Providing protection or encouraging holdup? The effects of labor unions on innovation

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Abstract

We examine the impact of unionization on the innovation activities of firms by exploiting a novel database of union election results. We find patent counts and citations, proxies for firms' innovativeness, decline significantly after firms elect to unionize. We find the opposite for firms that vote to deunionize. To establish causality, we use a regression discontinuity design relying on "locally" exogenous variation in unionization generated by union elections that pass or do not pass by a small margin of votes. Further, we find that the market reaction to firms that elect to unionize is negatively related to firms' past innovation productivity. Our evidence suggests unionization stifles innovation.

Keywords: Innovation; labor unions; holdup; patenting
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We are solely responsible for any errors or omissions.

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1. Introduction

There has been considerable debate about the impact of unionization on economic productivity and efficiency. In their influential paper, 'The Two Faces of Unionism,' Freeman and Medoff (1979) provide a summary of two opposing views on the matter (Table 1, page 75). The collective voice/institutional response view advocates the positive effects of unions. This notion argues that unions lead to increased productivity by reducing employee turnover, improving morale and cooperation among employees, and implementation of better policies that reflect the aggregate preferences of all employees. The monopolistic view, however, paints a negative picture of unions in that they raise wages above the equilibrium level, increase income inequality, and lower society's output because of the ability (and realization) of workers to go on strike.

While there are likely merits to both sides of these arguments, there is an unmistakable trend in unionization rates in the US—they have lost their luster. In 1954, Mayer (2004) reports that union membership in the US peaked at just over 28% of all employed workers. According to the Bureau of Labor Statistics, by 2012, union membership stood at just above 11.3%.

In this paper, we study the causal effect of labor unions on firm innovation. This topic is of particular interest to policy makers and firm stakeholders not only because innovation is a crucial driver of economic growth (Solow, 1957), but also because unions in the U.S. are regulated and can be altered by labor laws and regulations over time. We propose two competing perspectives developed from the prevailing views of unionization to examine the effect of unions on firm innovation activities.

Motivating innovation is a challenge for most firms and organizations. Unlike routine tasks such as marketing and mass production, innovation involves a long process that is idiosyncratic, uncertain, and with a high probability of failure (Holmstrom, 1989). Therefore, providing employees and inventors with protection against dismissal in bad faith is necessary to effectively motivate and nurture innovation. Acharya, Baghai, and Subramanian (2012) study wrongful discharge laws in the US and their impact on innovation.[1] They examine the passage of these laws across states and measure the pre-/post-innovation activities of firms compared to firms in states that did not adopt such laws. They show that wrongful discharge laws, particularly those that protect employees for termination in bad faith, foster innovation vis-à-vis increased employee effort. These findings are consistent with Manso (2011) who suggests that firms need to adopt contracts that tolerate failure in the short run and reward success in the long run to motivate innovation. In our context, unions provide employee protection against termination, so unions should promote corporate innovation. We term this view the *employee protectionism hypothesis*.

An alternative view makes the opposite empirical prediction. Investment in innovation requires considerable investment in intangible assets such as research and development (R&D), and the innovation process is long, risky, and idiosyncratic. Therefore, contracts that effectively motivate innovation are almost always incomplete. Once the investment has been made and the innovation process begins, workers may have incentives to expropriate rents by demanding higher wage concessions recognizing that the cost is sunk. This holdup problem in turn leads unionized firms to underinvest (Grout, 1984; Malcomson, 1997). Given that innovation is a special long-term investment in intangible assets, these viewpoints indicate that potential ex-post holdup due to unionization might lead to an ex-ante underinvestment in innovation projects. Likewise,

[1] These laws provide employees greater protection than employment at-will, where employees can be terminated with or without just cause.

unionization may raise wages above competitive levels, encourage shirking by employees, lower output through frequent strikes, and therefore reduce innovation productivity. We refer to a general decline in innovation activities due to unionization as the *holdup hypothesis*.

We test the above two hypotheses by examining whether unions promote or impede firm innovation. Following existing literature that uses patenting to capture firms' innovativeness (i.e., Aghion et al., 2005; Nanda and Rhodes-Kropf, 2012; Seru, 2012), we use the number of patents granted to a firm and the number of future citations received by each patent obtained from the National Bureau of Economic Research (NBER) Patent Citation database to measure innovation output. Specifically, the former captures the quantity of firm innovation and the latter captures the quality of firm innovation. We collect union election results from the National Labor Relations Board, which allows us to compare changes in innovation output for firms that elect to become unionized to those that vote against it. Our union election data also allow us to examine changes in innovation in firms that elect to deunionize.

Our baseline models suggest that unionization negatively affects innovation, consistent with the *holdup hypothesis*. We find that firms that elect to become unionized have significantly lower patent counts and patents with lower impact one to three years post-election compared to the pre-election period, while we find that firms that vote to deunionize experience the exact opposite. We find a 20.2% decline in patent counts and a 10.7% decline in the number of non-self citations per patent three years after successful union elections. For firms that successfully deunionize, we find a 12.5% increase in the number of patents three years post-election.

Our baseline models are likely to suggest a causal effect of unionization on innovation because union elections are collectively determined by all union members and represent a likely exogenous shock to the firm's unionization status. However, our empirical design could still be subject to concerns that union election results could be correlated with firm unobservable characteristics that affect firm innovation output (i.e., the omitted variable concern) and that firms with low innovation potential may be more likely to pass unionization elections (i.e., reverse causality), making difficult to draw causal inferences from unionization to firm innovation.

To further establish causality, we use a regression discontinuity design that relies on "locally" exogenous variation in unionization generated by union elections that pass or do not pass by a small margin of votes. This empirical approach compares firms' innovation output subsequent to union elections that pass by a small margin to those subsequent to union elections that do not pass by a small margin. It is a powerful and appealing identification strategy because for these close-call elections, passing is very close to an independent random event and therefore is unlikely correlated with firm unobservable characteristics. When we employ a regression discontinuity design in which we focus on elections that barely pass or barely fail the 50% threshold needed to win, we find even economically stronger results. For instance, innovation quantity (quality) of firms that pass union elections within a margin of 2.5 percentage points is 30.7% (45.1%) lower than that of firms that do not pass union elections within a margin of 2.5 percentage points three years subsequent to union elections.

Surprisingly, we find little evidence that investment in R&D changes as a result of unionization. This may seem counterintuitive and at odds with the prevailing consensus view in the empirical literature. However, our results suggest that the channel through which unionization impedes innovation is not an underinvestment in innovation input (i.e., R&D), but rather a decline in innovation productivity.

Our last series of tests examine the market reaction to union elections. The unconditional market-adjusted return around the union election is close to zero; however, we find that the market reacts significantly negatively to firms that elect to unionize and that have been successful innovators during the past three years before the election date. We interpret this evidence consistent with the view that market participants are at least somewhat cognizant of the potential adverse effects unionization can potentially have on firm innovation.

The rest of our paper will proceed as follows. Section 2 discusses the related literature. Section 3 describes the data and presents descriptive statistics. Section 4 provides empirical results and Section 5 concludes.

2. Relation to the existing literature

Our paper contributes to two strands of literature. First, our paper is related to the emerging literature that focuses on various determinants of innovation. Theoretical work from Holmstrom (1989) argues innovation activities may mix poorly with routine activities in an organization. Aghion and Tirole (1994) suggest the organizational structure of firms matters for innovation. Manso (2011) argues that managerial contracts that tolerate failure in the short-run and reward success in the long-run are best suited for motivating corporate innovation. Ferreira, Manso, and Silva (2012) show that a firm's ownership structure also affects innovation.

Empirical evidence shows that various firm and industry characteristics affect managerial incentives of investing in innovation. A larger institutional ownership (Aghion, Van Reenen, and Zingales, 2013), private instead of public equity ownership (Lerner, Sorensen, and Stromberg, 2011; Bernstein, 2012), lower stock liquidity (Fang, Tian, and Tice, 2012) and corporate venture capitalists rather than traditional venture capitalists (Chemmanur et al., 2012) alter managerial incentives and hence help nurture corporate innovation. Other studies have shown that product market competition, general market conditions, firm boundaries, CEO overconfidence, and financial analysts all affect firm innovation (Aghion et al., 2005; Nanda and Rhodes-Kropf, 2011, 2012; Hirshleifer, Low, and Teoh, 2012; Seru, 2012; He and Tian, 2013).

Our paper is closely related to Acharya, Baghai, and Subramanian (2011, 2012) who make an important attempt to link employee protection and firm innovation. They find that the adoption of dismissal laws and wrongful discharge laws that prevent employees from termination in bad faith leads to gains in innovation. Our paper has a different angle—we use firm-level union election results to identify the causal effect of unionization on firm innovation. While we show labor unions stifle innovation, which appears inconsistent with the findings of Acharya, Baghai, and Subramanian (2011, 2012), we believe our evidence supplements their findings. Our evidence coupled with theirs implies there might be an inverted-U-shaped relation between employee protection and firm innovation along the spectrum of employee protection. When the level of protection provided to employees is low, increasing labor protection (such as the adoption of wrongful discharge laws) provides job insurance against failure risk arising from innovative activities and therefore spurs innovation. However, on the other hand, providing too much employee protection (such as those afforded by labor unions) potentially triggers holdup problems once the innovation process begins or encourages shirking and therefore stifles innovation.

Second, our paper adds to the large literature about the costs and benefits of labor unions. This literature generally shows that unions can influence both investment and financing decisions of firms. Matsa (2010) documents firms that are unionized are more likely to use financial leverage. He argues this is the case because it allows unionized firms to shield their cash flows from union demands. Likewise, Klasa, Maxwell, and Ortiz-Molina (2009) argue that firms in unionized industries strategically hold less cash to maintain bargaining leverage with unions. Chen, Kacperczyk, and Ortiz-Molina (2012) find that the cost of equity is significantly higher in more unionized industries because of the limitations on unionized firms' operating flexibility. Lee and Mas (2012) show negative significant stock market reactions over a long period to union victories, implying that unionization destroys shareholder wealth. On the other hand, Chen, Kacperczyk, and Ortiz-Molina (2011) find that firms in unionized industries have a lower cost of debt because their interests are more aligned with bondholders. Chyz, Leung, Li, and Liu (2012) show that unions influence firms' tax policies. They find unionized firms are less likely to engage in aggressive tax strategies because such strategies increase the after-tax cash flows of the firm that are vulnerable to union exploitation.

Several papers directly examine the impact of labor unions on investment. Collectively, the evidence leans towards a negative union-investment impact. Grout (1984) and Malcomson (1997) implicitly assume that unionized firms underinvest because of the holdup problem. Connolly, Hirsch, and Hirschey (1986) show that intangible R&D investments in unionized firms add less to market value compared to non-unionized firms. Chung, Lee, and Sohn (2012) argue that the documented negative effects on unions and investment is not because unions force firms to underinvest per se, but instead because they limit overinvestment.

The only two studies we are aware of that examine the relation between unionization and innovation using U.S. data are Acs and Audretsch (1988) and Hirsch and Link (1987). Acs and Audretsch (1988) find a negative association between unions and counts of innovations based on one year of data (i.e., 1982) at the industry level. Hirsch and Link (1987) also find a negative association between unions and innovation based on 315 New York manufacturing firms in 1985 using firm responses to surveys on product innovation. Different from their work, we attempt to examine the causal effect of unionization on innovation at the firm level with a much longer time series, using a newly assembled sample of National Labor Relation Board union elections matched to the NBER patent and citation data.

3. Data and descriptive statistics

Our data are from several sources. We collect union election results from the National Labor Relations Board (NLRB) over 1977 to 2010. It contains the name of the firm, location, SIC code, the date of the election, the number of participants and outcomes of the voting. We initially begin with 128,351 unique elections. We eliminate observations if the election voting outcome is not available or if the number of employees participating in the election is less than 50. These firms are manually matched with Compustat because the NLRB data do not contain a unique identifier other than firm name. We are careful to ensure accurate matches by also requiring that the firm's headquarter location and 1-digit SIC code also match. In the case where there are multiple elections for a unique firm we retain the outcome for the largest participation of voters.

It is typical in recent innovation studies to proxy for firm innovativeness using firm patent information from the NBER Patent Citation database (see Hall, Jaffe, and Trajtenberg (2001) for more detailed discussion). This database contains all patents registered and granted by the US Patent and Trademark Office over the 1976 to 2006 time period. It provides annual information on patent assignee names, the number of patents, the number of citations received by each patent, and a patent's application as well as grant year, etc. Thus, we merge all patent data registered to firms in our union election sample.

To gauge a firm's innovativeness, we construct two measures. The first measure is a firm's total number of patent applications filed in a given year that are eventually granted. We use a patent's application year instead of its grant year because previous studies (such as Griliches, Pakes, and Hall, 1988) have shown that the former is superior in capturing the actual time of innovation. Although patent counts are straightforward and easy to calculate, it cannot distinguish groundbreaking innovation from incremental technological discoveries. Therefore, to assess a patent's impact, we construct a second measure of firm innovativeness by counting the total number of non-self citations each patent receives in subsequent years. Given a firm's size and its innovation inputs, patent counts capture its overall innovation quantity and the number of non-self citations per patent captures the significance and quality of its innovation output. To account for the long-term nature of the innovation process, our empirical tests relate firm labor unions and other characteristics in the current year to the above two measures of innovation output in one, two, and three years following election results.

Consistent with the existing literature, we correct for two truncation problems associated with the NBER patent database. First, there is a substantial lag between patent applications and patent grants because the approval process typically takes several years (the lag between a patent's application year and its grant year is about two years on average). Thus, toward the end of the sample period, particularly in the last two to three years, there is a significant decline in patent applications that are ultimately granted. Following Hall, Jaffe, and Trajtenberg (2001), we correct for this truncation bias in patent counts using the "weight factors" computed from the application-grant empirical distribution. Second, it usually takes time for a patent to generate citations, but we observe at best the citations received up to 2006. To alleviate these concerns, we use the shape of the citation-lag distribution advocated by Hall, Jaffe, and Trajtenberg (2001).

Table 1 about here

Panel A of Table 1 describes the union election data. There are a total of 1,460 union election observations that we are able to match with CRSP. Aggregating the votes, 44% are in favor of unionization with a standard deviation of 22%. The unionization passage rate is 31%, which suggests that on average less than half of all elections favor unions. Panel B reports the elections for deunionization. We are able to match 468 firms with deunionization elections with CRSP. On average, 51% of participants favor deunionization with a standard deviation of 19%. The deunionization passage rate is 52%, suggesting that about half of elections result in deunionization.

Panel C presents firm characteristics. The average firm generates approximately 9 patents, which is generally consistent with the literature. Likewise, the average patent generates 4.7 citations. The distribution of patent grants and citations is right skewed.[2] Therefore, we use the natural logarithm of the patent counts and the natural logarithm of non-self citations per patent as the main innovation measures in our analysis. To avoid losing firm-year observations with zero patents or citations per patent, we add one to the actual values when calculating the natural logarithm. The average firm has assets of $3.8 billion and has a return on assets of 5%. R&D/Assets and PPE/Assets are 0.1 and 0.38, respectively, indicating that the sample is highly capital intensive. The average debt ratio is 0.27 and capital spending is 0.08 of firm assets. The Herfindahl-Hirschman index (HHI) is 0.54, indicating a competitive marketplace that our average firm operates in.

Insert Table 2 about here

Table 2 reports an industry breakdown of our sample based on one-digit SIC codes. While unions are represented across all industries, not surprisingly the bulk of the elections occur in those characterized as labor intensive. Roughly 50% of the sample are clustered in SIC codes 2 and 3, which are primarily manufacturing. This holds for both firms that have an election to unionize and those that elect to deunionize. We also report firms' average number of patents over the past 3 years (relative to the election date). This varies considerably and firms in the mining/oil & gas and manufacturing industries tend to hold the most patents. With the exceptions of agriculture (SIC code 0), finance (SIC code 6) and public administration (SIC code 9) that have very small sample

[2] Firm-year observations with zero patents represent roughly 64% of our sample, which is lower but generally comparable to the 84% reported in Atanassov, Nanda, and Seru (2007) and the 73% reported in Tian and Wang (2012). Their samples include the universe of Compustat firms between 1974 - 2000 and VC-backed IPO firms between 1985 - 2006, respectively.

sizes, the passage rates for unionization are fairly similar across industries ranging from 25% to 41%. Passage rates for deunionization range from the mid-40% to mid-50% in industries with reliable representation in the sample.

Insert Figure 1 about here

Figure 1 plots a time series of union and deunion election frequencies and passage rates across our sample period. There is a considerable drop in the number of firms holding union elections in the early 1980s from over 100 elections per year to just over 40. Between 1983 and 2004 the number of firms holding union elections remains relatively stable ranging between 40 and 60. From 2005 to 2010 this declines below 40 elections per year. There are no noticeable trends in the number of firms holding elections to deunionize across time.

The second plot in Figure 1 shows passage rates for unionization and deunionization elections across time. In almost all years, deunionization passage rates exceed unionization passage rates. Overall, figure 1 alludes to the declining pattern in union rates observed in the U.S. That is, the number of firms holding union elections has been declining and the popularity of deunionization exceeds unionization based on passage rates.

4. Empirical results

4.1 Baseline results

We begin our empirical analysis with a general model of patent counts and citations by estimating various forms of the following model using the ordinary least squares (OLS):

$$Ln(Innovation_{i,t+N}) = \alpha + \beta Unionization_{i,t} + \gamma Z_{i,t} + Year_t + Industry_j + Firm_i + \varepsilon_{i,t} \qquad (1)$$

where *i* indexes firm, *j* indexes industry, and *t* indexes time. The dependent variable, *Innovation*, is one of our two main innovation variables, patent counts or non-self citation per patent. Since the innovation process generally takes several years, we examine the effect of unionization on firms' patenting activities one, two, and three years post-election (N=1, N=2, or N=3). In our case, the variable of interest is *Unionization*, which is a binary variable that equals one if the results of the union election led to unionization, zero if the results of the union election failed to lead to unionization. *Z* is a vector of controls and is described in the Appendix. *Year* captures calendar year fixed effects, *Industry* captures industry fixed effects, and *Firm* captures firm fixed effects. We cluster standard errors at the firm level to avoid inflated t-statistics.

Insert Table 3 about here

Panel A reports the regression results estimating Equation (1) with industry and year fixed effects included. The dependent variable is patent counts in columns (1) – (3). The coefficient estimates on *Unionization* are negative and significant at the 5% level in all columns. In columns (4) – (6), we replace the dependent variable with proxies for patent quality. The coefficient estimates on *Unionization* are all negative and significant at the 1% level, suggesting that the impact of the average patent is less influential post-unionization in the cross section. Regarding controls, consistent with the existing literature, larger, older, and firms with lower investments in PPE and with less leverage are more innovative. These preliminary findings suggest that there appears a negative relation between unionization and the number of patents a firm generates in the cross-section.

In Panel B, we explore time-series variation within a firm to study the effect of unionization on corporate innovation by including firm and year fixed effects. The reasons we include firm fixed effects are twofold. First, exploring within-firm variation in unionization allows us to directly test the effects of a passage of unionization elections on the firm's subsequent innovation output. Second, there is a concern that both firm innovation and the passage of unionization elections are both determined by certain firm unobservable characteristics. For example, weak management teams with poor quality are less likely to promote innovation, and unionization elections might be more likely to pass in firms managed by weak management teams. Therefore, unobservable attributes may bias the coefficient estimates of β. Firm fixed effects help mitigate the concern if the unobservable firm characteristics are constant over time.

The coefficient estimates on *Unionization* are negative and significant at the 1% level in all three columns when the number of patents is the dependent variable in columns (1) – (3). The economic significance is large. For example, based on the coefficient estimate in column (3), a favorable union election leads to a 20.2% reduction in its innovation quantity three years post-election. In columns (4) – (6), we replace the dependent variable with patent quality and find that the coefficient estimates on *Unionization* are negative and significant in all three columns.

In either case, our initial evidence suggests that unionization has a negative impact on the innovation activities of the firm, consistent with the holdup argument of unionization. Comparing the results reported in Panel A and Panel B, it appears that the main variation that generates the negative effect of labor unions on innovation mainly comes from the time series within the firm instead of from the cross-section.

Next, we examine the robustness of our baseline result by employing the negative binomial model. The negative binomial model is an alternative econometric specification that considers the discreteness of innovation output variables. Since the number of citations per patent is not a discrete variable, we replace it with the number of citations received by all patents generated by a firm in a year as the innovation quality proxy. Because the negative binomial model is non-linear and does not converge if firm fixed effects are included, we control for industry fixed effects instead. We report the regressions results in Table 4. Consistent with the OLS results from Panel A of Table 3, *Unionization* is negatively and significantly related to our measures of innovative output in all specifications. The control variables generally behave consistently between the two models.

Insert Table 4 about here

Overall, the results produced with the negative binomial specification suggest that our baseline results are robust to alternative econometric models that take into account the non-negative, discrete nature of innovation output variables.[3]

4.2 Deunionization

If unionization leads to a reduction in innovative output then we would expect that firms that elect to forgo unionization would experience the opposite, i.e., their innovation output should increase after the passage of the election. To test this conjecture, we collect a sample of unionized firms that hold elections to deunionize. This data are also collected from the NLRB. We apply the same filters and matching criteria as we do for the union election sample.

Insert Table 5 about here

Table 5 reports the regression results estimating Equation (1) with the main variable of interest replaced with *Deunionization*, which equals one if the results of the election led to deunionization, and zero if the election failed to lead to deunionization. Similar to our baseline results, the first 3 columns use citation counts as the dependent variable to capture firm innovation quantity and the last 3 columns use patent impact as the dependent variable to capture firm innovation quality. We estimate the model using OLS and control for firm and year fixed effects.

[3] We also consider Originality and Generality as alternative measures of innovation. Patents that cite a wider array of technology classes of patents are viewed as having greater originality; patents being cited by a wider array of technology classes of patents are viewed as having greater generality. Both patent originality and generality reflect the fundamental importance of the innovation being patented. Our results are robust. See Trajtenberg, Jaffe and Henderson (1997) for an explanation and construction of these variables.

The coefficient estimates on *Deunionization* are positive and significant at the 1% level in all three columns in which patent quantity is examined, suggesting that the number of patents firms generate significantly increases in the years following deunionization. The economic impact is large. For instance, based on the coefficient estimates reported in column (3), an election that favors deunionization leads to a 12.5% increase in the number of patents generated by the firm three years post-election. In columns (4) – (6), we replace the dependent variable with the patent quality proxy. While the coefficient estimates of *Deunionization* are all positive, they are not statistically significant, suggesting that deunionization does not appear to significantly affect post-election patent quality.

The evidence in this subsection suggests that firms that elect to forgo unionization experience a substantial increase in patent quantity. Together with evidence presented in previous sections, our findings suggest that labor unions stifle corporate innovation, consistent with the *holdup* hypothesis.

4.3 Regression discontinuity design

While our choice of using union election results to identify the causal effect of unionization on corporate innovation is unlikely to be subject to endogeneity concerns because union election results are collectively determined by all union members and represent an exogenous shock to a firm's unionization status, one may still argue that certain firm unobservable characteristics related with both union election results and innovation could bias the results (i.e., the omitted variable concern) or firms with low innovation potential may be more likely to pass union elections (i.e., reverse causality concerns). Thus, to further establish causality, we use a regression discontinuity design (RDD) that relies on the simple majority (50%) passing rule and explores a unique feature of the union election data—the percentage vote for unionization.

The RDD relies on "locally" exogenous variation in unionization generated by union elections that pass or fail by a small margin of votes around the threshold value. This empirical approach essentially compares firms' innovation output subsequent to union elections that pass by a small margin to those subsequent to union elections that do not pass by a small margin. It is a powerful and appealing identification strategy. For these close-call elections, passing is very close to an independent random event because of voters inability to precisely control the assignment variable (votes) near the known cutoff (Lee and Lemieux, 2009), and therefore passing is unlikely correlated with firm characteristics, which helps us identify the causal effect of unionization on firm innovation.

Following existing literature (i.e., Lee and Lemieux, 2010, Cunat, Gine, and Guadalupe, 2012), we examine the difference in subsequent innovation output between union elections that pass and ones that do not pass for increasingly small intervals around the election threshold (i.e., 50%). Throughout our paper we have selected the largest union election by a firm in the case of multiple elections. However, multiple union elections within a firm in a short time interval may contaminate the effect of labor unions on firm innovation. In this analysis, we have restricted the sample to only firms with a single election in our sample period. This procedure reduces our sample size and thus statistical power, but the RDD coupled with this sample restriction yields the most conservative estimates and lend credence to our statistic inferences.[4]

We first plot the number of patents and number of citations per patent (both are logarithm transformed) three years after union elections in Figure 2. The x-axis represents the percentage of votes for unionization. Firms that fail to unionize are to the left of the 50% threshold and firms that succeed in unionizing are to the right of the threshold. We add the fitted quadratic polynomial

[4] We have estimated the RDD with multiple elections and get qualitatively similar results.

estimate to the right and to the left of this threshold with a 90% confidence interval around the fitted value.[5] The figures shows a discontinuity in patent counts and citations per patent at the threshold and points to a causal effect of unionization on innovation. We next examine whether this discontinuity is statistically significant in a regression framework.

Insert Figure 2 about here

We start our regression discontinuity analysis with an estimation of a polynomial model that makes use of all the firms with union elections in the sample. Specifically, we are estimating the following model:

$$Ln(Innovation_{i,t+N}) = \alpha + \beta Unionization_{i,t} + P_l(v_i, c) + P_r(v_i, c) + Year_t + Industry_j + \varepsilon_{i,t} \qquad (2)$$

where *i* indexes firm, *j* indexes industry, and *t* indexes time. $P_l(v_i, c)$ is a flexible polynomial function for observations on the left-hand side of the threshold *c* with different orders; $P_r(v_i, c)$ is a flexible polynomial function for observations on the right-hand side of the threshold *c* with different orders; *v* is a total vote share (percentage of votes in favor). Because union elections win with a simple majority of support among the voters, *c* equals 50% in our setting. Here, β is the key variable of interest and its magnitude is estimated by the difference in these two smoothed functions at the cutoff, which captures the causal effect of passing a union election on firm innovation output N (N=1, N=2, or N=3) periods later. Note, however, that this coefficient should be interpreted locally in the immediate vicinity of the win threshold.

Insert Table 6 about here

We present the results estimating Equation (2) in Table 6 Panel A. We report the result with polynomials of order three, but our results are qualitatively similar using other polynomial orders.

[5] To facilitate presentation, we truncate y-axis by 2 although the polynomial regression estimates are estimated using all available union election data.

The coefficient estimates on *Unionization* are all negative, consistent with our baseline findings, and statistically significant when three years post-election innovation output is the dependent variable. Our estimation shows that the effect of passing a union election is -21.8% on patent quantity and -22.4% on patent quality. The economic significance is very comparable to that obtained from the OLS approach for patent quantity but significantly larger than the OLS estimate for patent quality.

Finally, we undertake the RDD in an alternative form by considering small 'bands' around the win/loss threshold of 50%. Thus, these firms either barely passed or failed to unionize per the election results. We report the results in Panel B. In the first test, we set the band at +/- 5%. The coefficient estimate on *Unionization* is negative in all specifications, generally consistent with our baseline findings, and marginally significant in model (3) in which three-year post-election patent count is the dependent variable. In the next series of tests, we further restrict the band to a more stringent margin, i.e., +/- 2.5%. Note that the sample size shrinks dramatically with only 39 firm-year observations; however, despite the small sample size, we find that both patent counts and citations are negatively impacted by unionization. Our estimates suggest that patent counts decline by 30.7% in years 2 and 3 following a passing union vote and that patent quality declines by 45.1% in 3 years following a passing union vote. The RDD with a narrow band (i.e., +/- 2.5%) surrounding the threshold value of passing a union election gives us a larger effect of unionization on firm innovation compared to what we obtain from the OLS regressions.

Given that the above results are obtained from a very narrow margin around the threshold value of union elections and to the extent that firms falling in this narrow margin are considered almost "identical" in other firm characteristics, the passage of elections is "locally" exogenous and therefore any subsequent differences in innovation output should be attributable to the passage of union elections. Hence, this test provides strong evidence that labor unions cause reductions in firm innovation.

In Panel C we present a series of placebo tests in which we artificially create a band in the failing and passing zones and examine if unionization around these artificial thresholds is related to firms' post-election innovation output. If our results are spurious, then we would likely see statistical significance around these simulated thresholds as well. We report two regressions for failing passage rates and two regressions for passing passage rates. For instance, in the first regression, we examine election results that received between 37.5% and 42.5% support for unionization. Thus, these firms all failed to unionize. However, we assume that 40% is the 'win' threshold and examine the results under this scenario. We repeat this analysis by artificially assuming 45%, 55%, and 60% are the "win" threshold in the next three regressions. In all 4 specifications, we observe that there is no differential effect at the corresponding placebo cutoffs.[6] This placebo test provides reassurance that the negative effect of unionization on firm innovation using the RDD documented in Panels A and B is not spurious.

To summarize, in this subsection, we use a regression discontinuity design that explores the "locally" exogenous variation in unions generated by union elections that pass or do not pass by a small margin of votes to further establish causality. Consistent with the collective evidence throughout our paper, we find a negative causal effect of labor unions on firm innovation, supporting the *holdup* hypothesis.

4.4 Channels of innovation decline

[6] We also examine larger bands of [20%, 40%] and [60%, 80%] and likewise do not find significant results.

Our evidence illustrates that innovation is negatively impacted by unionization. However, the specific mechanism(s) or channels through which labor unions impede innovation are not clear. The holdup hypothesis suggests two possible underlying mechanisms. First, ex-post holdup on the part of employees could lead to an ex-ante underinvestment in innovation inputs (e.g., R&D) by firm managers. Existing literature (e.g., Allen, 1988; Bronars and Deere, 1993; Connolly, Hirsch and Hirschey, 1986; Hirsch, 1992) tends to find a negative association between industry- or firm-level unionization rates and R&D expenditures. These studies assume that innovation inputs lead to innovation outputs. Second, holdup may also stem from employees unwillingness to participate in the innovation process. That is, investment in innovation could remain unchanged (or even increase) after unionization, but employees newly increased job security reduces innovation productivity leading to an overall decline in innovation output.

In this subsection, we attempt to examine possible underlying mechanisms through which unionization impedes firm innovation. Specifically, we revisit the relation between unions and R&D expenditures in our empirical setting using the union election data. To that end, we substitute R&D/Assets in Equation (1) for the dependent variable and report the regression results in Table 7. To save space, we suppress the coefficient estimates of all controls.

****Insert Table 7 about here****

Table 7 Panel A presents the regression results with industry and year fixed effects included. Similar to our main innovation proxies, we examine R&D expenditures in years 1 to 3 post-election. The coefficient on the unionization dummy is negative in all specifications, and is statistically significant at the 10% level in column (1). This result is generally consistent (but much weaker) with the existing studies. One possible reason for our much weaker results is that, unlike previous studies that use the industry- or firm-level unionization rate as a proxy for labor unions, we use variation in firm unionization status generated by union elections, which should be less subject to endogeneity concerns.

In Panel B, we repeat the regression with industry fixed effects replaced by firm fixed effects to absorb time-invariant firm unobservable characteristics that may be related to both R&D and unionization. In all specifications, the coefficient on the unionization dummy is essentially zero, suggesting that within-firm variation in unionization status has no effect on R&D expenditures over time. This result seems to be at odds with the existing literature studying the impact of unions on R&D expenditures. In addition to a more precise proxy than earlier studies to capture a firm's unionization status, this result suggests that controlling for unobservable firm characteristics is another possible reason that we find different results (Menezes-Filho and Van Reenen, 2003).

In Panel C, we further examine the causal relation between unionization and R&D in the RDD framework. In the top panel, we report the results from estimating a polynomial model specified in equation (2) with polynomials of order three. The coefficient on R&D is essentially zero. In the bottom panel, we report the results from close elections with bands of [45%, 55%] and [47.5%, 52.5%], respectively. Once again, we observe that unionization has no effect on R&D expenditures.

In untabulated analyses, we add R&D scaled by total assets as an independent variable in the regressions estimating equation (1). We find an almost identical effect of unionization on firm innovation. For example, the coefficient estimate of *Unionization* is -0.203 (t-statistic = -2.82) in model (3) of Table 3 Panel B and -0.105 (t-statistic = -1.83) in model (6) of Table 3 Panel B. This evidence confirms our finding in this subsection that unionization impedes firm innovation mainly through its adverse effects on innovation productivity.

In summary, our evidence suggests that innovation input as measured by R&D is not impacted by unionization, but innovation output as measured by the number and quality of patents significantly declines following unionization. These results appear to suggest that unionization impedes innovation not through a reduction in investment, but instead because of a decline in innovation productivity.[7]

4.5 Market reactions to union elections

Lee and Mas (2012) examine the market reactions to firms that elect to unionize. They find a substantial decline in the market value of firms that elect to unionize. However, this decline is generally slow to materialize. They find limited evidence of a negative market response initially on the election date, but approximately -10% average abnormal return in the 18 months following the election.

We are interested in whether the initial market response to union wins are related to a firm's current innovativeness. We have shown that unions negatively impact firm innovation. We conjecture that the more innovative a firm was leading up to the election, the bigger the threat to unionizing the work force and therefore the more negative the market response will be. Our assumption is that past innovation success reflects the possibility of more downside risk to firms' innovation activities and consequently firm value.

To test our conjecture, we first calculate market-adjusted 3-day cumulative abnormal returns (CARs) around the union election date [-1, +1]. We then estimate the following OLS regression:

$$CAR[-1+1]_i = \alpha + \beta_1 Unionization_i + \beta_2 Unionization_i * PastInnovation_i + \beta_3 PastInnovation_i + \gamma Z_i + Year_t + Industry_j + \varepsilon_i \quad (3)$$

[7] These findings are related to Cohen, Diether, and Malloy (2013) who argue that two firms can invest the same dollar value in R&D, but can have very different innovation paths.

where *i* indexes firm, *j* indexes industry, and *t* indexes time. The new variable that we create is *Past Innovation*, which is a dummy variable equal to one if the firm had been granted at least one patent in the past 4 years, and 0 otherwise. This variable proxies for a firm's past innovativeness. In our sample, 36.7% of our sample firms were granted at least one patent in the past 4 years before the union election. Thus, firms that we classify as past successful innovators are reflected in the upper one-third of the distribution. Our interest is in the market's reaction to the firms that both elect to unionize and have been successful in the patenting process. Therefore, our variable of interest is the interaction of *Unionization* and *Past Innovation*.

Insert Table 8 about here

Table 8 presents these results estimating Equation (3). Model 1 only includes the *Unionization* dummy for a benchmark test. Both the intercept and coefficient on *Unionization* are negative and insignificant. The economic magnitude is almost zero. This finding is consistent with the argument of Lee and Mas (2012) that it takes time for the market to materialize the negative effect of unionization on firm value.

In models 2 - 5 we introduce our proxy for past innovation success and its interaction term with unionization. Model 2 includes key variables of interest only. Model 3 includes industry fixed effects. Model 4 includes industry and year fixed effects and model 5 includes industry and year fixed effects and the control variables included in Table 3. The coefficient estimates of the interaction term between *Unionization* and *Past Innovation* are all positive and significant. Depending on the specification, the coefficient estimates on the interaction term range from -1.7% to -1.8%, implying that the market reacts between 1.7% and 1.8% lower for firms that have had past innovation success. The effect is economically large.

Our findings suggest that the market appears to be somewhat cognizant of the potential damage that unionization has on firms' future innovation productivity. Our results also suggest that the longer-term value destruction documented in Lee and Mas (2012) for firms electing to unionize could be partly attributable to a decline in innovation.[8]

5. Conclusion

In this paper, we examine the impact of unionization on the innovation activities of firms by exploiting a novel database of union election results. In our baseline analysis, we find patent counts and citations, proxies for firms' innovativeness, decline significantly after firms elect to unionize. We find the opposite for firms that vote to deunionize. To further establish causality, we use a regression discontinuity design relying on "locally" exogenous variation in unions generated by union elections that pass or do not pass by a small margin of votes. The results obtained from the regression discontinuity design are consistent with the baseline results. Next, we show that the channel through unionization impedes innovation is a decline in innovation productivity instead of an underinvestment in innovation input.

We also explore the market reaction to firms holding union elections. We find that the market reaction is negatively related to firms that both elect to unionize and have been successful innovators in the past. These firms are most likely to suffer the negative consequences of

[8] We also consider the effect of union elections on firms' long-run stock performance. We compute buy-and-hold abnormal returns (BHARs) over the two-year period beginning three months after a union election. We then run similar cross-sectional regressions as reported in Table 8 substituting the CAR with the BHAR. Our results are consistent with the evidence in Table 8. That is, firms that have been successful innovators that elect to unionize experience significant post-election underperformance. These results further suggest that the negative long-run performance following unionization documented in Lee and Mas (2012) could be attributable to a decline in innovation production, particularly for firms that have a proven innovation track record.

unionization. Overall, our evidence supports the hypothesis that labor unions lead to holdup problems, stifling corporate innovation.

While the existing literature suggests that to effectively motivate firm innovation, employees need to be tolerated for failures and to be provided protection against dismissal in bad faith, our paper shows that providing "too much" protection to employees, such as allowing employees to form labor unions, leads to potential holdup problems and stifles firm innovation. Our study has important implications for policy makers when they alter union regulations or labor laws to encourage innovation, which is one of the most important drivers of economic growth.

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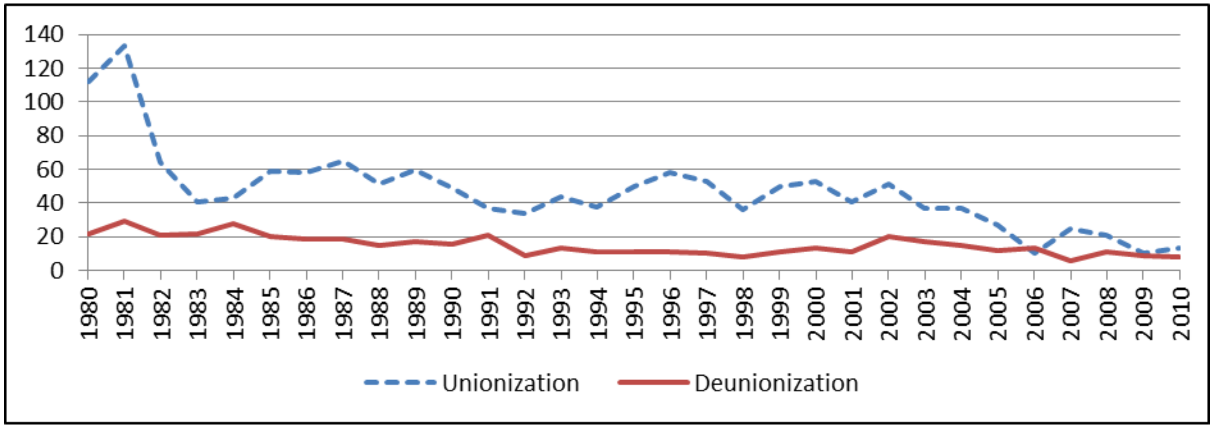
Figure 1
Elections and passage rates by year

This figure plots the number of union and deunion elections by year (top) and the passage rates for both types of elections by year (bottom). Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010.



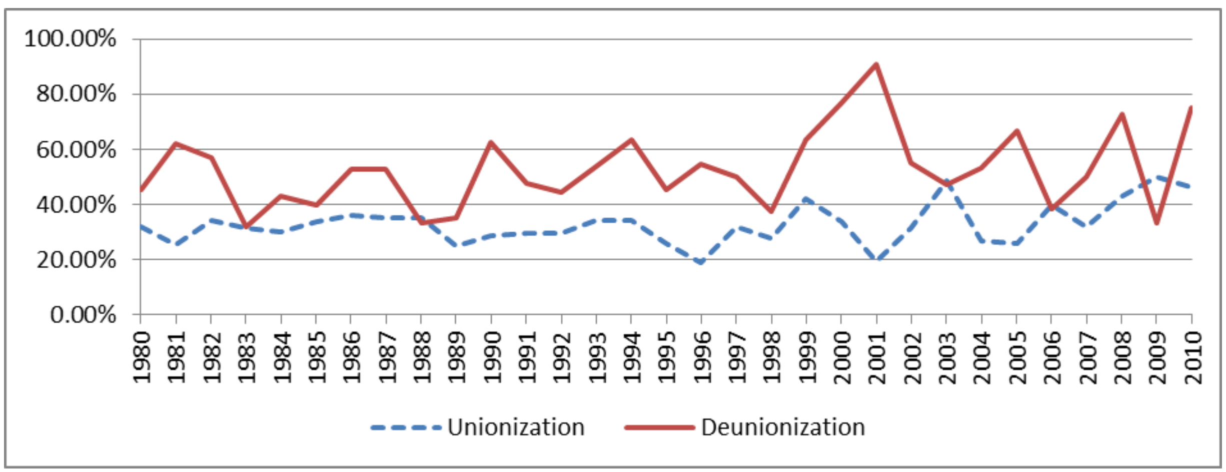
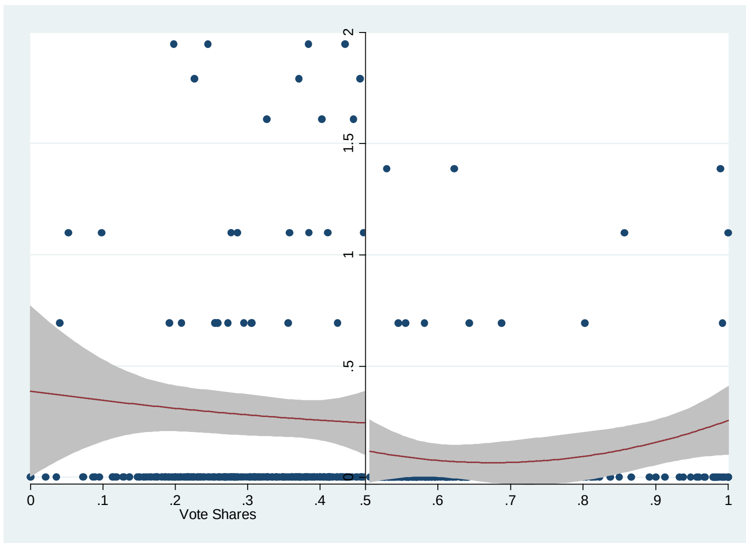


Figure 2
Innovation output discontinuity

The top figure plots Ln(1+Patents) three years post-union elections with quadratic polynomial regression estimates and 90% confidence bands. The bottom figure plots the corresponding Ln(1+Citations/Patents). The x-axis represents union election percentage votes with success identified at the 50% threshold. To facilitate presentation, we truncate the y-axis to 2, but the polynomial regression estimates are estimated using all available union election data.

Ln(1+Patents)



Ln(1+Citations/patents)

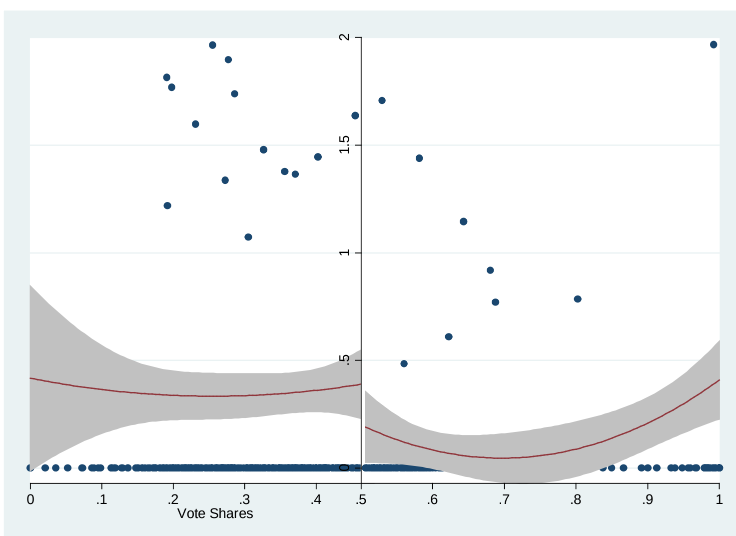


Table 1
Descriptive Statistics

This table presents descriptive statistics of our sample. Panel A (Panel B) reports statistics election results for firms that elect to unionize (deunionize). We present total union members, the percentage of votes for, and passage rates. Panel C presents firm characteristics. We report the number of patents, citations, citations/patents, Assets, ROA, R&D/Assets, PPE/Assets, Debt/Assets, CapX/Assets, Firm Age, BM, and HHI. See the Appendix for a detailed explanation of the variables. Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010. Patent data are from the NBER Patent Citation database over the 1977 to 2006 time period. Firm characteristics are from Compustat.

	Obs.	Mean	Std.	P25	Median	P75
Panel A. In case of unionization						
Vote for union (%)	1,460	0.44	0.22	0.29	0.40	0.55
Passage (%)	1,460	0.31	0.46	0.00	0.00	1.00
Panel B. In case of de-unionization						
Vote for de-union (%)	468	0.51	0.19	0.40	0.51	0.63
Passage (%)	468	0.52	0.50	0.00	1.00	1.00
Panel C. Firm characteristics						
Patents	16,439	8.81	41.92	0.00	0.00	2.00
Citations	16,439	113.65	637.35	0.00	0.00	17.73
Citations/Patents	16,439	4.66	10.43	0.00	0.00	7.02
Assets (Billion)	16,439	3.80	1.69	0.10	0.42	2.10
ROA	16,439	0.05	0.08	0.02	0.05	0.08
R&D/Assets	16,439	0.01	0.02	0.00	0.00	0.02
PPE/Assets	16,439	0.38	0.20	0.23	0.35	0.51
Debt/Assets	16,439	0.27	0.17	0.15	0.25	0.37
Capx/Assets	16,439	0.08	0.05	0.04	0.06	0.10
Firm Age	16,439	21.65	13.58	9.00	21.00	32.00
BM	16,439	0.81	0.66	0.40	0.66	1.05
HHI	16,439	0.54	0.28	0.29	0.47	0.76

Table 2
Industry classification

This table presents an industry classification of our sample based on one-digit SIC codes. We present the number of unionization and deunionization elections, average number of patents, and the passage rates for unionization and deunionization across industries. Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010. Patent data are from the NBER Patent Citation database over the 1977 to 2006 time period.

		No. of Elections		No. of Patents		Passage (%)	
SIC	Description	Unionization	Deunionization	Unionization	Deunionization	Unionization	Deunionization
0	Agriculture	15	3	0.40	0.00	20.00%	66.67%
1	Mining/Oil &Gas	51	19	6.32	3.93	25.49%	57.89%
2	Light manufacturing	291	94	4.21	6.87	29.21%	52.13%
3	Heavy manufacturing	438	139	6.97	15.07	29.00%	54.68%
4	Transportation	245	83	2.30	3.47	32.65%	43.37%
5	Wholesale trade	207	61	1.67	2.45	31.88%	52.46%
6	Finance	11	3	0.42	0.00	9.09%	33.33%
7	Services	126	39	1.43	1.48	41.27%	56.41%
8	Health services	74	25	0.45	0.49	40.54%	44.00%
9	Public Administration	2	2	0.00	0.00	100.00%	100.00%

Table 3
Baseline OLS Regressions

This table presents ordinary least squares (OLS) regressions where the dependent variable is innovation measures and the independent variables include a unionization dummy and a vector of control variables. The dependent variable in models 1-3 is the natural log of 1 + patent counts, which measures innovation quantity. In models 4-6, the dependent variable is the natural log of 1 + citation counts scaled by patents, which measures the quality of innovation. See the Appendix for a detailed explanation of the variables. Panel A includes industry and year fixed effects. Panel B included firm and year fixed effects. Standard errors are clustered by the firm. Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010. Patent data are from the NBER Patent Citation database over the 1977 to 2006 time period. Firm characteristics are from Compustat.

Panel A. Controlling for industry fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
		$Ln\ (1+Patents)_{t+N}$			$Ln\ (1+Citations/Patents)_{t+N}$	
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.167**	-0.174**	-0.175**	-0.159***	-0.160***	-0.153***
	(-2.15)	(-2.25)	(-2.34)	(-2.90)	(-2.99)	(-2.98)
Ln (Assets)	0.269***	0.267***	0.263***	0.173***	0.169***	0.165***
	(10.99)	(11.01)	(11.08)	(12.81)	(12.66)	(12.60)
Ln (1+BM)	-0.214***	-0.222***	-0.207***	-0.217***	-0.204***	-0.185***
	(-4.00)	(-4.10)	(-3.92)	(-4.84)	(-4.52)	(-4.10)
ROA	-0.611***	-0.605***	-0.610***	-0.323***	-0.344***	-0.397***
	(-6.48)	(-6.45)	(-6.66)	(-4.36)	(-4.67)	(-5.41)
PPE/Assets	-0.561***	-0.564***	-0.556***	-0.512***	-0.461***	-0.459***
	(-3.52)	(-3.60)	(-3.68)	(-4.31)	(-3.91)	(-4.02)
Debt/Assets	-0.474***	-0.503***	-0.511***	-0.464***	-0.508***	-0.500***
	(-4.19)	(-4.51)	(-4.69)	(-4.65)	(-5.18)	(-5.23)
Capx/Assets	1.699***	1.736***	1.815***	1.133***	1.085***	1.259***
	(5.20)	(5.34)	(5.61)	(4.11)	(3.99)	(4.78)
Ln (1+Firm Age)	0.136***	0.132***	0.123***	0.147***	0.141***	0.133***
	(4.32)	(4.25)	(4.05)	(5.01)	(4.94)	(4.83)
HHI	0.496	0.515	0.517	0.579*	0.607**	0.610**
	(1.22)	(1.27)	(1.30)	(1.92)	(2.03)	(2.05)
HHI^2	-0.154	-0.179	-0.184	-0.255	-0.298	-0.319
	(-0.47)	(-0.55)	(-0.57)	(-1.03)	(-1.21)	(-1.30)
Constant	-0.746***	-0.695***	-0.706***	-0.226*	-0.179	-0.197
	(-3.99)	(-3.73)	(-3.86)	(-1.74)	(-1.40)	(-1.58)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	16,439	16,439	16,439	16,439	16,439	16,439
R-squared	0.342	0.339	0.335	0.292	0.289	0.287

Panel B. Controlling for firm fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
		Ln (1+Patents)$_{t+N}$			Ln (1+Citation/Patents)$_{t+N}$	
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.202***	-0.207***	-0.202***	-0.133***	-0.117**	-0.107*
	(-2.74)	(-2.80)	(-2.80)	(-2.59)	(-2.13)	(-1.85)
Ln (Assets)	0.108***	0.108***	0.112***	0.069***	0.061**	0.065**
	(3.77)	(3.64)	(3.79)	(2.89)	(2.45)	(2.54)
Ln (1+BM)	-0.020	-0.022	0.004	0.002	0.015	0.032
	(-0.68)	(-0.69)	(0.11)	(0.06)	(0.47)	(0.89)
ROA	-0.029	-0.033	-0.068	0.020	-0.020	-0.100
	(-0.63)	(-0.75)	(-1.49)	(0.32)	(-0.36)	(-1.35)
PPE/Assets	-0.050	-0.051	-0.023	0.064	0.196	0.178
	(-0.32)	(-0.32)	(-0.15)	(0.49)	(1.54)	(1.35)
Debt/Assets	-0.068	-0.130	-0.160*	-0.084	-0.189**	-0.186**
	(-0.75)	(-1.45)	(-1.87)	(-0.95)	(-2.13)	(-2.05)
Capx/Assets	0.020	0.078	0.234	-0.203	-0.262*	0.093
	(0.14)	(0.55)	(1.55)	(-1.35)	(-1.70)	(0.54)
Ln (1+Firm Age)	0.016	0.034	0.071	0.153***	0.174***	0.214***
	(0.34)	(0.70)	(1.47)	(3.45)	(4.13)	(4.86)
HHI	-0.077	-0.048	-0.011	0.225	0.260	0.324
	(-0.24)	(-0.15)	(-0.03)	(0.77)	(0.87)	(1.04)
HHI^2	0.137	0.122	0.092	-0.120	-0.157	-0.232
	(0.56)	(0.48)	(0.36)	(-0.53)	(-0.67)	(-0.95)
Constant	0.182	0.179	0.017	0.032	0.032	-0.134
	(0.99)	(0.93)	(0.09)	(0.21)	(0.21)	(-0.86)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	16,439	16,439	16,439	16,439	16,439	16,439
R-squared	0.796	0.788	0.775	0.618	0.614	0.603

Table 4
Negative Binomial Model

This table presents negative binomial regressions where the dependent variable is innovation measures and the independent variables include a unionization dummy and a vector of control variables. The dependent variable in models 1-3 is the natural log of 1 + patent counts, which measures innovation quantity. In models 4-6, the dependent variable is the natural log of 1 + citation counts scaled by patents, which measures the quality of innovation. See the Appendix for a detailed explanation of the variables. Industry and year fixed effects are included. Standard errors are clustered by the firm. Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010. Patent data are from the NBER Patent Citation database over the 1977 to 2002 time period. Firm characteristics are from Compustat.

	(1)	(2)	(3)	(4)	(5)	(6)
		No. of Patents$_{t+N}$			No. of Citations$_{t+N}$	
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.550***	-0.568***	-0.635***	-0.742***	-0.885***	-0.993***
	(-3.74)	(-3.76)	(-4.11)	(-3.44)	(-4.07)	(-4.43)
Ln (Assets)	0.795***	0.794***	0.799***	0.785***	0.781***	0.774***
	(21.25)	(20.25)	(19.11)	(18.77)	(18.14)	(17.36)
Ln (1+BM)	-0.363**	-0.466***	-0.493***	-0.391*	-0.472**	-0.634***
	(-2.51)	(-3.17)	(-3.26)	(-1.91)	(-2.34)	(-3.16)
ROA	-1.127***	-0.864*	-0.895*	-0.450	-0.855	-1.093*
	(-3.51)	(-1.88)	(-1.85)	(-0.90)	(-1.22)	(-1.89)
PPE/Assets	-2.097***	-2.226***	-2.301***	-3.143***	-3.272***	-3.329***
	(-4.80)	(-5.13)	(-5.42)	(-6.49)	(-6.86)	(-6.74)
Debt/Assets	-1.457***	-1.665***	-1.898***	-1.050**	-1.742***	-1.884***
	(-4.29)	(-4.93)	(-5.35)	(-2.33)	(-3.95)	(-4.08)
Capx/Assets	4.065***	4.333***	4.668***	3.384*	4.494***	4.202***
	(3.20)	(3.51)	(4.06)	(1.88)	(2.85)	(3.01)
Ln (1+Firm Age)	0.395***	0.382***	0.355***	0.332***	0.350***	0.326***
	(4.58)	(4.35)	(3.97)	(2.79)	(3.09)	(2.84)
HHI	0.344	0.304	0.559	1.900*	2.349*	2.854**
	(0.38)	(0.32)	(0.56)	(1.65)	(1.93)	(2.10)
HHI^2	0.476	0.450	0.199	-0.661	-1.148	-1.665
	(0.62)	(0.57)	(0.24)	(-0.71)	(-1.20)	(-1.58)
Constant	-4.630***	-4.386***	-4.467***	-2.316***	-2.151***	-2.134***
	(-10.21)	(-9.17)	(-9.86)	(-3.96)	(-3.45)	(-3.75)
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	16,439	16,439	16,439	16,439	16,439	16,439
Chi-squared	0.000	0.000	0.000	0.000	0.000	0.000

Table 5
Deunionization

This table presents ordinary least squares (OLS) regressions where the dependent variable is innovation measures and the independent variables include a deunionization dummy and a vector of control variables. The dependent variable in models 1-3 is the natural log of 1 + patent counts, which measures innovation quantity. In models 4-6, the dependent variable is the natural log of 1 + citation counts scaled by patents, which measures the quality of innovation. See the Appendix for a detailed explanation of the variables. Firm and year fixed effects are included. Standard errors are clustered by the firm. Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010. Patent data are from the NBER Patent Citation database over the 1977 to 2006 time period. Firm characteristics are from Compustat.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (1+Patents)$_{t+N}$			Ln (1+Citation/Patents)$_{t+N}$		
	N=1	N=2	N=3	N=1	N=2	N=3
Deunionization	0.132***	0.118***	0.125***	0.047	0.036	0.052
	(3.23)	(2.68)	(2.86)	(1.04)	(0.83)	(1.19)
Ln (Assets)	0.134***	0.162***	0.189***	0.162***	0.151***	0.149***
	(7.91)	(9.00)	(9.91)	(6.95)	(6.67)	(6.51)
Ln (1+BM)	0.044	0.081**	0.102***	0.009	0.042	0.044
	(1.43)	(2.25)	(2.82)	(0.21)	(0.93)	(0.79)
ROA	0.243**	-0.031	-0.054	0.055	-0.097	-0.115
	(2.36)	(-0.34)	(-0.48)	(0.42)	(-0.75)	(-0.86)
PPE/Assets	0.169	0.277**	0.407***	0.075	0.197	0.314**
	(1.46)	(2.19)	(3.16)	(0.57)	(1.49)	(2.35)
Debt/Assets	-0.113	-0.276***	-0.249***	-0.254**	-0.226**	-0.127
	(-1.37)	(-3.17)	(-2.78)	(-2.40)	(-2.07)	(-1.12)
Capx/Assets	-0.266	-0.235	-0.089	-0.263	-0.139	0.009
	(-1.60)	(-1.27)	(-0.48)	(-1.17)	(-0.62)	(0.04)
Ln (1+Firm Age)	-0.082**	-0.057	-0.002	0.099*	0.155***	0.226***
	(-2.51)	(-1.62)	(-0.06)	(1.93)	(3.20)	(4.13)
HHI	-1.118***	-1.347***	-1.126***	-0.278	-0.419	-0.273
	(-3.35)	(-3.68)	(-2.97)	(-0.75)	(-1.15)	(-0.76)
HHI^2	0.889***	1.110***	1.045***	0.170	0.376	0.290
	(3.67)	(4.16)	(3.80)	(0.62)	(1.39)	(1.10)
Constant	0.491***	0.355**	-0.141	-0.078	-0.152	-0.495**
	(3.04)	(2.03)	(-0.78)	(-0.39)	(-0.77)	(-2.42)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	5,929	5,929	5,929	5,929	5,929	5,929
R-squared	0.798	0.801	0.791	0.627	0.624	0.616

Table 6
Regression Discontinuity

This table presents regression discontinuity design results. Panel A reports the results from estimating a polynomial model specified in Equation (2). Panel B reports the results where closely contested union elections are considered. Panel C reports placebo test results considering margins surrounding artificial thresholds. The dependent variable are innovation measures and the independent variables include a unionization dummy. The dependent variable in models 1-3 is the natural log of 1 + patent counts, which measures innovation quantity. In models 4-6, the dependent variable is the natural log of 1 + citation counts scaled by patents, which measures the quality of innovation. See the Appendix for a detailed explanation of the variables. Industry and year fixed effects are included. Standard errors are clustered by the firm. Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010. Patent data are from the NBER Patent Citation database over the 1977 to 2006 time period. Firm characteristics are from Compustat.

Panel A. Polynomial

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Ln (Patents)$_{t+N}$			Ln (Citations/Patents)$_{t+N}$	
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.226	-0.117	-0.218*	-0.153	-0.103	-0.224**
	(-1.54)	(-0.84)	(-1.74)	(-0.93)	(-0.98)	(-2.15)
Constant	0.127	0.134	0.076	0.405	0.185	0.154
	(0.75)	(0.81)	(0.50)	(1.05)	(1.06)	(0.94)
Polynomial (3)	YES	YES	YES	YES	YES	YES
Year/ Industry	YES	YES	YES	YES	YES	YES
Observations	568	568	568	568	568	568
R-squared	0.099	0.088	0.083	0.089	0.097	0.087

Panel B. Close elections

[45%, 55%]	(1)	(2)	(3)	(4)	(5)	(6)
		Ln (Patents)$_{t+N}$			Ln (Citations/Patents)$_{t+N}$	
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.194	-0.158	-0.235*	-0.222	-0.164	-0.246
	(-1.26)	(-1.04)	(-1.98)	(-1.14)	(-0.77)	(-1.38)
Constant	0.351***	0.340***	0.298***	0.471***	0.473***	0.402***
	(2.73)	(2.86)	(2.72)	(3.19)	(3.01)	(2.93)
Observations	79	79	79	79	79	79
R-squared	0.017	0.012	0.038	0.016	0.008	0.022

[47.5%, 52.5%]	(7)	(8)	(9)	(10)	(11)	(12)
		Ln (Patents)$_{t+N}$			Ln (Citations/Patents)$_{t+N}$	
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.249	-0.307*	-0.307*	-0.224	-0.315	-0.451**
	(-1.27)	(-1.73)	(-1.80)	(-0.94)	(-1.09)	(-2.06)
Constant	0.295	0.354**	0.307*	0.351*	0.490**	0.451**
	(1.55)	(2.06)	(1.80)	(1.75)	(2.12)	(2.06)
Observations	39	39	39	39	39	39
R-squared	0.027	0.050	0.052	0.019	0.027	0.065

Panel C. Placebo tests

[37.5%, 42.5%]	(1)	(2) Ln (Patents)$_{t+N}$	(3)	(4)	(5) Ln (Citations/Patents)$_{t+N}$	(6)
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.056	-0.105	-0.097	-0.095	-0.209	-0.108
	(-0.37)	(-0.68)	(-0.74)	(-0.44)	(-0.87)	(-0.48)
Constant	0.232*	0.256*	0.200*	0.363**	0.440**	0.332*
	(1.92)	(1.92)	(1.73)	(2.11)	(2.08)	(1.81)
Observations	59	59	59	59	59	59
R-squared	0.003	0.009	0.011	0.004	0.014	0.004

[42.5%, 47.5%]	(1)	(2) Ln (Patents)$_{t+N}$	(3)	(4)	(5) Ln (Citations/Patents)$_{t+N}$	(6)
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	0.316	0.231	0.108	0.225	0.246	0.071
	(1.46)	(1.10)	(0.51)	(0.72)	(0.86)	(0.28)
Constant	0.186*	0.180*	0.259*	0.447**	0.307*	0.331*
	(1.79)	(1.74)	(1.79)	(2.06)	(1.78)	(1.76)
Observations	46	46	46	46	46	46
R-squared	0.046	0.027	0.006	0.012	0.016	0.002

[52.5%, 57.5%]	(1)	(2) Ln (Patents)$_{t+N}$	(3)	(4)	(5) Ln (Citations/Patents)$_{t+N}$	(6)
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.038	-0.007	0.033	0.006	0.112	-0.151
	(-0.18)	(-0.03)	(0.22)	(0.02)	(0.36)	(-0.64)
Constant	0.249	0.295*	0.116	0.349	0.422*	0.285
	(1.64)	(1.77)	(1.38)	(1.66)	(1.94)	(1.38)
Observations	40	40	40	40	40	40
R-squared	0.001	0.000	0.001	0.000	0.003	0.012

[57.5%, 62.5%]	(1)	(2) Ln (Patents)$_{t+N}$	(3)	(4)	(5) Ln (Citations/Patents)$_{t+N}$	(6)
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.115	-0.050	0.050	-0.150	-0.151	-0.059
	(-1.00)	(-1.00)	(0.45)	(-1.00)	(-1.00)	(-0.53)
Constant	0.115	0.050	0.050	0.150	0.151	0.103
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Observations	28	28	28	28	28	28
R-squared	0.037	0.037	0.008	0.037	0.037	0.011

Table 7
R&D Expenditures

This table presents ordinary least squares (OLS) regressions and regression discontinuity regressions where the dependent variable is R&D expenditures scaled by total assets. See the Appendix for a detailed explanation of the variables. Standard errors are clustered by the firm. Panel A uses OLS regressions and includes industry and year fixed effects. Panel B uses OLS regressions and includes firm and year fixed effects. Panel C uses the regression discontinuity design. Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010. Patent data are from the NBER Patent Citation database over the 1977 to 2006 time period. Firm characteristics are from Compustat.

Panel A. Controlling for industry fixed effects

	(1)	(2)	(3)
		$(R\&D/Assets)_{t+N}$	
	N=1	N=2	N=3
Unionization	-0.003*	-0.001	-0.001
	(-1.80)	(-0.34)	(-0.63)
Constant	0.019***	0.020***	0.019***
	(4.34)	(3.27)	(3.16)
Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	16,439	16,439	16,439
R-squared	0.152	0.138	0.142

Panel B. Controlling for firm fixed effects

	(1)	(2)	(3)
		$(R\&D/Assets)_{t+N}$	
	N=1	N=2	N=3
Unionization	-0.000	-0.000	-0.000
	(-0.13)	(-0.06)	(-0.08)
Constant	0.014***	0.013***	0.011***
	(4.86)	(4.26)	(3.78)
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	16,439	16,439	16,439
R-squared	0.825	0.799	0.782

Panel C. Regression discontinuity

VARIABLES	(1)	(2)	(3)
	(R&D/Assets)$_{t+N}$		
	N=1	N=2	N=3
Unionization	-0.004	0.002	0.002
	(-0.61)	(0.36)	(0.50)
Constant	0.005	0.009	0.009
	(0.77)	(0.97)	(1.02)
Polynomial (3)	YES	YES	YES
Year/ Industry	YES	YES	YES
Observations	568	568	568
R-squared	0.073	0.073	0.079

	(1)	(2)	(3)	(4)	(5)	(6)
	[45%, 55%]			[47.5%, 52.5%]		
VARIABLES	(R&D/Assets)$_{t+N}$			(R&D/Assets)$_{t+N}$		
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.004	-0.001	0.002	0.002	0.001	0.006
	(-0.66)	(-0.17)	(0.42)	(0.34)	(0.06)	(0.70)
Constant	0.009**	0.007***	0.005**	0.008**	0.010**	0.007*
	(2.07)	(2.68)	(2.49)	(2.39)	(2.37)	(1.92)
Observations	79	79	79	39	39	39
R-squared	0.005	0.000	0.003	0.004	0.000	0.016

Table 8

Market Reactions around Labor Union Elections

This table presents market-adjusted cumulative abnormal returns (CARs) centered around union election dates. The dependent variable is the 3-day [-1, +1] market-adjusted CARs around union election dates. *Unionization* is a dummy variable if the firm elects to unionize, zero otherwise. *Past Innovation* is a dummy variable if a firm is granted at least one patent in the past 4 years, zero otherwise. See the Appendix for a detailed explanation of the variables. Industry and year fixed effects are included. Standard errors are clustered by the firm. Union election results are from the National Labor Relations Board (NLRB) over 1977 to 2010. Patent data are from the NBER Patent Citation database over the 1977 to 2006 time period. Firm characteristics are from Compustat. Stock market returns are from CRSP.

	(1)	(2)	(3)	(4)	(5)
			CAR [-1, +1]		
Unionization	-0.004	0.004	0.005	0.004	0.004
	(-0.79)	(0.70)	(0.77)	(0.60)	(0.55)
*Unionization * Past Innovation*		-0.017*	-0.018**	-0.017*	-0.017*
		(-1.94)	(-2.00)	(-1.73)	(-1.77)
Past Innovation		0.005	0.007	0.006	0.007
		(1.13)	(1.29)	(1.19)	(1.25)
Constant	-0.001	-0.004	-0.001	-0.008	-0.009
	(-0.69)	(-1.18)	(-0.17)	(-0.46)	(-0.36)
Controls	NO	NO	NO	NO	YES
Industry	NO	NO	YES	YES	YES
Year	NO	NO	NO	YES	YES
Observations	728	728	728	728	727
R-squared	0.001	0.007	0.016	0.037	0.048

Appendix
Variable Definitions

Variable Name	Definition	Source
Unionization	An indicator variable that equals one if a majority of employees votes for unionization in a given election and zero if a majority of employees votes against unionization in a given election.	NLRB and Thomas J. Homes website (http://www.econ.umn.edu/~holmes/data/geo_spill/)
Deunionization	An indicator variable that equals one if a majority of employees votes for deunionization in a given election and zero if a majority of employees votes against deunionization in a given election.	NLRB and Thomas J. Homes website
Vote for Union (%)	Voting shares given an election defined as a number of votes for unionization (or deunionization) divided by total votes for unionization in a given election	NLRB and Thomas J. Homes website
Passage (%)	An indicator variable that equals one if a firm is unionized (or deunionized) as a result of an election and otherwise zero	NLRB and Thomas J. Homes website
Patents	Total number of patents filed (and eventually granted) by firm *i* in a given year t+N, where N=1, 2, and 3, respectively	NBER Patent Citation Database
Citations	Total number of citations on the firm *i*'s patents in a given year t+N, where N=1,2, and 3, respectively	NBER Patent Citation Database
Citations/Patents	Total number of citations divided by the number of patents	NBER Patent Citation Database
Assets	Book value of assets at the end of fiscal year t and log-transformed [#6]	Compustat
ROA	Operating income before depreciation divided by total assets [#13/#6]	Compustat
R&D/Assets	Research and Development expenditure divided by total assets [#46/#6]	Compustat
PPE/Assets	Property, Plant & Equipment divided by total assets [#8/#6]	Compustat
Debt/Assets	Book value of debt divided by total assets [(#9+#34)/#6]	Compustat
Capx/Assets	Capital expenditure divided by total assets [#128/#6]	Compustat
BM	The ratio of book value to market value of equity for firm *i* [#60/(#25 * #199)]	Compustat
HHI	Herfindahl index based on the firm's sales in a given 4-digit SIC industry j	Compustat
Firm Age	Firm age is calculated by the difference between the firm's first year appeared in Compustat and the current year	Compustat
Past Innovation	An indicator variable that equals one if a firm is granted at least one patent in the past 4 years before a union election and zero otherwise.	NBER Patent Citation Database