More Cash, Less Innovation:
The Effect of the American Jobs Creation Act on Patent Value

ABSTRACT

We find that firms can become less innovative following a sudden “inflow” of cash. Specifically, multinational firms that were likely to repatriate cash to the U.S. under the 2004 American Jobs Creation Act (AJCA) generate less valuable patents than similar firms that could not benefit from this Act. This effect only exists among poorly governed firms and financially unconstrained firms, and is mainly driven by the reduction in exploratory innovation and in the value of U.S.-originated patents. Furthermore, there is no significant effect on the value of acquired innovation. These results appear to be consistent with the “quiet life” agency story.

JEL Classification: G32, G34, O32

Keywords: Financial Slack, Innovation, Free Cash Flow, Agency Problems.

I. Introduction

How does financial slack affect innovation? Conventional wisdom since Schumpeter (1942) suggests that more financial resources lead to more innovation since financial constraints may force firms to cut R&D spending and forgo positive NPV projects. On the other hand, abundant financial resources may lead to agency issues (i.e., the well-known free cash flow problems), especially for unconstrained firms or firms with weak governance. In the setting of innovation, free cash flow problems can be even more severe due to the unique nature of R&D activities, such as high uncertainty and information asymmetry. Furthermore, anecdotal evidence also suggests that more financial resources do not necessarily lead to more and better innovation.

For example, some question whether U.S. firms' heightened R&D investment generated commensurate inventions (*The Economist* (1990); Jensen (1993); Jaffe (2000); Lanjouw and Schankerman (2004)).[1] A recent report also shows that small biotechnology companies spend on aggregate around $28 billion annually on R&D, which is much lower than the $50 billion R&D spending for large pharmaceutical companies.[2] However, the dominance of large pharmaceutical companies in R&D spending did not make them the winners in discovering new drugs. Munos (2009) shows that the share of approved new drugs from large pharmaceutical companies has gradually declined from roughly 75% since the early 1980s to nearly 35% in 2008. At the same time, the share attributable to small biotechnology and pharmaceutical companies has jumped from 23% to nearly 65% during the same period. In other words, small firms collectively produce more

[1] Jensen (1993) shows that U.S. real R&D expenditures grow at an average annual rate of 5.8% from 1975 to 1990 without generating appropriate economic and financial gains. *The Economist* (1990) notes that "American industry went on an R&D spending spree, with few big successes to show for it." Jaffe (2000) and Lanjouw and Schankerman (2004) also observe that the escalating R&D investment does not generate commensurate patents since the 1980s.

[2] Life sciences: a 20/20 vision to 2020. http://www.burrillandco.com/content/BT08_execSum.pdf

for less.[3] These findings suggest that when it comes to innovation, more can sometimes be less.

The goal of this paper is to examine the relationship between financial slack and the value of innovation, particularly among firms that are likely to have free cash flow problems (such as financially unconstrained firms and firms with weak governance). Examining this question forces us to overcome two hurdles. First, we need to measure the value of innovation for shareholders. Traditional measures such as patents and patent citations received are not ideal for this purpose for the following reasons: the number of patents may not capture the economic value of innovation since it does not reflect the impact and quality of innovation output and are subject to the patent troll issue (see, e.g., Cohen, Gurun, and Kominers (2016)); a common criticism of the number of citations received by a patent is that these citations reflect the technological value rather than market value of inventions; citations are also subject to truncation bias since it takes time for a patent to receive citations, and they can vary significantly with a patent's technology class and grant year (Seru (2014)). We address this hurdle by leveraging on the recently developed method of evaluating patents via market reactions to patent grant news (Kogan, Papanikolaou, Seru, and Stoffman (2017)). This new methodology allows us to measure the total shareholder value of a firm's new patents (henceforth, "patent value") and how this value responds to a shock to financial slack.

The second hurdle is to design an identification strategy that allows us to measure the effect of financial slack on patent value for firms that are likely to have free cash flow problems. Simple measures of financial slack such as excess cash holdings are endogenous. Thus, a simple regression of patent value on excess cash holdings does not identify this effect. We adopt an identification strategy that draws on the American Jobs Creation Act (AJCA), following Cohn and Wardlaw

[3] See also Kortum and Lerner (1998).

(2016). Passed in late 2004, the AJCA provided a temporary tax holiday for U.S. multinationals with positive foreign income by allowing them to exclude 85% of repatriated foreign earnings in computing their tax liability. Firms responded enthusiastically to this Act. According to the Internal Revenue Service (IRS), the aggregate repatriation associated with this Act was $312 billion. Since this inflow of cash is due to changes in tax policy instead of changes in other corporate policies and firms eligible for repatriation under this Act are likely to be financially unconstrained, it provides us with an ideal setting to identify the effect of sudden financial slack on patent value, especially for firms that are likely to face agency issues.[4] Similar to Cohn and Wardlaw (2016), we define treated firms as those U.S. multinational firms with cumulative foreign income above 1% of their total assets prior to the AJCA in the main tests.[5] These firms were in a position to benefit from the AJCA. We discuss our identification strategy in more details in Section II.

Our main finding is that U.S. firms that are more likely to repatriate under the AJCA generate less valuable patents than otherwise similar firms after the windfall of cash associated with the AJCA. The economic magnitude of this difference in patent value is substantial. For example, the AJCA is associated with a decrease in patent value (scaled by pre-shock assets) that represents 26% of the pre-shock mean and 16% of the pre-shock standard deviation of the same variable. Our interpretation of this evidence is that the sudden increase in financial slack associated with the AJCA is responsible for the reduction in the aggregate value of patents generated by U.S.

[4] Blouin and Krull (2009), Dharmapala, Foley, and Forbes (2011), Faulkender and Petersen (2012), and Cohn and Wardlaw (2016) also use the repatriation tax holiday to study the effects of cash flow shocks on corporate policies.

[5] Blouin and Krull (2009) and Faulkender and Petersen (2012) show that many of the firms that took advantage of the tax holiday are in innovation-driven industries. For example, firms in the Drugs, Computer and Office Equipment, and Computer Programming industries repatriated $105 billion, $28 billion, and $19 billion, respectively, under the AJCA. Using hand-collected data, we find that innovation-related firms in our treated firms repatriated $116 billion under the AJCA.

multinational firms. Furthermore, we examine the effect of the AJCA on value of acquired innovation proxied by change in intangible assets on a firm's balance sheet. We find no significant effect. This test illustrates that the negative effect of increase in financial slack on patent value is not due to firms shifting more resources to acquiring innovation externally.

To support the interpretation above, we provide several pieces of evidence. We show that control firms have very similar characteristics to treated firms, prior to the AJCA. In particular, we match on lagged growth in patent value to ensure that trends in patent value are very similar for treated and control firms prior to the AJCA. We also conduct placebo tests that show no differential change in patent value for the two groups of firms in other time periods not surrounding the AJCA. Moreover, we find that the negative association between the financial slack associated with the AJCA and patent value exists in U.S.-originated patents, but not in non-U.S.-originated patents. This indicates that the impact of the AJCA on innovation activities is only related to managers and inventors within the U.S., which further supports our interpretation of the results since the AJCA increases financial slack only for the U.S. divisions of multinational firms. It is possible that firms implement R&D activities overseas before the AJCA and then transfer back to the US after the event. However, such relocation cannot explain the drop in U.S.-originated patent value after the AJCA. Furthermore, most R&D by US multinational corporations is still performed in the United States even with the globalized economy.[6]

To identify the channels through which the increase in repatriation reduced patent value for multinational firms, we examine the impact of financial slack on R&D spending. If the reduction in patent value were driven by deteriorating investment opportunities, we would observe a significant reduction in R&D for treated firms (in the absence of agency problems). However, we

[6] see https://www.nsf.gov/statistics/seind14/

do not find significant changes in R&D spending around the AJCA on average, suggesting that our main findings are less likely attributable to a change in innovation opportunities.

To examine the role of agency problems, we study how the AJCA effect varies with corporate governance and financial constraints. We first examine the effect of the AJCA within subsamples split by pre-shock governance measures based on anti-takeover provisions, specifically the G-index in Gompers, Ishii, and Metrick (2003) and the E-index in Bebchuk, Cohen, and Ferrell (2009). We find that the negative impact of the AJCA on patent value is stronger among firms with weaker pre-shock governance (i.e., firms with more anti-takeover provisions and entrenchments). This evidence suggests that agency problems play a significant role in our main findings.

Since free cash flow problems are more likely to occur in financially unconstrained firms, we expect that our treated firms are mostly unconstrained prior to the shock. We find that a majority of the treated firms are unconstrained, as measured by the Hadlock and Pierce's (2010) constraints index. Furthermore, unconstrained firms drive the AJCA effect on patent value. This test further supports the hypothesis that agency issues associated with more financial slack can hurt innovation.

We then examine the impact of financial slack on managerial choices in innovation strategy, proxied by the types of patents that firms generate. Following Katila and Ahuja (2002), we categorize patents into exploratory and exploitative patents based on the frequency a firm acquires new knowledge outside its existing knowledge. Exploratory patents rely more on knowledge that is new to the firm than on the firm's existing expertise. In contrast, exploitative patents build more on a firm's existing expertise. Specifically, exploratory patents cite more patents outside a firm's circle of expertise and are deemed more *risky*, while exploitative patents cite fewer patents outside a firm's circle of expertise and are deemed *routine*. We find a significant reduction in the total value of exploratory patents generated by treated firms after the AJCA, relative to control firms. But there is no significant reduction in the relative value of exploitative patents. We also find that on average exploratory patents are more valuable than exploitative patents. Therefore, our main findings appear to be driven by a reduction in exploratory innovation activities by firms that can benefit from the AJCA. In other words, managers tend to pursue less exploratory projects with more financial slack.

All these additional analyses appear to support a "quiet life" agency story (e.g., Jensen (1988); Blanchard, Lopez-de-Silanes, and Shleifer (1994); Bertrand and Mullainathan (2003); Atanassov (2013); Sapra, Subramanian, and Subramanian (2014)). Managers prefer a quiet life, avoid taking risk and exerting extra efforts, and do not feel pressure to innovate with a lack of financial constraints and takeover threat. The inflow of cash induces managers to reduce their exploratory innovation activities, which are riskier and possibly more time consuming than exploitation of existing innovation.

As discussed earlier, we define treated firms as those with significant foreign income (relative to assets) *prior* to the act, and thus a high likelihood of repatriating under the Act to ensure that our identification strategy does not rely on ex-post information and is therefore less subject to endogeneity issues. Furthermore, we examine the predicted and realized repatriation activity simultaneously following Faulkender and Petersen (2012). The benefit of their approach is that it allows for the separation of two effects controlling for the other: the difference between firms with and without tax advantage under the AJCA; and the difference between firms that repatriated and those that did not. We find that firms with tax advantage under the AJCA experience significantly more reduction in patent value after the AJCA than firms without. This is consistent with our main findings. Furthermore, controlling for the probability of repatriation (or tax advantage), firms that actually repatriated experience a significantly greater reduction in patent value than firms that did not repatriate.

This paper contributes to the literature in several ways. Prior studies suggest that firms with financial slack and stable internally generated funds can secure risky R&D projects (especially during economic downturn), benefit from internal technology spillovers, and thus generate more technological inventions (e.g., Schumpeter (1942); Henderson and Cockburn (1996); Cohen, Levin, and Mowery (1987); Aghion, Angeletos, Banerjee, and Manova (2010); Brown, Martinsson, and Petersen (2012); Acharya and Xu (2017)).[7] We argue that when poorly governed unconstrained firms experience a sudden increase in financial slack, their managers may take less risk and become less productive, which is consistent with the quiet life hypothesis.

Our paper also echoes Jensen's (1986) free cash flow problems by demonstrating a particular event—the American Jobs Creation Act (AJCA)—that adversely affects the productivity of multinational firms' innovation activities. Since innovative activities are more susceptible to agency problems because of high uncertainty, intangibility, and severe information asymmetry (e.g., Kumar and Langberg (2009); Hall and Lerner (2010)), our empirical results suggest that shareholders may want to tighten the monitoring of innovation activities following windfalls of cash.

Our study also highlights managers' choice of innovation strategies (i.e., exploratory or exploitative innovation strategies), which is an important channel that connects firms' financial status to the value of their innovation. Since March (1991) and Levinthal and March (1993), the

[7] The literature also presented abundant evidence on the important role of the financial sector in financing innovative firms. Brown, Fazzari, and Petersen (2009), Nanda and Rhodes-Kropf (2013), and Hsu, Tian, and Xu (2014) present evidence for the positive effect of equity financing on corporate innovation. For the banking sector, Amore, Schneider, and Zaldokas (2013) and Chava, Oettl, Subramanian, and Subramanian (2013) show that bank deregulation leads to more innovation, while Nanda and Nicholas (2014) show that bank distress hurts corporate innovation.

choice between exploration and exploitation has become an important research topic. Recent studies also find that the managerial choice of innovation strategies is subject to agency issues.[8] Our finding that managers reduce the pursuit of exploratory innovation after the sudden increase of financial slack due to the AJCA provides new evidence to the nexus of managerial behaviors, innovation strategies, and firm value.

Our findings also relate to recent psychological and managerial evidence that shows that people can become more creative in making the best out of what they have when facing resource constraints. Resource abundance can actually be counterproductive (see Sonenshein (2017)).

This paper continues as follows. Section II discusses the data, the AJCA, and the recently developed method of evaluating patents. Section III examines the effect of the AJCA on patent value. Section IV studies the channels. Section V studies the AJCA effect among firms that repatriated under the AJCA. Section VI concludes.

II. Methodology and Data

A. Identification Strategy

Endogeneity issues make it hard to draw inferences regarding the association between financial conditions and innovation outcomes. One possibility is the existence of omitted variables such as innovation opportunities: firms with better innovation opportunities may be able to get more funding from investors to support their innovation activities. Thus, both good financial conditions and valuable innovation output are caused by good innovation opportunities. The second

[8] Balsmeier, Fleming, and Manso (2017) find that the independent board directors reduce agency costs and increase firms' exploitative innovation. Hsu, Huang, Massa, and Zhang (2016) show that controlling families of public firms pursue exploratory innovation in order to diversify their wealth risk on the costs of minority shareholders. Tong and Younge (2017) show that when managers are better protected from takeover threat, the scope and breadth of firms' innovation drop.

possibility is that firms that were capable of innovation in the past tend to be more profitable and also more innovative in the future. It is thus necessary for us to use a research design that is less subject to the aforementioned endogeneity issues.

To identify the effect of financial slack on innovation, we examine how the value of innovation output is affected by a positive cash flow shock – the American Jobs Creation Act (AJCA) enacted in 2004. The AJCA created a temporary incentive for U.S. corporations to repatriate accumulated income earned abroad by offering a one-time opportunity for a deduction of 85% of certain foreign earnings that are repatriated. This shock has been shown to increase the financial slack of firms with profitable foreign subsidiaries.[9] We thus treat the AJCA as an event that generated an unexpected increase in financial slack for some firms. Such differential exposures to the cash flow shock enable us to conduct a difference-in-difference (DID) analysis. Furthermore, this cash flow shock is likely to induce free cash flow problems, because firms eligible for repatriation under this Act are likely to be financially unconstrained.

Specifically, we first identify treated firms as those with cumulative foreign income during 2002-2003 above 1% of their total assets in 2002 to ensure that treated firms have a high likelihood of repatriating under the Act. We also require treated firms to have at least one patent filed in 2001-2003. We then create our control group by matching each treated firm with a firm with at least one patent filed in 2001-2003 in the same industry on major characteristics that are likely to affect its innovation (more details in Sections II.C and II.D). Following Cohn and Wardlaw (2016), we only consider firm-year observations in 2002, 2003, 2005, and 2006 to ensure that the effect of the

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[9] For example, Blouin and Krull (2009), Dharmapala, Foley, and Forbes (2011), and Faulkender and Petersen (2012) study the effects of this shock on domestic investment, leverage, and firm payout policy. Moreover, Cohn and Wardlaw (2016) study the effects of this shock on workplace safety.

AJCA on innovation value is appropriately specified and is not contaminated by other factors or economic events.

To test the effect of the shock on innovation, we run the following pooled regression using the matched sample:

$$Innovation_{it} = \alpha + \beta\ Treatment_t \times\ Exposure_i + \gamma_i + \delta_t + \varepsilon_{it}, \tag{1}$$

where $Innovation_{it}$ denotes innovation output of firm i in year t. Innovation output is measured by the scaled value of patents (that are eventually granted by the U.S. Patent and Trademark Office) based on the method in Kogan et al. (2017). We scale patent value by lagged total assets (Compustat item at).[10] $Treatment_t$ equals one for post-shock observations (2005 or 2006), and zero for pre-shock observations (2002 or 2003). $Exposure_i$ equals one for treated firms and zero for control firms. We include firm fixed effects (γ_i) and year fixed effects (δ_t), and cluster standard errors at the firm level because the variation in the dependent variable is likely to be firm specific.

Our identification strategy requires us to make the parallel trends assumption, i.e., the treated and control firms would have followed similar trends in their patent value, in the absence of the AJCA shock. We ensure that this assumption is satisfied in the pre-shock period, by including pre-shock growth in patent values among the matching characteristics. As is standard in these types of tests, we cannot entirely rule out the possibility of an omitted variable that coincidentally affects treated and control firms differently after 2004. To help rule out such a possibility, we conduct the same DID test around two non-event years as placebo tests in Section III.B, and identify specific channels that are related to the AJCA effect in Section IV.

Our method to identify treated and control firms does not take into account some policy-related conditions that a firm needs to meet in order to be eligible to repatriate under the AJCA. Therefore,

[10] For post-shock observations (2005, 2006), we scale patent value by total assets in 2003 to avoid confounding effect from changes in total assets after the shock.

this method may classify firms that do not qualify to repatriate and firms that qualify but choose not to repatriate into the treated group. This measurement issue creates noise, and should make it harder for us to identify the hypothesized negative impact of the Act. Nevertheless, in Section V we consider an alternative method to identify treated firms that considers realized repatriation based on Faulkender and Petersen (2012), as a robustness check.

B. Measure of Patent Value

It is often difficult to measure the direct economic value of patents as the output of innovation activities. While patent counts and forward citations are two popular measures for the quantity and quality of innovation output, they are subject to various issues (e.g., Lerner and Seru (2015); Jaffe and de Rassenfosse (2016)). Patent counts are also subject to patent troll issue (see Cohen, Gurun, and Kominers (2016)). In addition, a common criticism of patent citations is that they reflect the technological value rather than the market value of patentable inventions.[11] Moreover, citations are also subject to truncation bias since it takes time for a patent to receive citations, and they can vary significantly with a patent's technology class and grant year (Seru (2014)). Such truncation bias makes it difficult for researchers to use forward citations to examine how corporate innovation responds to recent policy shocks, such as the 2004 AJCA.

A recent study (Kogan et al. (2017)) proposes to use a firm's stock price reaction around its patents announcement dates to proxy for the market value of its patents. Their dataset includes all patents *granted* to public firms by the U.S. Patent and Trademark Office (USPTO) from 1926 to 2010. The USPTO publishes the Official Gazette on every Tuesday to inform the general public of newly granted patents and related documents that include their technical details. The value of a

[11] Nevertheless, Trajtenberg (1990), Harhoff, Narin, Scherer, and Vopel (1999), and Hall, Jaffe, and Trajtenberg (2005) have presented evidence showing that firms' market value increase with patent citations.

patent is estimated as the change in total market capitalization in the three-day window starting from the announcement day (i.e., the Tuesday when the patent is officially announced in the Official Gazette) till the Thursday in the same week, after adjusting for aggregate market movements and idiosyncratic stock return volatility.

One issue with this patent value measurement is the lead-time required to obtain market information on patent grant dates. The average gap between patent application and grant dates is around three years. Since we use patent application year to measure innovation and infer its value based on market reaction in the patent grant year, our measure may be subject to truncation bias due to the application-grant lag, especially during the post-shock period. To reduce this potential bias, we manually search patents granted in 2011-2014 (but applied in our sample period, 2002-2006) in the Google Patent database. This effort increases the number of patents applied during 2002-2006 by 14% compared to Kogan et al. (2017). A majority of this increase occurs in the post-shock period: 56% of these additional patents were applied in 2006, and 32% in 2005.

We use the same method as Kogan et al. (2017) to estimate patent value. We summarize the method here for illustration purpose. Our estimated patent values have a correlation of 0.998 with the ones provided by Kogan et al. (2017) for patents granted in 1976-2010.[12] Table A2 in the Appendix provides a detailed comparison. Specifically, we model a firm's benchmark-adjusted three-day announcement return for newly granted patent j, r_j, as the sum of two parts: (i) p_j, the value of patent j as a fraction of the firm's market capitalization, which is assumed to follow a normal distribution with a truncated mean (zero) and a variance σ_p^2, and (ii) ε_j, the component of r_j that is unrelated to the newly granted patent and follows a normal distribution with a mean zero

[12] We thank Kogan, Papanikolaou, Seru, and Stoffman for making these patent value available at https://iu.app.box.com/v/patents.

and a variance σ_ε^2. If both σ_p and σ_ε are known, then we can estimate the following Bayesian updating:

$$E\left[p_j | r_j\right] = SNR \times r_j + \sqrt{SNR} \times \sigma_\varepsilon \times \frac{\emptyset\left(-\sqrt{SNR}\times\frac{r_j}{\sigma_\varepsilon}\right)}{1-\Phi\left(-\sqrt{SNR}\times\frac{r_j}{\sigma_\varepsilon}\right)},$$

where $\emptyset$ and Φ denote the probability density function and cumulative distribution function of a standard normal distribution, respectively, and SNR is the ratio of signal to noise as defined below:

$$SNR = \frac{\sigma_p^2}{\sigma_p^2 + \sigma_\varepsilon^2}.$$

To uncover *SNR*, we follow Kogan et al. (2017) by assuming that SNR is constant across firms (*f*) and times (t) and that σ_ε^2 and σ_p^2 vary across firms and times (i.e., $\sigma_\varepsilon^2 = \sigma_{\varepsilon ft}^2$ and $\sigma_p^2 = \sigma_{pft}^2$). We then run the following panel regression to compute the increase in volatility of firm returns around announcement days of newly granted patents:

$$\log(r_{fd}^2) = \gamma I_{fd} + cZ_{fd} + u_{fd},$$

where r_{fd} is the three-day market-adjusted return of firm *f* starting from day d, I_{fd} is a dummy for the day when there is newly granted patent(s), and Z is a vector of controls including the day-of-week fixed effect and the firm-year joint fixed effects. The estimation of the above equation allows us to recover $\widehat{SNR}$ using this relation: $\widehat{SNR} = \left(e^{\hat{\gamma}} - 1\right)\left(1 - 2C_0^2 + e^{\hat{\gamma}} C_0^2\right)^{-1}$, where $C_0 = \frac{\emptyset(0)}{1-\Phi(0)} = 0.7979$.

To uncover $\sigma_{\varepsilon ft}^2$, we first follow Anderson and Terasvirta (2009) to estimate the market-adjusted daily return variance, σ_{ft}^2, non-parametrically and annually. This assumption allows the firm's volatility to change at an annual frequency. Given our estimate for the daily stock return variance, σ_{ft}^2 , the fraction of trading days that are announcement days, d_{ft}, and our estimated $\hat{\gamma}$, we are able to recover the variance of the measurement error as $\sigma^2_{\varepsilon ft} = 3\sigma^2_{ft}\left(1 + 3d_{ft}\,\hat{\gamma}/(1-\hat{\gamma})\right)^{-1}$.

Finally, we estimate the market value of patent j, θ_j, as a function of the product of the estimated stock return associated with the patent grant news and the market capitalization of the firm that is granted with patent *j* on the day prior to the announcement of the patent issuance, M_j:

$$\theta_j = (1-S)^{-1}\frac{1}{N_j}E\left[p_j|r_j\right]M_j,$$

where S is the unconditional patent application success rate and N_j is the number of patents granted on the same day to the same firm as patent j.[13] By summing up the market value of all patents applied in the same year for each firm, we have a firm-level estimate of the market value of patents applied in each year (that are eventually granted) to construct the dependent variable in our baseline regression.

The patents from Kogan et al. (2017) only include internally generated patents. Firms experiencing a positive funding shock may choose to acquire rather than generate innovation internally. Therefore, to correctly interpret our results, we also examine the effect of the AJCA on externally acquired innovation. We use the change in intangible assets as a proxy for acquired innovation to consider this possibility.

C. Pre-Matching Sample

To implement the proposed DID tests as in Equation (1), we need to make sure that the sample firms are homogeneous in observable characteristics relevant to the research question. One way to achieve that is through matching relevant observable characteristics between the treated and

[13] We use a success rate of 56% as in Carley, Hegde, and Marco (2014) and Kogan et al. (2017).

control groups before the AJCA. We report characteristics of the pre-matching sample in this subsection and those of the post-matching sample in the next subsection.

We first construct a sample of Compustat/CRSP firm-year observations by requiring firms to have share code 10 or 11 and excluding regulated utility firms (SIC codes 4900-4949) and financial firms (SIC codes 6000-6799). We also exclude observations with non-positive total assets or R&D expenses. We also restrict the sample to firms that filed at least one patent from 2001 to 2003. Following Cohn and Wardlaw (2016), we restrict our sample to the two years before and two years after the implementation of the 2004 AJCA (2002-2003 and 2005-2006) to focus on the change around the shock. We remove firms that were delisted during the sample period. We define a firm as a treated firm and assign one to its *Exposure* if it has cumulative foreign profits (Compustat item pifo) from 2002-2003 above 1% of its 2002 total assets. *Exposure* is set to zero for the other firms.

We then calculate firm-level characteristics as follows. Leverage (Debt/Asset) is book debt (the sum of Compustat items dlc and dltt) divided by total assets (Compustat item at). Cash (Cash/Assets) is the total cash and cash equivalents (Compustat item che) divided by total assets. Cash flows (Cash flow/Lagged Assets) is the sum of income before extraordinary items (Compustat item ib) and depreciation and amortization (Compustat item dp), divided by lagged total assets. Firm size is the natural log of total assets. Sales turnover (Sales/Lagged Assets) is the ratio of total sales to lagged total assets. Market-to-book ratio (Q) is defined as the ratio of total asset plus market capitalization (Compustat item prcc_f multiplied by Compustat item csho) minus common equity (Compustat item ceq) minus deferred taxes (Compustat item txdb) divided by total asset. Capital expenditure (Capex/Lagged Assets) is capital expenditure (Compustat item capx) divided by lagged total took assets. Idiosyncratic volatility is the standard derivation of the daily residual returns estimated annually from the market model. We winsorize all of these variables at the 1st and 99th percentiles to reduce possible impact of extreme outliers, and lag those variables with numerators from the balance sheet by one year following Cohn and Wardlaw (2016).

In the left half of Panel A of Table 1, we compare the means of the aforementioned variables between the 320 treated and the other 544 firms (firms that are not assigned to the treated group), in the period prior to the AJCA (2002-2003). We find that treated firms are bigger and have higher cash flows, leverage, sales turnover, less cash, and lower idiosyncratic volatility. Treated firms also have lower market-to-book ratios than the other firms. These sharp differences are expected given that multinational firms with foreign profits may be very different from the rest of firms and suggest that it is important to conduct matching before the DID tests.

D. Post-Matching Sample

We therefore perform a within-industry propensity score matching. For each industry defined by the Fama-French 17-industry classification, we estimate a probit model by regressing the dummy variable, *Exposure*, on leverage, cash, cash flows, firm size, sales turnover, market-to-book, capital expenditure, growth of patent value scaled by lagged assets, and idiosyncratic volatility.[14] In the estimation of the probit model, we use the unmatched sample described in the previous subsection and use the pre-shock averages of those explanatory variables. The probit regression allows us to estimate each firm's propensity to be exposed. We then match each treated firm with an untreated firm with the closest propensity score with replacement. If multiple matches exist, we randomly choose one. This matching results in 135 firms in the control group and 317 firms in the treated group.

[14] Using the broad industry classification allows for sufficient number of firms in each industry so that we can find matching control firms.

In the right half of Panel A of Table 1, we compare the means of the aforementioned variables between the treated firms and the matched control firms in 2002-2003. The matching successfully eliminates differences in many of the relevant characteristics between the treated and control groups, except cash flows, Q, and capital expenditure. We therefore use this matched sample for all our tests. In addition, to make sure that our results presented later are not driven by the differences among these three dimensions, we conduct separate matching using only one of these three characteristics at one time. We find similar results (see Table A3 in the appendix). Therefore, it is unlikely that our results are driven by the differences in these characteristics.

As mentioned earlier, we include the pre-shock growth rate of the outcome variable (patent value scaled by lagged assets) in the matching to ensure that treated and control firms display parallel trends in the key outcome variable before the shock. As shown at the bottom of Panel A of Table 1, we find no statistically significant difference in the pre-shock growth rate of patent value before and after matching (see also Figure 1 for a visual illustration of the pre-shock trends).

III. Empirical Tests

A. Baseline Results and Economic Significance

We first estimate Equation (1) using pooled OLS regressions to examine whether the increase in financial slack associated with the AJCA has a differential effect on innovation activities for treated and control firms. The outcome variable of interest is patent value scaled by lagged assets. We include R&D scaled by lagged assets as another dependent variable as a channel test. Previous studies suggest that R&D has a strong effect on contemporaneous patent applications and a weak effect on subsequent patent applications (Hausman, Hall, and Griliches (1984); Hall, Griliches, and Hausman (1986); Lerner and Wulf (2007)). Therefore, we examine R&D in the year of patent applications for the channel test. As discussed earlier, patent value only reflects internally generated patents. However, the shock may drive treated firms to acquire innovation externally.[15] To make sure that our interpretation is correct, we also examine the effect of the AJCA on value of acquired innovation, proxied by change in intangible assets (Compustat item intan). This variable reflects the value of innovation acquired either through M&A or independent transactions. For post-shock variables, we scale them by assets in 2003 to avoid the confounding effect of changes in total assets after the shock.

Table 2 presents the estimated coefficients on $Treatment_t \times Exposure_i$ with R&D, patent value, and change in intangible assets as the dependent variables in Columns (1), (2) and (3), respectively. For R&D and acquired innovation value, we find that this coefficient is tiny and insignificant; suggesting that increases in financial slack due to the AJCA did not change treated firms' R&D spending or innovation acquisition activities significantly relative to the control group. For patent value, we find that this coefficient is negative, -0.087, and significant at the 1% level. In terms of economic significance of this impact on patent value, this decrease represents 26% of the pre-shock mean (0.33) and 16% of the pre-shock standard deviation (0.56) of patent value. This suggests that increases in financial slack due to the AJCA reduced treated firms' patent value significantly relative to the control group.

These findings indicate that financial slack can hurt innovation value. In particular, they suggest that treated firms become less capable of converting R&D investment into valuable patents since R&D spending did not change while patent value was reduced after the AJCA. Since R&D spending did not change, deterioration in investment opportunities is unlikely to explain the

[15] Bernstein (2015) shows that going public allows firms to acquire external innovation and to hire external talents through enhanced equity financing.

reduction in patent value. If innovation opportunities coincidently drop with the AJCA, then R&D and patent value should drop simultaneously.

There are two types of agency issues that may potentially explain the negative impact of financial slack on innovation value: a "quiet life" or excessive risk taking. The former suggests that firm managers enjoy better job security and a quiet life from increased financial slack and hence do not want to exert extra efforts or take extra risk in innovating (see Bertrand and Mullainathan (2003); Sapra, Subramanian, and Subramanian (2014)). The latter suggests that managers may take unwarranted risk by shifting their attention and R&D resources to overly ambitious innovation projects that eventually fail to deliver patents with high market valuation (e.g., Jensen (1993)). We conduct more tests to differentiate these two hypotheses later.

Figure 1 visualizes the effects of the AJCA on innovation by presenting the evolution of patent value in the three years before and two years after the shock for the treated and control groups. We present annual cross-sectional average patent value in solid and dashed lines for treated and control firms, respectively, from 2001 to 2006. In the horizontal axis, 0 denotes the AJCA year (2004), while -3, -2, -1, 1, and 2 denotes 2001, 2002, 2003, 2005, and 2006, respectively. The value of patent output of treated firms is similar to that of control firms before 2004. After 2004, we observe a substantial difference between the two groups: treated firms display a sharp drop in patent value *relative* to control firms. Figure 1 also shows that treated firms experienced a sharper drop in patent value in 2004. This effect may be due to firms anticipating the Act to be passed soon and responding to it in advance. As we show later, the treated firms are likely to be financially unconstrained, and are therefore able to respond in advance to the act.[16]

[16] The Act was introduced by Representative Bill Thomas on June 4, 2004, passed the House on June 17, the Senate on July 15, and was signed by President George W. Bush on October 22.

Figure 1 corroborates our baseline results reported in Table 2. Treated firms produce less valuable patents than control firms do. As a result, the DID analysis in Table 2 and the visual comparison in Figure 1 collectively point to potential agency problems associated with sudden increase in financial slack associated with the AJCA.

B. Placebo Tests

A potential concern regarding the DID approach is that there may exist unobservable forces that make firms produce less valuable innovation after 2004, especially when they rely more on overseas markets. One possibility is that non-U.S. markets are associated with weaker patent protection. When firms rely more on overseas markets, their patents may be subject to piracy and are therefore valued less by stock markets. However, based on the annual survey in *Global Competitiveness Report* and *World Competitiveness Yearbook,* foreign IP protection has, in fact, been improving over time, which biases against us finding the result.

To address this concern directly, we implement placebo tests by redoing the DID analysis around two pseudo-event years that are far from the real event year (1998 and 2011). As shown in Table 3, we do not find significant coefficients on $Treatment_t \times Exposure_i$ for patent value in these placebo tests. These findings indicate that treated firms do not show significantly different patent value around the pseudo-event years relative to the control firms. Therefore, the results reported earlier in Table 2 are likely driven by the AJCA instead of unobservable forces.

C. U.S.-Originated and Non-U.S.-Originated Patents

To further support the causal interpretation of the effect of the AJCA on patent value, we examine innovation activities of managers and inventors within the U.S. and out of the U.S.

separately. Since the AJCA is supposed to affect U.S. divisions' financial slack only, we expect the impact identified earlier to be driven by U.S.-originated patents. Utilizing the Harvard Business School (HBS) Patent and Inventor database (Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming, (2014)), we are able to track the residential location of most patents' inventors. For a patent with a single inventor, we classify it as U.S.-originated or non-U.S.-originated based on the inventor's residential location. For a patent with multiple inventors from multiple locations, we split its value into U.S.- and non-U.S.-originated parts by the proportion of its U.S. and non-U.S. inventors. We then estimate Equation (1) using U.S.-originated patents only or non-U.S.-originated patents only. Table 4 shows that the coefficient of $Treatment_t \times Exposure_i$ is significantly negative if we compute firm-level patent value using U.S.-originated patents only. In terms of economic magnitude, the coefficient of -0.091 is commensurate to that in our baseline results (see Table 2 Column 2). However, we do not find the same pattern for non-U.S.-originated patents. Such a contrast suggests that the AJCA effect only occurs within the U.S. since U.S.-based managers and inventors benefit more from the repatriation of cash under the AJCA.

One may argue that R&D activities may take place in foreign branches before the AJCA and are then moved back to the U.S. after the Act. However, relocating R&D activities cannot explain our findings that U.S.-originated patent value drops after AJCA but non-U.S.-originated patent value remains at the same level. Furthermore, most R&D by U.S. multinational corporations is still performed in the United States even with the globalized economy according to a recent National Science Board's *Science and Engineering Indicators 2014 report* (see https://www.nsf.gov/statistics/seind14/). Therefore, our findings are more likely attributed to factors specific to U.S.-based operations, and Table 4 lends further support to the causal interpretation of the AJCA effect identified earlier.

IV. Channel Tests

Our DID tests suggest that patent value significantly drops after an increase in financial slack, but R&D investment does not. Clearly, the significant reduction in patent value for the treated firms cannot be explained by a reduction in R&D inputs.

In this section, we examine other channels through which an increase in financial slack can lead to lower patent value. First, we examine the AJCA effects across strong and weak governance subsamples. Second, we examine the effects of increased financial slack on patent value across financial constraints groups. If agency issues drive the AJCA effect on patent value, we expect to see a stronger impact among poorly governed firms and financially unconstrained firms. Third, we examine the AJCA effect on the value of different types of patents based on their associated risks. This test helps differentiate the quiet life explanation from the excessive risk taking explanation. In particular, we classify a firm's patents into two types based on whether they are built more on new knowledge than existing knowledge. In general, patents built more on new knowledge are riskier (risky projects) and consume more managerial attention and efforts, while patents built more on exiting knowledge (routine projects) are easier to maintain. The quiet life explanation predicts that treated firms' patent value associated with risky projects drop more than that of control firms after the AJCA, while the excessive risk taking explanation predicts that treated firms' patent value from risky projects increases after the AJCA relative to control firms.

A. Corporate Governance

Table 5 presents the DID test within weak and strong governance subsamples. We classify the sample firms into two subsamples based on their G-index in 2004 from Gompers, Ishii, and

Metrick (2003) or E-index in 2004 from Behchuk, Cohen, and Ferrell (2009).[17] Firms with the G-index or E-index below median (9 or 3) are classified into the strong governance subsample, and firms with the index above the median are classified into the weak governance subsample.

The relation between financial slack and patent value exists only in firms with weak governance (see Columns 2 and 4), but not in firms with strong governance (see Columns 1 and 3). In addition, the coefficient of $Treatment_t \times Exposure_i$ for the weak governance group is -0.084 or -0.077, which is similar to the counterpart in Table 2 (-0.087) for the full sample. This drop in innovation output is statistically and economically significant. For example, the coefficient of -0.084 indicates that the positive cash flow shock from the AJCA is associated with a decrease in patent value that represents 25% of the pre-shock mean (0.33) and 15% of the pre-shock standard deviation (0.56) among high G-index subsample. This test suggests that the negative impact of the AJCA on innovation value may be due to agency issues associated with increases in financial slack.

B. Financial Constraints

Since free cash flow problems are more likely to occur in financially unconstrained firms, we expect that our treated firms are mostly unconstrained prior to the shock. When we define financially unconstrained firms as firms with the constraints index (Hadlock and Pierce (2010)) in 2003 below -3.2 (the sample median), 269 firms out of 317 treated firms are financially unconstrained.[18]

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[17] Since the AJCA was passed in late October 2004, and the G-index and E-index in 2004 are based on publication of Corporate Takeover Defenses in January 2004, the indexes in 2004 are pre-shock governance measures. This is also consistent with the classification in Dharmapala, Foley, and Forbes (2011).

[18] The Hadlock-Pierce constraints index is a combination of firm asset size and age. More constrained firms have higher index by construction.

Furthermore, we expect the negative impact of the AJCA on patent value to be stronger among unconstrained firms. Therefore, we split our firms into subsamples based on their pre-shock financial constraints status. In Table 6, we show that the AJCA effect on patent value happens mostly in unconstrained firms. These findings further support the hypothesis that agency issues associated with more financial slack can hurt innovation.

C. Exploratory Versus Exploitative Patents

To separate the quiet life explanation from the excessive risk taking explanation, we resort to the riskiness of innovative projects pursued by sample firms that can be proxied by the citation patterns of their patent portfolios. In particular, we adopt the concept of "new citations" developed by Katila and Ahuja (2002) that captures the frequency a firm acquires new knowledge outside of its existing knowledge.[19] For each patent, we look into the composition of citations made by this patent ("backward citations") and categorize each backward citation into new citation if it is not a self-citation and has never been cited by the firm's other patents filed over the past five years. We then use the ratio of new citations to all backward citations as a proxy for the riskiness of innovative projects. Following Katila and Ahuja (2002), we classify a patent as a risky patent (i.e., exploratory patent) if its new citation ratio is greater than or equal to 60%; one the other hand, we classify a patent as a routine patent (i.e., exploitative patent) if its ratio of old citations (i.e., citations that are not new) to all backward citations is greater than or equal to 60%. In our sample, the median value of an exploratory patent is $6.78 million, while the median value of an exploitative patent is $5.89

[19] Katila and Ahuja (2002) categorize patents into exploratory and exploitative patents based on the frequency a firm acquires new knowledge outside of its existing knowledge. Exploratory patents rely more on knowledge that is new to the firm than on the firm's existing expertise. In contrast, exploitative patents build more on a firm's existing expertise. Specifically, exploratory patents cite more patents outside of a firm's circle of expertise and are deemed riskier, while exploitative patents cite fewer patents outside of a firm's circle of expertise and are deemed routine.

million. We sum up the values of all risky patents (routine patents) filed by a firm in a year as its risky patent value (routine patent value).

Table 7 presents the results from estimating Equation (1) with the (scaled) value of either risky patents or routine patents as the dependent variable. The coefficient of $Treatment_t \times Exposure_i$ is significantly negative for the value of risky patents, suggesting that firms experiencing an unexpected increase in financial slack produce lower value of risky patents. On the other hand, the coefficient of $Treatment_t \times Exposure_i$ is insignificant for the value of routine patents. These results suggest that the negative impact of the AJCA on patent value is driven by its impact on the value of exploratory patents.

Our analysis based on the riskiness of patents do not seem to support the excessive risk taking explanation. If the firm shifts more resources toward riskier projects, we should observe a reduction in the value of routine patents. However, we do not observe this pattern. Therefore, these results support the conjecture that managers become lazier after an increase in financial slack, and thus cut riskier projects that demand more attention and efforts.

V. Observed Repatriation

Our interpretation of the results is that the change in patent values is driven by the inflow of cash associated with the AJCA. Since our definition of treated firms is based on pre-AJCA foreign income, it is useful to examine whether our treated firms actually repatriated cash following the Act. Out of 317 treated firms, 149 firms explicitly stated that they repatriated foreign cash and 144 of these firms reported the repatriation amount. The average and median of these firms' repatriated cash are \$1,382 and \$348 million, respectively. Moreover, the total amount of these firms' repatriated cash is \$199 billion.[20]

Furthermore, we examine the predicted and realized repatriation simultaneously following Faulkender and Petersen (2012). Specifically, we run the following DID test:

$$Innovation_{it} = \alpha + \beta_1 \Pr[Repat]_{it} + \beta_2(AJCA_{it} - \Pr[Repat]_{it}) + \theta X_{it} + \gamma_i + \delta_t + \varepsilon_{it},$$

where $Innovation_{it}$ denotes scaled patent value of firm i in year t. $\Pr[Repat]$ is the predicted probability that the firm repatriates under the AJCA in years 2004 and beyond, and is set to zero for years prior to 2004.[21] $AJCA$ is a dummy variable that equals one in the year the firm repatriated and following years, and zero otherwise. Following their specification, we include firm controls (X_{it}), firm fixed effect (γ_i) and year fixed effect (δ_t), and cluster standard errors at the firm level. Firm controls are defined in Section II.C and Table 1. In this test, we use the sample from 2000 to 2007, which is the same time period used by Faulkender and Petersen (2012).

This approach allows for the separation of two effects controlling for the other: the difference between firms with and without tax advantage under the AJCA, captured by β_1; and the difference between firms that repatriated and those that did not, captured by β_2. As shown in Columns 3 and 4 of Table 8, the coefficients on $(AJCA_{it} - \Pr[Repat]_{it})$, which measure the incremental effect of the actual windfall on innovation, are negative and significant at the 1% level. This suggests that, controlling for the repatriation probability, repatriating firms produce less valuable patents after the AJCA than non-repatriating firms do. The coefficients on $\Pr[Repat]_{it}$ are also

[20] These statistics are based on Faulkender and Petersen (2012). We independently hand-collect the repatriation information and find similar statistics. Considering that our treated firms include only patenting firms, our summary statistics are consistent with the ones reported in Blouin and Krull (2009).
[21] The repatriation probability is estimated based on a cross-sectional logit, where the dependent variable is whether the firm repatriated foreign income under the AJCA in 2004 or later. The independent variables are firm size, Q, earnings, permanent reinvested earnings, foreign earnings, estimated repatriation tax and tax loss carryforward in 2003. See Faulkender and Petersen (2012) for more details.

significantly negative, which is consistent with our main results in Table 2 based on purely ex-ante information.[22]

VI. Conclusion

This paper provides new evidence that suggests that abundant financial resources may not always benefit innovation, especially for firms that are more likely to have free cash flow problems, such as financially unconstrained firms and poorly governed firms. By examining the effect of the AJCA on patent value, we find that firms with a cash windfall experience a significant reduction in innovation. However, we find no significant effect on the value of acquired innovation. This negative effect of financial slack on innovation value only exists in firms with weaker governance and financially unconstrained firms prior to the AJCA and in patents created by U.S.-based inventors. We also find that the reduction in patent value is driven by a reduction in the value of exploratory patents. Furthermore, the effect of the AJCA on patent value is stronger when firms indeed repatriated foreign profits. Our evidence seems to be consistent with the "quiet life" hypothesis suggesting that managers exert less effort, take less risk, and slow down innovation activities because of a sudden increase in financial slack.

We end with an important caveat. Our results do not suggest that financial slack always reduces innovation. Our treated firms are multinational firms that are largely financially unconstrained. The quiet life agency story is probably more relevant for these types of firms as well. Financial

[22] Furthermore, when we apply the Faulkender and Petersen (2012) approach to the sample period from 2002-2006 (excluding 2004), we find that the coefficients on the probability of repatriation are also significantly negative.

slack can have a very different impact on the value of innovation for small, growing firms that face financial constraints.[23]

[23] For example, consistent with this hypothesis, the results in Acharya and Xu (2017) suggest that access to public equity markets increases R&D investments by external finance dependent public firms and benefits their patent portfolio.

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Table 1

Summary Statistics

This table reports summary statistics. Panel A presents mean characteristics of the treated, other, and control groups. The sample consists of non-financial and non-utility firms in the 2002-2003 and 2005-2006 periods. We also exclude observations with non-positive total assets or R&D expenses. A firm is in the treated group if it has cumulative foreign income during 2002-2003 above 1% of their total assets in 2002, and in the other group otherwise. The control group consists of matched firms using the propensity score matching to treated firms within each industry. The matching procedure is a one-to-one nearest-neighbor match with replacements. The covariates include leverage, cash, cash flow, firm size, sales turnover, Q, capital expenditure, idiosyncratic volatility, and lagged growth of patent value. All variables are defined in Appendix. The matching procedure is described in Section II.D. *t*-Diff denotes the *t*-statistics of the difference between the two groups in each panel. ***, **, and * indicate that the difference is statistically significant at the 1%, 5%, and 10% level, respectively, based on a *t*-test. Panel B presents the pre-shock mean and standard derivation of the outcome variable in the matched sample. All firms are required to have at least one patent filed in 2001-2003.

Panel A. Pre- and Post-matching Statistics

	Pre-Match			Post-Match		
	Mean			Mean		
Variable	Treated	Other	*t*-Diff	Treated	Control	*t*-Diff
Leverage	0.21	0.14	6.08***	0.21	0.23	-1.46
Cash	0.19	0.41	-12.81***	0.19	0.17	1.00
Cash Flow	0.08	-0.11	11.58***	0.08	0.06	3.13***
Firm Size	7.24	5.19	16.37***	7.25	7.39	-0.96
Sales Turnover	0.98	0.69	8.01***	0.98	0.95	0.70
Q	2.16	2.52	-3.08***	2.17	1.91	2.50**
Capital Expenditure	0.04	0.04	0.79	0.04	0.03	2.64**
Idio. Volatility	0.03	0.04	-15.01***	0.03	0.03	-0.40
Growth Rate of Patent Value/ Lagged Assets	0.42	0.57	-1.50	0.42	0.33	0.96
# of Unique Firms	320	544		317	135	

Panel B. Pre-shock Outcome Variables

	Observations	Mean	Std. Dev
Patent Value/Lagged Assets	1,268	0.33	0.56

Table 2

The Effects of the AJCA on R&D Investment, Patent Value, and Acquired Innovation

This table presents the estimated effects of the AJCA on R&D investment (Column 1), patent value (Column 2), and change in intangible assets (Column 3) for the matched sample following Equation (1). Treated firms are matched with untreated firms using propensity score matching in the same industry (with replacement). Both models include firm and year fixed effects. The sample is restricted to 2002-2003 and 2005-2006. *Treatment* is one for post-2004 observations and zero for pre-2004 observations. *Exposure* equals one for treated firms and zero for control firms as defined in Table 1. R&D investment is defined as annual R&D expenditure scaled by lagged total book assets. Patent value is estimated by the grant day market reaction based on the method of Kogan et al. (2017), divided by the lagged value of total book assets. Change in intangible asset, ΔIntangible Assets, is defined as the difference between current year intangible asset and previous year intangible asset. For post-2004 observations, we scale dependent variables by total assets in 2003. All variables are winsorized at the 1% and 99% level each year. Standard errors are clustered at the firm level and reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	(1) R&D/ Lagged Assets	(2) Patent Values/ Lagged Assets	(3) ΔIntangible Assets
Treatment x Exposure	-0.004	-0.087***	-0.006
	(0.003)	(0.028)	(0.013)
Constant	0.078***	0.310***	0.058***
	(0.002)	(0.021)	(0.012)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	2,536	2,536	2,536
Adjusted R-squared	0.064	0.038	0.013

Table 3

Placebo Test—Patent Value around 1998 and 2011

This table presents the estimates of the effects of a hypothetical shock in 1998 or 2011 on patent value. Columns (1) and (2) report the estimation results of Equation (1) with a hypothetical shock in 1998 and 2011, respectively. Both models include firm and year fixed effects. The sample is restricted to 1996-1997 and 1999-2000 (or 2009-2010 and 2012-2013). *Treatment* is one for post-1998 (or post-2011) observations and zero for pre-1998 (or pre-2011) observations. *Exposure* equals one if a firm has cumulative foreign income during the pre-shock period above 1% of total assets and zero otherwise. Treated firms are matched with untreated firms using propensity score matching in the same industry (with replacement). Same set of covariates are used as in Table 1. For post-1998 (or post-2011) observations, we scale patent value by total assets in 1997 (or 2010). All variables are winsorized at the 1% and 99% level each year. Standard errors are clustered at the firm level and reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on a *t*-test.

	(1)	(2)
Pseudo Shock Year	1998	2011
Dependent Variable	Patent Values/ Lagged Assets	Patent Values/ Lagged Assets
Treatment x Exposure	-0.030	0.060
	(0.195)	(0.042)
Constant	0.621***	-0.010
	(0.138)	(0.032)
Firm FE	Y	Y
Year FE	Y	Y
Observations	2,176	1,784
Adjusted R-squared	0.044	0.263

Table 4

The Effects of the AJCA on U.S.-Originated and Non-U.S.-Originated Patent Value

This table presents estimates of the effects of the AJCA on U.S.-originated patent value and non-U.S.-originated patent value. We classify each patent into U.S.-originated patent or non-U.S.-originated patent based on the location of its investors (details provided in the main text). Both models include firm and year fixed effects. The sample is restricted to 2002-2003 and 2005-2006. All explanatory variables are defined as in Table 2. All variables are winsorized at the 1% and 99% level each year. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on a *t*-test.

Dependent Variable	(1) US-Originated Patent Value/ Lagged Assets	(2) Non-US-Originated Patent Value/ Lagged Assets
Treatment x Exposure	-0.091***	0.001
	(0.026)	(0.005)
Constant	0.265***	0.041***
	(0.018)	(0.003)
Firm FE	Y	Y
Year FE	Y	Y
Observations	2,536	2,536
Adjusted R-squared	0.0501	0.000

Table 5

Corporate Governance and the AJCA Effects

This table presents the estimates of the effects of the AJCA on patent value in the strong and weak governance subsamples, measured by the G-index in Gompers, Ishii, and Metrick (2003) and E-index in Bebchuk, Cohen, and Ferrell (2009), respectively. Subsamples are based on the median, 9 for G-index and 3 for E-index, of the governance indexes in 2004. All models include firm and year fixed effects. The sample is restricted to 2002-2003 and 2005-2006. All explanatory variables are defined as in Table 2. All variables are winsorized at the 1% and 99% level each year. Standard errors are clustered at the firm level and reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on a *t*-test.

	(1)	(2)	(3)	(4)
Dependent Variable	Patent Values/ Lagged Assets			
Governance Index	G-Index		E-index	
Governance Subsample	Strong	Weak	Strong	Weak
Treatment x Exposure	-0.015	-0.084**	-0.043	-0.077**
	(0.071)	(0.036)	(0.064)	(0.037)
Constant	0.402***	0.275***	0.400***	0.303***
	(0.058)	(0.026)	(0.043)	(0.026)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	828	772	740	736
Adjusted R-squared	0.054	0.030	0.078	0.031

Table 6

Financial Constraints and the AJCA Effect

This table presents the estimates of the effects of the AJCA on R&D investment and patent value within the financially unconstrained and constrained subsamples, respectively. We define firms with a constraints index (as in Hadlock and Pierce (2010)) greater than -3.2 (sample median) in 2003 as constrained. All models include firm and year fixed effects. The sample is restricted to 2002-2003 and 2005-2006. All explanatory variables are defined as in Table 2. All variables are winsorized at the 1% and 99% level each year. Standard errors are clustered at the firm level and reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on a *t*-test.

	(1)	(2)
Dependent Variable	Patent Values/ Lagged Assets	
Financial Constraint	Unconstrained	Constrained
Treatment x Exposure	-0.106***	-0.009
	(0.033)	(0.060)
Constant	0.347***	0.166***
	(0.024)	(0.037)
Firm FE	Y	Y
Year FE	Y	Y
Observations	2,116	316
Adjusted R-squared	0.037	0.095

Table 7

The Effects of the AJCA on Risky Patent Value and Routine Patent Value

This table presents the estimates of the effects of the AJCA on risky patent value (in Column 1) and on routine patent value (in Column 2). For each patent, we look into the composition of citations made by this patent ("backward citations") and categorize each backward citation into new citation if it is not a self-citation and has never been cited by the firm's other patents filed over the past five years. We then use the ratio of new citations to all backward citations as a proxy for the riskiness of innovative projects. We classify a patent as a risky patent (i.e., exploratory patent) if its new citation ratio is greater than or equal to 60%; one the other hand, we classify a patent as a routine patent (i.e., exploitative patent) if its ratio of old citations (i.e., citations that are not new) to all backward citations is greater than or equal to 60%. Both models include firm and year fixed effects. The sample is restricted to 2002-2003 and 2005-2006. All explanatory variables are defined as in Table 2. All variables are winsorized at the 1% and 99% level each year. Standard errors are clustered at the firm level and reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on a *t*-test.

Dependent Variable	(1) Risky Patent Value/ Lagged Assets	(2) Routine Patent Value/ Lagged Assets
Treatment x Exposure	-0.052***	-0.023
	(0.017)	(0.014)
Constant	0.150***	0.119***
	(0.012)	(0.009)
Firm FE	Y	Y
Year FE	Y	Y
Observations	2,536	2,536
Adjusted R-squared	0.053	0.005

Table 8

Analysis based on Observed Repatriation

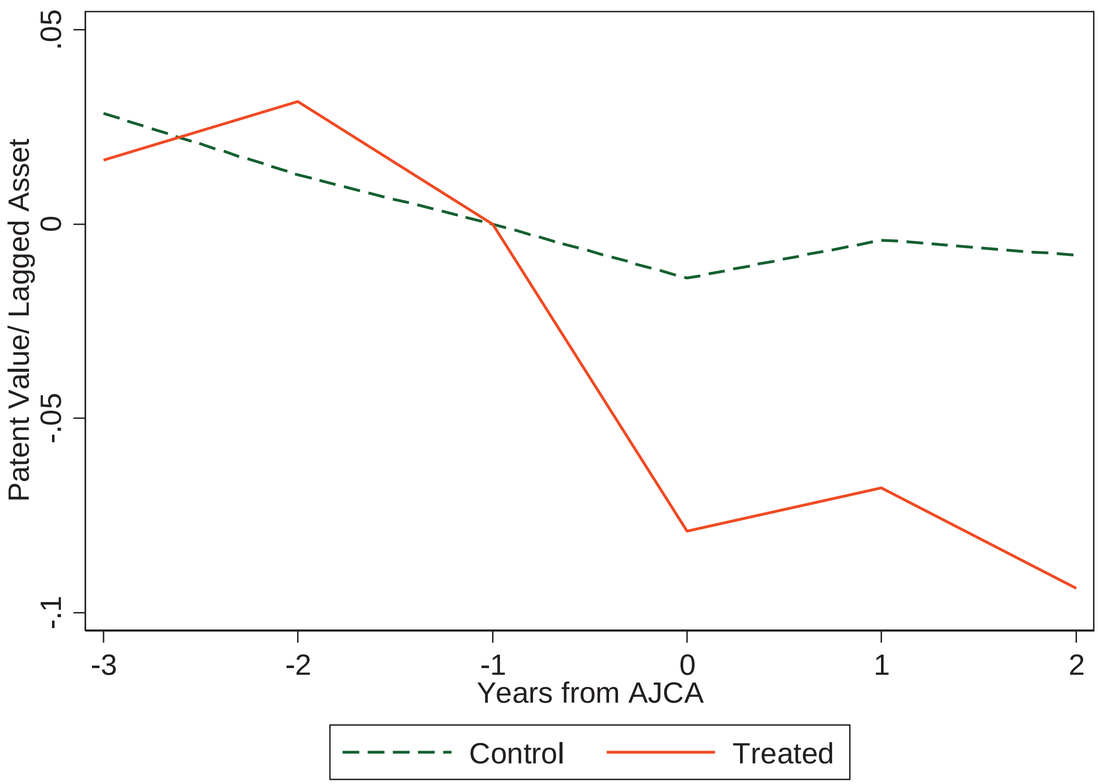
This table presents the estimates of panel regressions of patent value on observed repatriation and repatriation probability. Column 1 contains a dummy variable, AJCA, that equals one in the year the firm repatriated and later, and zero otherwise. Column 2 replaces the dummy variable by the probability (Pr[Repat]) that the firm repatriated under the AJCA in years 2004 and beyond. The probability is estimated based on Faulkender and Petersen (2012). Columns 3 and 4 include both the probability of repatriation and the residual, defined as the dummy variable in Column 1 (AJCA) minus the probability of repatration (Pr[Repat]) in Column 2. All models include firm and year fixed effects. The sample is from 2000 to 2007. Controls are defined as in Section II.C and Table 1. Controls are winsorized at the 1% and 99% level each year. Standard errors are clustered at the firm level and reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
AJCA	-0.130***			
	(0.032)			
Pr[Repat]		-0.212***	-0.235***	-0.255***
		(0.058)	(0.061)	(0.067)
AJCA − Pr[Repat]			-0.088***	-0.090***
			(0.029)	(0.032)
Controls	Y	Y	Y	
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	6,187	6,190	6,189	6,243
Adjusted R-squared	0.214	0.214	0.216	0.0860

Figure 1

Patent Value around the AJCA

This figure shows the evolution of average patent value of the treated and control groups around the AJCA. Patent value is the annual patent market value to lagged assets. For post-shock variables, we scale patent value by total assets in 2003. Treated and control groups are defined as in Table 1. In the horizontal axis, 0 refers to year 2004. -3, -2, -1, 1, and 2 refer to 2001, 2002, 2003, 2005, and 2006, respectively.



Appendix

Table A1

Variable Definitions

Variable Name	Description (variable definitions in parentheses refer to Compustat designations where appropriate)
Leverage	Debt/Assets: book debt (dlc+dltt) divided by total assets (at).
Cash	Cash/Assets: total cash and equivalents (che) divided by total assets.
Cash flow	Cash flow/Lagged Assets: sum of income before extraordinary items (ib) and depreciation and amortization (dp), divided by lagged total assets.
Firm size	Log(Assets): the natural log of total book assets.
Sales turnover	Total sales (sales) divided by lagged total assets.
Q	Market-to-book: total assets plus market capitalization (prcc_f*csho) minus common equity (ceq) minus deferred taxes (txdb) divided by total assets.
Capital expenditure	Capex/Lagged Assets: capital expenditure (capx) divided by lagged total book assets.
Idio. Volatility	Idiosyncratic volatility: the standard deviation of the daily residual return estimated annual by the market model.
R&D/Lagged Assets	R&D expenses (xrd) scaled by lagged total book assets (at). For post-2004 observations, we scale R&D by total assets in 2003.
Patent Value/Lagged Assets	The value of patent, estimated by the grant day market reaction based on the method of Kogan et al. (2017), divided by the lagged value of total book assets (at). For post-2004 observations, we scale patent value by total assets in 2003.
ΔIntangible Assets	The difference between current year intangible assets and previous year intangible assets (intan)
Risky Patent	For each patent, we look into the composition of citations made by this patent ("backward citations") and categorize each backward citation into new citation if it is not a self-citation and has never been cited by the firm's other patents filed over the past five years. We then use the ratio of new citations to all backward citations as a proxy for the riskiness of innovative projects. We classify a patent as a risky patent (i.e., exploratory patent) if its new citation ratio is greater than or equal to 60%. We sum up the value of all risky patents of a firm in a year as its patent value of risky patent.
Routine Patent	We classify a patent as a routine patent (i.e., exploitative patent) if its ratio of old citations (i.e., citations that are not new) to all backward citations is greater than or equal to 60%. We sum up the value of all routine patents of a firm in a year as its patent value of routine patent.
US-Originated Patent	For a patent with a single inventor, we classify it as U.S.-originated if the inventor is located in the U.S. For a patent with multiple inventors from multiple locations, we split its value into U.S.- and non-U.S.-originated parts by the proportion of its U.S. and non-U.S. inventors.

	We sum up the value of all U.S.-originated patents of a firm in a year as its patent value of US-originated patent.
Non-US-Originated Patent	For a patent with a single inventor, we classify it as non-U.S.-originated if the inventor is not located in the U.S. For a patent with multiple inventors from multiple locations, we split its value into U.S.- and non-U.S.-originated parts by the proportion of its U.S. and non-U.S. inventors. We sum up the value of all non-U.S.-originated patents of a firm in a year as its patent value of non-US-originated patent.

Table A2

Patent Value Estimation: Comparison with Kogan et al. (2017)

This table presents summary statistics of our patent value estimation and those in Kogan et al. (2017). The sample includes patents granted from 1976 to 2010. The table reports the number of patent value estimates, the correlation of patent value between the two samples, and the percentile of patent value for these two samples. P1 refers to the 1^{th} percentile, and so on.

Patent Value ($M)	Kogan et al. (2017)	Our Estimation
# of Patent Value Estimates	1,289,833	1,289,833
Patent Grant Year	1976-2010	1976-2010
Correlation	0.9977	
Mean	12.03	12.04
Std. Dev.	36.65	36.73
Percentiles		
p1	0.01	0.01
p5	0.03	0.03
p10	0.07	0.07
p25	0.58	0.58
p50	3.62	3.60
p75	10.34	10.33
p90	25.88	25.88
p95	45.90	45.97
p99	145.45	145.94

Table A3

The Effects of the AJCA on Patent Value: Characteristic-by-Characteristic Matching

This table presents estimates of the effect of AJCA on patent value using samples matched on individual firm characteristics. Treated firms are matched with untreated firms using propensity score matching in the same industry (with replacement). All models include firm and year fixed effects. The sample is restricted to 2002-2003 and 2005-2006. *Treatment* is one for post-2004 observations and zero for pre-2004 observations. *Exposure* equals one for treated firms and zero for control firms as defined in Table 1. Patent value is estimated by the grant day market reaction based on the method of Kogan et al. (2017), divided by the lagged book value of total assets. For post-2004 observations, we scale patent value by total assets in 2003. All variables are winsorized at the 1% and 99% level each year. The second column reports the mean of the characteristic for firms in the treated group. The third column reports the mean value of the characteristic for firms in the control group. The fourth column shows the t-statistic for the difference in means. The fifth column reports the coefficient on *Treatment* × *Exposure* and the sixth column reports its standard error. Standard errors are clustered at the firm level and reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on a *t*-test.

	Characteristics Mean			Treatment × Exposure	
Matched Characteristics	Treated	Control	t-diff	Coefficient	Std Err
Leverage	0.21	0.20	0.57	-0.056**	(0.022)
Cash	0.19	0.19	0.01	-0.067***	(0.020)
Cash Flow	0.08	0.08	0.20	-0.055**	(0.026)
Firm Size	7.01	6.99	0.18	-0.044*	(0.025)
Sales Turnover	1.00	1.01	-0.23	-0.031	(0.025)
Q	2.10	2.09	0.13	-0.063**	(0.025)
Capital Expenditure	0.04	0.04	0.51	-0.034	(0.027)
Idio. Volatility	0.03	0.03	-0.03	-0.046**	(0.023)