Rivals' Cash Holdings and Corporate Innovation

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Abstract

We examine the effect of rivals' cash holdings on corporate innovation. To establish causality, we employ an instrumental variable approach and use the American Jobs Creation Act as an exogenous shock to rivals' cash holdings. We find that when rivals hoard more cash, firms apply for significantly more patents, but generate fewer citations. Further analyses reveal the motivation for this phenomenon: firms strategically accelerate their patenting activity to (1) secure crucial competitive advantages which enhance product market performance and firm value and (2) to avoid intellectual property loss due to talent poaching and proprietary information expropriation from cash-rich rivals. This paper contributes to the understudied literature about the competitive effect of cash holdings, and shows evidence of a strategic use of innovation.

JEL Classification: G31, G32, O31, O32, G60

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1 Introduction

Innovation is the engine of economic growth (Solow 1957; Romer 1987, 1990) and one of the most important sources for firm growth (Kogan *et al.* 2017) and competitive advantage in the product market (Porter 1992). Specifically, firms that spearhead the innovation race can enjoy substantial and lasting competitive advantages over their competition and thus capture significant market share. The success of innovation depends not only on the complexity and compatibility with existing resources, but also the innovation's relative advantage (Angelmar 1990). To this end, firms constantly have to make decisions about the type, size and timing of their R&D investments while taking into account rivals' actions and characteristics. The existing literature on the intersection between innovation and finance primarily focuses on how a firm's own characteristics, such as governance and financing, affect innovation. This article aims to shed more light on the strategic aspect of innovation, investigating how innovation is shaped by the *rivals'* financial decisions.

We specifically focus on how rivals' cash holdings influence corporate innovation. Several distinct features of cash holdings make it an important strategic tool. First, cash is considered the financial war chest that firms use to fund their competitive strategies. Tesler (1966) and Bolton and Scharfstein (1990) argue that rivals with a strong balance sheet can challenge the bottom line of financially weak firms through aggressive pricing. Furthermore, cash balances can be used to finance other competitive strategies such as research and development, the location of stores or plants, construction of distribution networks, the use of advertising campaigns targeted against rivals and the acquisition of key suppliers or business partners (Campello 2006). Most importantly, cash indicates the ability to compete aggressively for human capital[1], which is a primary input in the creation of innovation. Recent theoretical and empirical studies support this view, showing that cash can enhance a firm's ability to engage in predatory poaching of talent and proprietary information expropriation (Kim 2014, He 2018).

Second, cash balances may signal better capacity and intention to innovate. Chief among the reasons is that cash is the preferred form of financing when it comes to risky R&D investments. Unlike external financing, cash allows firms to siege investment opportunities without delay and thus may be able to enjoy the first mover's advantage. Besides, cash holding can be used to smooth R&D expenses, leading to substantial cost-savings, enhanced efficiency and reduced risk of proprietary information and human capital loss (Brown and Petersen 2011). Additionally, large cash holdings enable firms to commercialize products fast, thus allowing them to capture the market and build up customer loyalty before rivals (Ma *et al.* 2014). Taken together, cash-rich rivals can compete rigorously in both product and labor markets as well as innovate quickly and efficiently. As a result, we propose that when faced by these rivals, firms have to respond strategically to maintain their competitive advantages.

Our study is also motivated by the long-standing literature on the relation between competition and innovation. Since Schumpeter (1943), numerous theoretical and empirical studies have been dedicated to answering this question without reaching a consensus. These studies, which based on different sets of assumptions or analyses of different industries, introduce contradicting predictions as well as empirical findings. This inconsistency calls for further investigation on the subject. We

[1] An example from the press is the article, Netflix's talent-poaching strategy: Pay 'em double, published on The Seatle Times on March 30, 2018.

contribute to the extant literature by focusing on the financial war chest that fuels competitive behaviors.

One empirical obstacle for studying the impact of rivals' policies on focal firm behavior is the reflection problem arising from the endogenous nature of a group and the member of the group (Manski 1993). We address this problem by deploying two complementary empirical techniques. The first one is an instrumental variable approach. Specifically, we use the lagged idiosyncratic volatility of rivals as an instrument for their cash holdings. The instrument must satisfy the relevance and exclusion conditions, meaning that it should be strongly correlated with *Rivals' Cash* and should not affect a firm's innovation directly. The relation between lagged idiosyncratic stock volatility and cash holdings has been largely documented in prior studies (Riddick and Whited 2009, and Panousi and Papanikolaou 2009). According to these studies, precautionary motives lead firms to hoard more cash to cushion cash shortfalls or to fund investment opportunities. Although the exclusion cannot be tested indirectly, it is likely satisfied. First, by construction, industry common factors are effectively removed from the relative idiosyncratic stock volatility measures; thus, it captures only firm-specific shocks and is distinct from industry stock volatility. Second, there is little reason to believe that rivals' idiosyncratic volatility can affect a firm's innovation output other than through the channel of financial policy.

There are, however, some potential drawbacks to this strategy. First, the true data generating process of stock return is unknown. Therefore, the estimated idiosyncratic volatility may contain common factors that are not orthogonal to the firm's own characteristics. To reinforce the validity of our findings, we use the American Jobs Creation Act to identify an exogenous shock to *Rivals' Cash*. The AJCA was enacted in 2004 and it allowed firms with profitable foreign operations to repatriate cash, on a one-time basis, to the U.S. at a significantly lower tax rate. To these firms, as long as it was an unexpected event, this event represents a cash windfall. However, to other firms that operate in the domestic market, the AJCA serves as a shock to *Rivals' Cash*. We provide a more detailed justification of this setting in Section 3.

Using both empirical strategies, we find that when rivals hoard more cash, firms experience a significant increase in the number of patents but a decrease in the number of citations per patent. Specifically, when *Rivals' Cash* increase by one standard deviation, the number of patents for the average firm increase by 12% and 7% 3 and 4 years later, respectively, while the number of citations per patent decreases by 15% and 18% 3 and 4 years later, respectively. These results suggest that firms strategically obtain more patents at the cost of lower scientific value for two reasons: (1) to quickly block out competition, gain competitive advantage and thus improve future market performance and firm value, and (2) to avoid intellectual property loss due to talent poaching and proprietary information expropriation from rivals.

To shed light on the strategic motives, we conduct additional tests that focus on future product market performance, firm value, and fluidity of the labor market. First, we argue that if obtaining more patents has some strategic components, then the strategy likely improves the firm's product market performance and value in the presence of cash-rich rivals. Consistent with this prediction, we find that having more patents effectively mitigates the negative impact of *Rivals' Cash* on a firm's market share growth. We also show that the stock market places a higher value on the number of patents, and not on the number of citations per patents, when *Rivals' Cash* is high. Notably, using a novel measure of the economic value of patents developed by Kogan *et al.* (2017), we find that while *Rivals' Cash* decreases the scientific value of patents, it increases the economic value of patents. This striking deviation suggests that even though patents have fewer citations, they help firms gain crucial advantages in the product market and, therefore, are highly valued by the market.

Second, we show that firms increase innovation partially due to the risk of human capital and proprietary information loss. Specifically, this risk increases when a firm faces cash-rich rivals (Kim 2014, He 2018), thus motivating firms to innovate and file for more patents to avoid the possibility that R&D projects are interrupted or proprietary information regarding important technologies is divulged to rivals. Consistent with this idea, we find that the positive effect of *Rivals' Cash* on the number of patent applications is much weaker when the labor mobility regime, measured by a state-level presence of non-compete agreements is more stringent.

We further test the heterogeneity of the effect by using tariff reductions as an exogenous variation to competition. We find that competition amplifies the positive effect of *Rivals' Cash* on the number of patents but alleviates the negative effect on the number of citations per patent. This finding suggests that intensified competition requires firms to innovate and obtain patents to block out competition, while maintaining scientific value. In addition, since our argument is based on the incentive to innovate ahead of rivals, it is crucial to examine the effect of the First Mover's Advantage on the relation between *Rivals' Cash* and innovation. Following Ma *et al.* (2014), we use two proxies of industry-level First Mover's Advantage and find that the main effects are much more pronounced when the First Mover's Advantage is greater.

Our study makes several contributions to the literature. First, while the cash holdings literature has broadened our knowledge about the key determinants of cash level, the real effect of cash holdings remains understudied. A notable study by Fresard (2010) documents that firms with large cash holdings relative to rivals' experience significant improvement in product market performance. Related to innovation, Almeida *et al.* (2018) investigates the effect of a firm's own cash on the economic value of patents and find evidence to support the "more is less" hypothesis. They argue that cash windfalls lead the managers to pursue excessive risk and private benefit via innovation projects thus produce significantly less valuable patents. However, this study focuses only on a firm's own cash holding in isolation and ignore the effect of *Rivals' Cash*. Our paper fills this gap by providing evidence that *Rivals' Cash* may have a pronounced effect on a firm's innovation output. Second, this paper contributes to the literature on competition and innovation. While a copious body of research has been done to address this question, no consensus likely exists. Studies supporting the Schumpeter (1943)'s view posits that less than perfect competition is ideal for innovation whereas Arrow (1962), among others, suggests that competition unambiguously encourages innovation. More recent research finds an inverted U-shape relation between competition and innovation (Aghion *et al.* 2005, Im *et al.* 2015). In this paper, we show that product market threats induced by cash-rich rivals can encourage patenting activity but may deter the scientific value of patents. Our work differs from most existing studies in that instead of focusing on competition itself, we focus on the financial war chest that firms use to fund their competitive strategies. Third, our paper shows evidence of a strategic use of innovation in response to rivals' characteristics. Along the same line, Grieser and Liu (2019) show that firms increase their investment and adjust their portfolio more aggressively when rivals are more financially constrained. They also find that firms' innovation output is improved in terms of both the number of patents and citations. We complement this study by showing that firms respond strategically to the level *Rivals' Cash*, which signifies the ability to compete aggressively in product market as well as innovation space. Furthermore, we highlight the strategic aspect by showing that obtaining patents when faced by cash-rich rivals is extremely valuable for firms even though these patents have little scientific value.

The paper is structured as follows. Section 2 provides detailed theoretical motivation and hypotheses development. Section 3 presents the methodology and data. Section 4 discusses the main results. Section 5 explores the heterogeneity of the effect and the potential channels through which rival cash can affect innovation. Section 6 concludes.

2 Hypothesis Development

Our paper is based on the literature investigating the relation between product market competition and innovation. Since the pioneering idea by Schumpeter (1943) who proposed that less than perfectly competitive market is ideal for innovation, this literature has sparked debate among scholars for decades. In general, there are two opposing predictions on how competition affects innovation. The studies that support the "Schumpeterian effect' argue that product market competition reduces the flow of rents to successful innovators thus reduces the incentives for innovation and growth (Aghion and Howitt 1992, Caballero and Jaffe 1993). On the contrary, other studies suggest that product market competition can encourage innovation (Aghion *et al.* 2001, 2005). Specifically, the incentives to innovate depend not only on post-innovation rents but also on pre-innovation rents. While competition can reduce post-innovation rents, as argued by Schumpeterian supporters, it can also reduce pre-innovation rent, possibly to a greater extent. Firms, therefore, are incentivized to innovate and "escape competition". In this paper, we argue that the competitive threats induced by cash-rich rivals can encourage innovation because these rivals can seriously reduce a firm's pre-innovation rent.

The competitive effect of cash is deeply rooted in the literature. In the spirit of the "Deep Pocket" by Telser (1966) and Bolton and Scharfstein (1990), firms with a strong balance sheet, characterized by large cash holdings, may implement aggressive pricing strategy to drive financially weak rivals out of business. Specially, these firms increase output and drive down prices, which in-turn induce unbearable losses for their rivals and drive them out of the market. Additionally, cash could be used to fund strategic choices other than predatory pricing. For instance, such strategies include R&D investments, location of stores or plants, construction of distribution networks, advertising targeted against rivals, talent poaching and proprietary information expropriation (Campello 2006). Recent empirical studies provide strong support for this view. Fresard (2010) shows that firms that hold relatively more cash capture significantly more market share at the expense of their rivals. Boutin *et al.* (2013) find that cash holding allows incumbents and the affiliated group to strengthen their competitive position and block out entrant group. Overall, this branch of research suggests that cash-rich firms can induce substantial competitive threats to their rivals through various competitive strategies.

Further, in the spirit of Telser's (1966) deep pockets argument, Kim (2014) shows theoretically that financially strong firms can engage in "predatory poaching" against a financially weaker rivals, i.e. offer higher wages to poach a rival's employees who know its trade secrets and deprive the rival of its competitive advantage. Empirical support for this view is provided by He (2018) who shows that firms hoard more cash to effectively compete in for talents when the labor market is more fluid. Large cash balance signals the ability to adopt aggressive talent-poaching strategies and the presence of a preemptive weapon to protect the workforce. Besides, firms often report that they face a higher risk of proprietary information loss through former employees when faced by financially strong rivals in product market. Taken together, cash holdings signal the ability to compete aggressively in the labor space, a primary input for innovation, and thus may affect other firms' decisions to innovate.

Rivals' cash is extremely relevant to their capacity and intention to innovate. First, cash is a preferred form of financing when it comes to R&D projects because obtaining external financing can be difficult and costly. The reason is that outsiders cannot evaluate these projects very accurately due to information asymmetry. Also, intangible capital cannot typically be pledged as collateral (e.g., Sim *et al.* 2013). Unlike external financing, cash allows the firm to finance its R&D project without delay and thus better take advantage of investment opportunities as they arise (Ma *et al.* 2014). Second, firms hoard cash to smooth R&D expenses to minimize the substantial adjustment cost associated with R&D investment. This practice can help improve efficiency and reduce the risk of proprietary information and human capital loss (Brown and Petersen 2011). This discussion implies that when faced by cash-rich rivals who can innovate efficiently and quickly, firms must react strategically to gain competitive advantage and prevent competition.

Several relevant studies have tapped on the relation between *Rivals' Cash* and innovation. Schroth and Szalay (2010) find that *Rivals' Cash* decrease a firm's probability of winning a patent race.[2] Lyandres and Palazzo (2016) show that a firm cash holding has a negative effect on its *Rivals' Cash*. The reason is that large cash holding increases the likelihood of a firm investing in innovative projects thus reduces their competitors' expected return to innovation and the marginal benefit of holding cash. This study, therefore, suggests that *Rivals' Cash* should deter a firm's incentive to innovate. In contrast, we show evidence that *Rivals' Cash* can encourage innovation. Another relevant study is Grieser and Liu (2019) who find that firms innovate more aggressively when rivals are more financially constrained. While being financially constrained is a passive outcome resulting from the firm's unique circumstances, hoarding cash is likely an active decision which directly related to competitive behaviors in product market.[3] Our study, therefore,

[2] Unlike in our paper, their specification is designed to capture the effect of cash holdings on the probability of winning a patent race. As such, they treat each patent as a race and then select a group of participants including incumbents and newcomers. Also, this study focuses only on Pharmaceutical Industry.

[3] The relation between cash holdings and financial constraints is not unambiguous. On one hand, firms could hold cash to buffer future needs because they have difficulties accessing external funds, i.e. they are financially constrained.

complements this study by showing another strategic use of innovation in response to heightened completive threats arising from cash-rich rivals. It is also important to note that firms innovate not only to compete with other incumbents but also to raise the entrant hurdle to block out potential newcomers. Therefore, unlike the three studies mentioned above, our empirical setting is not confined to a group of close rivals thus accounts for the competitive threats arising from a broader set of rivals who can innovate and compete with the incumbents.[4]

3 Methodology and Data

3.1 Measure of Innovation

The innovation data used in this paper is from Kogan *et al.* (2017) who compiled the data using Google Patents.[5] We use two measures of firm's innovative output. First, we start with a simple patent count for each firm-year observation. The relevant year is the year of patent application which is very close to the actual innovation and far before the innovation is commercialized and introduced to the market as a finished product (Hall *et al.* 2001). We then scale the patent count by the mean number of patents application by all firms during that year.[6] This weighting adjustment aims to correct for the truncation bias in patent grants. The problem arises from the fact that patents on average have a two years lag from application date to grant date

On the other hand, firms can have large cash holdings resulting from their successful business thus are not financially constrained.

[4] It is not uncommon that a cash-rich firm expands beyond their existing businesses to develop a new line of product and take over the market for that product. In 2007, Apple, who previously known only for iPod and iMac, introduced the first generation of iPhone, which has become the world's most popular smartphone. The rise of iPhone and Android devices then drove previous market leaders such as Nokia, Blacberry and Palm out of business. This scenario emerges again in the personal computers industry, competitive position of incumbents such as Dell and HP significantly erode after the introduction of Apple's iPad and Microsoft's Surface. All in all, a distant competitor can become a direct competitor through innovation. This scenario becomes more likely when they have financial flexibility.

[5] This database has two advantages over the traditional data from USPTO. First, Google includes additional metadata such as classification codes and citation information in their individual patent files whereas UPSTO does not do so in their bulk files. Second, "the quality of the text generated from optical character recognition (OCR) procedures implemented by Google is better in the individual files than in the bulk files provided by the USPTO. This is crucial for identifying patent assignees" (footnote 4, Kogan *et al.* 2017).

[6] The adjusted number of patents is denoted as *Pat*.

and only granted patent appears in the sample, leading to the omission of some patents filed toward the end of the sample (Hall *et al.* 2001).

The second dependent variable of interest is the number of citations per patent, which reflects the significance of a firm's innovative output. For each firm-year observation, citations per patent is computed as the cumulative citation counts until the end of the sample period for all patents applied during that year, scaled by the number of patent applications. This measure helps distinguish breakthrough innovations from incremental technological discoveries. The intuition is that if firms are willing to further develop a technology that is built upon an existing patent then that patent should be technologically influential and economically significant. Patent citation also suffers from truncation bias because the patent granted in earlier years can accumulate more citations just because they have more time to do so. We purge this bias by dividing each firm-year's citations per patent by the citations per patent received by all patents applied for in year *t*.[7]

3.2 Baseline Model

The sample examined in this paper includes 100334 firm-years observation of publicly traded firms over the period 1967-2008. We merge the innovation data compiled by Kogan *et al.* (2017) with financial data from Compustat and stock price data from CRSP.

To estimate the impact of *Rivals' Cash* on innovation, we employ the following empirical model:

$$Ln\left(1 + Innovation_{i,t+n}\right) = \alpha \; + \; \beta Rival's\; Cash_{i,t} \; + \; \delta X_{i,t} \; + \; Firm\,\&\,Year\; FE \; + \; u_{i,t} \quad (1)$$

where i indexes firms, t indexes time, $Ln(1 + Innovation_{i,t+n})$ is the dependent variable, which is *Ln(1 + Pat)* or *Ln(1 + Cit/Pat)* and n is the number of years ahead of the current time period t, and

[7] The adjusted number of citations per patent is denoted as *Cit/Pat*.

is equal to 1,2,3 and 4. We use the lead dependent variable to make sure that all rival's characteristics are observed and reflect in patenting activity of subsequent years. For each firm-year observation, *Rival's Cash* is the average of the ratio of pure cash (*CH*)[8] over total assets (*AT*) of all other firms operating in the same 3-digits SIC industry.[9] We control for time-invariant unobservable firm characteristics by including *Firm FE*. *Year FE* captures year fixed effects or market wide's shocks. To control for serial correlation, we cluster the standard errors at the firm level, as suggested by (Petersen 2009).[10]

We control for a comprehensive set of firm characteristics that may affect a firm's innovation output. The data on total assets, sales, industry SIC, R&D expenditures, book equity, book debt, net property plant and equipment, operating income, firm age, and market-to-book (*Q*) come from Compustat. We follow Hall and Ziedonis (2001), among others, and include *Ln(Sales)* to control for firm size. Following Aghion *et al.* (2005), we control for industry concentration using the *Herfindahl* index constructed at the 4-digit SIC level. We also use the squared Herfindahl index to control for non-linear effects of industry concentration. Following Whited and Wu (2016), we construct their index to control for financial constraints. For every firm's characteristics in the model, we also include those characteristics of rivals. We require that for each industry-year, there are at least 5 firm-year observations that have no missing value for *Cash* and other control variables.[11] All continuous variables are winsorized at the 1st and 99th percentiles to remove the influence of extreme outliers.

[8] We use pure cash because this is the most liquid and readily available source of fund to fuel competitive strategies. Nevertheless, the results remain quantitively similar when we use the total of pure cash and short-term investments, i.e. cash and cash equivalents (*CHE*).

[9] 3-digits SIC is commonly used in the literature of peer-firms' effect (see Leary and Robert 2014). Our results are robust to the breadth of industry definition.

[10] Unless stated otherwise, all models include *Firm* and *Year FE*. Standard errors are clustered at firm-level.

[11] Omission of this screening criteria does not affect the results.

3.3 Identification Strategies

Due to the endogenous nature of the relation between a group and its members, it is an empirical challenge to identify the effect of *Rivals' Cash* on innovation. This problem, referred to as reflection problem (Manski 1993), is a form of endogeneity that arises as researchers attempt to infer the effect of the group's actions or characteristics on those of a group's member. The endogeneity issue in our setting can arise from several sources. First, correlation might stem from omitted common factors. Firms operating in the same industry are exposed to the same institutional environment or investment opportunities that determine their financial policies and other characteristics. This problem requires that our identification strategy has to effectively remove the industry's common factors contained in *Rivals' Cash*. Second, reverse causality is plausible for the relation between *Rivals' Cash* and a firm's innovation. Innovative industries tend to be more volatile due to the risky nature of R&D projects and intense competition. Thus, firms are inclined to hoard more cash for precautionary purposes. To isolate the effect of *Rival's Cash* on innovation, we apply two identification strategies.

3.3.1 The Instrumental Variable Approach

We overcome the endogeneity hurdle by using an instrumental variable approach. Specifically, we use lagged rivals' idiosyncratic volatility as an exogenous variation to their cash holdings. Each rival's idiosyncratic volatility is computed as the standard deviation of its last year's daily idiosyncratic returns, which is estimated using the augmented CAPM model.[12] We discuss the construction of this variable in detail later in this section.

[12] The results remain quatitatively similar with the augmented Fama-French 4-factor model (market, style, size, momentum, and industry factors).

A valid instrument variable must satisfy the relevance and exclusion conditions. With regard to the first condition, the relation between idiosyncratic volatility and cash holdings is motivated by the precautionary motive of holding cash. Both theoretical and empirical studies have provided extensive support for this motive. Irvine and Pontiff (2009) find that idiosyncratic volatility is correlated with the volatility of future cash flow, which in turn determines cash holdings. Riddick and Whited (2009) theoretically and empirically show that income uncertainty, a manifestation of a firm's idiosyncratic risk, leads to higher marginal propensity of holding cash. Along the same line, Panousi and Papanikolaou (2012) find that cash holding is positively related to last period idiosyncratic risk.

The exclusion condition, although cannot be tested directly, is likely to be satisfied for several reasons. First, by construction, idiosyncratic volatility reflects a firm's unique circumstances which are unlikely affected by market and industry-wide factors. Moreover, the prior work by Leary and Roberts (2014) has set a solid foundation for the use of this instrument. They show that the return shocks to different firms within a peer group are largely uncorrelated with one another. Additionally, the shocks are not serially correlated and serially cross-correlated, implying that firms' shocks do not forecast future return shocks for themselves or for other firms. While these features do not guarantee homogeneity, they are reassuring because they suggest that peer firm return shocks contain little common variation. Besides, while a firm's idiosyncratic risk may correlate with their cash holdings, there is little reason to believe that idiosyncratic risk of rivals can directly affect a firm's innovation activity.

We estimate idiosyncratic return with CAPM augmented by industry factor:

$$r_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(rm_t - rf_t) + \beta_{ijt}^{IND}\left(\bar{r}_{-ijt} - rf_t\right) + \eta_{ijt} \quad (2)$$

where r_{ijt} is the total return of firm *i* in industry *j* over day *t*, $(rm_t - rf_t)$ is the excess market return, and $(\bar{r}_{-ijt} - rf_t)$ is the excess return on an equal-weighted industry portfolio excluding firm *i*'s return. We also use the 3-digit SIC code to define peer groups. The industry factor, although not a priced factor, is included in the model to remove industry's commonality. This equation is estimated on a daily rolling basis using daily returns from CRSP. I require that each date has at least 180 prior data points available and use up to 360 days for the estimation. The idiosyncratic return for each firm is computed using the following equations:

$$Expected\ Return_{ijt} \equiv \hat{r}_{ijt} = \hat{\alpha}_{ijt} + \hat{\beta}_{ijt}^{M}(rm_t - rf_t) + \hat{\beta}_{ijt}^{IND}(\bar{r}_{-ijt} - rf_t) \quad (3)$$

$$Idiosyncratic\ Return_{ijt} \equiv \hat{\eta}_{ijt} = r_{ijt} - \hat{r}_{ijt} \quad (4)$$

The annual idiosyncratic stock volatility is computed as the standard deviation of the estimated daily idiosyncratic stock return during that year. The annual periodicity allows us to match this data with the innovation data and accounting data from Compustat.

Nevertheless, we acknowledge that our instrument can be only as good as the existing asset pricing models. It is possible that some omitted common risk factors still remain in the residue thus plague our estimations. To reinforce the validity of our findings, we employ a quasi-natural experiment where rivals experience a positive shock to their cash holdings and reexamine the relation of interest.

3.3.2 The American Jobs Creation Act (AJCA)

To further tackle the endogeneity problem, we examine how a firm's innovation output is affected by a positive cash flow shock to its rivals through a quasi-natural experiment. Specifically, we exploit a provision in the American Jobs Creation Act (AJCA) enacted in 2004 that allows firms to pay a tax rate of 5.25% on repatriated foreign income on a one-time basis instead of the standard corporate tax rate of 35%. The 85% reduction can be regarded as a significant windfall in cash for firms with profitable foreign subsidiaries. Indeed, according to the IRS, firms repatriated an aggregate amount of $312 billion in response to the AJCA.[13]

For this experiment, we restrict the sample to 2002, 2003, 2005, 2006, which represents the two years before and after implementation of the AJCA. The event year, 2004, is removed to better isolate the effect of the shock. To be included in the sample, we require that all firms have at least one patent application during the period from 2002 to 2006 and data is available for all four years mentioned above. We assign *Post* to take the value of one for observation in 2005 and 2006 and the value of zero for observations in 2002 and 2003. To identify the *Multinational* firms, we calculate the cumulative foreign profits (*PIFO*) in 2002 and 2003 then label a firm *Multinational* when this number is at least 1% of total assets in 2002.[14] On the other hand, we categorize firms with zero cumulative foreign profits as *Domestic* firms. *Multinational* firms are likely to experience a significant windfall of cash following the enactment of AJCA when they can repatriate cash from their foreign subsidiaries with favorable tax treatment. Consequently, the *Domestic* firms that operate in the same industry with these *Multinational* firms will experience an increase in *Rivals' Cash*. Arguably, the effect will be more pronounced for *Domestic* firms who face many *Multinational* rivals as compared to those who face just a few *Multinational* rivals in product market. This distinction is the key feature of our empirical setting. Accordingly, we create a variable named *Count* which is computed as the number of *Multinational* firms operating in each SIC 3-digit industry. In 2003, one year prior to AJCA, we sort the *Domestic* firms in our sample

[13] Almeida *et al.* (2018) use this shock to study the impact of a firm's own cash on innovation. Unlike their approach, which focuses the difference between the value of innovation output of multinational firms and domestic firms, our empirical design focuses on the difference in the quantity and quality of innovation between domestic firms that have a large number of multinational rivals and domestic firms that have a small number of multinational rivals.

[14] Following Almeida *et al.* (2018), we add the 1% threshold to ensure that foreign profit is significant enough to be repatriated.

based on *Count* and create a dummy *Exposure* equals to 1 if *Count* belongs to the highest tercile across all *Domestic* firms and zero otherwise. Our setup ensures that firms with more *Exposure* experience an increase in *Rivals' Cash* because they have to face many *Multinational* rivals who are likely to repatriate cash as they have significant foreign profit before the AJCA. We run the following OLS regression using the sample of *Domestic* firms:

$$Ln\left(1 + Innovation_{i,t+n}\right) = \alpha \ + \ \beta Post\ x\ Exposure \ + \ \delta X_{i,t} \ + \ Firm\ \&\ Year\ FE \ + \ u_{i,t} \quad (5)$$

where *i* indexes firms, *t* indexes time, *Ln(1 + Innovation*$_{i,t+n}$*)* is the dependent variable, which is *Ln(1 + Pat)* or *Ln(1 + Cit/Pat)* and *n* is the number of years ahead of the current time period *t*, and is equal to 1,2,3 and 4. *Post* and *Exposure* are dummy variables as described above.

4 Main Results

4.1 Descriptive Statistic

Panel A of Table 1 compares the characteristics of firms that have at least one patent and firms have zero patents. Firms in the former group are on average larger, hoard more cash, spend more on significantly more money on R&D and face rivals with larger cash balance. Panel B splits the sample of firms that have at least one patent in two halves based on the number of citations per patent. Compare to firms below the median, firms above the median are slightly smaller, have larger own *Cash*, slightly larger *Rivals' Cash*. Columns 1-4 of Panel C present the summary statistic by *Rivals' Cash* quartiles. The last two Columns 5-6 show the mean and standard deviation for the full sample. We observe that all measures of innovation increase with *Rivals' Cash*.

4.1.1 Instrumental Variable Approach

In Table 2, we estimate the baseline model (Equation 1) using the instrumental variable approach. In Columns 1-4, we use *Ln(1 + Pat)* while in Columns 5-8 we use *Ln(1 + Cit/Pat)* as the dependent variable. The time indicator *n* ranges from 1 to 4. We proceed in this manner to make sure that *Rivals' Cash* is observed by the firm and account for the possibility that *Rivals' Cash* might affect innovation with a lag. In the first stage, we include as instruments for *Rivals' Cash* two of its own lag and the lag *Rivals' IdioVol*. The two own lags capture systematic changes in the level of *Rivals' Cash*, while *IdioVol* teases out the exogenous component of *Rivals' Cash*. For the first stage, we report the coefficients of these variables and the Cragg-Donald F-statistic as a test for weak instruments. In the second stage, we use the instrumented *Rivals' Cash* to explain a firm's innovation output.

Consistent with the precautionary motives, the coefficients of *Rivals' IdioVol* across all models are positive and statistically significant. This result, coupled with the extremely high F-statistic, strongly supports the relevant condition of the instrument. In the second stage, Columns 1-4 of Table 2 show that the coefficients on *Rivals' Cash* (0.576, 0.548, 0.43, and 0.255) are positive and statistically significant at the 1% level. More importantly, the effect is economically significant. These coefficients indicate that when *Rivals' Cash* increase by one standard deviation, the number of patents for the average firm increase by 16%, 15%, 12%, 7% in one, two, three, four years later. On the contrary, the number of citations per patent decreases in *Rivals' Cash*. In Columns 5-8, the negative and statistically significant coefficients on *Rivals' Cash* (-0.192, -0.380, -0.560, -0.680) represent a decrease of 5%, 10%, 15%, 18% in the number of citations per patent one, two, three, four years later. These findings suggest that firms respond to cash-rich rivals by innovating and filing for significantly more patents at the expense of patents' scientific value. In addition, we observe that the positive effect on *Pat* is concentrated in the earlier years while the negative effect on *Cit/Pat* is concentrated in later years. This finding alleviates the concern that the decrease in *Cit/Pat* is a by-product of the increase in (*Pat*) because if this is indeed the case, we would observe the magnitude of the effect on both variables following similar patents.

The coefficients on the other control variables used in Table 2 are largely consistent with existing studies. Larger and more R&D intensive firms have more patents and more citations per patent. Industry concentration has no significant impact on innovation, once firm fixed effects are used. *Leverage* is negatively related to the number of patents and the number of citations per patent. Intuitively, shareholders are more tolerant of innovative and risky projects, and thus less likely to shut them down than creditors. It is also possible that leverage reduces managerial flexibility (Graham and Harvey 2001), and thus leads to lower tolerance to experimentation, creativity and innovation. *Profitability* is negatively related to the number of patents, and unrelated to the number of citations per patent, while firms with more tangible assets have more patents. Furthermore, when firms are more financially constrained, the number of patents decreases significantly. The reason is that it is very difficult for these firms to finance demanding R&D investments. Consistent with Grieser and Liu (2019), the coefficients of *Rivals' WW Index* in Columns 1-4 are positive and significant, suggesting that firms innovate more when rivals are more financially constrained.

4.1.2 The American Jobs Creation Act

Consistent with the IV approach, we find that the increase in *Rivals' Cash* caused by the AJCA leads to an increase in the number of patents but a decline in the number of citations per patent.[15] Also, the effect follows a similar pattern; the effect is concentrated on earlier years for

[15] Grieser and Liu (2019) use the AJCA as an exogenous shock to rivals' financial constraints, thus implicitly assuming an unambiguous negative relation between cash and financial constraints. They find that both the number of patents and citations declined after the shock. Their results differ from ours for several reasons. First, they focus only on a restricted group of rivals, constructed base on product similarity and patent citation network. Hence, this approach ignore the competitive threats arising from the group of relatively more distant rivals who have the capacity to become direct a direct threat through innovation. Second, while Grieser and Liu (2019) determine the *Exposure* based only on the average of foreign income of *Multinational* rivals, our setting accounts for both the number of *Multinational* rivals and their individual magnitude of foreign income.

Pat while on later years for *Cit/Pat*. Columns 1-2 of Table 3 show that after the AJCA enacted in 2004, the number of patents for the average firm increase by 9% one year later, and 11% two years later.[16] However, there is an opposite effect on the number of citations per patent. Columns 7-8 of Table 3 show that after 2004, the number of patents for the average firm decreases by 37% three years later and 41% four years later. As a robustness check, we perform the same procedure with pseudo-event years starting from 1994 (10 years back) and find no similar results.

5 Channel Tests and Heterogeneity of the Effect

5.1 Market Share Growth

To highlight the strategic use of innovation as a counter play to competitive threats induced by cash-rich rivals, we examine the dynamic between *Rivals' Cash*, innovation, and market share growth. We argue that, if the change in innovation contains a valuable strategic component, it will ultimately manifest itself in the firm's product market performance. Following Campello (2003, 2006), we examine the model of change in market share:

$$\Delta MarketShare = \alpha + \beta_1 Rivals'Cash + \beta_2 Ln\left(1 + Innovation_{i,t}\right)$$
$$+ \boldsymbol{\beta_3 Rivals'Cash\ x}\ Ln\left(1 + Innovation_{i,t}\right)$$
$$+ \delta X_{i,t} + Firm\ \&\ Year\ FE + u_{i,t} \quad (6)$$

The dependent variable, *ΔMarket Share*, is the industry-adjusted sales growth (sales growth minus its industry average during that year). This measure thus captures a firm's market share growth in relation to that of its rivals. $X_{i,t}$ is a vector of control variables that determine product market performance including *Cash*, *Sales*, *Leverage*, *Market-to-Book* ratio, *Acquisition*, *Sale*

[16] The economic significant is calculated based on the sample used in this experiment (the mean of *Pat* is 0.33 and the mean of *Cit/Pat* is 0.36)

Acquisition and lagged *⊿Market Share*. The inclusion of 1- and 2-year lagged market share growth controls for the effect of rivals' strategic choices that may have driven product market performance in recent years (Fresard 2010). In this test, we focus on the coefficient of *Rivals' Cash*$_{t-2}$ and the interaction term. As argued in Fresard (2010), *Rivals' Cash* should have a strong negative effect on a firms' product market performance due to the heightened competitive threats, suggesting a negative and significant coefficient. Consequently, if innovation indeed is a strategic response to cash-rich rivals, it should mitigate this negative effect of *Rivals' Cash* thus we expect a positive and statistically significant coefficient for the interaction term.

The results are presented in Table 4. Consistent with the idea in Fresard (2010), the coefficients of *Rivals' Cash*$_{t-2}$ across all models are strongly negative and statistically significant, confirming the competitive effect of *Rivals' Cash* on a firm's future market share growth. Columns 1-2 of Table 4 show that the coefficients on the interaction term *Rivals' Cash*$_{t-2}$ *x Ln(1+Pat)*$_{t-2}$ are positive and significant at 5% level (1.320 and 1.490), suggesting that obtaining more patent help negate the negative effect of *Rivals' Cash*. In contrast, the scientific value of patents applied does not have the same effect. Columns 3-4 of Table 4 show that the interaction *Rivals' Cash*$_{t-2}$ *x Ln(1+Cit/Pat)*$_{t-2}$ is small and insignificant. In columns 5-6, models that include both *Pat* and *Cit/Pat* yields similar results. Overall, these findings suggest that innovating and filing for patents help firms gain competitive advantage and improve their product market performance. Furthermore, obtaining patents seems to be valuable to firms regardless of their scientific value.

5.2 Firm Value

In this section, we examine whether investors value innovation differently when the degree of *Rivals' Cash* changes. As argued in the hypothesis development section, innovating and obtaining patents fast takes a firm one step ahead of its rivals and thus enables it to enjoy first mover's advantage of innovation. Therefore, we posit that if accelerating innovation activity is a strategic move from a firm who faces cash-rich rivals, the strategy must add value to the firm. This discussion leads to our prediction that the market's valuation of innovation will be significantly higher when *Rivals' Cash* is high. We examine how patent applications and *Rivals' Cash* interact to affect firm value by estimating the following regression:

$$
\begin{aligned}
Ln(Q)_{i,t+n} = \alpha + \beta_1 Rivals'\ Cash + \ \beta_2\ Ln\left(1 + Innovation_{i,t}\right) \\
+ \boldsymbol{\beta_3 Rivals'\ Cash\ x\ Ln\left(1 + Innovation_{i,t}\right)} \\
+ \delta X_{i,t} + Industry\ \&\ Year\ FE + u_{i,t} (7)
\end{aligned}
$$

Firm's value is measured by Tobin's Q. $X_{i,t}$ is the same set of control variables used in the base-line model. In this model, we control for *Industry* and *Year FE*. Our main coefficient of interest is the interaction term *Ln(1+Innovation) x Rivals' Cash*. This interaction captures the change in market valuation of innovation due to changes in *Rivals' Cash*. We predict that the market will place a higher value on innovation in presence of cash-rich rivals, thus a positive and statistically significant coefficient for the interaction term.

Panel A of Table 5 reports the results estimating Equation (7). Columns 1-3 present models that include *Pat* only, while Columns 4-6 are for models that include *Cit/Pat*, and 7-9 are for models that include both. Each group includes the lead values of $Ln(Q)_{t+n}$ as the dependent variable, with *n* ranges from 1 to 3. Across all models, the coefficients of the interaction *Ln(1+Pat) x Rivals' Cash* are positive and significant at 1% level, suggesting that obtaining patents is extremely valuable to a firm faced by cash-rich rivals. For *Cit/Pat*, the interaction *Ln(1+Cit/Pat) x Rivals' Cash* is positive and significant at 5% level only when *Pat* and its interaction are not included. Consistent with the analysis on product market performance, these findings suggest that innovating and obtaining patents is extremely valuable for firms regardless of the scientific value.

To further emphasize the strategic use of innovation, we conduct additional tests using a new measure of innovation's economic value that is based on stock market reactions to patent grants. This measure was constructed by Kogan *et al.* 2017 and has several advantages over the traditional citations per patent measure. First, asset prices are forward-looking thus allows the measure to capture an estimate of the economics rent to the patent holder. Second, it is important to note that this private value does not necessarily reflect the scientific value of the patents. For example, a patent may have little scientific value but is very useful in fighting against the competition, thus generate substantial economics value. The authors generously provide both measures of the economic (*PatEco*) and scientific (*PatSci*) value computed based on the same set of patents granted to each film in a given year, allowing us to show the deviation between the two measures and thus highlight the strategic component.[17] *PatEco* is the dollar value of all patents granted in year t, scaled by the firm's total assets (*AT*). *PatSci* is the citation-weighted granted patent counts in year t, scaled by total assets (*AT*). [18] We posit that if the observed increase in firms' patenting activity has some strategic component, then the market will place a high value on granted patents even though they have little scientific value. This prediction suggests that *Rivals' Cash* decreases the scientific value of patents but increases the economic value of patents. We re-estimate our baseline model using the measure of patents' economic value and scientific value from Kogan *et al.* (2017).

[17] Kogan *et al.* 2017 suggest that their "methodology is potentially helpful in distinguishing between innovations that are scientifically important and those that have a large impact on firm profits."

[18] The relevant year in this test is grant year when patents are officially granted. As oppose to the previous test which focus on the value of innovating and *filing* for patents, this test focus on the value of patent granted in each year to highlight the motivation for firms to accelerate patenting activity.

Panel B reports the results from estimating Equation (1) with *PatEco* and *PatSci*. Columns 1-4 show that *Rivals' Cash* significantly increases the market value of patents. One standard deviation increase in *Rivals' Cash* results in a 32%, 30%, 27%, 28% increase in *PatEco* one, two, three, four years later. We argue that the premium for patents when *Rivals' Cash* motivates firms to file for more. In contrast, the negative and significant coefficients on *Rivals' Cash* in Columns 5-8 demonstrate that the same set of patents that are highly valued by the market actually have a lower scientific value. One standard deviation increase in *Rivals' Cash* results in a 21%, 19%, 27%, 31% decrease in *PatSci* one, two, three, four years later. This striking opposite effect of *Rivals' Cash* on the economic value and the scientific value once again highlights the strategic component of obtaining patents.

We perform another test to provide more support for the strategic use of innovation. In each technological class and grant year, we sort all patents by dollar value and number of citations. We define *Strategic Patent* (*StraPat*) as the ones that belong to the top 20% economic value and the bottom 20% scientific value. The intuition is that, if a patent has little scientific value yet greatly impact a firm's value, it should contain a strategic component. We then count the number of *Strategic Patents* a firm applies for in a given year and also scale this variable by the average number of patents applied by all firms in year *t*. We examine the effect of *Rivals' Cash* on *StraPat* using Equation (1). Panel C presents the result of this analysis. We observe that *Rivals' Cash* has a strong positive effect on *StraPat*. The coefficients, 0.102, 0.120, 0.118 and 0.109, are statistically significant and represent large increases of 42%, 50%, 49%, 45% in the number of *Strategic Patents*. This finding suggests that firms apply for more patents that have very low scientific value yet a very high impact on firm value because they might serve some strategic purposes.

5.3 Labor Mobility and Proprietary Information Protection

In previous sections, we have shown that product market performance and firm value motivate firms to innovate more in response to cash-rich rivals. We now explore another channel that is related to labor mobility. The departure of key personnel entails two possible consequences. First, an in-progress R&D project could be interrupted and the delay could render the outcome of these projects, even a success, worthless because rivals may obtain a patent and manage to commercialize the product first. Second, these key personnel can bring proprietary information to benefit their new firms, resulting in complete loss of the firm's prior innovating effort.[19] In this section, we posit that firms rush to innovate and obtain more patents to avoid the possibility that intellectual properties could be lost due to aggressive talent poaching and proprietary information expropriation from cash-rich rivals.

Rivals' Cash has important implications on a firm's human capital and proprietary information protection, which are the two most important inputs for innovation. He (2018) investigate the role of cash holding in talent competition and highlighted several key points. First, large cash holdings allow firms to fund strategic choices concerning talent. These practices include hiring talents, poaching talents, and protecting talents from poaching behaviors targeted against them. Second, cash holdings can act as a preemptive weapon that signals the firm's ability to adequately respond to talent poaching from rivals, thereby distorting rivals' incentives to implement talent raids ex-ante. Finally, skilled workers are attracted to financially strong employers for higher job security. Consistent with this idea, Brown and Matsa (2016) show that job applicants take into account a firm's financial condition and are more inclined to apply for

[19] A significant real-world example is the case of Intel Inc., the world's largest producer of computer processors. The company was founded when Fairchild Semiconductor International, Inc.'s former managers left the firm with proprietary information about the microprocessor (Rajan and Zingales 2001)

financially healthier firms. Taken together, a firm is exposed to a higher risk of talent loss when faced by cash-rich rivals.

There is ample evidence that the risk of proprietary information loss occurred through the channel of former employees. For example, a survey sponsored by PWC and the U.S. Chamber of Commerce cited former employees as the most significant risk factor associated with proprietary information and intellectual property loss. Besides, Almeling *et al.* (2010) report that former employees are responsible for the majority of legal cases related to trade secrets. Rivals' financial strength amplifies this risk. Firms often report in their 10-k that the risk of proprietary information loss, especially trade secrets, is significantly higher when they face financially strong rivals in product market. Thanks to their abundant internal funding, these rivals can act on this information and inflict great economic damage on the victim firm.

Overall, cash-rich rivals pose a substantial risk of proprietary information and human capital loss to a firm operating in the same industry. This risk jeopardizes potential or in-progress R&D projects and thus force a firm to push their innovation agenda. We argue that more stringent labor mobility regimes can mitigate this risk and thus reduce the need to rush innovation. To tests this prediction, we exploit two sources of exogenous variation to labor mobility.

First, we rely on the enforceability of Non-compete Agreement (NCA) contacts across different states. NCAs are contractual provisions that prohibit exiting employees from working for a competitor in a specified period of time (typically 1 or 2 years). More importantly, the use of NCAs is concentrated on sophisticated personnel. Specifically, while only 20% of the US workforce and 10% of low-skill workers are required to sign NCA, 50% of technical professions and 70% of executives have to sign the NCA (Starr *et al.* 2019, Garmise 2011). This key feature of NCA makes it extremely relevant to our research question. Additionally, while the use of NCAs could be endogenous within a firm, their enforceability is likely exogenous because it is determined at the state level based on the court ruling of precedent cases or actions of a legislative body. The state-level measure of Non-compete Agreements enforceability is from Garmaise (2011), who scrutinized 12 questions related to the level of enforcement and constructed an index.[20] Bird and Knopf (2015) and Ertimur *et al.* (2018) adopted this procedure and extended the index from 1992-2004 to 1976-1991 and 1980-2013, respectively. We supplement Garmaise (2011)'s data using these sources to cover the period from 1976 to 2010.

Second, we gauge the changes in the level protection of firms' proprietary information and human capital by examining the staggered adoption of the Inevitable Disclosure Doctrine by US state courts over the period from 1997 to 2011. The IDD can prevent a former employee from working for a rival firm if their employment would inevitably lead to divulgence of trade secrets to the rival. More importantly, The IDD is enforceable even without employees signing a non-compete or non-disclosure agreement, evidence of bad faith or actual wrongdoing. Klasa *et al.* (2018) show that the mobility of employees with knowledge of trade secrets actually decreases following the adoption of the IDD. Overall, the adoption of IDD would arguably reduce sophisticated personnel's mobility and thus the risk of proprietary information loss.

We test our prediction using the following model:

$$\begin{aligned} ln\left(1 + Innovation_{i,t+n}\right) = \alpha + \beta_1 Rivals'\ Cash + \ \beta_2\ Labor\ Mobility\ Restriction \\ + \boldsymbol{\beta_3 Rivals'\ Cash\ x\ Labor\ Mobility\ Restriction} \\ + \delta X_{i,t} + \ Firm\ \&\ Year\ FE + u_{i,t} (8) \end{aligned}$$

[20] According to Garmise (2011), this procedure assigns one point to each of the states when one of the twelve dimensions of enforcement exceeds a given threshold. The index ranges from 0 for states such as California where there is virtually no enforceability to 9 for states like Florida, where extremely strong enforcement is in presence.

Our main coefficient of interest is the interaction term *Rivals' Cash x Labor Mobility Restriction*. This interaction captures how the effect of *Rivals' Cash* on innovation changes when labor mobility regime changes. We predict that more stringent labor mobility law will reduce the need for firms to innovate fast and obtain patents, and thus a negative and statistically significant coefficient on the interaction term.

Panel A of Table 6 reports the analysis using NCA enforceability index. Columns 1-4 show the results for *Pat*. The coefficient on *Rivals' Cash x NCA* is negative and significant, suggesting that stronger NCA enforcement help reduce the risk of proprietary information and human capital loss thus reduce the need to obtain patents fast.[21] Panel B demonstrates the impact of the IDD. Consistent with previous analysis using NCA, we find that the effect of *Rivals' Cash* on the number of patent applications is mitigated after the IDD is adopted.

5.4 Product Market Competition

It is crucial to examine the relation between Rival's Cash and innovation when product market competition intensifies. Following Fresard (2010), we exploit the unexpected variations if industry-level import tariffs as exogenous shocks to competition.[22] The tariff cuts are identified using product-level US import data compiled by Feenstra and Hanson (1996) and Feenstra, Romalis, and Schott (2002). The data covers the period 1972-2001 and is at the 4-digit SIC industry level. An industry experiences a *Tariff Cut* when there is a negative change in tariff rate that has the absolute value 2, 2.5, or 3 times a larger than the mean of the absolute value of all changes

[21] NCA should matter the most for firms that face intense in-state competition because the NCA is effective only within a particular geographic scope. The risk that in-state competitors will poach employees and obtain proprietary information is higher for these firms. Thus, in a untabulated test, we also include a measure of instate *Rivals' Concentration* to account for this property of NCA. Our focus is the triple interaction *Rivals' Cash x NCA x Rivals' Concentration*. We observe that the mitigating effect is even stronger for firms who face intense in-state competition, evident from the strongly negative and significant coefficient on the triple interaction.

[22] See Fresard (2010) for more details about the validity of this shock.

occurred in that industry. Additionally, a *Tariff Cut* is not followed by an equivalently large increase in tariff rate in the subsequent 2 years. Following Fresard (2010), we defined *Cut* as a dummy that is equal to one if the industry experiences a *Tariff Cut* in the last two years (*t* and *t-1*), and zero otherwise. We estimate the following equation:

$$Ln\left(1 + Innovation_{i,t+n}\right) = \alpha \ + \ \beta Rivals'\ Cash\ x\ Cut \ + \ \delta X_{i,t} \ + \ Firm \,\&\, Year\ FE \ + \ u_{i,t} \quad (9)$$

The coefficient of interest is $Rivals'\ Cash\ x\ Cut$ which captures the effect of *Rival's Cash* on innovation, conditional on the intensity of product market competition. The model effectively takes the firms operating in industries that do not experience a *Cut* in year *t* as the control group and tease out the difference in innovation output.

The results are presented in Table 7. Columns 1-4 show that the coefficients on the interaction term *Rivals' Cash x Cut* are positive and significant, suggesting that the effect of *Rivals' Cash* is amplified when competition is stronger. On the other hand, the negative effect of *Rivals' Cash* on *Cit/Pat* is alleviated, as evident from the positive and significant coefficient of the interaction term in Columns 5-8. Taken together, these findings suggest that when product market competition becomes more intense, the need to obtain patents increases without a reduction in patents' scientific value.

5.5 First Mover's Advantage of Innovation

Ma *et al.* (2014) developed a model that relates first mover's advantage, R&D intensity and cash holdings. First Mover's Advantage (FMA) is characterized by the market share gains by firms who first succeed in the R&D process and manage to commercialize the product. An important implication from their model is that FMA increases the skewness of the market share distribution ex-post and the volatility of industry leaders' profitability. Specifically, when FMA is high, markets should be controlled by a small group of firms that possess the most advanced technologies. Besides, leaders should be constantly challenged by followers because the stake to be on top is extremely high in these industries. For each year, we compute the market share for each firm operating in a 3-digit SIC industry base on their sales. We then calculate the *Skewness* of the market share distribution for each industry-year observation. As for the second proxy of FMA, we start by identifying the industry's leaders. For each industry-year, we sort all firms by two metrics of success, namely *Profitability* and *Market Share*. *Leader*s are firms that belong to the highest quintile in both sorting schemes. *Leaders' ROA Vol* is computed as the average *ROA Vol* of *Leaders* group. *ROA Vol* is the rolling standard deviation of *Profitability* with a rolling window of 5 years, requiring at least three years of data. We posit that the FMA increases the need to respond strategically to cash-rich rivals, thus amplifying the effect of *Rival's Cash.*

$$ln\left(1 + Innovation_{i,t+n}\right) = \alpha + \beta_1 Rivals'\ Cash + \beta_2\ FMA$$
$$+ \boldsymbol{\beta_3 Rivals'\ Cash\ x\ FMA}$$
$$+ \delta X_{i,t} + Firm\ \&\ Year\ FE + u_{i,t} (10)$$

Consistent with our prediction, we find that for the models with *Pat* in Columns 1-4 of Table 8, the coefficients on *Rivals' Cash x Dummy Skewness* are positive and significant. Whereas, in Columns 5-8 with *Cit/Pat*, the coefficients on *Rivals' Cash x Dummy Skewness* are negative and significant. These results show that the effect of *Rivals' Cash* on innovation is more pronounced when FMA is stronger. We find similar results using *Leaders' ROA Vol.*

6 Conclusion

Using an instrumental approach and the American Jobs Creation Act as a quasi-natural experience, we find that when rivals hoard more cash, firms experience a significant increase in the number of patents but a decrease in the number of citations per patent. Specifically, when *Rivals' Cash* increase by one standard deviation, the number of patents for the average firm increase by 16%, 15%, 12%, 7% while the number of citations per patent decreases by 5%, 10%, 15%, 18% in one, two, three, four years later. We argue that the heightened competitive threats arising from cash-rich rivals require a firm to react strategically to remain competitive, resulting in an increase in the quantity of innovation. Further analyses shed more light on this motive. First, we show that, when *Rivals' Cash* is high, firms can improve their future market performance and firm value by innovating and applying for more patents, regardless of the patents' scientific value. This finding is consistent with the idea that a patent's scientific value does not always reflect its impact on the firm's profit (Kogan *et al.* 2017). Specifically, patents with little scientific value can be extremely valuable if it serves a strategic purpose, e.g. preventing competition. Second, the risk of human capital and proprietary information loss also contribute to a firm's decision to innovate. As this risk is higher when rivals hoard more cash, firms strategically increase their patenting activity to avoid interruption or loss related to R&D projects. We provide evidence for this channel by showing that the main effect is mitigated when labor mobility law is more stringent. Overall, our study adds to the understudied literature that investigates the real effect of rivals' cash holdings and shows evidence for a strategic use of innovation in response to competitive threats.

VARIABLES DESCRIPTION

1. **Patent (Pat):** Count of the number of patents in application year t by firm i divided by the mean number of patents of all firms in that year t (Source: Kogan et al. 2017).

2. **Citations/Patent (Cit/Pat):** Measures the number of citations per patent applied for in year t by firm i, divided by the total number of citations per patent received by all patents applied for in year t (Source: Kogan et al. 2017).

3. **Strategic Patent (StraPat):** Measures the number of Strategic Patents in application year t by firm i divided by the mean number of patents of all firms in that year t. Strategic Patents are patents that belong to the top 20% in dollar value and the bottom 20% in number of citations by technological class and grant year (Source: Kogan et al. 2017).

4. **Patent Economic Value (PatEco):** Measures the market value of patents granted in year t to firm i in year t based on stock market reaction on the patents' grant date, scaled by total assets (Source: Kogan et al. 2017).

5. **Patent Scientific Value (PatSci):** Measures the citation-weighted patent counts for all patents granted to firm i in year t, scaled by total assets (Source: Kogan et al. 2017).

6. **Rivals' Characteristics**: The average of the corresponding characteristic of all firms operating in the same 3-digit SIC industry, excluding firm i.

7. **Cash:** Pure cash (CH) of firm i in year t divided by its total assets (Source: Compustat).

8. **Sales:** Sales by firm i in year t (in $ million) (Source: Compustat)

9. **R&D:** Research and Development expenses divided by its total assets (Source: Compustat).

10. **Leverage:** Total debt of firm i in year t divided by its total assets (Source: Compustat).

11. **Profitability:** Earnings before interest depreciation taxes and amortization (EBITDA) of firm i in year t divided by its total assets (Source: Compustat)

12. **Tangibility:** Net property plant and equipment (NPPE) of firm i in year t divided by its total assets (Source: Compustat).

13. **Age:** Age of firm i in year t based on the years from a firm's IPO as reported in CRSP (Source: CRSP).

14. **Whited Wu Index:** Measures the degree of financial constraint, following Whited and Wu (2006). Equation: WW = - 0.091CF - 0.062DIVPOS + 0.021*TLTD - 0.044*LNTA + 0.102*ISG - 0.035*SG where TLTD is the ratio of the long-term debt to total assets; DIVPOS is an indicator that takes the value of one if the firm pays cash dividends; SG is firm sales growth; LNTA is the natural log of total assets; ISG is the firm's three-digit

industry sales growth; CASH is the ratio of liquid assets to total assets; CF is the ratio of cash flow to total assets. (Source: CRSP)

15. **Herfindahl:** Equal to the sum of the squared share of each firm in total industry sales. Herfindahl index of firm i in year t constructed based on sales at the 4-digit SIC code (Source: Compustat).

16. **IdioVol:** the standard deviation, on an annual basis, of daily Idiosyncratic Return which is estimated using the augmented Fama-French 4-factor model.

17. ***Δ*Market Share:** the change in sale ($\frac{sale_t - sale_{t-1}}{sale_{t-1}}$) minus the mean change of all firms in the 3-digit SIC industry in year t (Source: Compustat).

18. **Acquisition:** Acquisition (ACQ) divided by its total assets (Source: Compustat).

19. **Sale Acquisition:** Sale Acquisition (AQS) divided by its total assets (Source: Compustat).

20. **NCA:** The Non-compete Agreement enforceability index is from Garmaise (2011), Bird and Knopf (2015) and Ertimur et al. (2018), ranging between 0 (least restrictive) and 9 (most restrictive).

21. **Rivals' Concentration:** The portion of industry sales (exclude the firm's sales) produced by competitors headquartered in the same state (Source: Compustat).

22. **Cut:** A dummy that is equal to one if the industry experiences a Tariff Cut in the last two years (t and t-1). An industry experiences a Tariff Cut when there is a negative change in tariff rate that has the absolute value 2, 2.5, or 3 times a larger than the mean of absolute value of all changes occurred in that industry. Additionally, a Tariff Cut is not followed by an equivalently large increase in tariff rate in the subsequent 2 years (Source: Philip Valta's website).

23. **Cumulative Foreign Income (CFI):** Sum of foreign profit (PIFO)

24. **Multinational:** Firms who have Cumulative Foreign Income (CFI) during 2002 and 2003 at least equals to 1% of total assets in 2003 (Source: Compustat).

25. **Domestic:** Firms who have zero Cumulative Foreign Income (CFI) during 2002 and 2003.

26. **Count:** Number of Multinational firms in each 3-digit SIC industry in 2003.

27. **Exposure:** A dummy that takes the value of one when Count belongs to the highest tercile.

28. **Market Share:** The portion of 3-digit SIC industry sale produced by firm i in year t (Source: Compustat).

29. **Leaders:** In each industry-year, firms are sort into quintiles based on Market Share and Profitability. Leaders are firms that belong to the highest quintile in both sorting schemes (Source: Compustat).

30. **Skewness:** For each industry-year, skewness is the third moment divided by the square root of the second moment cubed, based on the distribution of Market Share (Source: Compustat).

31. **ROA Vol:** The rolling standard deviation of Profitability with a rolling window of 5 years, requiring at least 3 years of data.

32. **Leaders' ROA Vol:** The average of ROA Vol among industry's Leaders.

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Table 1: Summary Statistics

This table reports summary statistics for the key variables. Patent information comes Kogan *et al.* (2017). We also include all the firms in Compustat which operate in the same industries as the firms in the patent database, but don't have patents. Data on *Sales*, *R&D* expenditures, *Profitability*, *Tangibility*, *Leverage*, *Age*, the *Herfindahl Index*, the *Market-to-Book* ratio and the *Idiosyncratic Volatility* come from Compustat and CRSP. We exclude firms from the financial sector and utilities. Panel A presents information about firm-years for firms with (Columns 4-6) and without (Columns 1-3) at least one patent. Panel B presents information only for firm-years with at least one patent. They are divided into two sub-samples: firms with below (Columns 1-3) or above (Columns 4-6) the median of the number of citations per patent. Panel C presents information for firm-years for each rivals' cash quartile (Columns 1-5) and for the full sample (Columns 6-7). All continuous variables are winsorized at 1st and 99th percentiles. Data in this table are for the period 1967 to 2008.

Panel A: Firm Characteristics and Patent

	Patent = 0 (68938 firm-years)				Patent > 0 (31396 firm-years)				All Firms	
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Firm's Characteristics										
Cash	0.087	0.122	0.000	0.868	0.100	0.135	0.000	0.868	0.091	0.127
Ln(Sales)	4.612	2.107	-2.919	11.284	5.716	2.281	-2.847	11.284	4.958	2.223
R&D	0.028	0.077	0.000	1.196	0.070	0.108	0.000	0.870	0.041	0.090
Leverage	0.454	0.228	0.020	1.688	0.406	0.196	0.020	1.688	0.439	0.219
Profitability	0.089	0.185	-2.065	0.442	0.091	0.200	-1.716	0.442	0.089	0.190
Tangibility	0.321	0.238	0.000	0.935	0.270	0.170	0.001	0.932	0.305	0.221
Age	12.182	9.130	3.000	59.000	16.828	12.186	3.000	59.000	13.636	10.410
WW Index	0.432	0.111	0.069	0.881	0.367	0.120	0.069	0.881	0.412	0.118
Industry's Characteristics										
Herfindahl	0.262	0.186	0.044	1.000	0.271	0.189	0.044	1.000	0.264	0.186
Rivals' Characteristics										
Rivals' Cash	0.097	0.072	0.006	0.370	0.115	0.086	0.006	0.370	0.103	0.077
Rivals' Ln(Sales)	4.754	1.338	1.252	10.118	4.598	1.262	1.252	10.118	4.705	1.317
Rivals' R&D	0.037	0.065	0.000	0.549	0.073	0.084	0.000	0.549	0.048	0.073
Rivals' Leverage	0.462	0.117	0.137	3.296	0.426	0.091	0.156	3.296	0.451	0.111
Rivals' Profitability	0.064	0.131	-2.874	0.270	0.039	0.140	-2.874	0.270	0.056	0.134
Rivals' Tangibility	0.316	0.179	0.050	0.789	0.259	0.128	0.055	0.789	0.298	0.167
Rivals' Age	11.258	4.549	1.917	34.667	12.081	4.687	1.917	34.667	11.516	4.608
Rivals' WW Index	0.410	0.119	-0.911	2.946	0.412	0.107	-0.911	2.946	0.411	0.115

Panel B: Firm Characteristics and Citation/Patent for firms with at least one patent

	Citation/Patent <= Median (=0.87)				Citation/Patent > Median (=0.87)				All Firms	
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Firm's Characteristics										
Cash	0.095	0.135	0.000	0.868	0.105	0.135	0.000	0.868	0.100	0.135
Sales	5.781	2.334	-2.813	11.284	5.651	2.225	-2.847	11.284	5.716	2.281
R&D	0.066	0.115	0.000	0.852	0.075	0.101	0.000	0.870	0.070	0.108
Leverage	0.416	0.197	0.020	1.688	0.397	0.195	0.021	1.688	0.406	0.196
Profitability	0.086	0.200	-1.716	0.442	0.096	0.200	-1.716	0.441	0.091	0.200
Tangibility	0.281	0.176	0.002	0.910	0.259	0.162	0.001	0.932	0.270	0.170
Age	18.032	12.843	3.000	59.000	15.625	11.365	3.000	59.000	16.828	12.186
WW Index	0.361	0.122	0.069	0.881	0.372	0.118	0.069	0.881	0.367	0.120
Industry's Characteristics										
Herfindahl	0.275	0.189	0.044	1.000	0.267	0.187	0.044	1.000	0.271	0.188
Rivals' Characteristics										
Rivals' Cash	0.113	0.089	0.006	0.370	0.118	0.083	0.006	0.370	0.115	0.086
Rivals' Sales	4.737	1.333	1.252	10.118	4.459	1.169	1.252	10.118	4.598	1.262
Rivals' R&D	0.071	0.093	0.000	0.549	0.074	0.074	0.000	0.549	0.073	0.084
Rivals' Leverage	0.430	0.092	0.156	3.296	0.422	0.090	0.156	3.296	0.426	0.091
Rivals' Profitability	0.038	0.148	-2.874	0.270	0.041	0.131	-2.874	0.270	0.039	0.140
Rivals' Tangibility	0.269	0.135	0.055	0.789	0.249	0.120	0.057	0.772	0.259	0.128
Rivals' Age	12.790	4.945	1.917	34.667	11.373	4.298	2.400	34.667	12.081	4.687
Rivals' WW Index	0.401	0.120	-0.911	2.946	0.424	0.090	-0.911	2.946	0.412	0.107

Panel B: Firm Characteristics by *Rivals' Cash* Quartiles

	Rivals' Cash Quartiles				Full Sample	
	Mean	Mean	Mean	Mean	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Paternt Applications						
Patent (Pat)	0.318	0.298	0.474	0.547	0.406	2.940
Citation/Patent (*Cit/Pat*)	0.267	0.290	0.507	0.528	0.395	1.077
Strategic Patent (*StraPat*)	0.016	0.015	0.023	0.025	0.019	0.172
Patent Grants						
Patent Value (*PatEco*)	0.015	0.019	0.063	0.068	0.041	0.203
Citation-weighted Patent (*PatSci*)	0.017	0.032	0.065	0.070	0.045	0.417
Firm's Characteristics						
Cash	0.052	0.067	0.108	0.144	0.091	0.127
Sales	5.746	5.225	4.593	4.195	4.958	2.223
R&D	0.009	0.014	0.048	0.098	0.041	0.090
Leverage	0.467	0.466	0.411	0.410	0.439	0.219
Profitability	0.125	0.118	0.085	0.025	0.089	0.190
Tangibility	0.384	0.345	0.270	0.213	0.305	0.221
Age	16.136	14.332	12.934	10.895	13.636	10.410
WW Index	0.373	0.397	0.433	0.448	0.412	0.118
Industry's Characteristics						
Herfindahl	0.289	0.262	0.254	0.251	0.264	0.186
Rivals' Characteristics						
Rivals' Cash	0.040	0.073	0.123	0.181	0.103	0.077
Rivals' Sales	5.654	4.979	4.319	3.781	4.705	1.317
Rivals' R&D	0.009	0.016	0.055	0.119	0.048	0.073
Rivals' Leverage	0.486	0.474	0.420	0.419	0.451	0.111
Rivals' Profitability	0.115	0.096	0.050	-0.046	0.056	0.134
Rivals' Tangibility	0.384	0.337	0.262	0.200	0.298	0.167
Rivals' Age	14.142	12.233	10.810	8.617	11.516	4.608
Rivals' WW Index	0.373	0.395	0.436	0.442	0.411	0.115

Table 2: The Instrumental Variable Approach

This table reports the results for our Instrumental Variable analysis examining the impact of *Rivals' Cash* on quantity and quality of Innovation. We estimate a 2SLS model using *Rivals' Idiosyncratic Volatility* to instrument for their *Cash*. The results for the Number of Patents and the Number of Citations per Patent are reported in Columns 1-4 and Columns 5-8, respectively. *Idiosyncratic Volatility* is computed as the standard deviation, on an annual basis, of daily *Idiosyncratic Return* which is estimated using the augmented CAPM model. For each firm-year observation, *Rivals' Cash* is the average of *Cash* ratio (*CH/AT*) of all firms operating in the same 3-digit SIC industry, excluding firm *i*. Control Variables include *Cash*, *Ln(sales)*, *R&D*, *Leverage*, *Profitability*, *Tangibility*, *Age*, *Whited-Wu Index*, *Herfindahl*, and *Herfindahl*^{2}. For each firm's characteristic, we also control for the corresponding rivals' characteristic which is computed with the method similar to calculating *Rivals' Cash*. All continuous variables are winsorized at 1st and 99th percentiles. We include *Firm* and *Year FE* in all regressions to control for unobserved characteristics. Statistical significance is calculated based on firm-level clustered standard error to allow for correlation of errors within-firm as suggested by Peterson (2009) .***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	$Ln(1+Pat)_{t+1}$	$Ln(1+Pat)_{t+2}$	$Ln(1+Pat)_{t+3}$	$Ln(1+Pat)_{t+4}$	$Ln(1+Cit/Pat)_{t+1}$	$Ln(1+Cit/Pat)_{t+2}$	$Ln(1+Cit/Pat)_{t+3}$	$Ln(1+Cit/Pat)_{t+4}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rivals' $Cash_t$	0.576***	0.548***	0.430***	0.255*	-0.192*	-0.380***	-0.566***	-0.680***
	(5.02)	(4.36)	(3.16)	(1.76)	(-1.91)	(-3.50)	(-4.89)	(-5.54)
Firm's Characteristics								
$Cash_t$	0.015*	0.020**	0.027**	0.031**	0.018	0.009	0.046**	0.040**
	(1.66)	(1.98)	(2.51)	(2.52)	(1.12)	(0.52)	(2.44)	(2.00)
$Ln(Sales)_t$	0.034***	0.033***	0.032***	0.031***	0.016***	0.015***	0.012***	0.012***
	(9.83)	(8.83)	(7.87)	(7.00)	(5.80)	(5.06)	(3.62)	(3.27)
$R\&D_t$	0.064***	0.070***	0.064***	0.068**	0.213***	0.201***	0.142***	0.105**
	(3.24)	(3.17)	(2.61)	(2.43)	(5.10)	(4.62)	(3.08)	(2.16)
$Leverage_t$	-0.047***	-0.050***	-0.047***	-0.049***	-0.055***	-0.059***	-0.049***	-0.042***
	(-5.91)	(-5.62)	(-4.99)	(-4.77)	(-5.35)	(-5.33)	(-4.25)	(-3.50)
$Profitability_t$	-0.065***	-0.053***	-0.044***	-0.038***	-0.001	0.007	0.015	0.019
	(-6.66)	(-5.00)	(-3.76)	(-2.90)	(-0.11)	(0.47)	(0.99)	(1.17)
$Tangibility_t$	0.045***	0.050***	0.057***	0.066***	0.013	0.003	0.014	0.030
	(3.22)	(3.32)	(3.49)	(3.69)	(0.84)	(0.18)	(0.84)	(1.62)
Age_t	-0.003	-0.004	-0.003	-0.004	0.001	-0.003	-0.007	-0.007
	(-0.94)	(-1.18)	(-0.75)	(-0.79)	(0.19)	(-0.50)	(-1.11)	(-0.96)
WW $index_t$	-0.140***	-0.137***	-0.133***	-0.121***	-0.098***	-0.050*	-0.042	-0.051
	(-7.09)	(-6.28)	(-5.59)	(-4.77)	(-3.75)	(-1.76)	(-1.36)	(-1.49)
Industry's Characteristics								
$Herfindahl_t$	0.078	0.067	0.068	0.054	0.015	-0.021	0.020	0.015
	(1.33)	(1.07)	(1.02)	(0.76)	(0.31)	(-0.39)	(0.35)	(0.25)
$Herfindahl^2_t$	-0.043	-0.036	-0.039	-0.023	-0.010	0.032	-0.022	-0.020
	(-0.67)	(-0.54)	(-0.55)	(-0.30)	(-0.20)	(0.59)	(-0.37)	(-0.31)
Rival's Characteristics								
Rivals' $Ln(Sales)_t$	0.017***	0.018***	0.017***	0.018***	0.007	0.005	0.005	0.006
	(3.31)	(3.24)	(3.08)	(3.06)	(1.57)	(1.04)	(1.16)	(1.13)
Rivals' $R\&D_t$	-0.047	-0.035	0.022	0.105	-0.019	0.067	0.174*	0.167*
	(-0.72)	(-0.42)	(0.25)	(1.09)	(-0.29)	(0.82)	(1.94)	(1.74)
Rivals' $Leverage_t$	-0.004	-0.004	-0.012	-0.024	-0.060***	-0.066***	-0.066***	-0.084***

	(-0.27)	(-0.25)	(-0.73)	(-1.36)	(-3.24)	(-3.32)	(-3.19)	(-4.06)
Rivals' Profitability$_t$	0.024	0.024	0.021	0.011	-0.041**	-0.032	-0.034	-0.020
	(1.47)	(1.49)	(1.21)	(0.60)	(-2.02)	(-1.41)	(-1.39)	(-0.77)
Rivals' Tangibility$_t$	0.068*	0.058	0.030	-0.008	0.098**	0.075*	0.025	-0.044
	(1.69)	(1.32)	(0.64)	(-0.17)	(2.41)	(1.75)	(0.54)	(-0.91)
Rivals' Age$_t$	0.001	0.000	0.000	0.000	-0.002**	-0.002***	-0.002***	-0.002**
	(0.48)	(0.34)	(0.31)	(0.14)	(-2.22)	(-2.81)	(-2.61)	(-2.19)
Rivals' WW Index$_t$	0.031***	0.023***	0.020***	0.025***	-0.002	0.008	0.010	0.044***
	(4.88)	(3.28)	(2.81)	(3.08)	(-0.24)	(0.83)	(0.87)	(3.22)
First Stage's Estimation								
Rivals' IdioVol$_{t-1}$	0.261***	0.289***	0.303***	0.314***	0.261***	0.289***	0.303***	0.314***
	(12.54)	(12.90)	(12.83)	(12.52)	(12.54)	(12.90)	(12.83)	(12.52)
Rivals' Cash$_{t-1}$	0.455***	0.448***	0.444***	0.444***	0.455***	0.448***	0.444***	0.444***
	(69.61)	(66.75)	(62.59)	(59.11)	(69.61)	(66.75)	(62.59)	(59.11)
Rivals' Cash$_{t-2}$	0.051***	0.058***	0.059***	0.059***	0.051***	0.058***	0.059***	0.059***
	(8.96)	(9.72)	(9.32)	(8.62)	(8.96)	(9.72)	(9.32)	(8.62)
Cragg-Donald F statistic	2072.592	1947.116	1692.490	1499.083	2072.592	1947.116	1692.490	1499.083
Observations	100334	89854	80485	72107	100334	89854	80485	72107
R-squared	0.025	0.023	0.022	0.020	0.004	0.003	0.001	0.001
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM

Table 3: The American Jobs Creation Act

This table reports the results for our quasi-natural experiment using the American Jobs Creation Act enacted in 2004 as an exogenous shock to *Rivals' Cash*. This analysis includes data two years before and after the event, namely 2002, 2003, 2005, 2006. For each firm, we calculate the *Cumulative Foreign Income* (*CFI*) during 2002 and 2003 and use this variable to assign *Multinational* (*CFI* > 1% total assets) and *Domestic* firms (*CFI* = 0). We compute *Count* as the number of *Multinational* firms in each 3-digit SIC industry and then restrict the sample to keep *Domestic* firms only. *Exposure* is equal to one when *Count* belongs to the highest tertile in 2003, and zero otherwise. *Post* is equal to one if year is after 2004 and zero otherwise. Variables include *Cash*, *Ln(sales)*, *R&D*, *Leverage*, *Profitability*, *Tangibility*, *Whited-Wu Index*, *Herfindahl*, and *Herfindahl*^{2}. All continuous variables are winsorized at 1st and 99th percentiles. We include *Firm* and *Year FE* in all regressions to control for unobserved characteristics. Statistical significance is calculated based on firm-level clustered standard error to allow for correlation of errors within-firm as suggested by Peterson (2009) .***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	$Ln(1+Pat)_{t+1}$	$Ln(1+Pat)_{t+2}$	$Ln(1+Pat)_{t+3}$	$Ln(1+Pat)_{t+4}$	$Ln(1+Cit/Pat)_{t+1}$	$Ln(1+Cit/Pat)_{t+2}$	$Ln(1+Cit/Pat)_{t+3}$	$Ln(1+Cit/Pat)_{t+4}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post x Exposure	0.022**	0.026**	0.010	-0.013	-0.008	-0.030	-0.102**	-0.115***
	(2.09)	(2.00)	(0.60)	(-0.67)	(-0.22)	(-0.81)	(-2.54)	(-2.76)
Firm's Characteristics								
$Cash_t$	0.011	-0.007	-0.007	-0.018	0.057	-0.008	0.058	-0.014
	(0.95)	(-0.48)	(-0.46)	(-0.79)	(0.83)	(-0.11)	(0.83)	(-0.16)
$Ln(Sales)_t$	0.007*	0.001	-0.007	-0.008	-0.022	-0.033*	-0.030*	-0.022
	(1.68)	(0.25)	(-1.51)	(-1.47)	(-1.29)	(-1.96)	(-1.78)	(-1.15)
$R\&D_t$	-0.055**	-0.083***	-0.042	-0.016	-0.004	-0.012	-0.014	0.102
	(-2.40)	(-3.29)	(-1.41)	(-0.41)	(-0.02)	(-0.08)	(-0.09)	(0.56)
$Leverage_t$	-0.009	0.006	0.020	0.026	-0.021	0.036	0.080	0.065
	(-0.68)	(0.39)	(1.10)	(1.18)	(-0.36)	(0.58)	(1.17)	(0.68)
$Profitability_t$	-0.020	-0.019	0.015	0.026	-0.037	0.118	0.058	0.087
	(-1.36)	(-1.06)	(0.69)	(1.15)	(-0.40)	(1.33)	(0.57)	(0.83)
$Tangibility_t$	0.017	0.059	0.064	0.032	-0.043	-0.058	-0.015	-0.064
	(0.30)	(0.86)	(0.78)	(0.37)	(-0.27)	(-0.36)	(-0.09)	(-0.28)
WW $index_t$	-0.009	0.040	0.036	0.019	-0.058	-0.033	0.004	0.116
	(-0.30)	(1.27)	(0.89)	(0.43)	(-0.39)	(-0.18)	(0.03)	(0.60)
Industry's Characteristics								
$Herfindahl_t$	-0.001	0.052	0.005	-0.059	-0.890*	0.285	0.148	0.235
	(-0.01)	(0.48)	(0.04)	(-0.44)	(-1.81)	(0.56)	(0.28)	(0.39)
$Herfindahl^2_t$	0.010	-0.031	-0.013	0.032	0.935**	-0.512	-0.543	-0.449
	(0.12)	(-0.37)	(-0.11)	(0.27)	(2.18)	(-1.10)	(-1.12)	(-0.89)
Observations	2957	2816	2688	1986	2957	2816	2688	1986
R-squared	0.96	0.95	0.93	0.93	0.57	0.58	0.54	0.61
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM

Table 4: Rivals' Cash, Innovation, and Product Market Performance

This table reports the results relating patents and their scientific value with future market performance. Column 1-2, 3-4, 5-6 examine the effect of the number of patents (*Pat*), number of citations per patent (*Cit/Pat*), and both, respectively, on a firm's market share growth. For each firm-year observation, *Rivals' Cash* is the average of *Cash* ratio (*CH/AT*) of all firms operating in the same 3-digit SIC industry, excluding firm *i*. Control variables include *Cash*, *Ln(sales)*, *R&D*, *Leverage*, *Profitability*, *Tangibility*, *Age*, *Whited-Wu Index*, *Herfindahl,* and *Herfindahl*^{2}. For each firm's characteristic, we also control for the corresponding rivals' characteristic which is computed with the method similar to calculating *Rivals' Cash*. All continuous variables are winsorized at 1st and 99th percentiles. We include *Firm* and *Year FE* in all regressions to control for unobserved characteristics. Statistical significance is calculated based on firm-level clustered standard error to allow for correlation of errors within-firm as suggested by Peterson (2009) .***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Patent		Citation/Patent		Both	
VARIABLES	ΔMarket Share$_t$	ΔMarket Share$_t$	ΔMarket Share$_t$	ΔMarket Share$_t$	ΔMarket Share$_t$	ΔMarket Share$_t$
	(1)	(2)	(3)	(4)	(5)	(6)
Rivals' Cash$_{t-2}$	-1.217***	-3.029***	-0.911***	-2.771***	-1.095***	-2.977***
	(-4.02)	(-9.06)	(-2.79)	(-7.88)	(-3.37)	(-8.40)
Ln(1+Pat)$_{t-2}$	-0.033	0.036			-0.053	0.030
	(-0.31)	(0.31)			(-0.48)	(0.25)
Rivals' Cash$_{t-2}$ x Ln(1+Pat)$_{t-2}$	1.320**	1.490**			1.541**	1.578**
	(2.10)	(2.16)			(2.23)	(2.12)
Ln(1+Cit/Pat)$_{t-2}$			0.037	-0.009	0.074	0.025
			(0.61)	(-0.15)	(1.13)	(0.38)
Rivals' Cash$_{t-2}$ x Ln(1+Cit/Pat)$_{t-2}$			-0.402	0.047	-0.732	-0.304
			(-0.62)	(0.07)	(-1.06)	(-0.43)
Firm's Characteristics						
Cash$_{t-2}$		0.083		0.085		0.084
		(0.45)		(0.46)		(0.45)
Ln(Total Assets)$_{t-1}$		-0.107***		-0.097***		-0.107***
		(-4.35)		(-4.02)		(-4.31)
Leverage$_{t-1}$		0.001		0.002		0.001
		(0.01)		(0.02)		(0.01)
Leverage$_{t-2}$		-0.608***		-0.609***		-0.609***
		(-5.15)		(-5.16)		(-5.16)
ΔMarket Share$_{t-1}$		-0.142***		-0.142***		-0.142***
		(-22.56)		(-22.55)		(-22.57)
ΔMarket Share$_{t-2}$		-0.115***		-0.115***		-0.115***
		(-19.46)		(-19.45)		(-19.46)
Acquisition$_{t-1}$		0.510		0.494		0.509
		(1.57)		(1.53)		(1.57)
Acquisition$_{t-2}$		0.539*		0.524*		0.539*
		(1.93)		(1.88)		(1.93)
Sale Acquisition$_{t-1}$		0.388***		0.386***		0.388***
		(3.35)		(3.33)		(3.34)
Sale Acquisition$_{t-2}$		0.010		0.010		0.010
		(0.09)		(0.09)		(0.09)
M/B$_{t-1}$		0.075***		0.075***		0.075***
		(6.55)		(6.62)		(6.54)
M/B$_{t-2}$		0.038***		0.038***		0.038***
		(3.34)		(3.33)		(3.35)
Constant	-0.305***	0.293**	-0.324***	0.238*	-0.315***	0.287**
	(-10.10)	(2.16)	(-10.22)	(1.76)	(-10.00)	(2.10)
Observations	74078	74078	74078	74078	74078	74078
R-squared	0.22	0.24	0.22	0.24	0.22	0.24
Firm FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM

Table 5: The Value of Patents in the Presence of Cash-rich Rivals

This table reports the relation between Rivals' Cash Holdings, Innovation and Firm Value. Panel A presents a model of future Tobin's Q. Panel B performs the IV analysis with *PatEco* and *PatSci* are from Kogan *et al.* (2017). *PatEco* is the dollar value of all patents granted in year *t*, scaled by the firm's total assets (*AT*). *PatSci* is the citation-weighted granted patent counts in year *t*, scaled by total assets (*AT*). Panel C reports the IV analysis with *StraPat*. *StraPat* is the adjusted number of *Strategic Patent*s. *Strategic Patent*s are patents that belong to the top 20% in dollar value and the bottom 20% in number of citations by technological class and grant year. For each firm-year observation, *Rivals' Cash* is the average of *Cash* ratio (*CH/AT*) of all firms operating in the same 3-digit SIC industry, excluding firm *i*. Control Variables include *Cash*, *Ln(sales)*, *R&D*, *Leverage*, *Profitability*, *Tangibility*, *Age*, *Whited-Wu Index*, *Herfindahl,* and *Herfindahl*^{2}. For each firm's characteristic, we also control for the corresponding rivals' characteristic which is computed with the method similar to calculating *Rivals' Cash*. All continuous variables are winsorized at 1st and 99th percentiles. We include *Firm* (*Industry*) and *Year FE* in all regressions to control for unobserved characteristics. Statistical significance is calculated based on firm-level clustered standard error to allow for correlation of errors within-firm as suggested by Peterson (2009) .***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Rivals' Cash Holdings and the Contribution of Patents to Firm Value

	$Ln(Q)_{t+1}$	$Ln(Q)_{t+2}$	$Ln(Q)_{t+3}$	$Ln(Q)_{t+1}$	$Ln(Q)_{t+2}$	$Ln(Q)_{t+3}$	$Ln(Q)_{t+1}$	$Ln(Q)_{t+2}$	$Ln(Q)_{t+3}$
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rivals' $Cash_t$	-0.260***	-0.319***	-0.205**	-0.260***	-0.321***	-0.219**	-0.293***	-0.353***	-0.251**
	(-2.84)	(-3.33)	(-2.04)	(-2.86)	(-3.36)	(-2.18)	(-3.19)	(-3.65)	(-2.47)
$Ln(1+Pat)_t$	0.024	0.023	0.016				-0.007	-0.008	-0.012
	(1.49)	(1.42)	(1.00)				(-0.40)	(-0.47)	(-0.73)
$Ln(1+Pat)_t$ x Rivals' $Cash_t$	0.411***	0.384***	0.386***				0.414***	0.396***	0.389***
	(3.11)	(3.00)	(3.08)				(3.15)	(3.11)	(3.13)
$Ln(1+Cit/Pat)_t$				0.107***	0.108***	0.098***	0.116***	0.117***	0.109***
				(7.76)	(7.70)	(6.87)	(8.33)	(8.33)	(7.63)
$Ln(1+Cit/Pat)_t$ x Rivals' $Cash_t$				0.207**	0.186**	0.226**	0.064	0.043	0.077
				(2.25)	(1.97)	(2.28)	(0.68)	(0.45)	(0.77)
Observations	99283	89867	80434	99283	89867	80434	99283	89867	80434
R-squared	0.33	0.32	0.31	0.33	0.33	0.32	0.34	0.33	0.32
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM

Panel B: Economics Value versus Scientific Value

VARIABLES	$Ln(1+PatEco)_{t+1}$	$Ln(1+PatEco)_{t+2}$	$Ln(1+PatEco)_{t+3}$	$Ln(1+PatEco)_{t+4}$	$Ln(1+PatSci)_{t+1}$	$Ln(1+ PatSci)_{t+2}$	$Ln(1+ PatSci)_{t+3}$	$Ln(1+ PatSci)_{t+4}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rivals' Cash	0.163***	0.151***	0.138***	0.140***	-0.116***	-0.109***	-0.154***	-0.179***
	(5.79)	(4.98)	(4.15)	(3.74)	(-5.26)	(-4.61)	(-6.23)	(-6.57)
Cragg-Donald F statistic	2072.592	1947.116	1692.490	1499.083	2072.592	1947.116	1692.490	1499.083
Observations	100334	89854	80485	72107	100334	89854	80485	72107
R-squared	0.018	0.024	0.021	0.019	0.014	0.010	0.006	0.004
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM

Panel C: Strategic Patents

VARIABLES	$Ln(1+StraPat)_{t+1}$	$Ln(1+StraPat)_{t+2}$	$Ln(1+StraPat)_{t+3}$	$Ln(1+StraPat)_{t+4}$
	(1)	(2)	(3)	(3)
Rivals' Cash	0.102***	0.120***	0.118***	0.109***
	(4.83)	(5.07)	(4.64)	(4.12)
Cragg-Donald F statistic	2072.592	1947.116	1692.490	1499.083
Observations	100334	89854	80485	72107
R-squared	0.008	0.008	0.009	0.011
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM

Table 6: Rivals' Cash Holdings, Innovation and Labor Mobility Risk

This table reports the results relating Labor Mobility Risk and the effect of Rival's Cash Holdings on Innovation. Panel A reports the analysis using Non-compete Agreement (*NCA*) Enforceability Index. Panel B examines the adoption of the Inevitable Disclosure Doctrine. The NCA Enforceability Index ranges between 0 (least restrictive) and 9 (most restrictive). For each firm-year observation, *Rivals' Cash* is the average of *Cash* ratio (*CH/AT*) of all firms operating in the same 3-digit SIC industry, excluding firm ***i***. Control Variables include *Cash*, *Ln(sales)*, *R&D*, *Leverage*, *Profitability*, *Tangibility*, *Age*, *Whited-Wu Index*, *Herfindahl*, and *Herfindahl*^{2}. For each firm's characteristic, we also control for the corresponding rivals' characteristic which is computed with the method similar to calculating *Rivals' Cash*. All continuous variables are winsorized at 1st and 99th percentiles. We include *Firm* and *Year FE* in all regressions to control for unobserved characteristics. Statistical significance is calculated based on firm-level clustered standard error to allow for correlation of errors within-firm as suggested by Peterson (2009) .***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Non-Compete Agreement Enforceability Index

VARIABLES	$Ln(1+Pat)_{t+1}$	$Ln(1+Pat)_{t+2}$	$Ln(1+Pat)_{t+3}$	$Ln(1+Pat)_{t+4}$
	(1)	(2)	(3)	(4)
Rivals' Cash	0.547***	0.550***	0.538***	0.468***
	(4.10)	(3.85)	(3.54)	(2.95)
NCA	0.013***	0.012***	0.011***	0.010**
	(3.55)	(3.18)	(2.82)	(2.47)
Rivals' Cash x NCA	-0.090***	-0.092***	-0.088***	-0.081**
	(-3.18)	(-3.02)	(-2.68)	(-2.37)
Observations	83936	75593	67339	59999
R-squared	0.87	0.88	0.88	0.88
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM

Panel B: Inevitable Disclosure Doctrine

VARIABLES	$Ln(1+Pat)_{t+1}$	$Ln(1+Pat)_{t+2}$	$Ln(1+Pat)_{t+3}$	$Ln(1+Pat)_{t+4}$
Rivals' Cash	0.385***	0.381***	0.381***	0.345***
	(5.75)	(5.36)	(4.92)	(4.18)
IDD	0.003	0.006	0.008	0.011
	(0.29)	(0.51)	(0.71)	(0.86)
Rivals' Cash x IDD	-0.218***	-0.248***	-0.272***	-0.290***
	(-2.73)	(-2.93)	(-3.01)	(-3.00)
Observations	100334	90783	81275	72777
R-squared	0.88	0.89	0.89	0.89
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM

Table 7: The Impact of Product Market Competition.

This table reports how product market competition resulting from tariff reduction affects the relation between Rival's Cash Holdings and Innovation. *Cut* is dummy that is equal to one if the industry experiences a *Tariff Cut* in the last two years (*t* and *t-1*), and zero otherwise. An industry experiences a *Tariff Cut* when there is a negative change in tariff rate that has the absolute value 2, 2.5, or 3 times larger than the mean of the absolute value of all changes occurred in that industry. Additionally, a *Tariff Cut* is not followed by an equivalently large increase in tariff rate in the subsequent two years. For each firm-year observation, *Rivals' Cash* is the average of *Cash* ratio (*CH/AT*) of all firms operating in the same 3-digit SIC industry, excluding firm *i*. Control Variables include *Cash*, *Ln(sales)*, *R&D*, *Leverage*, *Profitability*, *Tangibility*, *Age*, *Whited-Wu Index*, *Herfindahl*, and *Herfindahl*^{2}. For each firm's characteristic, we also control for the corresponding rivals' characteristic which is computed with the method similar to calculating *Rivals' Cash*. All continuous variables are winsorized at 1st and 99th percentiles. We include *Firm* and *Year FE* all regressions to control for unobserved characteristics. Statistical significance is calculated based on firm-level clustered standard error to allow for correlation of errors within-firm as suggested by Peterson (2009) .***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	$Ln(1+Pat)_{t+1}$	$Ln(1+Pat)_{t+2}$	$Ln(1+Pat)_{t+3}$	$Ln(1+Pat)_{t+4}$	$Ln(1+Cit/Pat)_{t+1}$	$Ln(1+Cit/Pat)_{t+2}$	$Ln(1+Cit/Pat)_{t+3}$	$Ln(1+Cit/Pat)_{t+4}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rivals' Cash	0.381***	0.400***	0.411***	0.363***	-0.159	-0.225**	-0.419***	-0.404***
	(3.25)	(3.27)	(3.12)	(2.61)	(-1.51)	(-2.05)	(-3.83)	(-3.41)
Cut	-0.041***	-0.050***	-0.047***	-0.045***	-0.025	-0.025*	-0.038**	-0.027*
	(-3.45)	(-3.74)	(-3.36)	(-3.19)	(-1.63)	(-1.65)	(-2.43)	(-1.70)
Rivals' Cash x Cut	0.318***	0.366***	0.346***	0.308***	0.303**	0.270**	0.341***	0.301**
	(4.19)	(4.12)	(3.56)	(3.05)	(2.54)	(2.18)	(2.74)	(2.33)
Observations	36424	33812	31387	29169	36424	33812	31387	29169
R-squared	0.89	0.89	0.88	0.87	0.59	0.59	0.58	0.58
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM

Table 8: First Mover's Advantage

This table examines how First Mover's Advantage (*FMA*) affects the strategic use of Patent in response to cash-rich rivals. Following Ma *et al.* 2014, we use two proxies of *FMA*. The first proxy is *Skewness* that is the third moment divided by the square root of the second moment cubed, based on the distribution of *Market Share*. *Dummy Skewness* is equal to one if *Skewness* is greater than the median in a given year, and zero otherwise. The second proxy is *Leaders' ROA Vol* which is the mean of *ROA Vol* of industry-year *Leaders*. *Leaders* are firms that belong to the highest quintile of both *Profitability* and *Market Share*. *ROA Vol* is the rolling standard deviation of Profitability with a rolling window of 5 years, requiring at least three years of data. For each firm-year observation, *Rivals' Cash* is the average of *Cash* ratio (*CH/AT*) of all firms operating in the same 3-digit SIC industry, excluding firm *i*. Control Variables include *Cash*, *Ln(sales)*, *R&D*, *Leverage*, *Profitability*, *Tangibility*, *Age*, *Whited-Wu Index*, *Herfindahl*, and *Herfindahl*^{2}. For each firm's characteristic, we also control for the corresponding rivals' characteristic which is computed with the method similar to calculating *Rivals' Cash*. All continuous variables are winsorized at 1st and 99th percentiles. We include *Firm* and *Year FE* in all regressions to control for unobserved characteristics. Statistical significance is calculated based on firm-level clustered standard error to allow for correlation of errors within-firm as suggested by Peterson (2009) .***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	$Ln(1+Pat)_{t+1}$	$Ln(1+Pat)_{t+2}$	$Ln(1+Pat)_{t+3}$	$Ln(1+Pat)_{t+4}$	$Ln(1+Cit/Pat)_{t+1}$	$Ln(1+Cit/Pat)_{t+2}$	$Ln(1+Cit/Pat)_{t+3}$	$Ln(1+Cit/Pat)_{t+4}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rivals' Cash	0.143***	0.114***	0.113**	0.080*	0.083*	0.037	-0.004	-0.060
	(3.57)	(2.73)	(2.51)	(1.67)	(1.73)	(0.73)	(-0.06)	(-1.07)
Dummy Skewness	-0.028***	-0.028***	-0.025***	-0.020**	0.024***	0.022***	0.028***	0.032***
	(-3.21)	(-3.11)	(-2.64)	(-2.01)	(3.19)	(2.79)	(3.24)	(3.53)
Rivals' Cash x Dummy Skewness	0.320***	0.338***	0.305***	0.268**	-0.270***	-0.261***	-0.349***	-0.375***
	(3.45)	(3.49)	(3.03)	(2.56)	(-3.72)	(-3.39)	(-4.18)	(-4.34)
Observations	100249	90702	81185	72676	100249	90702	81185	72676
R-squared	0.88	0.89	0.89	0.89	0.59	0.59	0.59	0.59
Rivals' Cash	0.193***	0.174***	0.190***	0.171***	-0.064	-0.099*	-0.081	-0.145**
	(4.23)	(3.67)	(3.66)	(3.08)	(-1.24)	(-1.82)	(-1.41)	(-2.46)
Leaders' ROA Vol	-0.251***	-0.235***	-0.144	-0.088	0.030	0.060	0.248***	0.190*
	(-2.98)	(-2.68)	(-1.55)	(-0.88)	(0.36)	(0.70)	(2.64)	(1.94)
Rivals' Cash x Leaders' ROA Vol	3.089***	3.014***	2.020*	1.153	0.910	0.543	-2.761**	-2.909**
	(2.96)	(2.76)	(1.74)	(0.91)	(0.94)	(0.54)	(-2.57)	(-2.49)
Observations	100249	90702	81185	72676	100249	90702	81185	72676
R-squared	0.88	0.88	0.89	0.89	0.59	0.59	0.59	0.59
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM	FIRM