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Does Private Equity Affect Firm and Inventor Performance in Pursuing Innovation?

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ABSTRACT

This thesis investigates the effect of leveraged buyouts on target firms' innovation performance with the purpose of providing insights into the debate on whether private equity contributes with long-term value to portfolio companies. We construct a sample of 1,186 U.S. target firms in the years 1981-2008 and examine patent-based metrics around the time of the LBO to evaluate changes in patent performance. We find significant evidence indicating that private equity targets produce patents of higher quality after the takeover, achieved through increased performance of inventors staying with the target firm after the transaction. Our results are informative both for policy makers in regard to private equity as well as for other stakeholders of a firm approaching a potential takeover.

Keywords: *Innovation, Private Equity, Leveraged Buyout, Patent, Corporate Governance*

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Contents

1. Introduction

"[Private equity] is about aligning management and owners and bringing value to shareholders. Our focus on making companies more valuable has benefited the whole U.S. economy."[1]

During almost 40 years now, private equity has sparked much awe as well as criticism. One side of the discourse in the debate argues that the leveraged buyout (LBO) is an advantageous ownership structure, especially compared to the public corporation. According to Jensen (1989), the public corporation often lacks sufficient corporate governance due to many widespread shareholders. He also suggests that the leveraged buyout greatly reduce the distance between owners and management; it enables better corporate governance and stronger managerial incentives. The buyout is considered by many to create value through leverage; aside from being used as a mean to boost returns through favorable tax legislation and gearing, it is a mean to control the management's operations (Harbula 2015). However, due to the nature of private equity, which commonly entails short holding periods followed by a strategic exit (Kaplan, Strömberg 2009), skeptics criticize the LBO primarily for the short-term perspective of the private equity fund. Examples include the use of dividend recapitalizations and debt payments ruling out positive NPV-investments (Rauch, Umber 2015). Some say that the relatively short span of private equity ownership would reasonably incentivize the fund to quickly restructure, cut costs and boost short-term profits (Dutta, Ganguly et al. 2015). Critics continue arguing against private equity by claiming managers are enticed to accept takeover bids at the original shareholders' loss (Shleifer, Summers 1988) and that the PE-firms themselves have incentives to undertake excessive risk (Crotty 2009).

An important paper in this field assesses the longevity of private equity's investment horizon empirically. In *Private Equity and Long-Run Investment: the Case of Innovation*, Lerner, Sorensen, and Strömberg (2012) examine long-term investment through innovation performance at LBO target firms. The authors base the study on 472 LBOs 1985-2005 and find that the quality of patents granted for these firms seem to increase after the LBO. The authors thus provide

[1] David Rubenstein, co-founder and co-chief executive officer of the global private equity firm *The Carlyle Group*,

evidence against the critics claiming that private equity is an ownership form riddled with investment myopia.

This thesis revisits the topic of Lerner, Sorensen, and Strömberg (2012) for two primary reasons, which also serve as a useful starting point for constructing the hypotheses of interest.

The first reason is that the patent data available to the previous authors only stretched until 2006. Effectively, many private equity transactions could not be included in their sample. However, a group of researchers have now collectively disambiguated and created the U.S. Patent Inventor Database (Lai, D'Amour et al. 2015) that offers an opportunity to capture a broader patent sample. Consequently, a wider selection of LBOs can be included and especially the intense LBO-activity in the years preceding the financial crisis in 2008. Since there are no recent findings providing evidence against Lerner, Sorensen, and Strömberg's (2012) view, we propose the first hypothesis against the aforementioned critics of private equity:

H1. *Private Equity backed firms are as good as, or better, at producing innovation in terms of quality without sacrificing the fundamental nature of the research.*

Secondly, the U.S. Patent Inventor Database offers highly interesting possibilities of studying individual inventors' performance that can provide an explanation for some of the reasons behind the results of Lerner, Sorensen and Strömberg (2012). Focusing on the staying inventors' performance over time, we can infer whether it changes due to the shift in ownership. Different streams of literature provide conclusions indicating both improvement as well as deterioration. Findings, such as increased focus on core activities, a decrease in negative NPV-investments, reduced agency-costs and superior incentives, as well as an increase in layoffs among white collar workers, could all contribute to an increase in inventor performance (Lerner, Sorensen et al. 2012, Jensen 1988, Jensen 1989, Jensen 1986, Lichtenberg, Siegel 1990). On the other hand, Manso (2011) suggests that structures where management entrenchment prevails should experience higher innovational performance. The assumption that entrenchment is more common in companies with less active control, perhaps suggests that staying inventors' performance should decline post LBO. Conversely, given the findings of Lerner, Sorensen and Strömberg (2012), we propose a second hypothesis in line with the evidence in favor of improved inventor performance.

H2. *Inventors staying at target firms are as good as, or better, at producing innovation in terms of quality without sacrificing the fundamental nature of the research.*

Plenty of the aforementioned literature assesses private equity in contrast to the public firm, thus we are especially interested to measure whether or not the results are different for this group. Therefore, we will evaluate this potential effect by presenting a third hypothesis:

H3. *The effect on staying inventors' performance is different for inventors at firms going private.*

To summarize, revisiting Lerner, Sorensen, and Strömberg's (2012) topic allows for both providing evidence that their results hold for an essential period in private equity history, and also why this effect is observed. Given that we find that inventors are improving under private equity governance, it would give an indication in favor of Jensen's theory (1989). It would in essence provide results contradicting the theories stating that private equity governance results in sub-optimal short-term investment focus. Instead it would suggest that the firm itself could gain long-term benefits of an improved innovation activity. Not only would this conclusion benefit private equity funds, but it would also be informative both for policy makers as well as for target firm management deciding upon their stance in regards to a transaction.

To test our hypotheses, we create a sample of 1,186 target firms and match these to 10,829 patents from the U.S. Patent Inventor Database. This enables us to study the effects of a wider LBO-activity on both target firm and individual innovational performance, and can help develop the understanding of private equity's impact on long-term value creation. In accordance with previous literature, we use citation intensity as a primary measure to evaluate how the innovational quality changes after the LBO (Hall, Jaffe et al. 2001). This is supplemented with an analysis of the fundamental nature of the patents, assuring that it is not sacrificed in favor of quality. We apply a negative binomial regression model to estimate the effects on transactions between 1981-2008, due to the count-nature of patent citations. With our wider array of transactions, our result supports the findings of Lerner, Sorensen and Strömberg (2012), suggesting that target firm's innovation quality improves substantially after the LBO. We can therefore enforce the discourse in favor of private equity firms, as they indeed seem to create tangible value for portfolio companies, given the well-recognized link of citation intensity and firm value (Hall, Jaffe et al. 2005). The effect is robust to including various controls and using different model specifications.

Furthermore, we also provide evidence of *how* the improved innovation occurs, by observing a significant increase in patent quality for staying inventors after the LBO. The individual-level models observe the performance of inventors before and after the transaction through the quality of their patenting. Our findings are in line with previous research; not only do staying inventors maintain their previous patent quality, the results also suggest improvement under private equity governance. This offers an explanation of how private equity achieves the greater quality of innovation, and can reject the possibility that acquisition of human capital is the main cause of the innovation increase.

Relating to the literature on corporate governance's role and incentive schemes in motivating innovation, we isolate the particular effect of going-private transactions. Bernstein's (2015) findings suggest a negative effect on staying inventors' innovation after an IPO. If some of that IPO-effect is due to insufficient corporate governance, the LBO-effect might be stronger for the going-private group. Given that the change in performance of staying inventors is stronger than the rest of our sample, it would suggest that Bernstein's findings are partially reversible. The results are indeed in line with our hypothesis, public firms being purchased through an LBO experience a larger positive effect in the innovation performance of staying inventors.

The structure of the paper is as follows: the existing research relevant for our hypotheses is covered in Section 2, continuing with the sample data in Section 3. Section 4 covers our methodology, followed by statistical results in Section 5 and conclusion in Section 6. Section 7 describes the limitations to this study and suggestions for future research. Finally, references, tables (and figures) and the Appendix are found in Section 8, 9, and 10 respectively.

2. Previous Literature

Organizational forms and their effects on firm performance have been widely studied during the last 10-15 years, with special regards to private equity and the method of acquiring companies through LBOs. As Kaplan and Strömberg (2009) show, the overall private equity activity in the

US started slowly in the beginning of the 1980s until it peaked in the years preceding the IT-bubble. In the middle of the 2000s, the amount of completed LBOs saw an unprecedented high before the global financial crisis struck in 2008. This cyclicality between LBOs and the overall economic environment is likely linked to the buyout's use of leverage and the accessibility of debt in the market. Kaplan and Schoar (2005) shows that many new private equity funds enter the market during boom-times in the economy even though they seem to underperform compared to the industry average.

There are four branches of existing literature relevant to this thesis. Firstly, one branch regards the more general question of private equity's value creation, the second regards long-term investment and innovation performance, the third concerns how to evaluate innovation, and the last one focuses on mechanisms of motivating innovation.

2.1 Private Equity and Value Creation

The first branch concerns whether private equity creates value, both for the fund investors and the target firm stakeholders. The transaction through which the private equity firm purchases the target usually involves high levels of debt, hence the term leveraged buyout. During the time of private equity ownership, usually 5-7 years, the debt is repaid using cash flows from the target firms with the purpose of yielding a high return on equity upon exit (Kaplan, Strömberg 2009).

Generally speaking, the main mechanisms private equity use to create value is through financial structure, corporate governance and improved operations (Harbula 2015). The use of leverage enables higher return on equity (and risk) for the fund's investors, the concentrated ownership reduce wasteful spending through improved corporate governance and less-profitable parts of the operations are often down-sized or sold off. The use of leverage and risk during a short holding period is often claimed to be connected to short-term, and thus temporary, value increases. However, the possibility of improved corporate governance would rather suggest realized long-term return.

To conclude, these mechanisms for value creation could have ambiguous meanings in terms of the predominance of investment myopia, and this literature does not further examine any empirical evidence on private equity's choice of investment horizon. Interpreted collectively, the above mentioned research indicates that private equity is either a quick-flip construction, or a better form of governance, which due to the increase in control, debt, etc. provides opportunities for long-term realized gains.

2.2 Ownership and Innovation Performance

The second branch of research concerns the more specific connection of ownership structures and its implications on innovational output. Innovation has been found to have an essential role in stimulating economic growth through productivity increases already in the late 1950s (Solow 1957). One of the more prominent directions this branch takes is to provide insight into the debate regarding private equity firms' investment horizon.

As previously mentioned, the paper *Private Equity and Long-Run Investment: the Case of Innovation,* examines innovational performance for target firms after private equity transactions, based on a sample of U.S. target firms in the years of 1986-2005 (Lerner, Sorensen et al. 2012). They find significant evidence that these transactions result in targets focusing their innovation efforts into core activities as well as developing patents of a higher quality without sacrificing the fundamental nature of the research. However, compared to this thesis the authors' data contains fewer transactions in general and none from the LBO-intense period in between 2005-2008. Although they present interesting findings regarding the refocus toward key areas, they do not delve deeper into the underlying reasons for the change.

Apart from the private side of corporate innovation, publicly traded companies offer an attractive opportunity for research on long-term investment. One of the most important papers during the last years in this area studies how firms' innovation activity changes when choosing to undergo an IPO (Bernstein 2015). Bernstein (2015) captures the dynamic ownership change in private-to-public transactions and finds that innovational output measured by patent quantity do not change after the IPO, but the innovational strategies do. Newly public firms seem to shift their strategies from in-house patent development to patent acquisitions. The paper uses an interesting approach by analyzing the effect on innovation on the inventor level. Moreover, the IPO also seem to reduce the innovational performance of inventors staying with the firm.

Publicly traded firms also face challenges to long-term innovation that private firms do not. Active trading of company shares leads to continuous transferring of ownership and higher turnover can have stifling effects on the long-term perspective of the operations (Fang, Tian et al. 2014). Fang, Tian et al. (2014) find that high stock market liquidity negatively affect corporate innovation, mainly due to the increased risk of hostile takeovers and institutional investors' inactive ownership of their investments. These findings are in line with the aforementioned paper by Bernstein (2015), and help construct a picture of how innovational strategies and risks are handled in public corporations as well as emphasizing the importance of measuring going-private transaction separately.

2.3 Measuring Innovation

Given that the horizon of investment have been measured using various methods, a note on different metrics' appropriateness is suitable. Both creating and measuring long-term investment and return can be a tricky business. Absolute R&D-expenditure or R&D-intensity (R&D/Sales) as a measure innovation investment has previously been used as an indicator of a firm's investment horizon (Lichtenberg, Siegel 1990). However, even though R&D-based measures offer a picture of a firm's priorities of long-term investment, an apparent flaw arises because the metric does not necessarily allow conclusions of innovation *performance*. Jensen (1993) argues explicitly that only measuring R&D-expense might be irrelevant because it is often wasteful and yield low returns.

The choice of assessing longevity of investment through innovational quality is not novel. Bound, Griliches, Jaffe et al. (1982) pioneered the use of patent-based metrics already in the 1980's. Today, patenting metrics have become an accepted method of evaluating a firm's actual innovation performance and strategy. Especially since the quality of patenting has been found to be positively correlated to firm value (Hall, Jaffe et al. 2005), it becomes an attractive proxy for the investment horizon, as qualitative research requires a long-term focus. The availability and great detail of US-patenting data, enable a construction of several innovation metrics for both public and private firms. Patenting measures are thus a prominent tool for assessing the connection between ownership, corporate governance and long-term investment.

2.4 Mechanisms in Motivating Innovation

The final branch of literature focuses on how individuals in firms behave under varying ownership and incentive structures. The importance of understanding a firm's link between financials, governance and organization is suggested to be a key in how marginal labor productivity can be handled successfully within firms (Jensen 1993). An interesting theory in this area is presented by Manso (2011) who connects several factors to successfully motivate innovation. Especially relevant for our hypotheses is the connection between control and innovation. Too much pressure, e.g. through low employment security and extrinsic rewards, can create a negative environment for successful innovation. Given that one of the most mentioned changes for firms becoming private equity backed is increased active control, Manso's theory suggests that the innovational performance of human capital might decrease. Our stated hypotheses thus contradict Manso's reasoning (2011).

Tirole (2001) presents three mechanisms which contribute to aligning investor and management's incentives (decreasing agency conflicts); the extrinsic incentive, intrinsic incentive and control structure. Tirole argues that both a passive and active control structure, similar to what Manso (2011) refers to as pressure, is economically preferable. These control structures reduce the required extrinsic incentive (such as monetary reward) required to make the manager exert effort. In the case for innovation, Manso (2011) is conversely arguing that *less* control is preferable *for innovation*, as it results in structures more accepting of short-term failure.

Furthermore, Manso (2011) also argues that tolerance for failure and long-term compensation schemes are necessary ingredients to encourage innovation, and that pay-for-performance schemes with punishment for bad short-run performance are deterrent of long-terms gains. In fact, a later article by Ferreira, Manso and Silva (2014), postulates the hypothesis that private companies are more allowing of early-stage failure, thus fostering innovation, and that the reason behind exiting and entering equity markets might be due to different requirements during a firm's life cycle. Some stages demand more technological advancement, and thus benefit from an environment where innovation flourishes. To conclude, the implication of Manso's (2011) theories of the combined effect of increased control and acceptance of failure on innovation remains ambiguous.

3. Data

This thesis is based on several data sources: patent and inventor data from the U.S. Patent Inventor Database supplemented with information from the patent database of the National Bureau of Economic Research (NBER), and finally transaction data from SDC Platinum and Capital IQ. Combined, these components allow us to measure and compare innovation performance for LBO firms. This section first describes the patent data, continues with the choice and identification of relevant transactions, and then concludes how the match between the two is made to create the final sample.

3.1 Patenting Data

Comprehensive and updated data on patent filings and subsequent citations comes from the U.S Patent Inventor Database, provided by Harvard Business School (Lai, D'Amour et al. 2015). These data sets contain all awarded patents with respective information (e.g. assignee, class etc.), within the United States for the years 1975-2010[2].

There are two issues with the patent data worth mentioning. Firstly, filings that are still pending are not included, which cause a truncation problem towards the end of our time interval as only patents granted before December 2010 are included in the sample. Secondly, due to human errors, the patent databases contain spelling errors and ambiguous assignees. However, we have no reason to believe the errors to be serially correlated with any of the variables in the models that we later specify and eventual errors will thus only provide noise, not bias. Also, given that we only use patents we surely can attribute to a certain firm reduces the potential faults in the sample.

Even though the citing activity of patents is a well-established measure of evaluating a firm's innovation performance, there are crucial aspects to be considered. One issue mentioned by Hall, Jaffe et al. (2001) is the problem of citation activity through time. The computerization of patent records results in an increasing citation activity after the 1980s. Variations in citation frequency can also be caused by shifts in the importance of certain technologies or alterations of the patent classification system (Hall, Jaffe et al. 2001). Figure II shows how the sample patents' citation counts have changed over the years. As can be seen, the number of citations experienced a gradual increase during the 1990s, which then plateaus. This is due to the combined effect of an increase in citation intensity over time, and that earlier patents have more time to garner citations.

[2] In total, the data sets from NBER and the U.S. Patent Inventor Database combine to approximately 9 million unique granted patents and 40 million patent citations in the years 1975-2010.

3.2 Inventor Data

The U.S. Patent Inventor Database also provides extensive records of individual inventors linked to patents (Lai, D'Amour et al. 2015), allowing an evaluation of their movements between firms and performance over time. There are unfortunately difficulties that arise when tracking inventors in the data. The individual observations are only registered by name and geographical location, which cause uncertainty through the approximately 2.6 million different inventors. First names are sometimes abbreviated and many of the individuals have similar or identical names, which cause difficulties in accurately tracking all observations, especially combined with occasional uncertainty in connecting patents to a specific organization (Lai, D'Amour et al. 2015). However, as most of the problems arising during the name disambiguation process concern Asian names, due to the different structure in terms of first-, middle- and last names, that should not concern too many of our American transactions' patents.

3.3 LBO-transactions

We identify LBOs during the period 1979-2008 by using data from Capital IQ primarily and SDC Platinum as a supplement. Both of the databases contain American transaction data for completed deals made by public and private entities, and Capital IQ in particular has since 1999 thoroughly recorded American deals as well as back-filled deal information towards the beginning of our time interval. The time period is chosen based on the availability of patent data, which stretches from 1975 through 2010. To minimize the truncation problem, we include LBOs up until the financial crisis in 2008.

We start by choosing transactions where the acquirer is a private firm and have leverage as a primary financing method. Deals where the management has used their own funds to purchase a firm (pure MBOs) and deals where the target firm remains public ("PIPEs") are excluded from the sample, since the goal is to distinguish the effect of leverage and private equity ownership on the investment horizon. When supplementing the Capital IQ-data with SDC Platinum, we make certain that no duplicate entries of the same transaction are included based on target and acquirer names, transaction dates and geographical locations. This results in approximately 45,000 LBOs when combining the two datasets, before matching them with patents.

When evaluating the sample of LBO target firms, an endogeneity issue arises. Targets that are attractive to private equity firms are likely those where the buyer sees potential for improvement.

In the worst case, the potential does not reside in prospective changes made by the private equity firm, but rather that the target is already on a trajectory of improvement. This is definitely a caveat in the construction of our sample as it could question the causality we are trying to infer. Albeit important to keep in mind throughout this thesis, we will further discuss this issue in section 5.3.

3.4 Matching LBOs to Patents

With the transaction data in place, we use firm identifiers[3] to match transactions to the patent-assignee registry established by the U.S. Patent Inventor Database. Due to identifiers not staying constant over time, we only include firms where we are certain of a patent-assignee match. This leaves us with 982 transactions matched through firm identifiers[4]. The remaining transactions are linked to patents using a name-based match with the patent registry. A complication with the method is that different entries of same firm are registered in different ways. The entries contain both misspellings and different ways of identifying the same firm. For example, Capital IQ may register a transaction target as “RJR Nabisco” while the U.S. Patent Inventor Database have the same firm’s patents registered to “r.j.r. nabisco Ltd”. We sidestep the issue by removing all generic components of firm names as “Corp.”, “PLC”, “Ltd.”, etc., all spaces and characters apart from A-Z, etc. to minimize the discrepancies in the name registrations. Once a match is made to a unique patent, the U.S. Patent Inventor Database provides disambiguated assignee identifiers. Thus the name-matched transactions can be connected with the full patent registry. Perfect matches are manually examined, controlling for the geographical location of the firm and patent classification. In other words, if a target firm matches with the patent registry but the patent class or geographical location does not, we exclude the transaction from the sample to minimize errors. After the second match based on firm names, our sample consists of 2,578 LBO target firms matched with at least one patent in the combined patent and inventor databases.

Further screening requires that the target firm have at least one patent granted within a window of three years prior to, or five years after the transaction. This yields a sample of 1,149 firms

[3] Capital IQ uses the identifier “Company ID” while SDC Platinum uses “CUSIP”. We implement the match with GVKEYs either directly through CompanyIDs, else using the merged CRSP/Compustat database to match Cusip-only transactions with GVKEYs.
[4] NBER uses the identifier ”assignee number” as a unique patent assignee code to which all of a firm’s patents are registered, these identification numbers are the same in the U.S. Patent Inventor Database. This identifier is matched with GVKEYs where applicable in the patent database.

going through 1,187 transactions matched against a total of 12,832 unique patents. One sample firm, Seagate Technologies PLC, is the assignee of 2,003 sample patents, which accounts for roughly 16% of the entire sample. As a comparison, the 2nd, 3rd and 4th most active patentees together combine for ~7% of the sample patents, and we therefore exclude Seagate Technologies from the analysis. This reduces the final sample to 1,186 LBOs matched with 10,829 patents.

Table I shows the industries attributed to target firms and patents. Target firms are categorized into the Fama-French 12 industry classification based on the firms' SIC-codes. Patents are referred to the same category as the target owning the patent. The fractions of LBO-industries are quite similar to the fraction of patents assigned to these, indicating that there is no industry with a particularly high patenting activity. One exception is "Business Equipment"-LBOs which constitute ~16% of the target sample but ~22% of the patent sample.

Table II illustrates the lag between patent applications and grants in the event window. The average processing time of a sample patent has approximately been 18-30 months in the years 1990-2008[5]. Thus, many of the patents granted in the years preceding the LBO are filed for before the window starts, and consequently, the patents granted in the first year after the transaction have likely been applied for before the private equity firm seized control. The effect of the ownership change is therefore expected to appear successively, due to the lag in the patent grant process.

Table III offers a more detailed view of the types of LBOs in the sample. The LBOs are divided into the categories "Public-to-private", "Secondary Buyout", "Divisional Buyout", "Privatization" and "Private-to-private". Roughly 47% of the sample is categorized as private-to-private transactions, followed by divisional buyouts as the second most common type. The divisional buyout, constituting almost 30% of the sample, is an increasingly common transaction type for private equity firms (Kaplan, Strömberg 2009). It is not a majority of this sample due to the large number of sample transactions prior to the overall divisional-buyout increase, as can be seen in Figure I. The categorization is useful as the conditions pre transaction varies between categories. Therefore, this categorization allows us to differentiate by, and control for, different types of transactions.

[5] The United States Patent and Trademark Office provides annual performance reports of the average pendency periods of patents. http://www.uspto.gov/web/offices/ac/ido/oeip/taf/ann_rpt_intermed.htm

One issue that arises with the LBO-sample is that it contains 34 LBO-targets that have more than one transaction attributed to the firm. The subsequent transaction(s) for each firm are classified as a "Secondary Buyout" since the acquirer in the first transaction also is a financial sponsor. The implications of this are that a patent attributed to a certain firm may be counted more than once, if the firm has two transactions close in time with patenting in between. For further discussion of this issue see section 5.3.

4. Methodology

In preparing the final sample for the regression analysis, we commence with constructing the dependent variables of interest. Various patenting measures are created to analyze several aspects of patenting, such as quality and importance. The section continues with details of the inventor level metrics, followed by a specification of the regression model used.

4.1 Constructing Patenting Metrics

The accumulated citations received per granted patent gives an indication of the quality or impact a certain patent has had on subsequent inventions, much as judging an influential paper on its subsequent citations. The patent citation data contains all citations made from a patent's grant date, until 2010, which means that patents granted earlier in the sample period would have had a longer time to garner citations. This truncation problem is handled by limiting each patent's citation accumulation to three years after its grant date (Lerner, Sorensen et al. 2012). As mentioned above, an inter-temporal and intra-industry related issue arise since patenting activity varies greatly between different time periods and industries. These issues are resolved by using *scaled* patenting citations as a secondary measure for patent quality (Hall, Jaffe et al. 2001). The scaling compares a patent's citing activity to a citation average for the same grant year and USPTO-class[6], thus offering a better perspective of the relative firm-level patenting performance. The patents a sample patent is scaled with are henceforth referred to as a sample patent's "reference group". Each sample patent's relative citation measure is calculated as:

[6] The United States Patent and Trademark Office (USPTO) classify all patents with a three-digit code. The link: http://www.uspto.gov/web/patents/classification/selectnumwithtitle.htm offer a more detailed explanation of the system.

$$Rel.citations \ = \#\,patent\ citations\ [0,+3] - avg\ citations\ ref.group\ [0,+3] \qquad (1)$$

Where the average citation count $\gamma_{k,t}$[7] in the reference group is calculated:

$$\gamma_{k,t} = \frac{Total\ citations_{k,t}}{Number\ of\ patents_{k,t}} \qquad (2)$$

Subtracting the average citations of a patent's reference group reduces the effect of intra-industry and inter-temporal citation activity.

The two further metrics give information about the importance or fundamental nature of patents[8]. The "generality" measure offers information of how many different USPTO-classes have drawn inspiration from a particular patent. The "originality" measure is based on the reverse relationship, thus how many different USPTO-classes a patent has drawn inspiration from. See Figure V in the Appendix for more a detailed explanation. Following the method by Trajtenberg, Henderson and Jaffe (1997) we construct the generality measure as one minus the Herfindahl index of citation patent classes:

$$Generality_i = 1 - \sum_{k=1}^{N_i} \left(\frac{NCiting_{i,k}}{NCiting_i}\right)^2 \qquad (3)$$

$NCiting_i$ is the total number of patents citing the sample patent, $NCiting_{i,k}$ is the number of patents citing a patent for each USPTO-class k, and N_i is the number of different classes the citing patents belong to. Important to note is that $0 \leq Generality_i \leq 1$ and that a higher value implies higher generality. $Originality_i$ is calculated in the same way as Equation (2), except the two differences that $NCiting_i$ is interpreted as the number of patents *cited by* a sample patent and consequently, N_i is the number of USPTO-classes these cited patents belong to. The relative measures of generality and originality are calculated analogously as in Equation (1). These

[7] k denotes the USPTO- class and t denotes grant year

[8] The United States Patent and Trademark Office (USPTO) classify all patents with a three-digit code. The link: http://www.uspto.gov/web/patents/classification/selectnumwithtitle.htm offer a more detailed explanation of the system.

measures of patents' fundamental nature help create a more nuanced picture of a firm's overall innovational activity; defining whether a firm's patents can be seen as a brand new discovery or just a smaller brick to an already existing house.

4.2 Inventor Classification

We begin the inventor level study by categorizing inventors as Stayers, following the method of Bernstein (2015), if an inventor has at least one patent granted with a target firm both before and after the effective date of the transaction.

As previously mentioned, the U.S. Patent Inventor Database (Lai, D'Amour et al. 2015) contain roughly 2.6 million inventors attributed to patents and we manage to categorize 2,920 of these as Stayers based on our sample transactions. We follow the aforementioned method in the patent data sample and only account for the inventors we accurately can categorize into one of the above categories. The issues with ambiguous names and geographical locations with inventors are solved by not categorizing these inventors as Stayers. Moreover, some inventors who have been attributed a patent only once cannot be classified into the above categories due to the lack of observations, but these individuals may not be the ones of primary interest due to their low patenting activity. When a patent has two or more inventors assigned to it, we count it as if each inventor has one patent. Models are specified specifically on the patent quality and importance for this inventor type.

4.3 Model Specification

The variable of main interest is the one of patent quality, i.e. citations per patent. In order to specify the appropriate model, our starting point is the standard Poisson model since count data often follow a Poisson distribution, with a decreasing probability of finding observations with a high citation count. However, since the likelihood of patent citation data having a variance larger than the expected mean is high, the Poisson model will be unable to accurately predict probabilities (Cameron, Trivedi 2013). We instead use the negative binomial regression to estimate the probabilities of citation intensity. The model has a similar distribution as the Poisson count model, but have an extra error term for the expected variance that better captures the effect of overdispersion.

Although patent data is overdispersed in general, we validate the model by testing the sample for overdispersion using a likelihood-ratio test. The results confirm that the error terms in fact are larger than the mean, strengthening the choice of the model. Furthermore, the risk of an excessive amount of zero-observations in measures of citation intensity, originality and generality is prominent, due to many patents in the sample receiving one or zero citations.

Results of Vuong-tests suggest that we cannot reject the null hypothesis stating there is no zero-inflation our sample, motivating the use of the standard negative binomial distribution. Details of the negative binomial distribution and model validation-tests are found in the Appendix.

Using the negative binomial distribution, we construct the dynamic model:

$$Y_i = \beta_0 + \beta_1 EventYear_{-3} + \beta_2 EventYear_{-2} + \ldots + \beta_8 EventYear_5 + \varepsilon_{1i} \tag{4}$$

The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the dependent variable Y_i. The dependent variable will be patent citation intensity, originality or generality (both scaled and unscaled measures). Furthermore, we also construct the more parsimonious model:

$$Y_i = \beta_0 + \beta_1 PostDealPlusOne + \varepsilon_{1i} \tag{5}$$

Where "Post Deal Plus One" accounts for all sample patents granted from event year one through five. Another important feature of the negative binomial distribution is that negative observations (counts) are not allowed. We thus use the unscaled measures and use the average citation intensity as an independent variable with the coefficient fixed at 1.0.

Continuing with the inventor performance models, we measure Stayers patent quality through the negative binomial regression as in Equation (4) and (5).

The theories of corporate governance highlight the large differences between public and private enterprises; thus we add an interaction term to the regression. This will test whether there is a different effect for inventors transitioning from working in a public firm to a private equity-owned firm. Adding this interaction term to the parsimonious model yields the specification:

$$Y_i = \beta_0 + \beta_1 PostLBO + \beta_2 PostLBO * GoingPrivate + \varepsilon_{1i} \quad (6)$$

In this model, β_2 will estimate the potential extra effect on citation intensity of inventors' patents for in going private firms.

For the two remaining measures, generality and originality, we construct the model with the same functional form as in Equation (4) and (5), but use an OLS-regression instead of the negative binomial in accordance with previous literature (Lerner, Sorensen et al. 2012).

5. Results

The evaluation of our hypotheses starts by briefly analyzing the summary statistics of pre and post transaction subsamples. We continue by predicting firm-level patent performance, followed by an analysis of inventor-level patent performance. Finally, we perform robustness checks of important factors that might bias our results.

5.1 Observing Means of Pre and Post Subsamples

5.1.1 Firm-level Patent Performance

A natural starting point for the analysis is considering the differences in means of patent performance metrics (citation intensity, generality and originality) for firms receiving private equity backing. Citation intensity accounts for the economic importance of the patent whilst generality and originality accounts for the fundamental nature of patents.

As Table IV, Panel A, shows, comparing the means of patents granted before and after the transaction[9] generates both an initial indication of our results, as well as a confirmation of the importance of scaling the performance measurements. Patents granted in the three years before the transaction receive on average 1.53 citations, whereas patents granted in the year succeeding the transaction and five subsequent years only receive 1.40 citations. This would suggest a decrease in the economic importance of patents post transaction. However, this indication is highly biased since, collectively, the average citations of patents in each sample patent's reference group also decreased significantly. The joint effect of both the change in citation count

[9] For an illustration of the different windows see Figure VI in the Appendix

and the inter-temporal differences in patenting activity results in a positive effect on citation count post deal, approaching a 95% significance level. The raw measures of the fundamental nature of patents suggest a slight decrease in generality and an increase in originality. However, these results are not robust to controlling for the average generality and originality of reference groups. This initial analysis are thus in line with both previous research and our first hypothesis.

Due to the lag in patent applications and grants, we also measure the difference between patents granted in the three years before, *and* in the year of the transaction, versus patents granted in the five years after the transaction year[10]. As can be seen in Table IV, Panel B, the results are only marginally different. To maintain prudent in our multivariate estimations, we will primarily use this separation between pre and post transaction, as to avoid most of the bias caused by the lag between applications and grant dates.

5.1.2 Inventor-level Patent Performance

In Table V, Panel A, the same comparison is made for a subsample of patents attributed to inventors staying with the firm after the LBO. Patents granted in the three years before and in the year of the transaction receive on average 1.59 citations, whereas the patents granted in the five subsequent years receive 1.60 citations on average. The raw citation counts thus provides little evidence for an increase in the economic importance of Stayers' patents post transaction. However, as for the whole sample, a positive effect is observed on scaled citation count post deal, significant on a 99% level.

Both scaled and raw measures of the fundamental nature of Stayers' patents suggest a slight insignificant decrease in generality and a significant increase in originality. Thus, these initial results are in line with the hypothesis that inventors staying with the firm are contributing to the increase in patenting performance. They therefore contradict the idea that the increase in patenting performance only results from window-dressing by acquisition and inefficient innovation maintenance. Due to the lag in patent application and grants (Table II) this mean comparison is only reported as the more prudent pre and post division, where the grants occurring in the year after the transaction are attributed to pre transaction.

[10] For an illustration of the different windows see Figure VI in the Appendix

5.2 Analysis of Firms and Inventors' Innovational Performance

To further analyze the connection between private equity and innovation we turn to a multivariate analysis. The analysis is divided into two sections: firm level patenting and individual inventors' performance, and corresponding subsections. The first section begins with presenting and analyzing the results of the whole sample, where the unit observation is a patent assigned to a sample firm. Its first subsection concerns models predicting citation intensity and the second subsection predicts the fundamental nature of patents. The results are then delved deeper into, through presenting and analyzing the results of staying inventors in the following section. The unit of observation is a patent-inventor pair connected to a sample firm. The first subsection concern models predicting citation intensity both for the whole Stayer sample as well as specifically for inventors in firms going private, while the second subsection estimates the fundamental nature of the patents of staying inventors.

5.2.1 Model of Firm Patent Performance and Nature

5.2.1 a) Patent Performance

Results of the negative binomial model predicting citation count are presented below in Table VI and VII. To account for the variation between different LBO-waves, as well as the placement within a wave, the regressions in Table VII control for the fixed effect of the transaction's announced year. The announced year serves as a proxy for the quality of private equity funds, as these vary with LBO-cycles. We believe this specification to be more in line with previous research and to better capture the general effect of private equity on patent quality (see further discussion in the preceding section 2). Note that the coefficients reported are incidence rates, i.e. an Event Year X-coefficient of 1.223 is interpreted as that year increasing the citation rate by 22,3%, above the respective reference group, in relation to the year of the transaction.

In Table VI, the first two regressions in Column (1) and (2) are presented with separate variables categorizing each patent's grant year in relation to the year of the transaction. The last four columns show the results of the parsimonious model specification, where citation intensity is predicted using the variable Post Deal or Post Deal Plus One Year, which indicate if a patent is granted in the period after the transaction or the subsequent years after the transaction year, respectively[11]. Column (1) in Table VI uses the absolute measure of citation count, and (in line

[11] For an illustration of the different windows see Figure VI in the Appendix

with our summary statistics) barely shows any significance except for two years before the transaction, which suggests an almost significant positive effect on citation intensity pre transaction. Turning to the more parsimonious models of raw citation count, both regressions show a value higher than one but neither is significant on any conventional level.

Column (2), (4), and (6) predict citation intensity adjusted for each patent's reference group average and generate significant results. Column (2) generates a barely significant negative effect for Event Year -1 and a significant ~15% increase in citation intensity for Event Year 4. Both parsimonious models with Post Deal and the more prudent Post Deal Plus One Year as independent variables suggest a significant ~7% increase in citation rate post-transaction.

Turning to the models with transaction announced-year random and fixed effects in Table VII, the results become much more clear, significant and remain in line with our first hypothesis. As the scaled citation activity already has been proven to be a more prominent metric, all regressions in Table VII use average citation count as an offset variable. Thus the interpretation of the dependent is the scaled citation rate. The control metric, announced year, *should not* be correlated to the occurrence of patenting in particular event years. However, due to the construction of the sample there will be a truncation that could lead to correlation for late and early announced years in relation to the sample. E.g. a transaction announced in December 2009 only have patents included in event years [-3, +1], as only patents granted until December 2010 are observed. Also, if there are periods where the private equity industry changed the quantity of internal patenting (previous research find no effect on the quantity of patenting (Lerner, Sorensen et al. 2012)) this could lead to correlation between independent variables and the transaction announced years. To be certain that the model is not wrongly specified, we report both fixed and random effects regressions of each specification with control for the announced year. As can be seen in Table VII the effect of using random or fixed effects is marginal.

The effect of private equity backing is larger in the regressions with control for announced year fixed effects, as well as highly significant. To observe the effect more clearly, the coefficients and respective 99% confidence intervals from Column (1) in Table VII are reported in Figure III. All event years before the transaction show a negative effect, significant for Event Year -2 (99%) as well as for Event Year -1 (90%). All event years after the transaction are significantly positive at the 99% level, and the economic magnitude is quite large.

Figure III also illustrates that the majority of the effect seems to be concentrated for Event Year 2, 3 and 4, and seems to decline in Event Year 5. The decrease in Event Year 5 could be due to shorter holding periods for parts of our sample. Previous research suggests that around 12% of all private equity firms between 1970 and 2005 exit their investment before 24 months have passed and 42% exit before 60 months, i.e. before the end of Event Year 4. If the hypothesis that private equity backing is a as good as, or a better form of governance (in terms of patent quality) is taken to be true, and the exit is strategic (non-financial buyer) or an IPO, some of the decrease could be attributed to a large part of the sample exiting early in the window (Kaplan, Strömberg 2009).

Collectively, the Event Years 1 to 5 suggest an increase of ~165% in citation rate over each patent's reference group average, which can be seen in Column (3), Table VII. These results persist when adding firm fixed effects (in combination with announced year fixed effects) although the economic magnitude decreases. With this combined control, the effect of becoming backed by private equity suggests an increase in scaled citations of 17% (see Column (6)). This decrease in economic magnitude when adding fixed effects could to be due to the loss of firms patenting less frequently. As all the between-firm variation is lost, the sample is likely to be fundamentally different given that the effect of private equity might differ based on the patenting frequency of firms.

5.2.1 b) Fundamental Nature of Patents

To make certain that firms are not only shifting focus toward patents that will generate more citations, but are less important in terms of generality and originality, we also study the effect of LBOs on these measures. As can be seen in Table VIII, the suggested effect is a slight decrease in generality and a slight increase in originality, however the results are insignificant on all conventional levels for the scaled measures. We are thus unable to reject the hypothesis that private equity has no effect on the fundamental nature of patenting. In unreported regressions, the model is specified both without the announced year fixed effects, and with both firm and announced year fixed effects. The difference is marginal and generates no significant results for the scaled metrics.

5.2.2 Model of Inventor Patent Performance and Nature

By observing the change in patent performance of staying inventors, we can further disambiguate the results from section 5.2.1 a). For these results to support Jensen's (1989) theory of private equity as a superior form of governance, we would expect that inventors staying with the firm also experience an increase in citation rate without a decrease in fundamental nature. Otherwise, we cannot discard the eventuality that private equity firms actually improve their portfolio companies through "purchasing" innovation (e.g. new hires and add-on acquisitions).

5.2.2 a) Inventor Patent Performance

Beginning in Table IX, we measure the citation rate of Stayers using the negative binomial model with year announced fixed effects and find significant results in favor of our second hypothesis. In contrast to the results for the whole sample however, Stayers in general outperform their respective reference groups in Event Year -3 and Event Year -1. These results are quite intuitive; the Stayers in general outperform their reference group compared to their peers before the transaction. This could be a result of these inventors' superiority to their leaving colleagues, their presence in a division where the firm is superior or, most likely, a combination of the two. The outperformance *after the transaction* is however much larger for all event years. Looking at the more parsimonious Column 2, the post transaction patents' scaled citations collectively outperform their reference groups in relation to the years before the transaction by 103%. The results are illustrated in Figure IV where coefficients and 99% confidence intervals are reported. The outperformance post transaction is definitely superior to that pre transaction. Also noteworthy is that the predicted model for Stayers also follows the general shape from the full sample; the majority of the increase occurs in Event Year 2, 3, and 4, and a significant decrease is observed in Event Year 5.

Moreover, we attempt to answer the hypothesis of whether this effect is stronger or weaker for inventors staying in firms going private. As Table IX, Column (3) shows, there clearly is a stronger effect for that subgroup; the interaction term increases the scaled citation rate by ~151%. In unreported regressions we test if these results are robust to firm fixed effects, and although the sample changes and some significance is lost, as most inventors only patent once in the 9-year window, the conclusion holds nonetheless.

5.2.2 b) Inventor Patent Fundamental Nature

Once again, it is essential to examine that staying inventors do not sacrifice the fundamental nature of the research, since that would suggest a shift of focus rather than an improvement in performance. Thus, for the sample of Stayers, we also investigate the effect on generality and originality. As can be seen in the dynamic model of scaled generality, Column (2), Table X, most years post transaction suggest a significant but small underperformance in relation to patent's reference groups (although Event Year 4 suggests a significant but small over performance). Collectively there is no significant under or over performance post transaction in terms of generality. Thus, these results might suggest that Stayers outperform the reference group in terms of generality *to a greater extent*, in the year of the transaction. Even so, the effect is slight, and not of large economic significance.

The predictions of originality however, yield some interesting results. In the dynamic scaled originality model of Column (6) in Table X, the years before the transaction mostly show negative although insignificant estimates, while the coefficients of Event Year 1-5 are positive and some even highly significant. These results collectively suggest an outperformance relative to their reference groups of 2,3% in relation to patents granted before Event Year 1.

All in all, the most important finding is that Stayers do not sacrifice the fundamental nature of their innovation activity for increased economic importance (patent citations) and the conclusions from section 5.2.1 a) hold. We find no indication of the increase in patent quality primarily being a result of a change in strategy, rather it seems that private equity, due to e.g. increased control, effective use of leverage, and increased focus on core activities results in better performance of the "original" firm and its inventors.

5.3 Robustness Checks

There are issues with both data and model that presents a challenge for interpreting our results. The main concerns put forth by Lerner, Sorensen and Strömberg (2012) are cherry picking of target firms, divisional buyouts, secondary buyouts, and choice of citation window. Recently, some critique has been published toward the negative binomial regression in combination with fixed effects, and we thus check that the effect still holds when using the less effective circumventive method suggested by Allison and Waterman (2002).

The first issue concerns causality. Given that we have no ability to create an appropriate counterfactual group, e.g. firms chosen as a target of a transaction that for some reason fell through, we are unable to completely resolve the causality issue. Clearly there is a potent risk that the group of firms in our sample suffers from a self-selection bias. Targets may be cherry-picked by private equity firms and thus the effect of increased innovation quality might be due to factors present before the change in control. However, just as Lerner, Sorensen and Strömberg (2012) found in their results of transactions until 2005, the majority of the effect occurs in the later years, primarily Event Year 2, 3 and 4. It thus seems less likely that private equity firms in general would be able to spot which firms will to produce important patents three to five years after the transaction is effective. However, this caveat should be kept in mind when interpreting our results.

A second concern considers divisional buyouts, as there might be attribution issues if the most important patents pre transaction are assigned to the corporate parent and not the purchased division (Lerner, Sorensen et al. 2012). As only patents assigned to the corporate parent are kept by the seller, it makes economic sense to make such a decision. If this is a common occurrence in the sample, it would bias the results in favor of our hypothesis and it is therefore essential to test whether the results still hold whilst controlling for this effect. In Table XI in the Appendix, the regressions for the full sample have been repeated excluding the divisional buyouts, as can be seen both in the dynamic event year model of Column (1) and the parsimonious model of Column (3). The effect of becoming private equity backed still holds, although it is somewhat diminished.

A third concern considers secondary buyouts, where a private equity firm purchases a target company from another private equity firm. These transactions present an issue as they might result in double-counting of patents, as post-LBO patents for the first private equity holding period and pre-LBO patents in the second transaction might coincide (Lerner, Sorensen et al. 2012). One could also argue that including these transactions might dampen the measured economic implication, as a transaction from one private equity firm to another would not measure the effect of private equity ownership on innovation. Rather, any change would represent differences in efficiency between the private equity firms. Table XII in the Appendix, shows regression estimates for the whole sample excluding secondary LBOs. As expected, the effect remains and the difference between pre and post transaction becomes slightly larger.

A fourth concern is the limitation issue when including fixed effects in a negative binomial regression. This accepted method is derived by Hausman, Hall and Griliches (1984) and several statistical programs use it. However, the method has received critique for not controlling for changing covariates. Essentially, it includes individual-specific variation in the dispersion parameter rather than in the conditional mean, resulting in time-invariant covariates and output variables estimated to deviate from zero (Allison, Waterman 2002). The primary issue with this simplification, made primarily for computational ease, is that non-time variant variables will not be omitted. As all our variables are time-variant and all groups contain more than one observation, this should not constitute too much of a problem. Despite the lack of severity for our specific case, Table XIII in the Appendix presents a robustness check for this issue. Following Allison and Waterman's (2002) suggested circumvention, we have applied an unconditional estimation of the fixed effects negative binomial model. Although the unconditional fixed effects currently have no proof for unbiased estimators, Allison (2002) states that the preliminary results presented in their paper give the procedure much certainty. As can be seen in Table XIII in the Appendix, the main results are robust to the unconditional model, although we naturally lose some significance.

A fifth concern relates to heteroskedasticity. It seems reasonable to assume that there might be an occurrence of clustered errors for firms, both when the unit of observation is patents and patent-inventor pairs. Unfortunately, there is no option to produce cluster standard errors with the announced year (and/or firm) fixed effects negative binomial regression with any readily available statistical program. Thus, using the unconditional fixed effects produces an opportunity to test whether the results are robust to clustered standard errors. As presented in Table XIII in the Appendix, the less effective unconditional negative binomial model's results hold for robust standard errors, and for clustered standard errors on the firm level. The results are however weakly significant and do not hold for the parsimonious model. Observing the dynamic model suggests that the unconditional fixed effects predict the connection as even more gradual, and testing the effect of an even later collective period might capture it better. As hypothesized, we find significantly positive effect for later years (Post Deal Plus Two Years), and considering the lag between patent application and grant, these years are most interesting in terms of measuring the private equity effect. Thus, we can conclude that although we lose economic effect using an econometrically less efficient model, private equity firms still increase performance of their targets' patents in relation to their reference groups, and that the results are, albeit weakly, robust to corrections for heteroskedasticity.

6. Conclusion

We examined private equity's effect on target firms' innovation performance, based on a sample of 1,186 American transactions between the years of 1979-2008. The dynamic models suggest a sharp increase in the likelihood of higher performance in relation to each patent's reference group, an effect robust to several controls and specifications. Neither do we find any indication that these results are a consequence of a decrease in the fundamental nature of patents. This enforces the results of Lerner, Sorensen et al. (2012), with a sample containing LBOs from the peak of the private equity era before the financial crisis.

Most interestingly, we can provide evidence for the underlying reason behind the improved innovation performance of target firms. Our results suggest that inventors staying with the firm develop patents of higher quality after the change in ownership. We can therefore tie these results to theories of corporate governance and provide evidence in favor of the opinion that the presence of private equity encourages the staying employees of target firms to perform better. More concentrated ownership, better control, and/or other factors associated with the takeover appear to have a significantly positive effect on the individual performance. If the theories by Manso (2011) are taken to be true, our results suggest that the effect of increasing the acceptance of failure outweigh the effect of increased control.

Given the improvement of staying inventors' performance, we can successfully supply contradictory evidence against the theories suggesting that private equity only concentrates on quick flips and window-dressing of target firms. Just as we began this paper with the words of David Rubenstein, stating that private equity has benefitted the whole U.S. economy (Sender 2013), our findings suggest that private equity actually improves operations.

These results not only benefit private equity funds and provide further fodder in a long line of discourse pro and against the ownership form; they also generate implications for firm executives. Management of a target firm deciding upon their stance in regards to a private equity takeover can in light of our results feel more confident, as they suggest that the firm itself could reap long-term benefits of a takeover.

7. Limitations and Suggestions for Future Research

7.1 Limitations

Considering the data availability issue, we are unable to capture all patenting activity for target firms towards the end of the sample. This truncation issue results in our inability to observe all patenting and citations of target firms purchased between the years of 2005-2008[12]. This limitation of our sample does weigh the number of patents on the post category toward the earlier transactions as those targets' patenting is observed over the whole window. Given that this is the most updated data available at this time we will leave to future researchers the possibility to repeat similar research with an even wider sample.

Another limitation that arises in the inventor-level study is the fact that inventor movements only can be connected through the grant dates of the patents assigned to the individuals. This causes somewhat of an uncertainty of the exact timing of their relocation and therefore difficulties when classifying these individuals. The most active inventors in terms of patent frequency over time have higher chances of a receiving a classification as a Stayer due to the better traceability of their movements. Consequently, we are unable to include infrequently patenting inventors' movements, resulting in a sample likely consisting of "key-inventors" within the sample firms.

This study confirmed the stated hypotheses, but the model itself may have its limitations. As stated in the robustness section of this thesis, the options available for fixed effects estimation of the negative binomial regression model has been criticized. However, given that the ineffective circumvention of unconditional fixed effects held for our conclusion, we consider this as less of an issue.

Moreover, as previously mentioned, the direct causality of LBOs on targets' performance is difficult to generalize due to the aforementioned self-selection problem and lack of an instrumental variable or counterfactual. The concern is nevertheless mitigated by the fact that the largest improvements in innovational quality are estimated several years after the transaction.

[12]This effect is evident in Figure I as the number of sample patents granted in these years sharply decline.

7.2 Suggestions for Future Research

Given our findings, we see two main directions for future research. First off, the results that firms going private experience a sharper increase in patent quality for the staying inventors naturally makes one wonder whether more of the effects captured by Bernstein (2015) are reversed upon delisting. Aside from a decrease in quality of staying inventors Bernstein (2015) finds both evidence of an inventor exodus and an increase in patent acquisitions, suggesting a complete change in innovational strategy. It would be interesting to see if this change in strategy, attributed to excess of cash generated upon an IPO as well as the availability to raise more funds subsequently, is generally reversed when a public firm is taken private again.

Secondly, as previously stated, many suggestions have been put forth as the underlying factors to why employees of companies going through an LBO would experience a change in productivity. Among these non-mutually exclusive factors are an increased focus on core activities (Lerner, Sorensen et al. 2012), a decrease in negative NPV-investments due to the reduced agency-costs and superior incentives from a decrease in free cash flow (Jensen 1986, Jensen 1988) and an increase in layoffs among white collar workers which in turn might increase incentives among employees (Lichtenberg, Siegel 1990). For the case of innovation, it would be interesting to see if evidence can be found for which of these mechanisms are the underlying drivers of the increased productivity of staying inventors. Answering that question could provide useful implications for managers and private equity firms in effectively improving human capital.

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9. Tables and Figures

Table I

Sample Industry Composition

NOTE*: the sample is based on firms being purchased through an LBO during 1979-2008. All firms have had at least one patent granted in the United States between three years prior to five years after the effective date of the purchase, adding up to 1,148 target firms and 1,186 transactions. All 10,829 patents included in the sample have been granted within the [-3,5] year window based on the effective date of the transaction.*

	Target firms		**Patents**	
Industry	**Frequency**	**Fraction of sample**	**Frequency**	**Fraction of sample**
Business Equipment	191	16,1%	2 369	21,9%
Chemicals	49	4,1%	490	4,5%
Consumer Durables	57	4,8%	471	4,3%
Consumer Non-durables	66	5,6%	780	7,2%
Energy, Oil & Gas	8	0,7%	58	0,5%
Healthcare	84	7,1%	741	6,8%
Manufacturing	400	33,7%	3 092	28,6%
Money & Finance	11	0,9%	41	0,4%
Shops, Wholesale, Retail	63	5,3%	236	2,2%
Telecom	11	0,9%	39	0,4%
Utilities	1	0,1%	2	0,0%
Other	245	20,7%	2 510	23,2%
Total	**1 186**	**100%**	**10 829**	**100%**

Table II

Lag Between Patent Applications and Grants

NOTE*: the sample is based on firms being purchased through an LBO during 1979-2008. All firms have had at least one patent granted in the United States between three years prior to five years after the effective date of the purchase, adding up to 1,148 target firms and 1,186 transactions. All 10,829 patents included in the sample have been granted within the [-3,5] year window based on the effective date of the transaction.*

	Patent applications		Patents granted	
Year	**Frequency**	**Fraction of sample**	**Frequency**	**Fraction of sample**
Before window	2 638	24%	N/A	N/A
Event Year -3	1 248	12%	1 072	10%
Event Year -2	1 370	13%	1 098	10%
Event Year -1	1 373	13%	1 236	11%
Event Year 0	1 232	11%	1 346	12%
Event Year 1	1 140	11%	1 345	12%
Event Year 2	916	8%	1 403	13%
Event Year 3	654	6%	1 200	11%
Event Year 4	251	2%	1 140	11%
Event Year 5	7	0%	989	9%
Total	**10 829**	**100%**	**10 829**	**100%**

Table III

Transaction Sample by LBO-type

NOTE*: the sample is based on firms being purchased through an LBO during 1979-2008. All firms have had at least one patent granted in the United States between three years prior to five years after the effective date of the purchase, adding up to 1,148 target firms and 1,186 transactions. All 10,829 patents included in the sample have been granted within the [-3,5] year window based on the effective date of the transaction.*

Transaction type	Frequency	Fraction of sample
Divisional Buyout	341	29%
Private-to-Private	553	47%
Privatization	52	4%
Public-to-Private	159	13%
Secondary Buyout	81	7%
Total	**1 186**	**100%**

Table IV: Univariate Tests of Means

NOTE*: the sample is based on firms being purchased through an LBO during 1979-2008. All firms have had at least one patent granted in the United States between three years prior to five years after the effective date of the purchase, adding up to 1,148 target firms and 1,186 transactions. All 10,829 patents included in the sample have been granted within the [-3,5] year window based on the effective date of the transaction*

Panel A: Comparing Patents Filed in Years [-3,-1] and [0,5].

	Mean [-3,-1]	Obs	Mean [0,5]	Obs	Diff.	P-value, t-test
Citations	1.5331	3406	1.3971	7423	-0.1360	0.0111
Avg. Citations	1.5084	3406	1.2785	7423	-0.2299	0.0000
Scaled Citations	0.0248	3406	0.1187	7423	0.0939	0.0611
Generality	0.1074	3406	0.0947	7423	-0.0127	0.0033
Scaled Generality	0.0065	3406	0.0081	7423	0.0016	0.6968
Originality	0.3809	3406	0.4320	7423	0.0511	0.0000
Scaled Originality	0.0231	3406	0.0284	7423	0.0053	0.3151

Panel B: Comparing Patents Filed in Years [-3, 0] and [1, 5]

	Mean [-3,0]	Obs	Mean [1,5]	Obs	Diff.	P-value, t-test
Citations	1.5143	4752	1.3818	6077	-0.1325	0.0082
Avg. Citations	1.4757	4752	1.2531	6077	-0.2227	0.0000
Scaled Citations	0.0386	4752	0.1287	6077	0.0901	0.0548
Generality	0.1054	4752	0.0934	6077	-0.0120	0.0030
Scaled Generality	0.0067	4752	0.0083	6077	0.0016	0.6742
Originality	0.3897	4752	0.4365	6077	0.0467	0.0000
Scaled Originality	0.0230	4752	0.0297	6077	0.0067	0.1738

Table V: Univariate Tests of Means, Stayers

NOTE*: the sample is based on firms being purchased through an LBO during 1979-2008. All firms have had at least one patent granted in the United States between three years prior to five years after the effective date of the purchase, adding up to 1,148 target firms and 1,186 transactions. All 10,829 patents included in the sample have been granted within the [-3,5] year window based on the effective date of the transaction*

Panel A: Comparing Patents of Stayers Filed in Years [-3,0] and [1,5]

	Mean [-3,0]	Obs	Mean [1,5]	Obs	Diff.	P-value, t-test
Citations	1.5910	4137	1.6029	5892	0.0118	0.8182
Scaled Citations	0.1773	4137	0.3375	5892	0.1602	0.0011
Generality	0.1118	4137	0.1055	5892	-0.0063	0.1520
Scaled Generality	0.0194	4137	0.0204	5892	0.0010	0.8036
Originality	0.3863	4137	0.4257	5892	0.0394	0.0000
Scaled Originality	0.0192	4137	0.0418	5892	0.0226	0.0000

Table VI

Negative Binomial Model of Citation Intensity

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. The dependent variable is number of citations received in the three years after the grant date. The reported coefficients are incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. Robust standard errors are reported in parenthesis below each coefficient. The complete sample comprises of 10,829 patents of 1139 firms announcing a private equity transaction in between 1979 and 2008. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The sample used is a subsample of 9,655 patents that were granted until December 2007, meaning that all patents have three years to garner citations. *, **, and, *** indicates that the coefficient is statistically significantly different from one at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Absolute Citations	Scaled Citations	Absolute Citations	Scaled Citations	Absolute Citations	Scaled Citations
Event Year -3	0.963	0.995				
	(0.0581)	(0.0633)				
Event Year -2	1.113*	1.074				
	(0.0658)	(0.0673)				
Event Year -1	0.928	0.886*				
	(0.0542)	(0.0549)				
Event Year 1	1.070	1.034				
	(0.0628)	(0.0638)				
Event Year 2	0.961	1.003				
	(0.0571)	(0.0624)				
Event Year 3	1.032	1.055				
	(0.0641)	(0.0684)				
Event Year 4	1.069	1.150**				
	(0.0667)	(0.0749)				
Event Year 5	1.039	1.086				
	(0.0671)	(0.0733)				
Post Deal			1.027	1.069**		
			(0.0316)	(0.0348)		
Post Deal Plus One Year					1.033	1.076**
					(0.0304)	(0.0332)
Constant	1.539***	0.315***	1.537***	0.309***	1.538***	0.311***
	(0.0633)	(0.0137)	(0.0382)	(0.00816)	(0.0327)	(0.00701)
Observations	9,655	9,655	9,655	9,655	9,655	9,655
Year Ann. Fixed Effects	No	No	No	No	No	No

Table VII

Negative Binomial Model of Citation Intensity

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. As the average citation intensity for the reference group is offset, the dependent variable is interpreted as scaled citations measured in a three-year window. The reported coefficients are incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. Standard errors are reported in parenthesis below each coefficient. The complete sample comprises of 10,829 patents of 1139 firms announcing a private equity transaction in between 1979 and 2008. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The sample used is a subsample of 9,655 patents that were granted until December 2007, meaning that all patents have three years to garner citations. *, **, and, *** indicates that the coefficient is statistically significantly different from one at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

VARIABLES	(1) Scaled Citations	(2) Scaled Citations	(3) Scaled Citations	(4) Scaled Citations	(5) Scaled Citations	(6) Scaled Citations
Event Year -3	1.003	0.999			0.954	
	(0.0573)	(0.0572)			(0.0536)	
Event Year -2	0.550***	0.551***			0.710***	
	(0.0313)	(0.0314)			(0.0405)	
Event Year -1	0.906*	0.906*			0.852***	
	(0.0471)	(0.0471)			(0.0440)	
Event Year 1	2.053***	2.051***			1.167***	
	(0.103)	(0.102)			(0.0604)	
Event Year 2	2.549***	2.543***			1.134**	
	(0.132)	(0.132)			(0.0593)	
Event Year 3	2.644***	2.638***			1.078	
	(0.143)	(0.143)			(0.0606)	
Event Year 4	2.550***	2.542***			1.141**	
	(0.141)	(0.141)			(0.0655)	
Event Year 5	1.530***	1.533***			0.611***	
	(0.0925)	(0.0929)			(0.0385)	
Post Deal Plus One Year			2.648***	2.646***		1.174***
			(0.0753)	(0.0755)		(0.0378)
Constant	0.0512***	0.0512***	0.0429***	0.0429***	0.171***	0.148***
Observations	9,655	9,655	9,655	9,655	(0.00808)	(0.00544)
Announced Year Random Effects	Yes	No	Yes	No	No	No
Year Ann. Fixed Effects	No	Yes	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	No	Yes	Yes

Table VIII

Model of Fundamental Nature of Patents

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the fundamental nature of the patent. The dependent variable is the generality and originality measured on citations received or made in the three years after the grant date. The reported coefficients are normal OLS coefficients; a coefficient higher than zero suggests the variable has a positive effect on the dependent variable. Robust standard errors are reported in parenthesis below each coefficient. The complete sample comprises of 10,829 patents of 1139 firms announcing a private equity transaction in between 1979 and 2008. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. *, **, and *** indicates that the coefficient is statistically significantly different from zero at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Generality	Scaled Generality	Generality	Scaled Generality	Originality	Scaled Originality	Originality	Scaled Originality
Event Year -3	0.00765	0.00114			-0.0644***	-0.00509		
	(0.0110)	(0.0122)			(0.0192)	(0.0170)		
Event Year -2	0.0141	0.00442			-0.0318**	-0.00780		
	(0.0135)	(0.00964)			(0.0129)	(0.0110)		
Event Year -1	0.00526	-0.00470			0.000329	0.0117		
	(0.00919)	(0.00791)			(0.0112)	(0.00861)		
Event Year 1	-0.0104	-0.00365			0.0130	0.00278		
	(0.00827)	(0.00706)			(0.00989)	(0.00729)		
Event Year 2	-0.0111	0.000760			0.0189	0.00288		
	(0.0126)	(0.0113)			(0.0127)	(0.00706)		
Event Year 3	-0.0218*	-0.00439			0.0413***	0.0148		
	(0.0127)	(0.0108)			(0.0134)	(0.0110)		
Event Year 4	-0.00819	0.0121			0.0647***	0.0163		
	(0.0189)	(0.0118)			(0.0115)	(0.0110)		
Event Year 5	-0.0307*	-0.00831			0.0555***	-0.00766		
	(0.0171)	(0.00881)			(0.0141)	(0.0110)		
Post Deal Plus One Year			-0.0218**	-0.000622			0.0570***	0.00582
			(0.00977)	(0.00489)			(0.00868)	(0.00638)
Constant	0.105***	0.00786	0.111***	0.00791***	0.405***	0.0233***	0.384***	0.0235***
	(0.00793)	(0.00653)	(0.00548)	(0.00275)	(0.00696)	(0.00591)	(0.00487)	(0.00358)
Observations	10,829	10,829	10,829	10,829	10,829	10,829	10,829	10,829
Year Ann. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IX

Negative Binomial Model of Citation Intensity of Stayers

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. The unit of observation is a patent attributed to an inventor whose company received Private Equity backing the years 1979 and 2008. As the average citation intensity for the reference group is offset, the dependent variable is interpreted as scaled citations measured in a three-year window. The reported coefficients are incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. Eform standard errors are reported in parenthesis below each coefficient. The complete sample comprises of 23,735 observations of 10489 patents of 11796 inventors of 1136 firms announcing a private equity transaction in between 1979 and 2010. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The inventor patent sample is smaller than the original as some inventors are not registered. The sample used is a subsample of 8,092 observations of 4,638 patents that belong to stayers and were granted until December 2007, meaning that all patents have three years to garner citations. *, **, and *** indicates that the coefficient is statistically significantly different from one at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations
Event Year -3		1.632***		
		(0.127)		
Event Year -2		1.003		
		(0.0745)		
Event Year -1		1.301***		
		(0.0856)		
Event Year 1		2.024***		
		(0.131)		
Event Year 2		2.583***		
		(0.163)		
Event Year 3		2.723***		
		(0.181)		
Event Year 4		3.166***		
		(0.201)		
Event Year 5		1.761***		
		(0.118)		
Post Deal Plus One Year	1.064		2.032***	1.529***
	(0.0580)		(0.0672)	(0.0567)
Going Private * Post Plus One				2.508***
				(0.184)
Going Private				0.382***
				(0.0243)
Constant	1.317***	0.0575***	0.0671***	0.0905***
	(0.0580)	(0.00326)	(0.00232)	(0.00342)
Observations	8,834	8,092	8,092	8,092
Year Ann. Fixed Effects	No	Yes	Yes	Yes

Table X

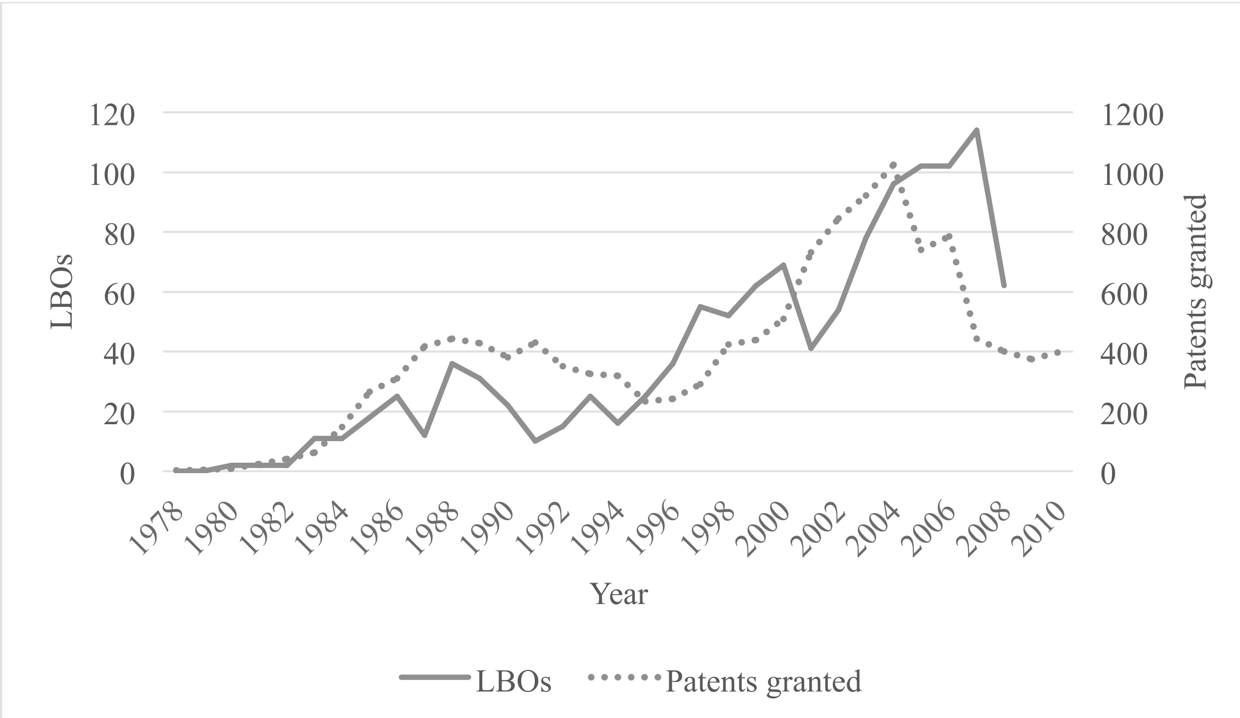
Model of Fundamental Nature of Patents of Stayers

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the fundamental nature of the patent. The unit of observation is a patent attributed to an inventor whose company received Private Equity backing the years 1979 and 2008. The dependent variable is the generality and originality measured on citations received or made in the three years after the grant date. The reported coefficients are normal OLS coefficients; a coefficient higher than zero suggests the variable has a positive effect on the dependent variable. Robust standard errors are reported in parenthesis below each coefficient. The complete sample comprises of 23,735 observations of 10489 patents of 11796 inventors of 1136 firms announcing a private equity transaction in between 1979 and 2010. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The inventor patent sample is smaller than the original as some inventors are not registered. The sample used is a subsample of 8,092 observations of 4,638 patents that belong to staying inventors and were granted until December 2007, meaning that all patents have three years to garner citations. *, **, and *** indicates that the coefficient is statistically significantly different from zero at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Generality	Scaled Generality	Generality	Scaled Generality	Originality	Scaled Originality	Originality	Scaled Originality
Event Year -3	-0.0272**	-0.0219*			-0.0728***	-0.0110		
	(0.0121)	(0.0114)			(0.0163)	(0.0143)		
Event Year -2	0.00693	0.00288			-0.0138	-0.00330		
	(0.0119)	(0.0112)			(0.0149)	(0.0128)		
Event Year -1	0.000608	-0.00983			-0.00267	0.00206		
	(0.0108)	(0.0102)			(0.0136)	(0.0117)		
Event Year 1	-0.0317***	-0.0243***			0.00174	0.000185		
	(0.00978)	(0.00935)			(0.0128)	(0.0112)		
Event Year 2	-0.0333***	-0.0275***			0.0253**	0.0355***		
	(0.00964)	(0.00917)			(0.0125)	(0.0109)		
Event Year 3	-0.0260**	-0.0216**			0.0354***	0.0166		
	(0.0102)	(0.00960)			(0.0131)	(0.0115)		
Event Year 4	0.0244**	0.0208**			0.0596***	0.0326***		
	(0.0105)	(0.00991)			(0.0128)	(0.0113)		
Event Year 5	-0.0143	-0.0182*			0.0587***	0.0177		
	(0.0101)	(0.00961)			(0.0131)	(0.0117)		
Post Deal Plus One Year			-0.0130***	-0.00762			0.0526***	0.0230***
			(0.00500)	(0.00469)			(0.00653)	(0.00566)
Constant	0.122***	0.0344***	0.119***	0.0280***	0.390***	0.0207**	0.373***	0.0187***
	(0.00785)	(0.00751)	(0.00414)	(0.00389)	(0.00975)	(0.00853)	(0.00534)	(0.00458)
Observations	8,834	8,834	8,834	8,834	8,834	8,834	8,834	8,834
Year Ann. Fixed Effects	No	No	No	No	No	No	No	No

Figure I

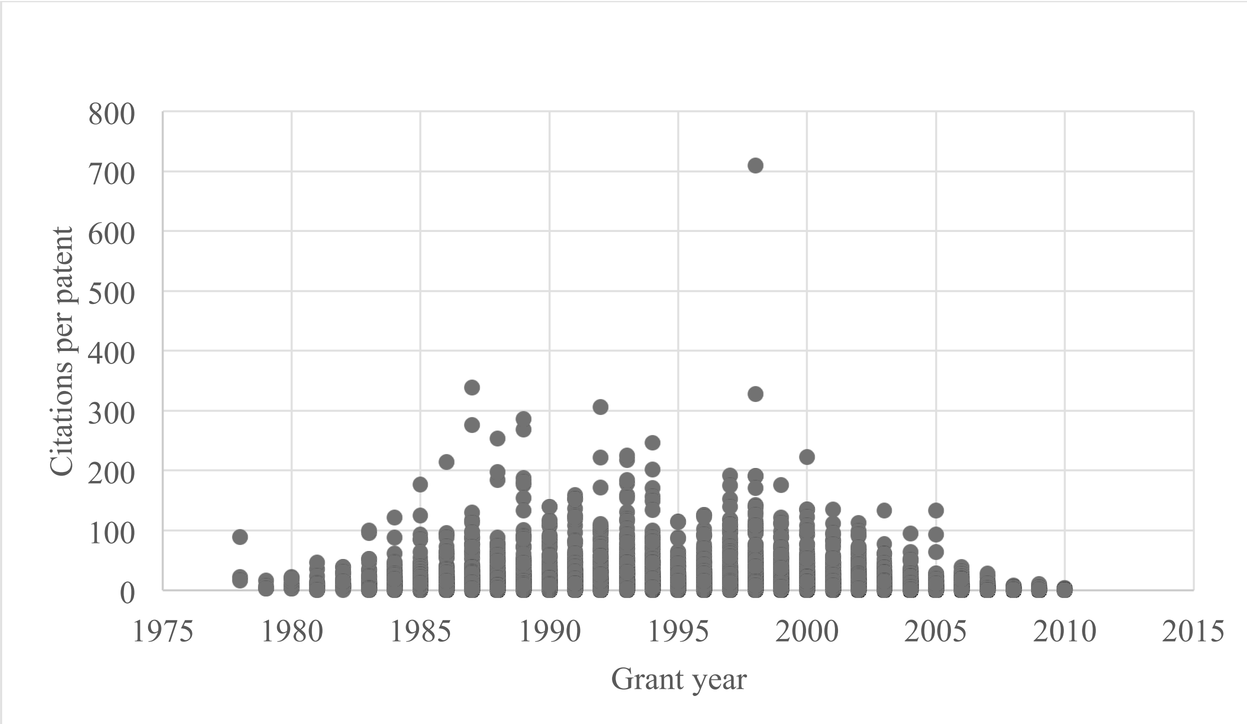
Development of Leveraged Buyouts and Target Firm Patenting Activity



Note*: the sample is based on firms being purchased through an LBO during 1979-2008. All firms have had at least one patent granted in the United States between three years prior to five years after the effective date of the purchase, adding up to 1 148 target firms and 1 186 transactions. All 10 829 patents included in the sample have been granted within the [-3,5] year window based on the effective date of the transaction.*

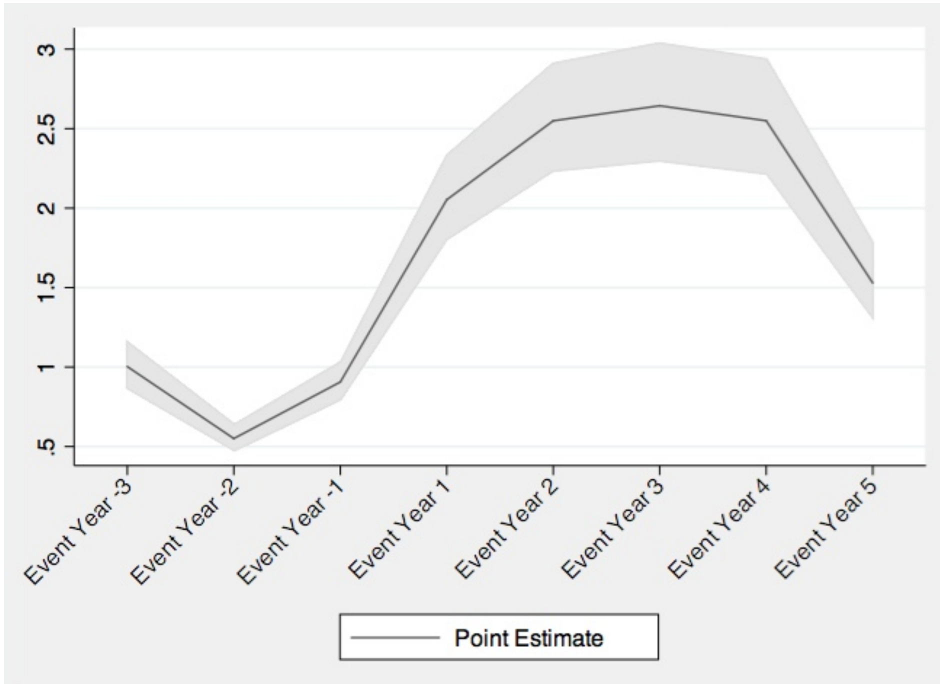
Figure II

Sample Patents' Citation Count (Without Three-year Window)



Note*: the sample is based on firms being purchased through an LBO during 1979-2008. All firms have had at least one patent granted in the United States between three years prior to five years after the effective date of the purchase, adding up to 1 148 target firms and 1 186 transactions. All 10 829 patents included in the sample have been granted within the [-3,5] year window based on the effective date of the transaction.*

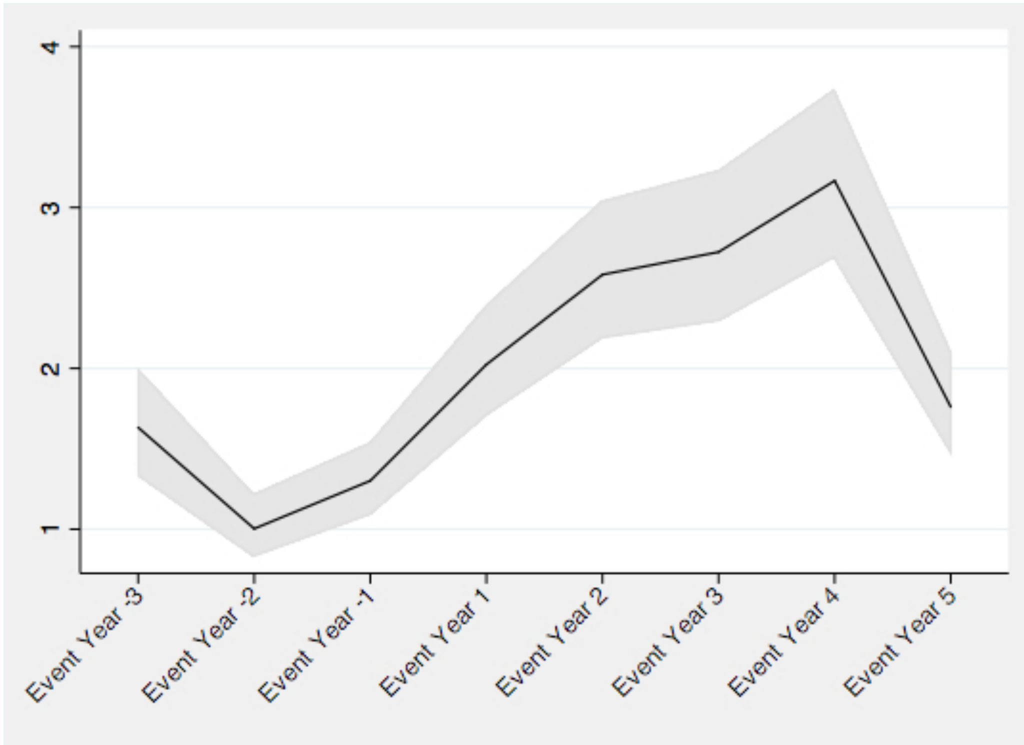
Figure III
Citation Intensities from Negative Binomial Regression with Ann. Year Random Effects



NOTE: *The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. As the average citation intensity for the reference group is offset, the dependent variable is interpreted as scaled citations measured in a three-year window. The point estimates are coefficients reported as incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. The marked area is the 99% confidence interval. The complete sample comprises of 10,829 patents of 1139 firms announcing a private equity transaction in between 1979 and 2010. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The sample used is a subsample of 9,655 patents that were granted until December 2007, meaning that all patents have three years to garner citations.*

Figure IV

Citation Intensities of Stayers from Negative Binomial Regression with Ann. Year Fixed Effects



NOTE: *The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. The unit of observation is a patent attributed to an inventor whose company received Private Equity backing the years 1979 and 2008. As the average citation intensity for the reference group is offset, the dependent variable is interpreted as scaled citations measured in a three-year window. The point estimates are coefficients reported as incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. The marked area is the 99% confidence interval. The complete sample comprises of 23,735 observations of 10489 patents of 11796 inventors of 1136 firms announcing a private equity transaction in between 1979 and 2010. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The inventor patent sample is smaller than the original as some inventors are not registered. The sample used is a subsample of 8,092 observations of 4,638 patents that belong to stayers and were granted until December 2007, meaning that all patents have three years to garner citations.*

10. Appendix

Variable Definitions

Variable	Description
Absolute citations	The number of citations awarded for each sample patent in a three-year period from the grant date.
Scaled Citations	The sample patent's accumulated citations in a three year subtracted by the citation average of the reference group. The reference group is defined as the patents with the same grant year and USPTO-classification as a sample patent.
Originality	Measure of the class dispersion of the patents *cited by* a sample patent, based in the cited patents' USPTO-classification.
Scaled Originality	The originality measure for a sample patent subtracted by the average originality of the patent's reference group
Generality	Measure of the class dispersion of the patents *citing* a sample patent, based on their USPTO-classification.
Scaled Generality	The generality measure for a sample patent subtracted by the average generality of the patent's reference group.
Event Year	Dummy-variables defining which year a sample patent has been granted in the [-3, +5]-year window.
Post Deal Plus One Year	Dummy-variable equal to one if a sample patent has been granted in the event years 1-5.
Going Private * Post Plus One	Interaction term between Post-LBO and the transaction being categorized as public-to-private.
USPTO-class	The classification made by the U.S. Patent and Trademark Office. Is defined more detailed than an industry classification and is based on a three-digit code. Contains roughly 500 different patent classes.

Figure V

NOTE: *the originality and generality measures, as described by* (Trajtenberg, Henderson et al. 1997). *The more varied USPTO-classes a sample patent cites itself (classes of the "parent-patents") will increase its originality. The generality of a sample patent increases the more different classes it is being cited by (the classes of the "child-patents"). Both generality and originality are measured as a coefficient from 0-1, 1 being the highest. The generality measure in this thesis is based on a three-year window after the grant date of the sample patent.*

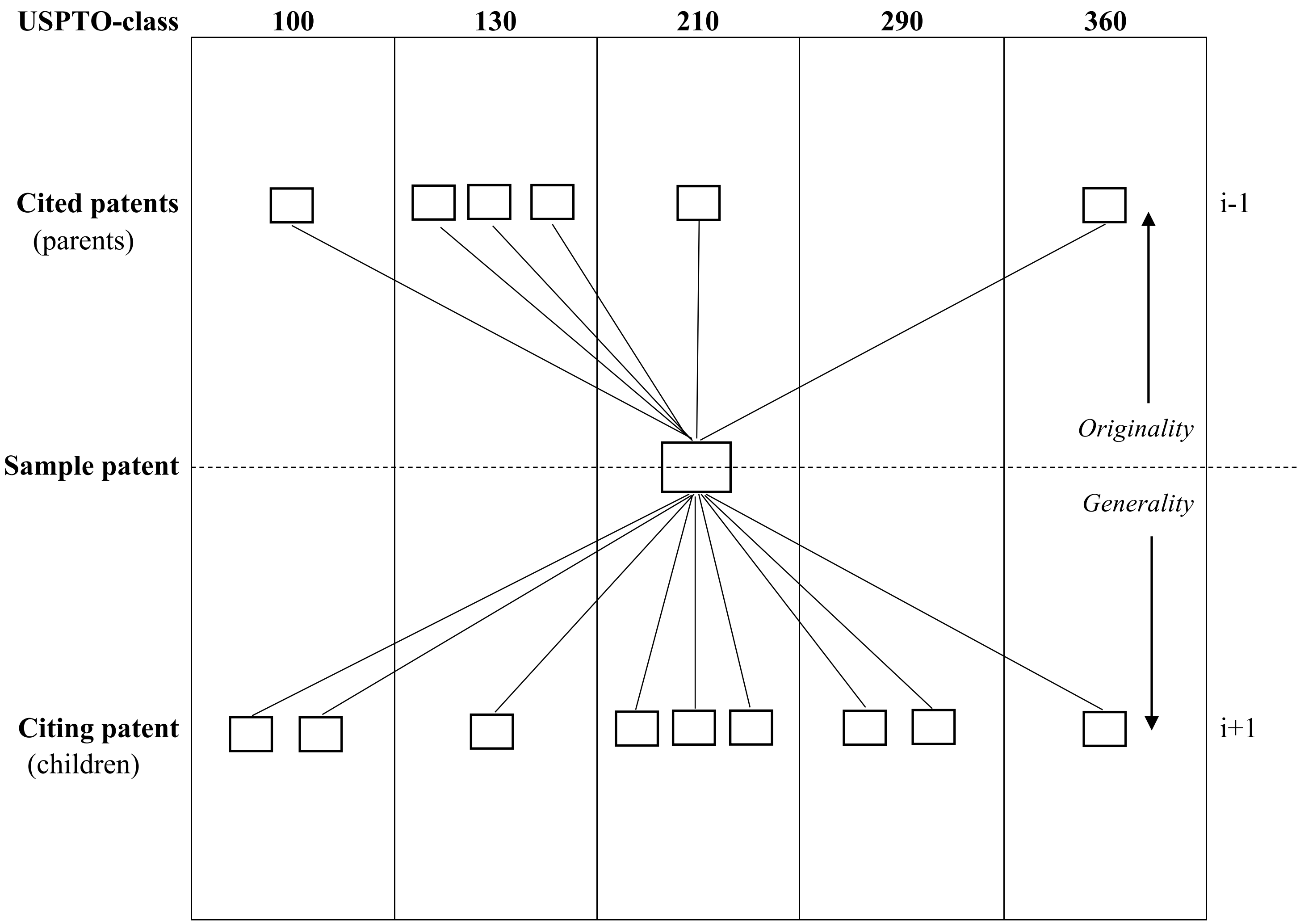


Figure VI

NOTE: *A detailed illustration of the different dependent variables used in the parsimonious model. The arrows indicate where the variable is equal to one. To exemplify, if a patent is granted in the year after the year of the transaction (Event Year 1), Post Deal and Post Deal Plus One will equal one whereas Post Deal Plus Two will equal zero.*

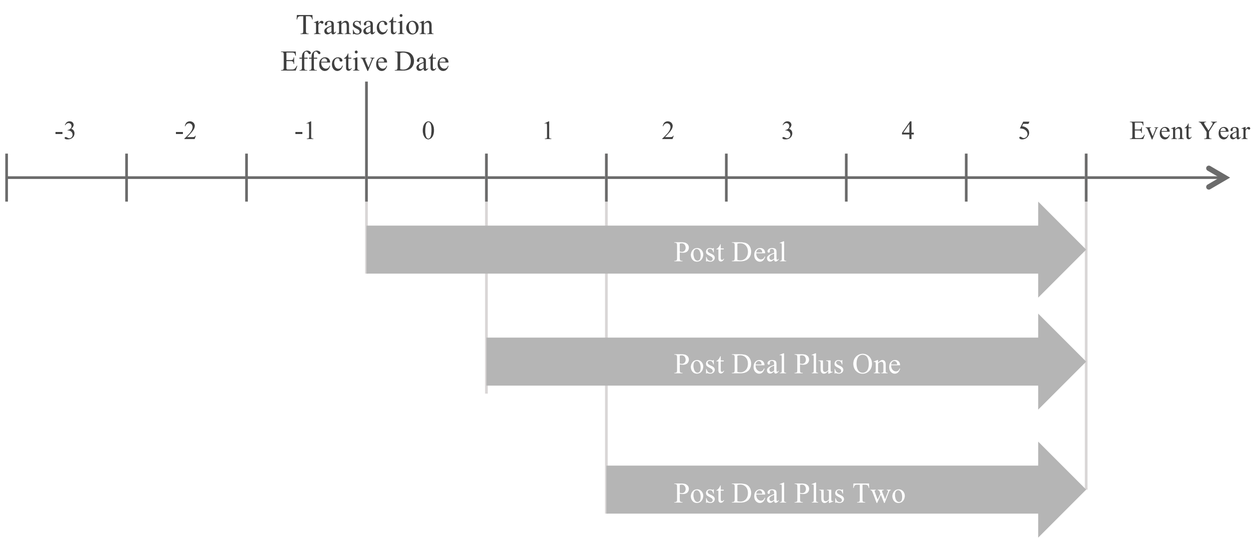


Table XI
Robustness Check of Secondary Buyouts

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. As the average citation intensity for the reference group is offset, the dependent variable is interpreted as scaled citations. The reported coefficients are incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. Eform standard errors are reported in parenthesis below each coefficient. The complete sample comprises of 10,829 patents of 1139 firms announcing a private equity transaction in between 1979 and 2008. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The sample used is a subsample of 9,203 patents that were granted until December 2007 and not identified as a Secondary Buyout, meaning that all patents have three years to garner citations. *, **, and *** indicates that the coefficient is statistically significantly different from one at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations
Absolute Citations				
Event Year -3	1.003	0.999		
	(0.0588)	(0.0587)		
Event Year -2	0.540***	0.541***		
	(0.0315)	(0.0316)		
Event Year -1	0.891**	0.891**		
	(0.0476)	(0.0476)		
Event Year 1	2.037***	2.035***		
	(0.104)	(0.104)		
Event Year 2	2.578***	2.572***		
	(0.136)	(0.136)		
Event Year 3	2.624***	2.618***		
	(0.145)	(0.145)		
Event Year 4	2.577***	2.569***		
	(0.145)	(0.145)		
Event Year 5	1.530***	1.533***		
	(0.0939)	(0.0944)		
Post Deal Plus One Year			2.669***	2.670***
			(0.0779)	(0.0776)
Constant	0.0499***	0.0499***	0.0414***	0.0414***
	(0.00218)	(0.00218)	(0.00124)	(0.00124)
Observations	9,203	9,203	9,203	9,203
Year Announced Fixed Effects	No	Yes	No	Yes
Year Announced Random Effects	Yes	No	Yes	No

Table XII

Robustness Check of Divisional Buyouts

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. As the average citation intensity for the reference group is offset, the dependent variable is interpreted as scaled citations measured in a three-year window. The reported coefficients are incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. Eform standard errors are reported in parenthesis below each coefficient. The complete sample comprises of 10,829 patents of 1139 firms announcing a private equity transaction in between 1979 and 2008. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The sample used is a subsample of 6,693 patents that were granted until December 2007 and not identified as a Divisional Buyout, meaning that all patents have three years to garner citations. *, **, and *** indicates that the coefficient is statistically significantly different from one at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations
Event Year -3	0.698***	0.701***		
	(0.0467)	(0.0471)		
Event Year -2	1.040	1.038		
	(0.0649)	(0.0649)		
Event Year -1	0.878**	0.879**		
	(0.0543)	(0.0544)		
Event Year 1	0.889**	0.888**		
	(0.0518)	(0.0518)		
Event Year 2	1.334***	1.327***		
	(0.0789)	(0.0786)		
Event Year 3	1.301***	1.296***		
	(0.0811)	(0.0809)		
Event Year 4	1.323***	1.328***		
	(0.0867)	(0.0873)		
Event Year 5	0.795***	0.796***		
	(0.0555)	(0.0558)		
Post Deal Plus One Year			1.200***	1.196***
			(0.0391)	(0.0392)
Constant	0.109***	0.109***	0.0975***	0.0976***
	(0.00544)	(0.00544)	(0.00336)	(0.00337)
Observations	6,693	6,693	6,693	6,693
Year Announced Fixed Effects	No	Yes	No	Yes
Year Announced Random Effects	Yes	No	Yes	No

Table XIII

Robustness Check of Unconditional Fixed Effects

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. As the average citation intensity for the reference group is offset, the dependent variable is interpreted as scaled citations measured in a three-year window. The reported coefficients are incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. Robust standard errors are reported in parenthesis below each coefficient for column 1 & 2, whilst column 3 and four have standard errors clustered on the firm level. The complete sample comprises of 10,829 patents of 1139 firms announcing a private equity transaction in between 1979 and 2008. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The sample used is a subsample of 9,655 patents that were granted until December 2007, meaning that all patents have three years to garner citations. *, **, and *** indicates that the coefficient is statistically significantly different from one at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations
Event Year -3	1.001		1.001		
	(0.0700)		(0.0900)		
Event Year -2	1.063		1.063		
	(0.0728)		(0.101)		
Event Year -1	0.884*		0.884*		
	(0.0567)		(0.0639)		
Event Year 1	1.032		1.032		
	(0.0621)		(0.0682)		
Event Year 2	0.988		0.988		
	(0.0598)		(0.0782)		
Event Year 3	1.056		1.056		
	(0.0673)		(0.0876)		
Event Year 4	1.156**		1.156*		
	(0.0779)		(0.0948)		
Event Year 5	1.094		1.094		
	(0.0738)		(0.0989)		
Post Deal Plus One Year		1.075**		1.075	
		(0.0364)		(0.0607)	
Post Deal Plus Two Years					1.109*
					(0.0691)
Constant	0.504	0.510	0.504*	0.510*	0.500*
	(0.219)	(0.217)	(0.194)	(0.201)	(0.191)
Year Ann. Unconditional Fixed Effects	Yes	Yes	Yes	Yes	Yes
Std. Errors	Robust	Robust	Cluster, firm	Cluster, firm	Cluster, Firm

Table XIV
Robustness Check of Serial Correlation in Citations

NOTE: The regression measures the effect of a patents grant year, in relation to the transaction's effective date, on the number of received citations. It differs from the previous models of citation intensity as citations are counted in a five-year window instead of the main assumption of three. Thus the regression serves to check for whether the assumption of serial correlation in citations holds. As the average citation intensity for the reference group is offset the dependent variable is interpreted as scaled citations measured in a three-year window. The reported coefficients are incidence rates; a coefficient higher than one means the variable is positively correlated to the dependent variable. Eform standard errors are reported in parenthesis below each coefficient. The complete sample comprises of 10,829 patents of 1139 firms announcing a private equity transaction in between 1979 and 2008. Firms are only included in the sample if they apply for a patent in the three years before or five years following the transaction calendar year. The sample used is a subsample of 8,658 patents that were granted until December 2005, meaning that all patents have five years to garner citations. *, **, and *** indicates that the coefficient is statistically significantly different from one at the 10%, 5%, and 1% levels, respectively. Further variable definitions can be found in the Appendix.

	(1)	(2)	(3)	(4)
VARIABLES	Scaled Citations	Scaled Citations	Scaled Citations	Scaled Citations
Event Year -3	2.066***	2.062***		
	(0.117)	(0.116)		
Event Year -2	0.251***	0.251***		
	(0.0140)	(0.0140)		
Event Year -1	0.495***	0.495***		
	(0.0256)	(0.0256)		
Event Year 1	3.033***	3.032***		
	(0.145)	(0.145)		
Event Year 2	7.273***	7.260***		
	(0.430)	(0.430)		
Event Year 3	3.353***	3.350***		
	(0.219)	(0.218)		
Event Year 4	6.265***	6.243***		
	(0.402)	(0.401)		
Event Year 5	0.942	0.942		
	(0.0579)	(0.0579)		
Post Deal Plus One Year			4.902***	4.897***
			(0.153)	(0.152)
Constant	2.04e-05***	2.04e-05***	1.14e-05***	1.14e-05***
	(8.22e-07)	(8.22e-07)	(2.63e-07)	(2.63e-07)
Observations	8,658	8,658	8,658	8,658
Year Announced Fixed Effects	No	Yes	No	Yes
Year Announced Random Effects	Yes	No	Yes	No

The Negative Binomial Distribution

Count data is often described using the standard Poisson probability mass distribution, specified as:

$$\Pr(Y = y \mid \lambda) = \frac{e^{-\lambda}\lambda^{n}}{n!} \tag{7}$$

This distribution assumes equidispersion in the sample (expected value $E[y] = \lambda$ and variance $Var[y] = \lambda$). If the sample is overdispersed, the negative binomial regression estimates add an extra error term in the variance ($E[y] = \lambda$ and $Var[y] = \lambda + \alpha\lambda^2$). The probability mass function in the negative binomial regression is given by:

$$\Pr[Y = y|\lambda, \alpha] = \frac{\Gamma(\alpha^{-1} + y)}{\Gamma(\alpha^{-1})\Gamma(y + 1)}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda}\right)^{\alpha^{-1}}\left(\frac{\lambda}{\lambda + \alpha^{-1}}\right)^{y} \tag{8}$$

The conditional probability Y is interpreted as the likelihood of a patent receiving a citation with $\mathrm{E}[y] = \lambda$ and $\mathrm{Var}[y] = \alpha\lambda^2$.

Likelihood Ratio-test

To verify the choice of our model, we perform a likelihood ratio-test that compares the goodness-of-fit between the Poisson and negative binomial model. The test controls for overdispersion in the citation count using the null hypothesis:

$H_0\!: Var[y_i|x_i] = E[y_i|x_i]$

$H_1\!: Var[y_i|x_i] = E[y_i|x_i] + \alpha(E[y_i|x_i])^2$

The test is performed by implementing the auxiliary regression:

$$\frac{((y_i - \hat{\mu}_i)^2 - y_i)}{\hat{\mu}_i} = \alpha\hat{\mu}_i + error \tag{9}$$

The coefficient α for $\hat{\mu}_i$ is of main interest and our results determine that the coefficient α is significantly larger than zero, given the conditional sample variance $Var[y_i|x_i]$ being larger than the conditional sample mean $E[y_i|x_i]$, in line with previous literature.

Vuong-test for Zero-inflation

Due to many patents in the sample only receiving one or zero citations, the risk of an excessive amount of zero-observations of citations, originality and generality is prominent. The zero-inflated negative binomial model (ZINB) better fits the data in the event of sample zero-inflation (Vuong 1989). The Vuong-test evaluates the null hypothesis that the two models (NB and ZINB) fit the data equally through the metric Kullback-Leibler Divergence (KLD). The metric compares the distance between two probability distributions (Desmarais, Harden 2013). The null hypothesis is specified as:

$H_0: D_{KL}(g_t||NB) = D_{KL}(g_t||ZINB)$
$H_1: D_{KL}(g_t||NB) \neq D_{KL}(g_t||ZINB)$

Where $D_{KL}(g_t||NB)$ denotes the KLD between the model tested (NB and ZINB) and the true model g_t which generated the data. Performing the test on the patent sample estimates yield a resulting Vuong-statistic preventing us from rejecting the null hypothesis, thus validating the use of the standard negative binomial model.