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**Option trading and firm innovation**

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## **Abstract**

We investigate whether active derivatives markets stimulates or inhibits firm innovation within R&D- intense industries. This is done by estimating the relationship between the volume on the option written on the firm's stock and established measures of firm innovation. We find the relationship to be positive and robust for a number of innovation proxies. Specifically, firms with higher option volume generate more innovation per euro invested in R&D, assuming time-invariant heterogeneity in our sample. Our baseline model suggests an increase in innovation by 24% when option trading increase by 400%. This is in line with the hypothesis of the reduced information asymmetry associated with options trading activity leading to more efficient allocation of funds. We find that option volume impacts innovation almost exclusively through increasing R&D productivity, rather than also partly stimulating R&D spending. This is in contrast with earlier findings from in particular Blanco and Wehrheim (2017), who find both effects to be significant. We also briefly propose possible economical mechanisms for these findings, related to management's incentives and market competition.

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# 1. Introduction

Continuous innovation is crucial for firms' long-term organic growth and survival in a competitive environment ([Cantwell, 2006](#); [Clark and Guy, 1998](#)). The capital market is of significant importance in funding these projects and its effect on innovation is a widely debated topic and somewhat ambiguous. It is claimed that the associated increase in monitoring and disciplining requirements, as well as a potentially less concentrated stock-ownership, may in fact have an inhibiting effect on innovations ([Holmström, 1989](#); [Francis and Smith, 1995](#)). We will oppose this established view and claim that the increase in monitoring from option trading will lead to better allocation of funds as well as giving management incentives to innovate, thus in fact spurring firm innovation. Hence our hypothesis is that higher monitoring associated with more active option markets will enhance innovation in the underlying stock's firm.

One effect of the development of capital markets, is an exploding increase in option-trading volume. In this paper, we use this fact to investigate one element of what drives the innovation propensity in European firms. More specifically, test if higher trading volumes in option written on the firm's stock are associated with higher innovation. We take the same approach and hypothesis as [Blanco and Wehrheim \(2017\)](#) and apply it to the European market. We know that option trading increases the price informativeness of the underlying stock, hence making it more efficient ([Biais et al, 1994](#)). This is due to the fact that option markets incentivize investors to gather more information about the stock. When the efficiency increases, value improving activities are reflected faster in the stock price, giving the management a higher incentive to engage in these activities. With this reasoning, option markets might offset some of the information asymmetry that comes with R&D activities.

We investigate whether option trading boosts innovation within firms in R&D-intensive industries. The industries in which firms invest comparatively high in R&D, generally rely more on innovations since it is a crucial element in their competitiveness ([Grabowsky, 2002](#)). Naturally, to protect these innovations, the company might be restricted in their exposure, thus

being more prone to asymmetric information problems. We use level of option trading as proxy for information asymmetry, since the literature claims that more informed investors are involved in option trading ([Cao, 1999](#)). Thus, an increase in option trading- volume is an indicator of a decrease in asymmetric information. Due to its nature, R&D- intense industries will be the main focus for our analysis.

Our measurement for innovation is patents. Specifically, the number of granted patents in combination with the number of patent- citations on these, serving as proxies for innovation level and quality, respectively. We use the same method as [Blanco and Wehrheim \(2017\)](#), who performs a similar analysis on the US markets. Their result suggest that firms that are listed on option markets have more incentives for innovation. They argue that option markets give more incentives for enlightened market participants, which in turn leads to the stock price being more efficient. More efficient stock prices leads to more informed fundamental investors, which reduces the asymmetric information associated with R&D and in turn induces firm management to participate in innovation- generating activities.

In our paper we have the natural logarithm of patent citations as the dependent variable, which serves as main proxy for firm innovation. The independent variable of interest is the natural logarithm of public trading volume on options written on the stock. We control for institutional ownership, sales, capital/labor, firm age, and we include dummy variables for year and industry. In our full model we also include controls for firm fixed effects which implies that we assume time-invariant heterogeneity within our sample. In our baseline regression we get a significant coefficient of 0.06, indicating that an increase in option trading with 100% increase innovation by 6%.

## 2. Literature Review

### 2.1 Information asymmetry and management incentives

The literature suggests that more informed investors are involved in option trading, hence a higher level of option volume is associated with a lower level of information asymmetry. A low level of information asymmetry in turn spurs productive innovation through managerial incentives. Relevant literature suggests that insiders and informed traders are more likely to trade on the option market. [Chakravarty et al \(2004\)](#); [Hu \(2014\)](#) argues that this is due to the increased leverage and the built-in downside protection of options. [Chakravarty et. al \(2004\)](#) further concludes that this implies that price discoveries is present in the option market before the stock market itself. [Cao \(1999\)](#); [Zhang \(2018\)](#) argues that because of this, a firm that has options traded in a market with the stock as the underlying asset attracts more informed investors. In turn, the stock price itself is more efficient and informative of the true value of the firm. Future price reactions is smaller in future earnings announcements. [Cao \(1999\)](#) further argues that this gathering of information is not possible without options so introducing options might decrease market volatility due to a higher price- efficiency.

[Biais et al \(1994\)](#) goes along the same line of thought; that the stock market is more informative after adding options. In particular, the market is informed of the innovativeness of the firm when options are introduced. [Glosten and Milgrom \(1985\)](#); [Brown and Yang \(2017\)](#) argues that if option trades conveys information about the underlying stock, then a market with more informed traders, which appear on the option market, will be more efficient. [Pan and Poteshman \(2006\)](#) argues that the information gets incorporated in the stock by informed and uninformed trades. The more informed investors trading in a security, the faster the adjustment to price changes than securities with less informed investors ([Brennan and Subrahmanyam, 1995](#)). This implies that any effects from option trading depend on the option volume. Markets with high volumes are in turn where informed traders is able to make a profit because their trades are camouflaged by uninformed trades ([Kyle, 1985](#); [Inci et al 2010](#)), further incentivizing informed investors to participate.

With this reasoning in mind, managers have an incentive to innovate and increase the true value of the firm since the value increase will also be reflected in the stock price. The higher trading volume on the option market, the higher the incentive. Since publicly traded firms are monitored by the market, [Holmström and Tirole \(1993\)](#); [Ben-Nasr and Alshwer \(2016\)](#) claims that this raises management's incentive to engage in value-increasing projects. In the same manner, [Faure-Grimaud \(2004\)](#) suggests that a more active market means more investors to feed with information about value enhancing activities, hence increasing management incentive to do so. [Dow and Gorton \(1997\)](#) argues that the aggregate information on the market is higher than managers information which indicate that the current stock price has a prospective role in management decisions. The implications of the literature is a relationship between option trading volume and innovation in the underlying stock's firm. An increase in trading volume is associated with an increase in innovation.

Further argumentation upon the same topic is proposed through the *quiet life*- hypothesis, widely recognized and used in several analysis, e.g [Bertrand and Mullainathan \(2003\)](#), [Naoshi et al \(2018\)](#), which pinpoints this mechanism between management incentives and empire building. When there are information asymmetry between management and shareholders, hence managers are badly monitored, managers might pursue visions that is not in line with the interest of their shareholders. Depending on the characteristics of the manager, some might prefer to invest aggressively in pursue of building an empire, while others might enjoy the quiet life, avoiding difficult investment or restructuring decisions and taking excessive risks. The higher the monitoring, the closer the managers incentives are connected with the shareholders' and thus are more likely to allocate funds efficiently.

## **2.2 Market competition and innovation**

Why innovation is of particular interest is due to its characteristics and significance in firm survival and growth, being even more pronounced in R&D intense industries ([Grabowski, 2002](#)). [Cantwell \(2005\)](#) concludes that for a firm to maintain growth in an internationally competitive

environment, one have to stay differentiated among competitors and does so by innovating. He also argues that innovation is a positive sum game which spurs further innovation and which effect outweighs the potential negative effects of creative destruction ([Schumpeter, 1942](#)). The same line of thought goes with [Clark and Guy \(1998\)](#) in their extensive work on summarizing analysis from earlier researchers as well as doing surveys on the area on innovation and competitiveness. Based on their empirical evidence, their main conclusions is that innovation has a positive effect on competitiveness.

### **2.3 Patents as proxy for innovation**

The use of variables associated with patents as measurement of innovation are associated with some imperfections. [Roper \(2015\)](#) emphasizes potential issues with this method by showing a weak negative (rather than positive) effect of existing knowledge stock, measured by number of patents, on innovation output. [Acs et al \(2002\)](#) further highlights the difficulties in measuring and finding appropriate proxies for innovations and their paper aims to test whether patent data is in fact a reliable proxy for innovative activities. They examine the relationship between innovation and patents using a regression- based approach, arguing that patent count serves as a fairly good, although not perfect, measurement of innovation.

Patents are used as a measure for innovation in several studies, however. Specifically, [Crosby \(2000\)](#) investigates the effect of policy changes on innovation and growth in Australia and uses patent data to proxy for economy innovation. [Grabowski \(2002\)](#) breaks down the pharmaceutical industry and examines the history of the innovation process. He argues that pharmaceutical firms are subject to major free rider problems, due to the high costs associated with drug innovation and relatively low imitation costs, hence patents are of major importance to benefit from innovation compared to other R&D- intense industries.

Another factor that is taken into consideration when using patents as a measurement of innovation, is that not all inventions are in fact patented for various reasons, both legal and strategic. Its propensity also varies heavily from firm to firm. A study to find an explanation for



innovation should therefore control for this by choosing patent propense industries; firms rely more heavily on protecting innovation by using patents, hence increasing the probability for applying for patents.

## 2.4 Patent citations - innovation quality

Of particular interest is to measure the output of innovation, hence its *quality*. [Aristodemou and Tietze \(2018\)](#) use a forward citation-based measure, referred to as *Citation Index*, which is simply the count of citations received on a patent from subsequent patents. The more forward-citations on a patent indicates higher quality of innovation, hence a higher technological and economic impact. This method strands from earlier literature, in particular [Lanjouw and Schankerman \(1999\)](#) who use a latent variable model to specifically investigate the quality of patented innovations, within four technology areas in the US, using four different key indicators. They find forward citations to be the least noisy of the chosen indicators and of primary importance in explaining innovation quality.<sup>1</sup>

[Marku \(2018\)](#) looks at firms operating within the (high-)tech- industry and aims to address their innovation quality and uses forward citations as proxy. She argues that patents with many citations have more inventions built upon it, hence have a more significant technological impact, i.e a higher quality. [Kalutkiewicz and Ehman \(2014\)](#) investigate the federal R&D contribution on future development and economic activity, which they translate into innovation and uses forward- citation weighted patents to proxy for innovation in the same manner. They argue that the mere number of patents is an imperfect and noisy measurement of innovation but that the widely accepted approach is to use forward citations in combination with the raw patent count.

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<sup>1</sup> The indicators used are; number of claims, forward citations, backward citations and patent family size. By using multiple indicators simultaneously they manage to capture the fraction of the variation in each variable that is related to ‘quality’. The indicator with the highest variation explained by ‘quality’ is the most important one, hence the least ‘noisy’. Forward citations had a variation of as much as 30 percent being related to ‘quality’, expressed in the terms of Lanjouw and Schankerman’s work.

## 2.5 R&D- spending and patents

The input that leads to innovation and thus patents, as suggested by the literature, is the level of R&D spending. In particular, [Jaffe \(1986\)](#) uses this relationship and measures the knowledge spillover from R&D and [Artz et. al \(2010\)](#) specifically investigate whether there is a positive relationship between R&D spending and patents.

## 2.6 Ideas production function

In our full model, the choice of variables means that we are in fact regressing output from historical R&D investments, i.e forward patents citations, on R&D expenditures and option volume today. This means that when all controls are included and in particular R&D expenditures, we relate historical patent citations with citations today. Specifically, we relate differences in innovation quality output per euro invested in R&D historically. This approach is referred to as the “ideas production function”, building upon the ideas of productivity growth by [Romer \(1990\)](#) and used by e.g [Porter & Stern \(2000\)](#). The key relationship is the *intertemporal spillover*, relating historical innovation quality with innovation quality today. The coefficient on option volume in turn measures how strong this (positive) relationship is.

## 2.7 Hypothesis

Related to the literature, the same argumentations as of [Blanco and Wehrheim \(2017\)](#) is what our thesis will build upon; a solution to the agency problems is active option markets. With active option markets, the price informativeness and effectiveness of the stock will be enhanced, which in turn improves allocation of funds by giving management incentives to invest in value-increasing activities. [Blanco and Wehrheim \(2017\)](#) examine this by studying the relationship between option trading volume with the stock as the underlying asset and firm innovation. As a proxy for innovation they use patent counts and future citations on those patents. They find that there is a positive relationship between option trading volume and firm innovation. More specifically, what they conclude is that an increase in option volume by 200% increase firm innovation by 31%. Thus, building on the same argumentation and relevant literature, we expect the same relationship by studying the european market.

## 3. Method

### 3.1 Industries

We investigate what impact option trading activity, with the firm's stock as underlying, has on firm innovation, in the same manner as [Blanco and Wehrheim \(2017\)](#) in their research on firms in the U.S. We are applying the same analysis to European firms within the same five manufacturing industries: pharmaceutical (SIC code: 283), industrial and commercial machinery and computer equipment (35), electronics and communications (36), transportation equipment (37) and instruments and related products (38). R&D spending is of major importance for competition and survival historically in these industries. We use the same industries as Blanco and Wehrheim (2017) since it makes it more relevant to draw parallels between our results, as well as these industries being evidently the industries with the highest spendings on R&D also in Europe (Organization of Economic Cooperation and Development, 2017).

#### 3.1.2 Innovation *level* and *quality*

For the most accurate interpretation, the regression output from the raw patent count as dependent variable is used in combination with the result using number of forward citations. We use number of patents for the firm as a proxy for the *level* of firm- innovation. Generally, in order for a variable to work as a measurement of innovation, it must be of great significance in protecting inventions and intellectual innovation among these industries we choose. It also has to be one main contributor to development, innovation and survival. Earlier literature suggests that patents are a relatively good measurement of innovations in particular within these industries, hence have been used in several studies (e.g [Crosby, 2000](#); [Grabowski, 2002](#)).

From the granted patents we extract the number of forward patent citations, which serves as proxy for productivity or *quality* of innovations. This is in accordance with previous research stating that forward citations is of particular importance in measuring quality of innovation ([Lanjouw and Schankerman, 1999](#); [Marku, 2018](#)). The idea is to investigate not only the correlation between option- trading volume and quantity of innovation (patents) but rather the

future citation- count of patents to capture the relative importance of the innovations ([Blanco and Wehrheim, 2017](#)).

### 3.2 Model

To obtain the relationship between innovation and option volume, we use ordinary least squares (OLS) with our main proxies for innovation as dependent variables and option volume as main explanatory variable. Assuming our full model, the number of forward citations is regressed on option volume in the following form:

$$Y_{i,t} = \alpha + \beta O_{i,t} + \gamma Z_{i,t} + \delta_t + \lambda_t + \varepsilon_{i,t}$$

where  $Y_{i,t}$  is the natural logarithm of one plus the number of citation-weighted patents for firm  $i$  at time  $t$  and  $O_{i,t}$  is the logarithmic transformation of the options trading volume at the same time and within the same firm. Since both the dependent and independent variables are logged,  $\beta$  will in turn be expressed as the *elasticity* of citation-weighted patents to option trading volume.  $Z_{i,t}$  is a vector of the same control variables used by [Blanco and Wehrheim \(2017\)](#), all affecting firm innovation.  $\delta_t$  is the time- dummies to account for potential time- variation in the relationship between innovation and option trading. Because innovation metrics are likely to be autocorrelated over time, all of our models will allow the standard errors to have arbitrary heteroskedasticity and autocorrelation by using standard errors clustered by firm. The result in this thesis will be considered to be significant whenever the p-value is below 0.05. In addition to this, the tables will highlight when the p-values are below 0.1, 0.05 or 0.01.

In our main regression,  $Z_{i,t}$  consist of the variables: *sales*, *capital/labor*<sup>2</sup>, *firm age*, *institutional ownership* and *R&D expenditures*, in the same manner as [Blanco and Wehrheim \(2017\)](#). If we exclude R&D expenditures from the regression, the coefficient on option volume  $\beta$  measures the combined effect of how R&D expenditures and R&D productivity impacts innovation through option volume. When R&D expenditures is included, the function can be interpreted as a sort of

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<sup>2</sup> The ratio between our data on fixed asset and employees.

productivity function measuring the output of innovation, i.e forward patent citations, per Euro invested in R&D historically. By accumulating patent citations over time, we relate historical innovation quality with the quality of new innovation today.  $\beta$  in turn measures the strength of this relationship. This approach is referred to as the “ideas production function”, representing the intertemporal spillover of ideas ([Porter and Stern, 2000](#)). The baseline regressions is further extended by using various other dependent variables, trying to pinpoint what is the main driver for our result, providing more robustness.

To control for variations in patent- citations, specifically for patents granted later and having less time to be cited, we include time dummies for each year as well as performing an unweighted patent count estimation. To control for variations between industries we also include the industry- dummies  $\lambda_t$ . In order to take into account time invariant heterogeneity we include controls for firm fixed effects. By including this we are adjusting for omitted variables that might affect our results but is rather stable over time, i.e firms being traded on different exchanges and ruled under different regulations etc. When we control firm for fixed effects we do not need to use industry-dummies since they do not vary over time.

## **4. Data**

### **4.1.1 Option volume**

Option trading volumes for the firms within chosen industries are available in the Bloomberg database. The sample period is 2008-2016 with yearly observations. After sorting for firms listed on European exchanges within the prespecified industries and obtaining data on option trading volumes for each firm available, our sample consists of 47 firms. We use yearly data and gather total option turnover expressed in Euro. The options have the firm's stock as underlying asset.

### **4.1.2 Patents**

We extract the data associated with patents manually from the Google-patents database. Thus, the three variables related to this; granted patents, number of future citations on these granted patents and number of patent applications. The data is collected yearly by the date of application. Our sample ends at 2016 since after this year many patent- applications are still under examination and have not been granted yet. This also allows for a window of over 2 years of forward citations for the last granted patents.

### **4.1.3 Controls**

Data related to firm size, ownership, age and expenditures are all downloaded from Bloomberg. We also consider differences in innovation input between firms and use R&D expenditures to control for this. This is also obtained from Bloomberg and in some cases where the data is missing we extracted it manually for each firm and each year from their respective financial reports. Since we are only considering listed firms, this information is publicly available.

**Table 1.** Descriptive statistics of the variables.

Variable	Mean	Stdev	Min	Max	Median	Obs	Source
No.of Patents	109.4	239.9	0	1801	22	414	Google Patents
Citations	527.8	1556	0	16487	52	414	Google Patents
Applications	308.9	695.1	0	4244	47	414	Google Patents
Option volume (€M)	761.4	1977.5	0	21003	30.2	414	Bloomberg
Sales (€M)	3232	5700.5	0	31252	7480.3	414	Bloomberg
Employees (thousands)	57.8	75.2	0.03	425	29	414	Bloomberg
R&D expenditures (€M)	2321.5	5239.5	0	36004	219.6	414	Bloomberg
Fixed assets (€M)	9438.6	22590	0.2	150429	1214.7	414	Bloomberg
Institutional ownership (%)	47.6	21	0.23	100	46.9	414	Bloomberg
Firm age (years)	64.2	55.8	4	214	33	414	Bloomberg

## 4.2 Variables intuition

Our main dependent variable is patent citations. We need a proxy for innovation quality to relate to asymmetric information and as suggested by earlier literature (e.g [Lanjouw and Schankerman, 1999](#); [Marku, 2018](#)), that patent citations is of particular importance in measuring innovation quality. Further, we also run the regression using the raw patent count as the dependent variable, measuring the relationship between asymmetric information and the mere quantity of innovation, rather than the quality. The average firm in our sample has 109 granted patents per year and 529 forward citations on these granted patents. Though with a median value of 22 patents with 52

forward citations, we are looking at a sample which is highly skewed. Therefore we are using the natural logarithm of patent citations in our tests. Option volume on the other hand is the main independent variable, serving as a measurement of the level of asymmetric information. The main idea is that option volume works as a monitoring mechanism, hence a higher volume indicates lower asymmetric information, leading to induced management incentives for innovation ([Holmström and Tirole, 1993](#); [Ben-Nasr and Alshwer, 2016](#)). The average firm has options traded for 761.4 million Euro with a median of 30.2 million per year. These numbers are also highly skewed, hence the natural logarithm of option volume is used in our regressions.

Option volume being an endogenous variable by nature, we need to use a number of control variables to capture this endogeneity and we use the same controls as [Blanco and Wehrheim \(2017\)](#). Intuitively, one major factor impacting option volume is firm- size. Larger firms in terms of sales, capital and labor, are more likely to have a higher option volume, partly since they are more likely to have a higher share of informed investors who are generally more likely to participate in the option market ([Glosten and Milgrom \(1985\)](#); [Brown and Yang \(2017\)](#)). Hence, we want to control for this and preferably use variables that is not purely exogenously determined, thus we use sales, total fixed assets as presented in the firms annual reports (both expressed in Euro), as well as number of employees.

Assuming option volume positively associated with innovation, as the theory suggests, we can pinpoint whether option volume impacts innovation through stimulating R&D spending or boosting R&D productivity, by controlling for R&D expenditures. Specifically, if R&D expenditures is excluded, the coefficient on option volume measures the *combined* effect of the two.

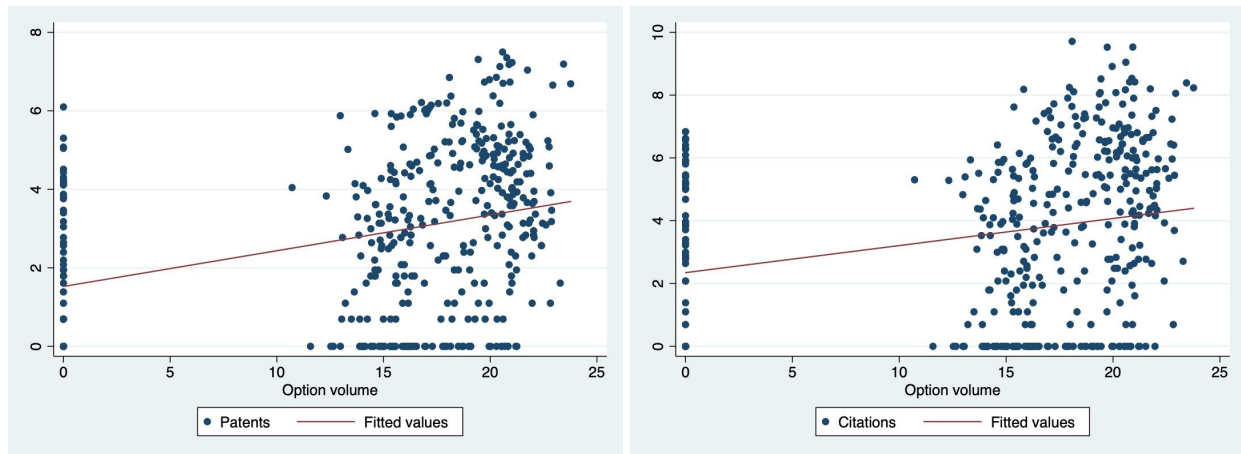
Apart from Blanco and Wehrheim (2017), the choice of variables is suggested by research addressing firm innovation and patent production functions.  $\ln(K/L)$ ,  $\ln(\text{Sales})$  and R&D expenditures are used by [Amore et al \(2013\)](#); [Tian and Wang \(2014\)](#) and [Aghion et al \(2013\)](#) whom also suggested that institutional ownership has an impact on firm innovation. If a larger



share of the outstanding shares are owned by institutional owners, this would imply that they have more informed investors, thus is positively correlated with option volume. Along the same line of thought, older firms are more likely to have higher option volume, thus is controlled for by including the firm age, i.e number of years since the firms where founded.

## 5. Results and Discussion

**Figure 1.** Scatterplots of annual option volumes graph against patent counts and patent citations, respectively. The trend line suggests a positive relationship between the two variables. The graph represents the entire sample period from 2008 to 2016.



First off, figure 1 serves as a visual representation of the relationship between our innovation measures and option volume, in form of a scatter plot. The first panel shows the relationship between the natural logarithm of (one plus) the number of granted patents (unweighted patents count) and the natural logarithm of annual option volume. The second panel shows the same relationship but with our main proxy for innovation quality; the natural logarithm of (one plus) the number of patent citations. The fitted line indicates that there is indeed a positive relationship.

### 5.1 Main regression

#### 5.1.1 Regression output

Table 2 shows our first regression results, with the main innovation proxy, patent citations, as the dependent variable. The independent variable of main interest is  $\ln(option\ volume)$ . We use ordinary least square (OLS) regressions in all 4 columns. This result shows that option volume is positively correlated and significant with innovation within the firm, for all cases except for in column 3, where we include R&D expenditures and do not account for firm fixed effects. In this

**Table 2.** The table shows our baseline regression with number of citations as dependent variable with yearly observations. There are 47 firms in the sample and the time period is 2008-2016. Time dummies are included in the regression for all the years and industry dummies are included when we do not account for fixed effects. Additionally we control for Institutional ownership, capital/labor ratio, Sales and Age of the firm. We are using clustered standard errors. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Yearly	OLS			
Dependent variable	Ln(1+citations)			
	(1)	(2)	(3)	(4)
Ln(option volume)	0.0788** (0.0396)	0.0626*** (0.0239)	0.0229 (0.0333)	0.0607*** (0.0233)
Institutional ownership	0 (0.0152)	-0.0019 (0.0094)	0.0078 (0.0117)	-0.0008 (0.0086)
Ln(K/L)	0.0742 (0.288)	-0.379 (0.3068)	-0.1539 (0.2326)	-0.3889 (0.3038)
Ln(Sales)	0.161* (0.0863)	0.0713 (0.0513)	0.1371* (0.0727)	0.071 (0.0504)
Ln(Age)	-0.0886 (0.3139)	0.3656 (1.147)	-0.0083 (0.2932)	0.4159 (1.1341)
Ln(R&D expenditures)			0.2213*** (0.0365)	0.04166 (0.0319)
Firm fixed effects	No	Yes	No	Yes
R-squared	0.3933	0.3039	0.5028	0.3465
Observations	414	414	414	414

case the coefficient is positive but insignificant. Column 4, which is our full model, suggests that with a coefficient of 0.0607, an increase by 400% in option volume is associated with an increase in innovation by approximately 24%<sup>3</sup>.

Starting in column 1, the natural logarithm of (one plus) the number of citations is regressed on option volume, including controls for *Institutional ownership*,  $\ln(K/L)$ ,  $\ln(\text{sales})$  and  $\ln(\text{age})$ . We also include dummies for industries and time. The relationship illustrated by figure 1 is present and significant in the regression. In line with Blanco and Wehrheim (2017), we also control for firm fixed effects, which are significant. Since industries do not vary over time though, these dummy variables are omitted in the fixed effects model. Even though including fixed effects lower the coefficient for option volume, it is indeed consistent with our hypothesis that there is a positive and significant relationship between option volume and innovation. In column 1 and 2 where R&D expenditures are not controlled for, the coefficient on  $\ln(\text{option volume})$  measures the combined effect of changes in R&D productivity<sup>4</sup> and the level of spending on R&D.

In columns 3 and 4, we also include the natural logarithm of R&D expenditures,  $\ln(\text{R\&D expenditures})$ . Column 4 shows the full model where both R&D expenditures and firm fixed effects are controlled for. The models in column 3 and 4 can be interpreted as a production function, showing the relationship between past R&D investments and innovative output (R&D productivity). The coefficient on option volume  $\beta$  in turn measures how strong the relationship between option volume and R&D productivity is, expressed in future patents citations per Euro invested in R&D today.

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<sup>3</sup> Blanco and Wehrheim (2017) use a move of 200% as benchmark in their sample, since the option volume increased with 188% during the sample period. In our sample option volume increased by 400% during the sample period.

<sup>4</sup> More innovative output (citations) per Euro invested in R&D

### 5.1.2 Relation to earlier findings

In the same regressions by [Blanco and Wehrheim \(2017\)](#), thus when R&D expenditures are controlled for,  $\beta$  declines by approximately 25% when firm fixed effects are included and around 32% when excluded. A drop in  $\beta$  indicates that when separating between the two impacts option volume has on innovation (enhancing R&D productivity and stimulating R&D spending), by including the control for R&D expenditures, some of the impact can be attributable to R&D spending. They argue that this rather sharp decline indicates that option volume impacts *both* through boosting innovation output in terms of R&D productivity, but also by stimulating the input being R&D spending. A drop around the magnitude of 30% in both cases however, indicates that the impact is larger through the prior.

This reasoning is consistent with the mechanics of the model, since the model including R&D expenditures separates between the effect of changes in the level of R&D expenditure and R&D productivity, rather than measuring the combined effects in  $\beta$  as when the variable is excluded. Hence, the larger the drop in  $\beta$  after this separation, the higher the option volume impact on innovation by stimulating R&D expenditures relative to boosting R&D productivity. On the other hand, the lower the drop, the more of the effect is driven by option volume impacting R&D productivity.

This is not entirely consistent with our findings, however. In our main regression, controlling for R&D expenditures leads to the variable on option volume  $\beta$  dropping sharply, but becoming insignificant, when firm fixed effects are not included. On the other hand, it declines only marginally and remains significant when firm fixed effects are included. In context of the analysis on Blanco and Wehrheim (2017), assuming our full model (firm fixed effects included), including R&D expenditures leads to an almost negligible drop of approximately 3% from 0.0626 to 0.0607 on the coefficient on option volume. This implies that the option volume operates almost *exclusively* on innovation by impacting R&D productivity, in contrast to the case of Blanco and Wehrheim (2017) where the effect to some degree is attributable to stimulation of R&D expenditures. The coefficient on R&D expenditures is insignificant in our result, in

contrast to being significant in Blanco and Wehrheim (2017), which further supports this mechanism. Higher R&D spending do not enhance firm innovation and option volume does not stimulate the prior.

### **5.1.3 Intuition**

These differences implies that within European firms, lower information asymmetry feeds innovation with the main (almost exclusive) driver being a higher number of citations per Euro spent on R&D (R&D productivity). I.e, higher option volume results in more patent citations, which implies that increased monitoring results in more efficient R&D spending rather than a higher level of spending. This is in contrast to US firms ([Blanco and Wehrheim, 2017](#)), where both number of citations as well as level of R&D spending is enhanced by a higher option volume, however with a comparably stronger effect on productivity. This part of the result is what mostly contradicts earlier literature and in particular the result of Blanco and Wehrheim (2017). Specifically, we found no proof of level of R&D spending being positively associated with innovation quality, even though patents and in turn patent citations is indeed a result from R&D spending, widely recognized by the literature ([Jaffe, 1986](#); [Artz et. al, 2010](#)). Our results do imply however that option volume leads to enhanced firm innovation quality. This indicates that lower information asymmetry leads to more patents being cited, hence managers being more careful and participating in more value-creating R&D spending, rather than spending more, thus allocating existing funds more efficiently and increasing the mere quality of innovations.

### **5.1.4 Drawbacks**

Another major difference between our results and the results from [Blanco and Wehrheim \(2017\)](#), is how dependent our results are to firm fixed effects being included or not. A possible reason for this sensitivity within our sample, could be the rather narrow data available on european firms for this specific subject, compared to the data available in the US. The european market is lagging the US in terms of development of derivatives markets and in turn option volume. Consequently, we could only obtain data on option trading from 2008 and onwards and we had to use a sample period later than Blanco and Wehrheim (2017) used (in US there are option data

available from 1996). This fact also results in a bias downwards in the quality of innovation within our sample, since patents that have been around for a longer time naturally has more citations and thus more recent patents will look less “innovative” than they really are. In addition to this we have less firms in our sample which will result in higher sensitivity to outliers which results in a higher variance.

## **5.2 Alternative innovation measures and robustness checks**

### **5.2.1 Innovation output**

By using alternative innovation measurements, we elaborate upon our main finding by investigating whether it is innovation input (R&D expenditures) or output (R&D productivity) that drives our result of the positive relationship between firm innovation and option volume. In the first two columns of *table 3*, we replace patent citations with raw patent counts as the dependent variable, to investigate whether innovation output is a significant driver. The coefficient on option volume is again positive, but slightly lower than for patent citations. However it is only significant when we control for fixed effects. These results are very similar to the result from our full model in *table 2*, again with the variable R&D expenditure being insignificant. Hence, these findings provides support of output being the main driver of our result in the same way as we argue for with patent citations. Specifically, level of R&D spending does not increase innovation.

### **5.2.1 Innovation input**

In column 3 and 4 of *table 3*, we substitute the dependent variable with R&D expenditures and remove it from the control variables, since we are now interested in inputs. Naturally, this is done to conclude whether R&D spending is in fact a driver of our result. By doing this we rely on a conditional fixed- effects estimator on option volume, which is the exact same approach as [Blanco and Wehrheim \(2017\)](#) uses. Our results differ also in this regression, both being consistent with our respective earlier findings. Blanco and Wehrheim (2017) finds a positive

**Table 3.** This table show the result with alternative measures of innovation as dependent variable (number of patents in column 1 and 2, R&D expenditures in column 3 and 4). The regression is the same with yearly observations and clustered standard errors. There are 47 firms in all regressions. The time period is 2008-2016 and time dummies are included for each year. Additionally we control for Institutional ownership, capital/labor ratio, Sales and Age of the firm. In the regression without fixed effects we also include industry dummies. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Yearly Dependent variable	OLS			
	Ln(1+Patents)		Ln(1+R&D expenditures)	
	(1)	(2)	(3)	(4)
Ln(option volume)	0.0179 (0.0287)	0.0564*** (0.0149)	0.2562*** (0.0934)	0.0461 (0.0587)
Institutional ownership	0.0039 (0.0103)	-0.0009 (0.0052)	-0.035 (0.0334)	-0.0276 (0.0344)
Ln(K/L)	-0.1272 (0.2263)	-0.2344 (0.205)	1.0306* (0.5419)	0.2363 (0.4431)
Ln(Sales)	0.1298** (0.0616)	0.0462* (0.0272)	0.1079 (0.0911)	0.0065 (0.1029)
Ln(Age)	0.0197 (0.2551)	0.2244 (0.8068)	-0.3629 (0.2773)	-1.2077 (2.5018)
Ln(R&D expenditures)	0.1655*** (0.0373)	0.0169 (0.0134)		
Firm fixed effect	No	Yes	No	Yes
R-squared	0.4161	0.2248	0.2947	0.0628
Observations	414	414	414	414

relationship between option volume and R&D expenditures and thus supporting their result of input to some extent driving innovation, although not being the only driver. Again, assuming the



complete regression with firm fixed effect controlled for (column 4), our variable is insignificant, hence providing support to our result that input is not the main driver of innovation.

### **5.2.2 Robustness checks**

Notably, the results from the first two columns of *table 3* provides robustness to the results from our baseline model also in terms of the time aspect. Intuitively, older patents will have more citations than more recent patents. By regressing with the raw patent count as the dependent variables we remove the aspect of future events. The downside is of course that the results does not take into account the relative importance (in terms of technologic and economic impact) of the patents applied and granted for, since a patent with more forward citations are considered more important than a patent with few forward citations. The idea is that it is in itself not a perfect proxy for innovation quality, but in combination with patent citations it strengthens the hypothesis of a positive relationship between option volume and firm innovation.

In column 1 and 2 of *table 4*, the dependent variable is replaced with the raw patent applications count. This is an extension of the previous regressions, however with a third potential proxy for innovation, using the mere number of patent applications. Intuitively, the probability to obtain a higher number of patent counts and citations should be higher the more patent applications, hence they should be positively associated. Thus, applications works as a slightly looser proxy for innovation.

Again, the results and thus the analysis are very similar to our main regression. When controlling for firm fixed effects, the coefficient on option volume is positive and significant. Its magnitude is almost identical to the baseline model. The variable Ln(R&D expenditures) is insignificant, both when firm fixed effects are included and excluded.

In column 3 and 4 in *table 4* we have citation frequency as the dependent variable. Citation frequency is the number of citations divided by the number of years the patent has been active.

**Table 4.** This table shows the result with alternative measures of innovation as dependent variable (number of applications in column 1 and 2 and citation frequency in column 3 and 4). The regression is the same with yearly observations and clustered standard errors. There are 47 firms in all regressions. The time period is 2008-2016 and time dummies are included for each year. Additionally we control for Institutional ownership, capital/labor ratio, Sales and age of the company. In the regression without fixed effects we also include industry dummies. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Yearly Dependent variable	OLS			
	Ln(1+applications)		Ln(1+citation frequency)	
	(1)	(2)	(3)	(4)
Ln(option volume)	0.0386 (0.0298)	0.0642*** (0.0208)	0.0294 (0.0262)	0.054*** (0.0186)
Institutional ownership	0.0036 (0.0111)	-0.0012 (0.0057)	0.0036 (0.0089)	-0.0003 (0.0062)
Ln(K/L)	-0.0439 (0.237)	-0.194 (0.2742)	-0.0998 (0.1876)	-0.2218 (0.2346)
Ln(Sales)	0.1333* (0.0706)	0.0387 (0.0227)	0.0942 (0.0522)	0.0467 (0.0316)
Ln(Age)	0.1248 (0.2747)	0.0707 (0.9637)	0.0066 (0.2292)	0.3993 (0.9369)
Ln(R&D expenditures)	0.1943*** (0.0411)	0.0262 (0.0187)	0.1503*** (0.0289)	0.0232 (0.0201)
Firm fixed effect	No	Yes	No	Yes
R-squared	0.4351	0.2589	0.4528	0.2976
Observations	414	414	414	414

By dividing the number of patents with its active years, we adjust for older patents having more time to be cited. The result again are very similar to our baseline regression with the variable of interest being positive (its magnitude slightly smaller) and only significant when we include firm

fixed effects. Again, the variable Ln(R&D expenditure) are not significant. This shows that our results are robust and holds even after adjusting for the time factor in active patents.

The idea of using numerous proxies for innovation is that if one is arguably loose on its own, it could provide intuition in combination with others. The same shape in the results from all regressions connected to innovation output makes it clear that the relationship suggested by our hypothesis is indeed consistent within our sample.

### **5.3 Possible mechanisms**

Assuming our full model, which makes the assumption of time-invariant heterogeneity and thus includes firm fixed effects, the relationship between option volume and innovation is positive and robust for a number of alternative innovation measures. This is consistent with our main hypothesis of option volume enhancing firm innovation and holds when controlling for possible endogeneity in option volume. According to our results, the increased monitoring that is associated with higher option volume, only increases the mere quality of R&D spending rather than its level, thus improving innovation quality (i.e number of citations per Euro invested in R&D historically). Elaborating upon the results from the model with our main dependent variable, patent citations, there are a number of possible explanations to why this relationship seems to exist. We will suggest a couple of possible mechanisms, both of which are subject for further testing and investigation.

#### **5.3.1 Management characteristics and incentives**

One exposition, associated with management characteristics, is the increased monitoring effect induced by option trading and how this changes management incentives. The option trading serves as a monitoring mechanism, suggesting that the higher the volume, the lower the information asymmetry. If the information asymmetry between managers and shareholders is high, incentives for managers to act in their own best interests could be pronounced. As proposed by e.g [Bertrand and Mullainathan \(2003\)](#) and [Naoshi et al \(2018\)](#), managers might prefer to live the “quiet life”, hence the higher associated monitoring forces managers to invest in accordance

with their shareholders, even if reluctant. In terms of our results this would then imply that shareholders prefer managers to *focus* the R&D spending rather than *increase* it, thus leading to a more efficient allocation of funds, increasing the number of patent citations. Assuming shareholders want to maximize their ROE, this is likely to be true on average.

On the other hand, some managers are more concerned about their career and “building an empire” rather than to live the quiet life. Assuming this management characteristic, our result implies that increased monitoring give incentives to participate in more value-creating investments to boost their reputation. This scenario is probably less likely, since aggressive managers intuitively also increase R&D spending. However, these two very contradictory management characteristics could both realistically be explanatory for the same effect, and which of them that dominates in this context is subject for further investigation. Intuitively, an increase in the mere quality of innovation associated with higher monitoring is more likely to be directed by shareholder incentives through their increased influence.

Another aspect further affecting manager incentives, is that managers are considered insiders of the firm in the way that they have an information advantage compared to the market. If they want to trade on their information, they are more likely to trade on the option market ([Chakravarty et al, 2004](#); [Hu, 2014](#)). This potentially gives managers higher incentives to increase innovation quality to boost the stock price, thus making a profit on the option market. This mechanism of managers incentives to make a profit as well as being more likely to participate on the option market, would in turn increase the volume traded on the option market, hence explaining the positive relationship between option volume and innovation.

### **5.3.2 Market competition and innovation quality**

The second proposition is indirectly linked to management incentives, although highly likely to be one explanation to this relationship. As e.g [Cantwell \(2005\)](#) and [Clark and Guy \(1998\)](#) argues, firm innovation is crucial in a competitive environment. The larger the firm, the more areas it operates within, among an increasing number of competitors. This means that larger firms are

more exposed to competition and therefore they need to be more innovative (in absolute terms) to sustain its position. Thus, a more competitive environment indirectly affects management by forcing them to innovate. Under the assumption that stock options on large firms have higher volumes than options on small firms, we can think of a positive relationship between option volume and firm size. Under these two propositions; higher innovation quality in more competitive environments and thus within larger firms, and higher volumes on large firms stock options, our results could be attributable to market competition. Again, assuming the results from our full model, this implies that the positive relationship between option volume and innovation quality is due to firms being more prone to competition, resulting in enhanced innovation quality to compete. Rather than competition, the same line of thought could be attributable to factors like higher competence or resources generally being higher in larger firms.

R&D spending not being associated with higher innovation quality indicates that, regardless of the mechanism suggested, lower information asymmetry results in more citations per Euro invested in R&D and is not due to greater spending. Specifically, greater insight into the firm leads to R&D spending being more *focused* rather than *increasing* its level, thus to a more efficient allocation of available funds.

## 6. Conclusion

Do option trading volume increase or impose innovation in the firm of the underlying stock? This is what we have been investigating throughout this thesis. [Blanco and Wehrheim \(2017\)](#), which has been the benchmark paper throughout our analysis, approach the same issue on US firms and finds a clear and consistent relationship between option volume and firm innovation. The result show that option volume has an impact on innovation both through stimulating the level of R&D spending, as well as increasing R&D productivity, being robust for a number of different innovation measurements. This is in line with the hypothesis and what the literature suggests; option volume serves as a monitoring mechanism, reducing asymmetric information, thus giving incentives for managers to invest in innovation. This relationship is particularly distinct within R&D intense industries, since these are industries where innovation is of major importance for competition and growth.

Approaching this issue on european firms does not give quite the same clear picture, however. The relationship is still positive and robust for a number of innovation proxies, but the way that option volume impacts innovation is a bit more ambiguous. First off, the relationship is positive and significant only when we control for fixed effects and the dependent variable is associated with innovation output. This means that our main variable for innovation input, R&D expenditures, had no significant relationship with option volume, thus is not a driver behind the enhanced innovation level associated with higher option volume. Strictly speaking, this means that a higher level of innovation quality associated lower level of asymmetric information, is not due to an increase in R&D expenditures.

This result however stands and falls with the assumption whether it is reasonable to account for fixed effects, since the coefficient on option volume is only significant when these are accounted for. Arguably, it is reasonable to assume that there are indeed time-invariant heterogeneity in our sample (e.g. traded on the different exchanges, ruled under different legislations), and in that case, we can conclude that option volume do effect firm innovation. That is, option volume is in

fact an effective tool of monitoring, reducing asymmetric information and thus giving managers incentive to innovate. On the other hand, if we cannot make that assumption, we cannot draw any conclusions from our result, being in stark contrast with the findings of Blanco and Wehrheim (2017). This high dependency is probably partly due to the natural shortcoming of our analysis being the lack of depth in available data on the European option markets, resulting in a more sensitive result as well as a bias downwards in terms of innovation quality.

Put together, under reasonable assumptions, there is no doubt that there is a robust and positive relationship between option volume and innovation within European firms. It is clear that an active option market is an efficient monitoring mechanism, spurring firm innovation. What is actually the main driver behind this result is not crystal clear, however. It seems to be the case that lower asymmetric information leads to an increase in R&D productivity, but the result does not provide support to the idea of R&D spending being one driver, which is in stark contrast to established literature. This would imply that when managers are being closely monitored, they participate in more productive R&D investments rather than increasing its level. Possible mechanisms behind this positive relationship is related to management incentives and market competition. Breaking down this information and pinpointing potential drivers is subject for further investigation.

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