the future, it would be good to consider including other firm-level control variables, such as, productivity, performance, and profitability, as well as incorporating other firm-level characteristics, such as export intensity, into the selection equation. We may also need to compare three groups of firms: (1) the regularly supported, (2) the sometimes supported, and (3) the general population-matched control group (from IUK's grant holders found on the Gateway2Research). Finally, we could explore the literature on patenting further to come up with a more developed explanation of the economic benefits, in addition to building a model to show the economic benefit of patenting earlier i.e., building on the idea that "time is money".

REFERENCES

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage, *Journal of Management* 17, 34-56

Bewick V, Cheek L, Ball J. (2004). Statistics review 12: survival analysis. *Crit Care*. 8(5):389-94. doi: 10.1186/cc2955.

Beall RF, Hwang TJ, Kesselheim AS. (2019). Pre-market development times for biologic versus small-molecule drugs. *Nat Biotechnol*. 37(7):708-711. doi: 10.1038/s41587-019-0175-2. PMID: 31213674.

Cox, D. R. (1972). Regression models and life tables', *Journal of Royal Statistical Society* 34, 187-220.

Ericson, R., and A. Pakes (1995). Markov Perfect Industry Dynamics: A Framework for Empirical Work, *Review of Economic Studies* 62, 53-82.

Esteve-Pérez, S., Mañez-Castillejo, J.A (2008). The Resource-Based Theory of the Firm and Firm Survival. *Small Bus Econ* **30,** 231–249. https://doi.org/10.1007/s11187-006-9011-4

Eccleston-Turner M (2016). The Economic Theory of Patent Protection and Pandemic Influenza Vaccines: Do Patents Really Incentivize Innovation in the Field? *American Journal of Law & Medicine*. 42(2-3):572-597. doi:10.1177/0098858816658280

Fan, L., Laine E.T., & Fan, L. (2019). Addressing Extreme Propensity Scores via the Overlap Weights, *American Journal of Epidemiology*, 188 (1): 250–257, https://doi.org/10.1093/aje/kwy201

In J, & Lee DK. (2018). Survival analysis: Part I - analysis of time-to-event. *Korean J Anesthesiol*. 71(3):182-191. doi: 10.4097/kja.d.18.00067.

Kang, J., Chan W, Kim MO, & Steiner PM. (2016). Practice of causal inference with the propensity of being zero or one: assessing the effect of arbitrary cutoffs of propensity scores. *Commun Stat Appl Methods*. 23(1):1-20. doi: 10.5351/CSAM.2016.23.1.001. Epub 2016 Jan 31. PMID: 31467864; PMCID: PMC6714558.

Kim JM, Lee H, Ha T, Na S. (2018). Perioperative factors associated with pressure ulcer development after major surgery. *Korean J Anesthesiol*, 71: 48-56.

Langinier, C., and Moschini, G. (2002). The Economics of Patents: An Overview. Working Paper 02-WP 293. https://www.card.iastate.edu/products/publications/pdf/02wp293.pdf

Lee JH, Kang SH, Kim Y, Kim HA, Kim BS (2016). Effects of propofol-based total intravenous anesthesia on recurrence and overall survival in patients after modified radical mastectomy: a retrospective study. *Korean J Anesthesiol*, 69: 126-32.

Lexchin J. (2021). Development Time and Patent Extension for Prescription Drugs in Canada: A Cohort Study. *Int J Health Policy Manag*. 10(8):495-499. doi: 10.34172/ijhpm.2020.100. PMID: 32610816; PMCID: PMC9056197.

Harrigan, K.R., and DiGuardo, M.C. (2017). Sustainability of patent-based competitive advantage in the U.S. communications services industry. *J Technol Transf* **42,** 1334–1361 (2017). https://doi.org/10.1007/s10961-016-9515-2

Melitz, M. J. (2003). The Impact of Trade in Intra-Industry Reallocations and Aggregate Industry Productivity, *Econometrica* 71, 1695-1725.

Plant, A. (1934). The Economic Theory Concerning Patents for Inventions. *Economica*, *1*(1), 30–51. https://doi.org/10.2307/2548573

Segarra, A. and M. Callejón (2002). New firms' survival and market turbulence: new evidence from Spain, *Review of Industrial Organization* 20, 1-14

Toledo, E. (2018). Epidemiological and Nutritional Methods, in Almudena Sánchez-Villegas, Ana Sánchez-Tainta, The Prevention of Cardiovascular Disease Through the Mediterranean Diet. Academic Press, Pages 25-34, ISBN 9780128112595, https://doi.org/10.1016/B978-0-12-811259-5.00002-0

ANNEX

Table A1. Robustness Cox Regression by trimming high pscore observations

```
Cox regression -- Breslow method for ties

No. of subjects =        3,426                  Number of obs    =      3,426
No. of failures =          405
Time at risk    =        31388
                                                LR chi2(1)       =       3.27
Log likelihood  =   -3274.9579                  Prob > chi2      =     0.0706
```

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
group	1.261447	.1581895	1.85	0.064	.9865649	1.612918

```
.                  estat phtest, detail

      Test of proportional-hazards assumption

      Time:  Time
```

	rho	chi2	df	Prob>chi2
group	0.01549	0.10	1	0.7552
global test		0.10	1	0.7552

Figure A1. Survival Probabilities

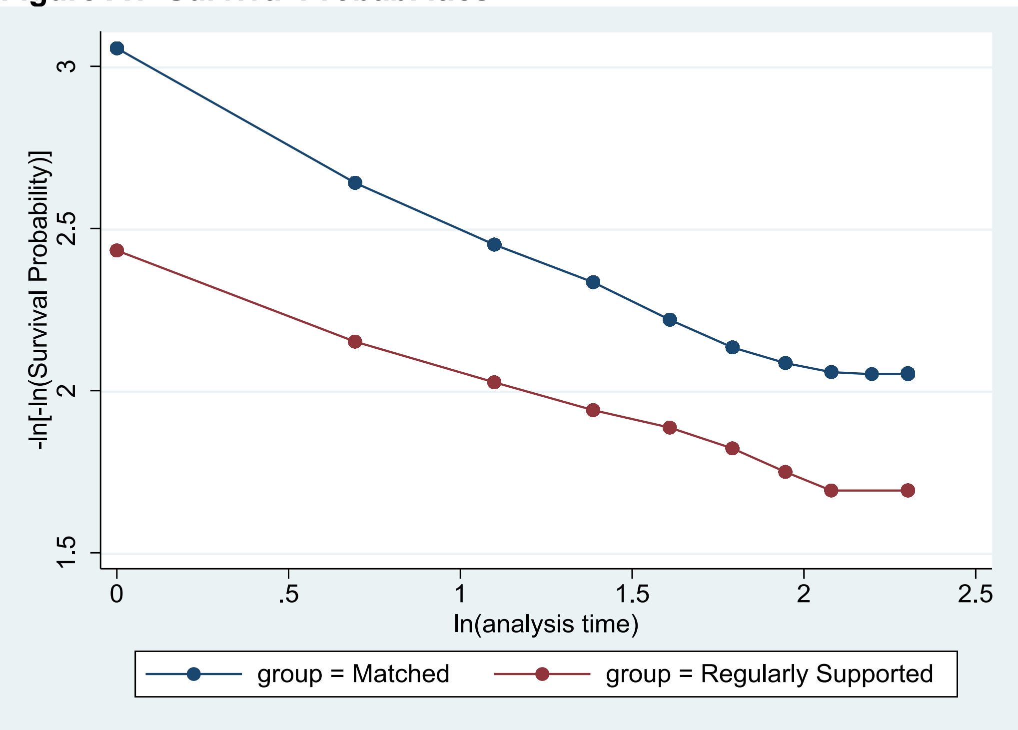


Figure A2. Survival Probabilities

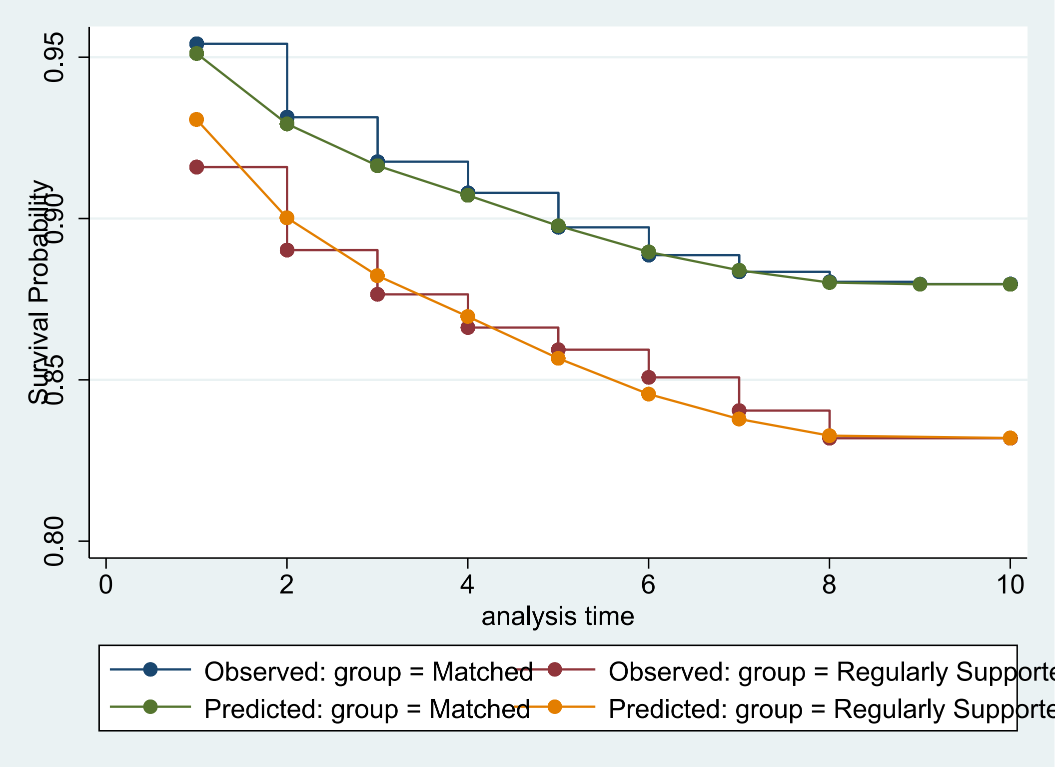


Table A2. Duration analysis

Censored-normal regression	Number of obs	=	3,484
	LR chi2(4)	=	248.63
	Prob > chi2	=	0.0000
Log likelihood = -1813.1817	Pseudo R2	=	0.0642

ltimetopatent	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
treated	-.310492	.1740916	-1.78	0.075	-.651824	.0308399
dLnassets0108_h2	-1.271682	.1541897	-8.25	0.000	-1.573993	-.9693705
rdintensity	-.3812246	.0691745	-5.51	0.000	-.5168514	-.2455978
past_grants	-1.615638	.1755836	-9.20	0.000	-1.959895	-1.271381
_cons	6.616654	.2364138	27.99	0.000	6.15313	7.080178
/sigma	2.524117	.1040677			2.320077	2.728157

```
            0  left-censored observations
          447     uncensored observations
        3,037 right-censored observations

.          scalar b1 = e(b)[1,1]

.          di exp(b1) - 1
-.26691382
```