The causal effect of labor unions on innovation

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Abstract

We examine the causal effect of unionization on firm innovation. To establish causality, we use a regression discontinuity design relying on "locally" exogenous variation generated by elections that pass or fail by a small margin of votes. Passing a union election leads to an 8.7% (12.5%) decline in patent quantity (quality) three years after the election. A reduction in R&D expenditures, reduced productivity of current and newly hired inventors, and departures of innovative inventors appear plausible mechanisms through which unionization impedes firm innovation. Our paper provides new insights into the real effects of unionization and has important implications for policy makers when they alter union regulations or labor laws to encourage innovation.

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1. Introduction

In March 2013, right-to-work laws were enacted in the state of Michigan, prohibiting membership and financial support of a labor union as preconditions of employment. This controversial legislation generated a significant amount of media attention not only because of the enormous power and presence of labor unions in Michigan, but the legal, political, and economic ramifications in this state and beyond are enormous, particularly as other states grapple with passing similar laws.[1,2] In addition to the political debate, there is a vibrant and equally controversial literature revolving around 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 workers, 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, encourage shirking, 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. The impact of unions on innovation is of particular interest to policy makers and firm stakeholders not only

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[1] Indiana, which borders Michigan to the South, passed similar legislation a year earlier. Linn (2011) provides a discussion on the potential impact to other non-right-to-work states. http://www.nbcnews.com/business/michigans-right-work-laws-will-ripple-across-us-1C7559684

[2] In a highly publicized case, in 2009 Boeing decided to expand into South Carolina to manufacture its new Dreamliner airplane rather than expanding its existing facility in Washington. South Carolina is a right-to-work state whereas Washington is not. The CEO was cited saying the reason for the move was because that the company couldn't afford to have "strikes happening every three to four years." http://online.wsj.com/article/SB10001424052748704570704576275351993875640.html

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 as in Michigan's recent experience. We propose two competing hypotheses 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 or mass production, innovation involves a long process that is idiosyncratic, uncertain, and with a high probability of failure (Holmstrom, 1989). Therefore, providing employees with protection against dismissal in bad faith is necessary to effectively motivate and nurture innovation. Acharya et al. (2014) study wrongful discharge laws in the US and their impact on innovation.[3] 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 contracts that tolerate failure (and therefore provide protection in case of failure) in the short-run and reward success in the long-run best motivate innovation. To the extent that unions provide employees perhaps the strongest form of protection against termination, unions could promote firm innovation. We term this view the *employee protectionism hypothesis*.

An alternative hypothesis makes the opposite empirical prediction. Unionization may create misaligned incentives among employees, impeding firm innovation. There are at least three plausible reasons for such a reduction in innovation. First, since innovation requires considerable investment in intangible assets such as research and development (R&D), 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 costs are sunk. This ex-post holdup problem on the part of employees in turn leads to an ex-ante underinvestment in R&D (Grout, 1984; Malcomson, 1997), which ultimately impedes innovation. Second, unionizing the workforce could encourage shirking because the negative consequences for supplying less effort are reduced. That is, unionization reduces the probability of dismissal, so it lowers the cost of shirking and could lead to lower productivity among workers. Third, unions alter the distribution of worker wages, leading to a reduction in wage inequality among workers (Frandsen, 2012). To

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

the extent that innovative and talented workers are in demand in the labor market, reduced wage gaps may force out innovative employees, which contributes to the decline in innovation in unionized firms. While the three underlying mechanisms discussed are different, they are all related in the sense that unionization creates misaligned incentives and impedes innovation. We refer to the general decline in innovation after unionization stemming from any one or all of these potential consequences as the *misaligned incentives hypothesis*.

We test the above two hypotheses by examining whether unions promote or impede firm innovation. Following existing literature that uses patenting data to capture firms' innovativeness (i.e., Aghion et al., 2005; Acharya et al., 2014; Nanda and Rhodes-Kropf, 2013), 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. 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 (NLRB), which allows us to compare changes in innovation output for firms that elect to become unionized to those that vote against it.

The empirical challenge of our study is to identify the causal effect of unionization on firm innovation. A standard ordinary least squares (OLS) approach that regresses innovation output on a unionization variable suffers from potentially severe identification problems. Union election results could be correlated with firm unobservable characteristics that affect firm innovation output (the omitted variable concern) or firms with low innovation potential may be more likely to pass unionization elections (the reverse causality concern). Both problems could make it difficult to draw causal inferences from unionization to innovation. To establish causality, we use a regression discontinuity design (RDD) that relies on "locally" exogenous variation in unionization generated by these elections that pass or fail by a small margin of votes. This approach compares firms' innovation output subsequent to union elections that pass to those 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.

After performing various diagnostic tests to ensure that the key identifying assumptions of the RDD are satisfied, we show that unionization has a causal, negative effect on firm

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innovation. According to our nonparametric local linear regression estimation, passing a union election leads to an 8.7% decline in patent counts and a 12.5% decline in patent citations three years after the election. This result is robust to alternative choices of kernels and bandwidths, and is absent at artificially chosen thresholds that determine union election outcomes. The negative effect of unionization on innovation is present in both manufacturing (where most unions form) and non-manufacturing industries, but is statistically insignificant in firms located in states with right-to-work legislation where unions have less power to expropriate rents. Finally, we show that a cut in R&D spending, reduced productivity of current and newly hired inventors, and the departure of innovative inventors are possible underlying mechanisms through which unionization impedes firm innovation.

We are not the first to study this topic. It has been empirically examined over the past several decades with mixed results. However, we differ from the existing literature in at least three important dimensions. First, and perhaps most importantly, we use the regression discontinuity design as our main identification strategy allowing us to establish a causal link between unionization and innovation, which the existing literature has not adequately addressed. Second, studies focusing on unionization and innovation almost exclusively use R&D expenditures as a proxy for innovation, which is only one *input* to innovation. Instead, our main focus is on innovation *output*—a firm's patenting activity.[4] Third, we make an attempt to pinpoint possible underlying economic mechanisms through which unions affect firm innovation.

The rest of our paper proceeds as follows. Section 2 discusses background and related literature. Section 3 describes the data and presents descriptive statistics. Section 4 provides our main results. Section 5 investigates underlying economic mechanisms. Section 6 concludes.

2. Background and relation to the existing literature

2.1 Background discussion

We study the causal effect of labor unions on firm innovation in this paper. At first blush, one may believe that a unionized workforce has very little to do with the innovation activities of

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[4] In fact, a recent paper by Cohen, Diether, and Malloy (2013) suggests that two firms with the same level of R&D can have very divergent innovation production paths. Thus, R&D spending may not be a reliable proxy for innovation.

a firm for several reasons. First, most unions form in the manufacturing sector of the economy and thus may not be viewed as the traditional 'tech firms' that innovation is usually associated with. Second, the types of workers that tend to join unions are traditionally blue collar. Scientists, engineers, executives, and inventors rarely join unions in the private sector but these individuals are most often credited with innovation production.

However, both of these views are largely misconceived. First, according to the 2008 Business R&D and Innovation Survey (BRDIS) by the National Science Foundation (available at http://www.nsf.gov/statistics/infbrief/nsf11300), the manufacturing industry is the most innovative industry. Their statistics indicate that 22% of manufacturing firms introduced product innovation compared to only 8% of non-manufacturing firms in the period of 2006-2008.[5] Using the NBER patent data, we confirm this view based on the number of overall patents and the number of citations per patent.

Second, blue collar workers could have both a direct and an indirect effect on innovation. Blue collar workers may have a direct effect on innovation because they are the ones closest to production. Many innovative ideas begin with the production workers and flow up to upper management. In our conversations with a CFO and VP of Research of a large, global publicly-traded manufacturing firm, they indicated that the 'floor' workers are critical in their innovation process. We were told that in many cases a patentable idea was initially generated by a production worker and ultimately developed through their R&D center.

In addition to direct effects caused by unionizing, blue collar workers may have indirect effects on non-unionized scientists or engineers in the R&D center via spillovers. Greater employee protections afforded by unions may facilitate workers to provide more input and ideas because they are not afraid to voice their opinions leading to innovation gains. On the other hand, floor workers may demand wage concessions after they are unionized, drying out resources available to innovative scientists. Also, floor workers often serve as supporting staff for scientists and engineers. These workers can reduce the innovation productivity of researchers if they shirk or frequently engage in strikes. Finally, unionization alters the wage distribution among workers

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[5] In terms of process innovation (such as new or significantly improved methods for manufacturing or production; supportive activities; logistics, delivery, or distribution), 22% of manufacturing firms introduced process innovation compared to 8% of non-manufacturing firms in the same period.

and reduces wage inequality, which may force the most talented and innovative workers to pursue better career opportunities outside of the firm.

2.2 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 innovation. Ferreira, Manso, and Silva (2012)'s model suggests that a firm's ownership structure 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), lower stock liquidity (Fang, Tian, and Tice, 2013) and corporate rather than traditional venture capitalists (Chemmanur, Loutskina, and Tian, 2013) alter managerial incentives and hence help nurture innovation. Other studies show that product market competition, market conditions, firm boundaries, banking competition, CEO overconfidence, financial analysts, and investors' attitudes toward failure all affect firm innovation (Aghion et al., 2005; Nanda and Rhodes-Kropf, 2012, 2013; Hirshleifer, Low, and Teoh, 2012; Seru, 2012; Cornaggia et al., 2013; He and Tian, 2013; Tian and Wang, 2014).

Our paper is closely related to Acharya et al. (2013, 2014) who make an important attempt to link employee protection provided by laws and firm innovation. They examine the effects of labor laws and wrongful discharge laws on innovation and find that more employee protection leads to innovation gains. Our paper has a different angle—we use firm-level union election results to identify the causal effect of unionization on innovation. While we show unions stifle innovation, which appears inconsistent with the findings of Acharya et al. (2013, 2014), we believe that our evidence supplements their findings.[6] Our evidence coupled with theirs implies

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[6] In fact, consistent with our findings, they do find that employee representation, which is a component of labor laws dealing with the right to form unions, is negatively related to innovation. We also add to this paper by examining how state-level right-to-work legislation alters the impact of unionization and innovation.

that there likely is an inverted-U-shaped relation between employee protection and firm innovation along the spectrum of protectionism. 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 voluminous 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) finds that firms that are unionized are more likely to use financial leverage 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 (2011a, 2011b) find that the cost of equity is significantly higher in more unionized industries but the cost of debt is lower in these industries. Lee and Mas (2012) show negative abnormal returns over a long period to union victories, implying that unionization destroys shareholder wealth. Chyz et al. (2013) find unionized firms are less likely to engage in aggressive tax strategies.

Several papers directly examine the impact of labor unions on investment. Collectively, the evidence leans towards a negative union-investment relation. 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 than non-unionized firms. However, DiNardo and Lee (2004) find that unions have a small impact on business survival, employment, output, productivity, and wages.

The only two studies we are aware of that directly 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 union rates 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 union rates 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 NLRB 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 result data from the NLRB over 1980 to 2002.[7] It contains firm name, location, SIC code, the date of the election, the number of participants, and outcomes of the voting.[8] 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 100, consistent with Lee and Mas (2012). We then manually match these firms by firm name with the NBER for both publicly-traded and privately-held firms. We are careful to ensure accurate matches by requiring that the firm's headquarter location and 1-digit SIC code also match for publicly-traded firms when this information is available. In the case where there are multiple elections occurring within a three-year period for a unique firm, we retain the outcome from the first election.[9] Our final sample contains 8,809 unique union elections.

We proxy for firm innovativeness using patent information from the NBER Patent Citation database (see Hall, Jaffe, and Trajtenberg (2001) for more detailed discussion about the database). This database contains all patents registered and granted by the United States Patent and Trademark Office (USPTO) 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 and 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

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[7] The union election sample ends in 2002 to allow for post-election innovation output information available in the NBER Patent Citation database that provides patent information up to 2006.

[8] For a thorough discussion of the union election process, see DiNardo and Lee (2004, pages 1,388 - 1,392).

[9] We keep the first election and eliminate those elections occurred within the subsequent three years because our main focus is on firm innovation output within the first three years post-election.

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 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 and innovation data. Aggregating the votes from the 8,809 elections in our sample, 48% are in favor of unionization with a standard deviation of 23%. The unionization passage rate is 36%, which suggests that on average approximately one third of all elections favor unions. The average firm generates approximately 0.34 patents and the average patent generates 0.52 citations. This is lower than what is typically reported in the literature because our sample includes a mix of publicly-traded and privately-held firms, while existing studies in the literature rely on public firms because these firms have accounting and financial data available. Public firms are much larger with greater financial resources and thus own more patents. The distribution of patent grants and citations is right-skewed. Therefore, we use the natural logarithm of the patent counts and the natural logarithm of

the number of 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.

Panel B provides an industry distribution of key variables. Not surprisingly, the bulk of elections are concentrated in the manufacturing industry (one-digit SIC codes of 2 and 3, light and heavy manufacturing, respectively). The highest passage rates are in the health services industry (one-digit SIC code 8) while the lowest are in heavy manufacturing. The most innovative industry is also heavy manufacturing.

<center>***Insert Figure 1 about here***</center>

Figure 1 plots a time series of union election frequencies and passage rates across our sample period. There is a considerable spike followed by a sharp decline in the number of firms holding union elections in the early 1980s. Beyond this period, there is a gradual increase that continues to trend between roughly 300 and 400 elections per year. The second plot in Figure 1 shows passage rates for union elections across time. There is considerable variation through time, but in each year the majority of union elections fail to pass.

4. RDD and main results

We present our main empirical strategy and results in this section. Section 4.1 discusses our empirical strategy and reports various diagnostic tests for the validity of using regression discontinuity design (RDD). Section 4.2 presents our main RDD results. Section 4.3 reports a variety of sensitivity tests to check the robustness of the main results. Section 4.4 considers industry membership and section 4.5 examines how right-to-work legislation alters the main results.

4.1 Empirical strategy and diagnostic tests

A naïve approach to evaluate the effect of unionization on firm innovation is to estimate the following model using the ordinary least squares (OLS) in a firm-year panel:

$$Ln(Innovation_{i,t+N}) = \alpha + \beta Unionization_{i,t} + \gamma' Z_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where i indexes firm, t indexes time, and $N = 1$, 2, or 3. The dependent variable, *Innovation*, is one of our two main innovation variables: patent counts or the number of citations per patent.

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The variable of interest is *Unionization*, which is a binary variable that equals one if the union election leads to unionization, and zero if the union election fails to lead to unionization. *Z* is a vector of observable determinants of a firm's innovation output.

However, firm unobservable characteristics related with both union election results and innovation could bias the results (omitted variables) or firms with low innovation potential may be more likely to pass union elections (reverse causality). Thus, β cannot be interpreted as a causal effect of unionization. To establish causality, we use RDD that rests on the assignment of a firm's unionization status based on a simple majority (50%) passing rule and exploits a unique feature of the union election data—we observe the percentage vote for unionization in every union election.

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 50% threshold. Conceptually, this empirical approach compares firms' innovation output subsequent to union elections that pass by a small margin to those union elections that do not pass by a small margin. It is a powerful and appealing identification strategy because for these close-call elections, randomized variation in firm unionization status is a consequence of the RDD, which helps us to identify the causal effect of unionization on firm innovation. Another advantage of the RDD is that we do not have to include observable covariates, *Z*, in the analysis because the inclusion of covariates is unnecessary for identification (Lee and Lemieux, 2010). Thus, we are able to include privately-held firms in our sample, which have limited firm-specific information available.

A key identifying assumption of the RDD is that agents (both voters and employers in our setting) cannot *precisely* manipulate the forcing variable (i.e., the number of votes) near the known cutoff (Lee and Lemieux, 2010).[10] If this identifying assumption is satisfied, the variation in union recognition status is as good as that from a randomized experiment. To check the validity of this assumption, we perform two diagnostic tests.

Insert Figure 2 about here

First, Figure 2 shows a histogram of the sample distribution of union vote shares in 40 equally-spaced vote share bins (with a bin width of 2.5%) and the x-axis represents the percentage of votes favoring unionization. If there is systematic sorting of firms within close

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[10] Lee (2008) shows that even in the presence of manipulation, as long as firms do not have precise control over the forcing variable, an exogenous discontinuity still allows for random assignment to the treatment.

proximity of the threshold, this sorting would be observed by a discontinuity in the vote share distribution at the 50% vote threshold. The figure shows that the vote share distribution is continuous within close proximity of the cutoff and thus no evidence of precise manipulation is observed at the cutoff point.

Insert Figure 3 about here

Second, we follow McCrary (2008) and provide a formal test of a discontinuity in the density. Using the two-step procedure developed in McCrary (2008), Figure 3 plots the density of union vote shares.[11] The x-axis represents the percentage of votes favoring unionization. The dots depict the density and the solid line represents the fitted density function of the forcing variable (i.e., the number of votes) with a 95% confidence interval around the fitted line. The density appears generally smooth and the estimated curve gives little indication of a strong discontinuity near the 50% threshold. The discontinuity estimate is 0.14 with a standard error of 0.09. Therefore, we cannot reject the null hypothesis that the difference in density at the threshold is zero.[12] Overall, it appears that the validating assumption that there is no precise manipulation by voters at the known threshold is not violated.

Another important assumption of the RDD is that there should not be discontinuity in other covariates that are correlated with firm innovation at the cutoff point. In other words, firms that vote to unionize should not be systematically different ex ante from firms that vote not to unionize. We perform this diagnostic test by comparing the covariates of firms that fall in a narrow band of vote shares [48%, 52%] around the winning threshold. Therefore, we are comparing firms that win or lose by a very small margin. While our sample consists of both privately-held and publicly-traded firms, we must rely on the sample of publicly-traded firms for which accounting data exist to examine various dimensions of firm characteristics for firms that elect and do not elect to unionize. Appendix A provides a detailed description of variable definitions.

Insert Table 2 about here

We report the results in Table 2. Observable covariates including firm size (*Ln(Assets)*), growth opportunities (*Ln(1 + BM)*), profitability (*ROA*), asset tangibility (*PPE/Assets*), routine

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[11] See http://emlab.berkeley.edu/~jmccrary/DCdensity for a detailed discussion of the algorithm.
[12] Although our sample periods are different, DiNardo and Lee (2004) also find little evidence of precise manipulation of union votes around the 50% threshold, which is consistent with our findings.

investment (*Capx/Assets*), leverage (*Debt/Assets*), and firm age (*Ln(1 + Firm age)*) in the union election year are similar between firms that barely unionize and those that barely elect not to. More importantly, we do not observe the innovation outcome variables, *Ln(Patents)* and *Ln(Citations/Patent)*, are significantly different across these two groups of firms in the union election year.

Overall, the diagnostic tests presented above suggest that there does not appear to be a precise manipulation by voters within close proximity of the 50% threshold. Further, there is no discontinuity in other covariates at the cutoff point.

4.2 Main RDD results

We present the main RDD results in this subsection. Because the innovation process generally takes considerable time, we examine the effect of unionization on firms' patenting activities one, two, and three years post-election. We first present RDD results in Figure 4 to visually check the relation around the cutoff. The left-hand figures present plots for the number of patents and the right-hand plots present the number of citations per patent (both are logarithm transformed). The x-axis represents the percentage of votes for unionization. We once again divide the spectrum of vote shares into 40 equally-spaced bins (with a bin width of 2.5%).[13] In all plots displayed, 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. The dots depict the average value of innovation outcome variables in the bins. The solid line represents the fitted quadratic polynomial estimate with a 95% confidence interval around the fitted value.

Insert Figure 4 about here

The figures show a discontinuity in both patent counts and the number of citations per patent at the threshold in each of the three years after the union election. Specifically, within close proximity of the threshold, patent counts and citations drop significantly once the percentage of votes in favor of unionization crosses the 50% cutoff point. This observation points to a causal effect of unionization on firm innovation.

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[13] The choice of the bin width reflects a tradeoff discussed in Imbens and Lemieux (2008). The bin width needs to be large enough to have a sufficient amount of precision so that the plots look smooth on either side of the threshold, but small enough to make the jump around the threshold clear. We use alternative bin widths and get similar results from both plots and regressions.

We next present the regression discontinuity analysis with an estimation of a global polynomial series model (e.g., Cuñat, Gine, and Guadalupe, 2012), using the entire support of all union election observations in our sample. Specifically, we estimate the following model:

$$Ln(Innovation_{t+N}) = \alpha + \beta Unionization_t + P_l(v,c) + P_r(v,c) + \varepsilon_t \qquad (2)$$

where t indexes time and $N = 1, 2,$ or 3. P_l (v, c) is a flexible polynomial function for observations on the left-hand side of the threshold c with different orders; P_r (v, c) is a flexible polynomial function for observations on the right-hand side of the threshold c with different polynomial 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.

In this estimation, 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 ($N = 1, 2,$ or 3) years later. Note, however, that because RDD estimates are essentially weighted average treatment effects where the weights are the ex-ante probability that the value of an individual union elections falls in the neighborhood of the win threshold (Lee and Lemieux, 2010), this coefficient should be interpreted locally in the immediate vicinity of the win cutoff.

Insert Table 3 about here

We present the results estimating Equation (2) in Table 3. We report the result with polynomials of order three, but our results are qualitatively similar using other polynomial orders. The coefficient estimates on *Unionization* are all negative and statistically significant in all years, suggesting a negative, causal effect of unionization on innovation output. Economically, when three years post-election innovation output is the dependent variable, the estimates suggest that passing a union election leads to a 9.5% decline in patent quantity and 11.5% decline in patent quality.

While the results from the global polynomial estimation using all union election data suggest there likely exists a causal, negative effect of unionization on firm innovation, Bakke and Whited (2012) point out the importance of using a local linear estimation technique because of RDD's strong local, but weak external validity. Fan and Gijbeles (1992) and Hahn, Todd, and van der Klaauw (2001) suggest that local linear estimations are rate optimal and have attractive bias properties. Therefore, we employ a nonparametric local linear estimation in the

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neighborhood around the 50% threshold, using the optimal bandwidth defined by Imbens and Kalyanaraman (2012) that minimizes the mean squared error (MSE) in a sharp regression discontinuity setting. In Table 4, we report the local linear estimation results using both a rectangular and triangular kernel.[14]

<center>***Insert Table 4 about here***</center>

The coefficient estimates on *Unionization* are all negative and significant at the 1% level across all columns, consistent with the findings from the global polynomial estimation. The magnitudes of the coefficients are also very comparable to those reported in Table 3. Specifically, in the top panel based on the estimation using a rectangular kernel, a union election win leads to an 8.7% decline in patent quantity and 12.5% decline in patent quality three years after the election. The corresponding values using a triangular kernel are similar (a drop of 8.9% and 12.1%, respectively). Overall, the evidence presented in this subsection suggests a negative, causal effect of unionization on firm innovation.[15] These findings are consistent with the *misaligned incentives hypothesis*.

4.3 Robustness checks

We perform a variety of robustness checks that examine the sensitivity of our RDD results. First, we examine whether our local linear estimates are robust to alternative bandwidths. The choice of bandwidth reflects a tradeoff between precision and bias. Using a wider bandwidth includes more observations and yields more precise estimates. However, a wider bandwidth can bias the estimates because the linear specification is less likely to be accurate. The reverse occurs if we use a narrower bandwidth. Therefore, we perform the first robustness test to ensure that our results are not sensitive to alternative bandwidths.

Specifically, we repeat the regression for different bandwidths around the threshold with a triangular kernel, and plot the results in Figure 5. The x-axis represents bandwidths where "100" represents the optimal bandwidth based on Imbens and Kalyanaraman (2012) and used in

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[14]As Imbens and Lemieux (2008) point out, the choice of kernel typically has little impact on estimation in practice. The statistics literature has also shown that a triangular kernel is optimal for estimating local linear regressions at the boundary, because it puts more weight on observations closer to the cutoff point.

[15] For completeness, we estimate Equation (1) using OLS, but rely on the sample of publicly-traded firms that have firm characteristic data available. We estimate the regression with year and firm fixed effects. These untabulated results also suggest that unionization is negatively related to innovation.

<center>15</center>

the estimations reported in Table 4, "200" represents twice the optimal bandwidth, and so forth. The left-hand figures plot the number of patents and the right-hand plots the number of citations per patent. The solid line represents the RDD estimators and the dotted lines represent 95% confidence intervals.

Insert Figure 5 about here

From Figure 5, we observe that the RDD estimates are always negative and are stable in both economic and statistical significance over the spectrum of bandwidth choices, suggesting that the baseline RDD results using local linear regressions are robust to alternative choices of bandwidths. We observe a similar pattern if we use a rectangular kernel instead.

Next, we do a series of placebo tests to check if we are still able to observe a discontinuity in innovation output at artificially chosen thresholds that are different from the true 50% threshold. We first randomly select an alternative threshold along the spectrum of union vote shares between 0 and 1 other than 0.5. We then assume it is the threshold that determines union election outcomes and re-estimate the local linear model with a triangular kernel. We repeat this placebo estimation 1,000 times and plot a histogram of the distribution of the RDD estimates from these placebo tests in Figure 6. We also include a dashed vertical line that represents the RDD estimate at the true threshold reported in Table 4.

Insert Figure 6 about here

The histogram is centered at 0, which is consistent with the conjecture that the treatment effect of unionization on firm innovation is absent at artificially chosen vote thresholds. It also suggests that the negative effect of unionization on firm innovation we document is unlikely driven by chance and therefore our RDD estimates are unlikely spurious.

4.4 Industry analysis

Having established a causal, negative effect of unionization on the innovation activities of firms, we examine if industry membership plays a role. Table 1 Panel B illustrates that the bulk of union elections are concentrated in 1-digit SIC codes 2 and 3, which are the manufacturing sectors of the economy. The results in this table also indicate that these sectors are the most innovative based on patent counts and citations per patent. This latter result is not a sample selection issue conditional on holding union elections. Using all publicly-traded firms

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from Compustat merged with the data in the NBER patent database, we confirm that firms in 1-digit SIC codes 2 and 3 generate the most patents and citations per patent. Given that the manufacturing industry not only holds the most union elections, but is also the most innovative sector, we investigate if the impact of unionization on firm innovation is the same for manufacturing versus non-manufacturing industries.

Insert Table 5 about here

Table 5 reports these results. We define manufacturing as firms with 1-digit SIC codes of 2 or 3, else firms are classified as non-manufacturing. We report the results for manufacturing firms in the top panel and non-manufacturing firms in the bottom panel. We use the local linear regression with the optimal bandwidth following Imbens and Kalyanaraman (2012) and a triangular kernel. We verify that the results are consistent using alternative bandwidths and kernels.

Across both sets of manufacturing and non-manufacturing firms, innovation production declines in each year following unionization. Economically, the estimates are roughly the same for both types of industries although the effects are generally slightly smaller in non-manufacturing firms. Thus, the evidence suggests that unionization has a negative effect on innovation in both manufacturing and non-manufacturing industries.

4.5 Right-to-work legislation

As discussed in the introduction of the paper, states that have adopted right-to-work legislation cannot force employees to join the union and pay union dues as preconditions of employment. Therefore, in right-to-work states, unions have considerably less bargaining power than in non-right-to-work states. A potential consequence of weaker union bargaining power is that a unionized workforce in a right-to-work state will have less of an impact on innovation than in states without similar legislation. We test this conjecture in this subsection.

Insert Table 6 about here

Table 6 reports the results for firms with union elections located in right-to-work states compared to those located in states without right-to-work legislation, using local linear RDD estimations as in Table 4. The top panel presents the results for firms located in right-to-work

states, while the bottom panel reports the results for firms located in states without right-to-work legislation.[16]

In states with right-to-work laws, we find that the coefficient estimates on *Unionization* are negative, but statistically insignificant across all three post-election years for innovation measures gauging quantity and quality. On the other hand, reported in the bottom panel, firms winning union elections in states without right-to-work legislation (which affords unions more bargaining power) have a large economic and statistical impact on innovation output. Specifically, in each post-election year for both patent counts and citations, the coefficient estimates on *Unionization* are negative and significant at the 1% level, suggesting that unionization leads to a decline in innovation output.

5. Underlying mechanisms

We find pervasive evidence favoring the *misaligned incentives hypothesis*. In this section, we explore possible underlying economic mechanisms through which this occurs. A cut to R&D spending could be an underlying mechanism. Because unionized workers have incentives to expropriate rents once the innovation process starts knowing that the costs are sunk, firms cut their investments in R&D because they recognize this *ex ante* holdup problem. Thus, this contributes to the reduction in innovation output. Section 5.1 examines this mechanism.

Because of newly increased job security from unionization, workers' incentives to shirk may increase. To test this conjecture, we examine the productivity of individual inventors who stay in the firm pre- and post-unionization in addition to newly hired innovators who join the firm after union elections in a difference-in-differences (DiD) framework in Section 5.2. Finally, if unionization leads to a reduction in wage inequality (Frandsen, 2012), innovative employees may leave the firm pursuing better job opportunities in a competitive labor market. We examine whether unionization leads to job departures for innovative employees in Section 5.3. It is important to point out that while these three plausible mechanisms could affect firm innovation independently, they need not be mutually exclusive. In fact, it is more likely they are jointly related and have compounded effects on firm innovation output.

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[16] States with right-to-work legislation as of 2002 (our union election sample end year) include Alabama, Arizona, Arkansas, Florida, Georgia, Idaho, Iowa, Kansas, Louisiana, Mississippi, Nebraska, Nevada, North Carolina, North Dakota, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, and Wyoming.

5.1 R&D spending

In this subsection, we examine whether a cut in R&D expenditures after a successful union election is a possible underlying mechanism through which unionization impedes firm innovation. Because of misaligned incentives between employees and firms after unionization, unionized employees cannot credibly commit that they will not demand higher wages once the innovation process has started and the costs are sunk, so this ex-post holdup on the part of employees could lead to an ex ante underinvestment in innovation inputs (e.g., R&D) by firms. While previous studies (e.g., Allen, 1988; Bronars and Deere, 1993; Connolly, Hirsch and Hirschey, 1986; Hirsch, 1992) tend to find a negative association between industry- or firm-level unionization rates and R&D expenditures, to the best of our knowledge, a causal relation has not been established.

We revisit this relation and attempt to establish a causal link between unionization and R&D expenditures in our RDD framework, using firm-level union election data. Because R&D expenditures are not available for privately held firms, for this test we focus on the sample of publicly-traded companies. R&D expenditures and firm total assets are from Compustat. We use the local linear regression RDD with the optimal bandwidth advocated by Imbens and Kalyanaraman (2012) with a triangular kernel. We substitute *R&D/Assets* as the dependent variable for our innovation output measures. We present the results in Table 7.

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

The coefficient estimates on *Unionization* are all negative and significant, suggesting that there is a negative, causal effect of unionization on R&D expenditures. The negative effect of unionization on R&D spending is statistically significant beginning in year 1 and this negative effect is persistent through year 3 post-election.

The evidence presented in this subsection suggests that at least some of the decline in innovation output that we document can be attributed to a decline in the innovation input due to the misaligned incentives between unionized employees and firms.

5.2 Inventor productivity

A second possible mechanism leading to a decline in innovation is an increase in employee shirking because job security increases after a successful union election. As discussed

before, because (unlike routine tasks) innovation is an exploration of untested approaches and the innovation process is long, risky, and idiosyncratic, innovation requires a significantly higher level of effort, persistence, and motivation on the part of employees. Unions that prevent employees from punishment for shirking (e.g., loss of job) impede innovation. Note that shirking may not be restricted only to inventors but could also occur among unionized hourly employees who serve as supporting staff, which indirectly affects inventors' productivity. We test this conjecture by examining the change in innovation productivity of individual inventors surrounding union elections in a DiD framework.

To mitigate firm heterogeneity concerns, we first match firms that win the union election (treatment firms) with those that fail the union election (control firms) using a nearest-neighbor propensity score matching algorithm. Because we cannot observe accounting information for privately-held firms, we match firms based on firm industry and union election year. We ensure each treatment firm is matched to a unique control firm.

We collect individual inventor data from the Harvard Business School (HBS) patent and inventor database available at http://dvn.iq.harvard.edu/dvn/dv/patent. The HBS patent and inventor database provides information for both inventors (the individuals who receive credit for producing the patent) and assignees (the entity that owns the patents, which could be a government, a firm, or an individual). It provides a unique identifier for each inventor so that we are able to track the mobility of individual inventors.[17] We define two groups of inventors. "Stayers" are inventors who produce at least one patent in the firm holding union elections both three years before and after the election year. "New hires" are inventors who produce at least one patent within three years after the union election year in the firm holding union elections, but produce at least one patent in a different firm within three years before the union election year.

****Insert Table 8 about here****

Table 8 presents the DiD results. We compute the DiD estimate by first subtracting the total number of patents per inventor over the three-year period preceding the election from the total number of patents per inventor over the three-year period after the election for each control firm. The difference is then averaged over the treatment firm and reported in column (1). By doing this, we count each firm once regardless of the number of inventors it has.

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[17] See Lai, D'amour, Yu, Sun, and Fleming (2013) for details about the HBS patent and inventor database.

To evaluate the quality of the patents, we first compute the citation ratio per inventor for each control firm by counting the total number of patents it generates three years before (or after) the union election as well as the total number of citations received by these patents, and dividing the latter by the former. We then calculate the difference in citation ratios before and after the election and average it over all control firms. We report it in column (1). We repeat the same procedure for treatment firms and report the average change in the total number of patents (citation ratios) surrounding the union election year in column (2). The DiD estimate is simply the difference in differences for the treatment and the control firms, and is reported in column (3). We report the *p*-values of the DiD estimates in column (4).

We first compare "stayers" in treatment firms with those in matched control firms. The DiD estimator for patent counts is negative and significant at the 1% level, suggesting that stayers of unionized firms become less innovative after the union election compared to their counterparts in non-unionized firms after the union election. The DiD estimate for patent quality is negative and significant at the 1% level, because the drop in patent quality produced by the inventors of treatment firms is significantly larger than that produced by the inventors of control firms.

Next, we compare the innovation productivity of "new hires." The DiD estimates for both patent quantity and quality are negative and statistically significant, suggesting that the inventors who newly join the unionized firms after the union elections become less innovative than those who newly join the firms that fail to unionize, compared to their own productivity in their previous firms.

Overall, the evidence presented in this subsection is consistent with the view that shirking by scientists or their supporting staff may be another possible explanation for the reduction in innovation output after union election wins.

5.3 Inventor departures

In this subsection, we discuss a third possible underlying mechanism through which unionization impedes firm innovation—the departure of innovative employees. While DiNardo and Lee (2004) find little evidence on the effect of unionization on average employee wages, they ignore the distribution of employee earnings. Frandsen (2012) shows that unionization

substantially reduces wage gaps between the lower end and the upper tail. To the extent that innovative individuals have better job prospects and are in high demand in the labor market, reduced wage gaps due to unionization may force out innovative employees as they seek better career opportunities. This could also contribute to the reduction in innovation output after successful union elections.

To test this conjecture, we again use the inventor information obtained from the HBS patent and inventor database and define "Leavers." Leavers are inventors who produce at least one patent in the firms holding union elections within three years before the election year and at least one patent in a different firm within three years after the union election year.

****Insert Table 9 about here****

The top panel of Table 9 reports the DiD results for leavers. Column (1) suggests that leavers of unionized firms on average generate a larger number of patents after the union election, while column (2) suggests that leavers of firms that fail to unionize on average generate fewer patents after the union election. The DiD estimator for patent counts is positive and significant at the 5% level. Focusing on the number of citations per patent, while both groups of leavers generate patents that have a significantly lower impact after the union election, the drop in patent quality is smaller among those that depart unionized firms. This difference leads to a positive and significant DiD estimate reported in column (3).

Finally, we directly test whether unionization leads to the departure of innovative and talented inventors. We perform this test in the RDD framework and report the results in the bottom panel of Table 10. The dependent variable in columns (1) and (2) is *No. of Top Leavers*, which is the number of top inventors who leave the firm within the first three years after the union election. We define a top leaver if a leaver is in the top 5 percentile distribution of innovation productivity three years before the union election year among all leavers. In columns (3) and (4), we use *Ln (1+No. of Top Leavers)* as the dependent variable. We report the results from the global polynomial estimations in columns (1) and (3) and from nonparametric local linear regressions in columns (2) and (4).

The coefficient estimates on *Unionization* are positive in all columns and statistically significant except for column (2), suggesting that unionization is positively related to the number of top leavers. According to the magnitude of *Unionization* in column (4), unionized firms have

2% more top inventors that leave the firm than non-unionized firms in the first three years after the union election.

Overall, the evidence suggests that leavers of unionized firms are more innovative than those of firms that fail to unionize and a larger number of top inventors leave firms after they win union elections, which is consistent with our conjecture that the departure of innovative inventors is a possible underlying mechanism that allows unionization impedes firm innovation.

6. Conclusion

In this paper, we examine the causal effect of unionization on the innovation activities of firms. Our main contribution to the literature is threefold. We use RDD to establish a causal link from unionization to innovation. Second, our proxy for innovativeness is patenting activity, the output of innovation whereas most other studies in this literature proxy for innovation using R&D. Third, we attempt to pinpoint the mechanisms in which unionization impacts innovation.

We find patent counts and citations decline significantly after firms elect to unionize. Economically, passing a union election leads to an 8.7% decline in patent counts and a 12.5% decline in the number of citations per patent three years after the election. We provide a battery of diagnostic and robustness tests and find our conclusions are unchanged. Next, we show that the results are statistically insignificant in states with right-to-work legislation where unions have less bargaining power to expropriate rents. Finally, a reduction in R&D expenditures, reduced productivity of existing and newly hired inventors, and the departure of innovative individuals appear plausible underlying mechanisms through which unionization impedes innovation.

How do firms respond to union election wins? While this is beyond the scope of this paper, we make an initial attempt to address this question. In Appendix B, we consider the locality of innovation activities within a firm. That is, we compute the percentage of local patents to total patents and citations to total citations generated by firms in states where union elections are held, estimated in a local linear RDD framework. As the results indicate, the percentage of innovation output generated in states where unions win decline significantly. This finding suggests that firms may shift their innovation activities to states where the workforce is not unionized. This type of behavior is somewhat consistent with Boeing's experience to build their Dreamliner jet in South Carolina, which has more business-friendly labor laws than

Washington's where its existing plants are located. While our preliminary results are consistent with this view, we leave a thorough analysis of this question to future research.

While the existing literature suggests that to effectively motivate firm innovation, employees need to be tolerated for failures and be provided protection against dismissal in bad faith, our paper shows that providing "too much" protection to employees such as those afforded to employees by powerful labor unions leads to potential misaligned incentive 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 perhaps the most important driver of economic growth.

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Figure 1

Number of union elections and passage rates by year

This figure plots the number of union elections by year (top) and the average passage rates by year (bottom). Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002.
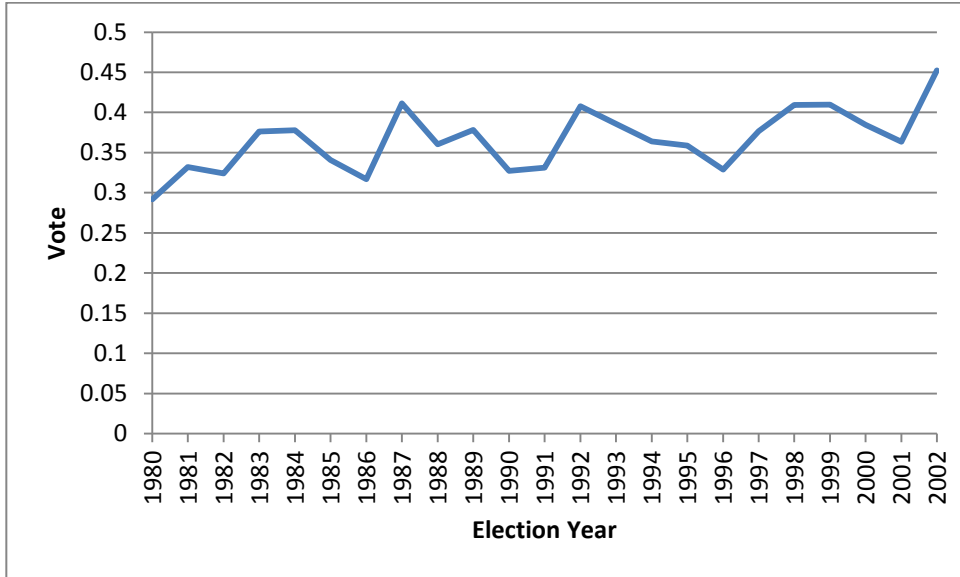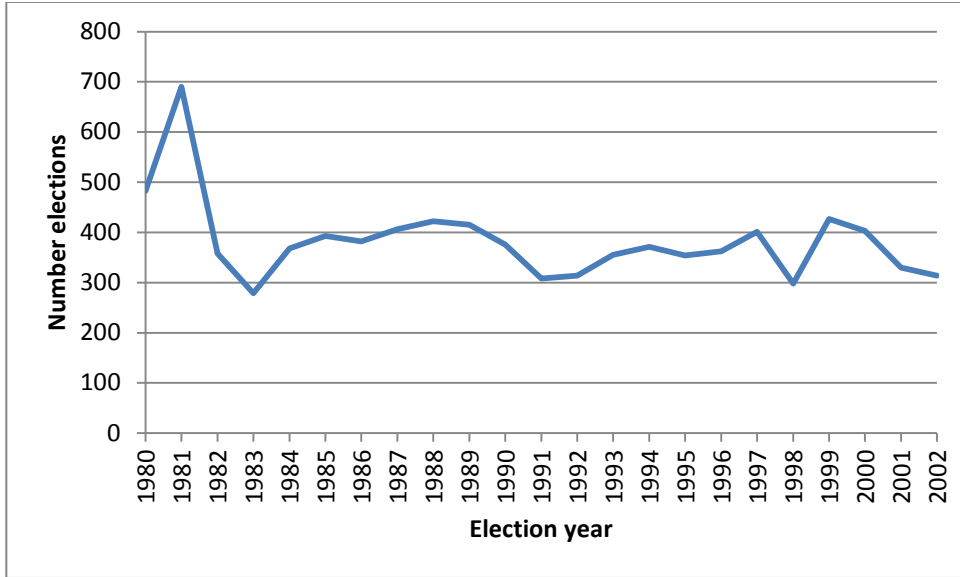
Figure 2
Distribution of votes

This figure plots a histogram of the distribution of the number of elections with the percentage of votes for unionizing in our sample across 40 equally-spaced bins (with a 2.5% bin width). For instance, there are approximately 100 union elections that generate between 12.5-15% votes in support for unionizing as shown in the figure. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002.
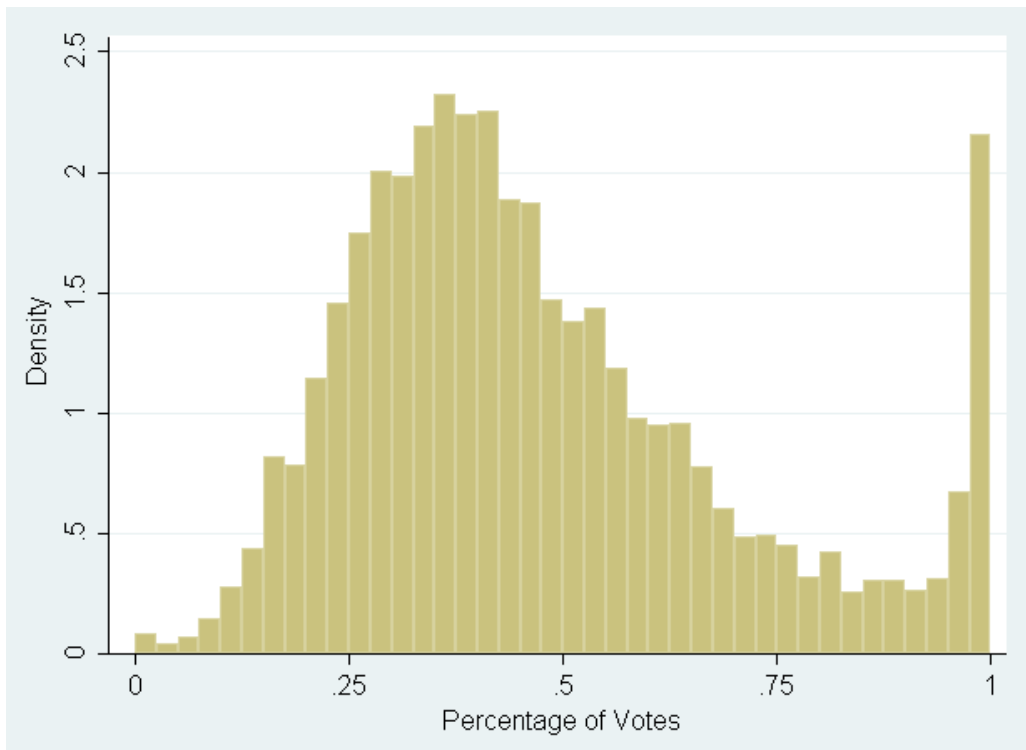
Figure 3
Density of union vote shares

This figure plots the density of union vote shares following the procedure in McCrary (2008). The x-axis is the percentage of votes favoring unionization. The dots depict the density estimate. The solid line represents the fitted density function of the forcing variable (the number of votes) with a 95% confidence interval around the fitted line. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002.
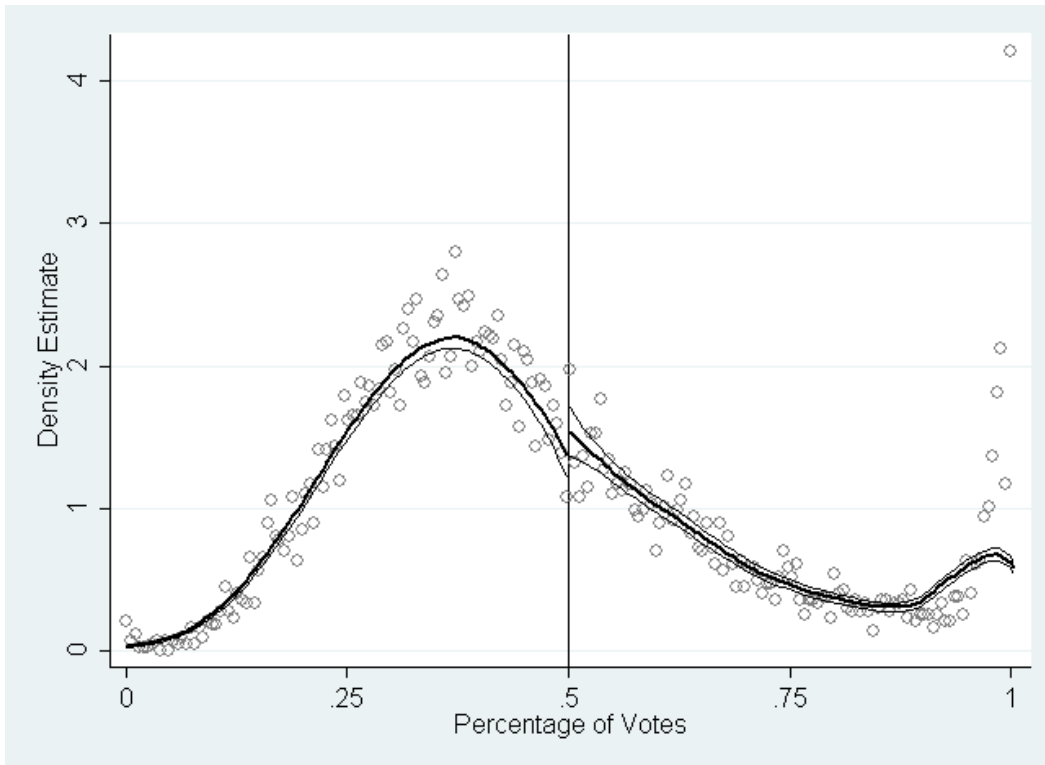
Figure 4
Regression discontinuity plots

This figure presents regression discontinuity plots using a fitted quadratic polynomial estimate with a 95% confidence interval around the fitted value. The x-axis is the percentage of votes favoring unionization. The dots depict the average innovation outcome variables in each of 40 equally-spaced bins (with a bin width of 2.5%). Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.
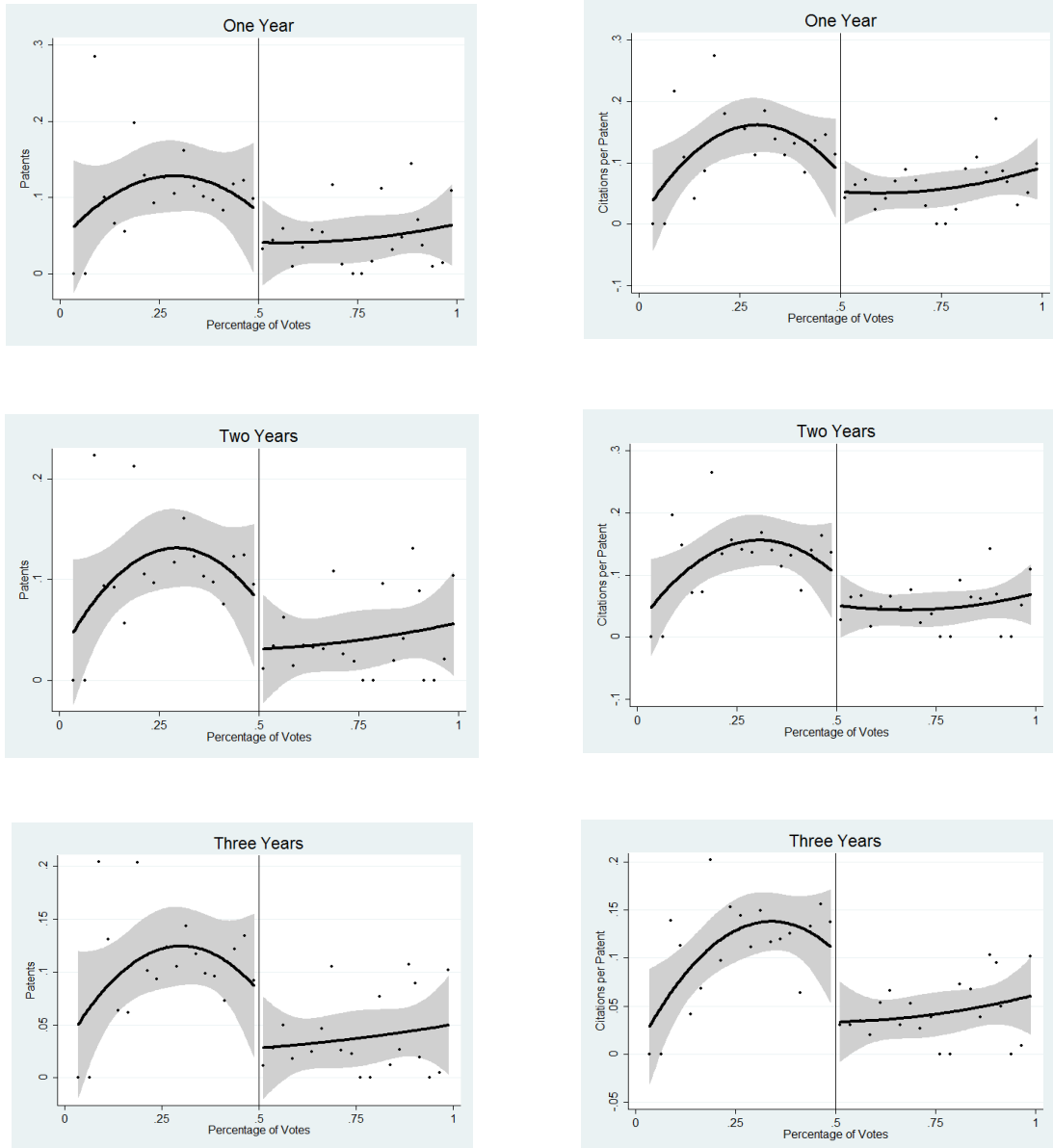
Figure 5
RDD bandwidths
This figure plots the RDD estimates with alternative bandwidths using the local linear regression with the choice of optimal bandwidth following Imbens and Kalyanaraman (2012). The x-axis represents the bandwidth where '100' is the optimal bandwidth reported in Table 4, '200' is 2 times the optimal bandwidth, etc. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.
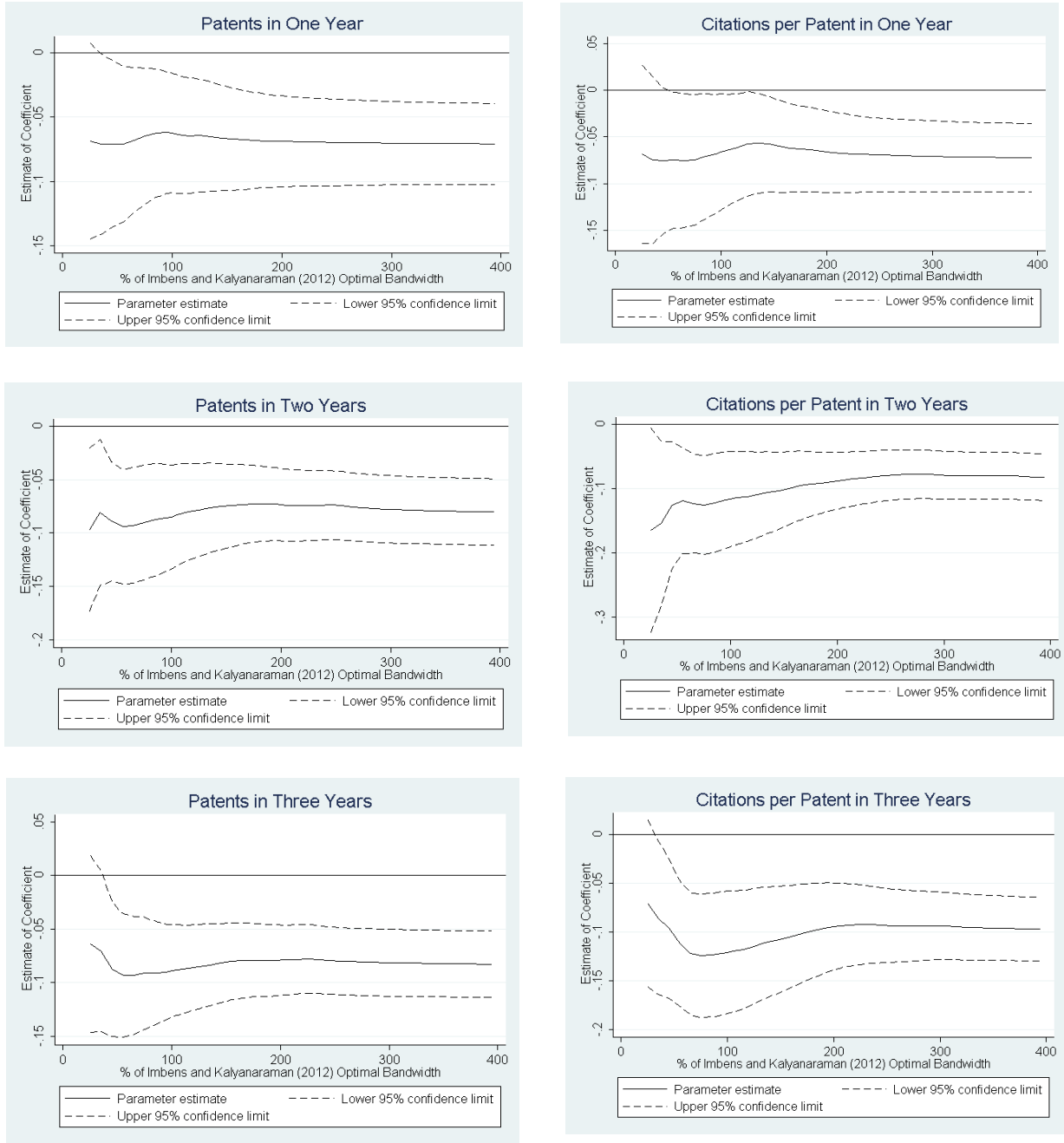
Figure 6
Placebo tests
This figure plots a histogram of the distribution of the RDD estimates from placebo tests. The x-axis represents the RDD estimates from a placebo test that artificially assumes an alternative threshold other than 50%. The dashed vertical line represents the RDD estimate at the true 50% threshold. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.

Table 1
Descriptive Statistics

This table presents descriptive statistics of our sample. Panel A reports union election statistics and innovation measures. Panel B reports industry statistics. "Vote for union" is the total number of votes for unionization divided by total votes for unionization in a given election. "Passage" is an indicator variable that equals one if a firm is unionized as a result of an election and otherwise zero. All other variables are defined in Appendix A. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.
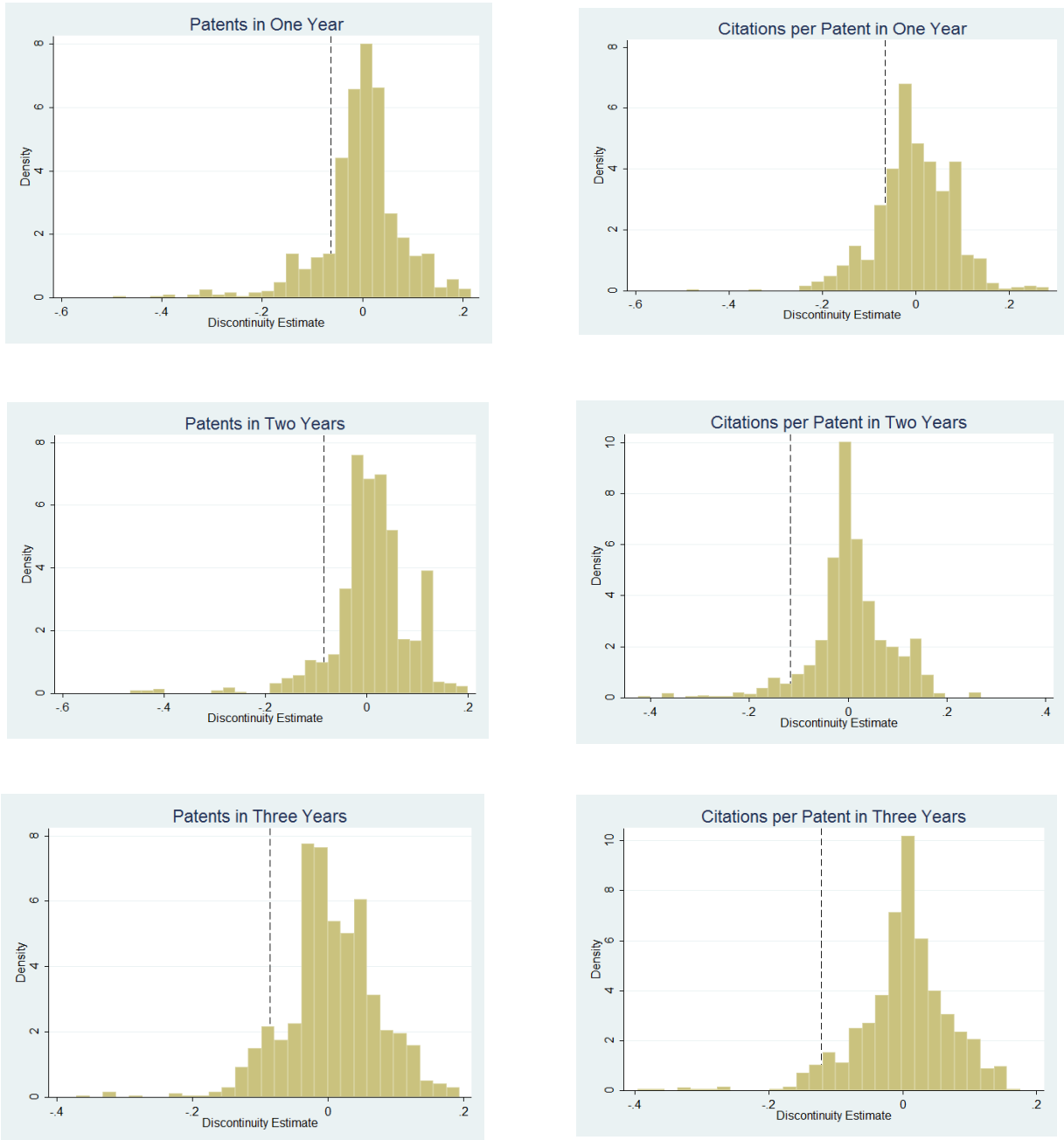
Panel A: Election and innovation statistics

	Obs.	Mean	Std. Dev.	Median
Union election statistics				
Vote for union	8,809	0.48	0.23	0.42
Passage	8,809	0.36	0.48	0.00
Innovation statistics				
Patents	8,809	0.34	2.09	0.00
Citations/Patents	8,809	0.52	2.56	0.00

Panel B: Industry statistics

SIC	Description	No. of Elections	Passage	No. of Patents	Citations/ Patents
0	Agriculture	76	0.33	0.04	0.15
1	Mining	318	0.42	0.16	0.51
2	Light manufacturing	1,670	0.32	0.50	0.76
3	Heavy manufacturing	2,466	0.29	0.59	0.91
4	Transportation	908	0.37	0.25	0.30
5	Wholesale trade	837	0.29	0.25	0.44
6	Finance	59	0.31	0.03	0.59
7	Services	665	0.41	0.17	0.20
8	Health services	1,790	0.51	0.03	0.03
9	Public Administration	21	0.48	0.00	0.00

Table 2
Difference in observable characteristics between unionized and non-unionized firms

This table shows differences in observable characteristics between firms that participate in union elections and win versus those that lose by a small margin (vote shares within the interval of [48%, 52%]). Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period. Firm characteristics are from Compustat.

	Win=1	Win=0	Difference	p-value
Ln(Patent)	0167	0.186	0.019	0.950
Ln(Citations/Patent)	0.418	0.218	-0.201	0.374
Ln (Assets)	6.136	5.689	-0.447	0.560
Ln (1+BM)	0.525	0.567	0.042	(0.685
ROA	0.053	0.018	-0.035	0.167
PPE/Assets	0.490	0.378	-0.112	0.120
Capx/Assets	0.079	0.058	-0.022	0.105
Debt/Assets	0.363	0.305	-0.058	0.395
Ln (1+Firm Age)	2.022	2.625	0.603	0.163
HHI	0.235	0.219	-0.017	0.833

Table 3
Regression discontinuity: Global polynomial

This table presents RDD results from estimating a polynomial model specified in Equation (2). The dependent variables are innovation measures and the variable of interest is a unionization dummy. The dependent variable in columns (1) – (3) is the natural logarithm of one plus patent counts, which measures innovation quantity. In columns (4) – (6), the dependent variable is the natural logarithm of one plus citation counts scaled by patents, which measures the quality of innovation. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.

	(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	-0.062*	-0.080**	-0.095***	-0.064*	-0.089**	-0.115***
	(-1.69)	(-2.19)	(-2.67)	(-1.65)	(-2.34)	(-3.18)
Constant	0.098***	0.096***	0.100***	0.122***	0.140***	0.135***
	(4.12)	(4.12)	(4.42)	(4.94)	(5.70)	(5.83)
Polynomial order	3	3	3	3	3	3
Observations	8,809	8,809	8,809	8,809	8,809	8,809

Table 4
Regression discontinuity: Nonparametric local linear regression

This table presents local linear regression results using the optimal bandwidth following Imbens and Kalyanaraman (2012). Results using rectangular and triangular kernels are reported. The dependent variable in columns (1) – (3) is the natural logarithm of one plus patent counts, which measures innovation quantity. In columns (4) – (6), the dependent variable is the natural logarithm of one plus citation counts scaled by patents, which measures the quality of innovation. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.

Rectangular kernel

	(1)	(2)	(3)	(4)	(5)	(6)
		$\text{Ln (Patents)}_{t+N}$			$\text{Ln (Citations/Patents)}_{t+N}$	
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.057***	-0.079***	-0.087***	-0.056**	-0.117***	-0.125***
	(-3.05)	(-3.36)	(-3.86)	(-2.28)	(-3.32)	(-4.14)

Triangular kernel

	(1)	(2)	(3)	(4)	(5)	(6)
		$\text{Ln (Patents)}_{t+N}$			$\text{Ln (Citations/Patents)}_{t+N}$	
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.062***	-0.085***	-0.089***	-0.066***	-0.116***	-0.121***
	(-3.37)	(-3.91)	(-4.32)	(-2.82)	(-3.37)	(-4.16)

Table 5

Manufacturing and non-manufacturing industries

This table presents local linear regression results using the optimal bandwidth following Imbens and Kalyanaraman (2012) for manufacturing and non-manufacturing firms. Results using a triangular kernel are reported. The dependent variable in columns (1) – (3) is the natural logarithm of one plus patent counts, which measures innovation quantity. In columns (4) – (6), the dependent variable is the natural logarithm of one plus citation counts scaled by patents, which measures the quality of innovation. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.

Manufacturing industries (1-digit SIC codes 2 and 3)

	(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	-0.073**	-0.082***	-0.101***	-0.073*	-0.115**	-0.133***
	(-1.96)	(-2.86)	(-3.58)	(-1.68)	(-2.28)	(-3.32)

Non-manufacturing industries (1-digit SIC codes 0-1, 4-9)

	(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	-0.065**	-0.088***	-0.072***	-0.086***	-0.099***	-0.119***
	(-2.32)	(-3.00)	(-2.71)	(-2.50)	(-2.89)	(-2.97)

Table 6
Right-to-work laws

This table presents local linear regression results using the optimal bandwidth following Imbens and Kalyanaraman (2012) for firms located in states with right-to-work laws versus in states without right-to-work laws. Results using a triangular kernel are reported. The dependent variable in columns (1) – (3) is the natural logarithm of one plus patent counts, which measures innovation quantity. In columns (4) – (6), the dependent variable is the natural logarithm of one plus citation counts scaled by patents, which measures the quality of innovation. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.

States with right-to-work laws

	(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	-0.059	-0.076	-0.068	-0.035	-0.054	-0.064
	(-1.45)	(-1.46)	(-1.49)	(-0.64)	(-0.90)	(-1.16)

States without right-to-work laws

	(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	-0.065***	-0.089***	-0.098***	-0.091***	-0.135***	-0.148***
	(-3.27)	(-4.06)	(-4.70)	(-2.95)	(-3.82)	(-4.61)

Table 7
R&D expenditures

This table presents local linear regression results using the optimal bandwidth following Imbens and Kalyanaraman (2012) for R&D spending. Results using a triangular kernel are reported. The dependent variable is R&D expenditures scaled by total assets in years $t + N$ relative to the union election year. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. R&D spending and total assets are from Compustat.

	(1)	(2)	(3)
	$(R\&D/Assets)_{t+N}$		
	N=1	N=2	N=3
Unionization	-0.006***	-0.004*	-0.006***
	(-2.90)	(-1.65)	(-3.79)

Table 8
Inventor productivity

This table presents difference-in-differences (DiD) estimation results. "Stayers" are inventors who produce at least one patent in the firm holding union elections both three years before and after the election year. "New Hires" are inventors who produce at least one patent within three years after the union election year in the firm holding union elections and also at least on patent within three years in a different firm before the union election year. We compare the total number of patents (or the number of citations per patent) per inventor during the three years before and after the union election. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Individual inventor information is obtained from the Harvard Business School (HBS) patent database.

Innovation Productivity: Stayers

	Treat Diff. (after-before)	Control Diff. (after-before)	DiD (treat-control)	P-value
	(1)	(2)	(3)	(4)
Patents	0.119	0.442	-0.323***	0.001
Citations/Patents	-5.799	-2.306	-3.493***	< 0.001

Innovation Productivity: New Hires

	Treat Diff. (after-before)	Control Diff. (after-before)	DiD (treat-control)	P-value
	(1)	(2)	(3)	(4)
Patents	0.698	3.516	-2.818***	0.008
Citations/Patents	-8.769	2.382	-11.151**	0.022

Table 9
Inventor departures

This table presents the estimation results for the effect of unionization on the departure of innovative inventors. The top panel presents DiD estimation results. The bottom panel presents RDD results. "Leavers" are inventors who produce at least one patent in firms holding union elections within three years before the election year and at least one patent in a different firm within three years after the union election year. "Top leavers" are leavers that are in the top 5 percentile distribution in terms of innovation productivity three years before the election year among all inventors that depart the firm. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Individual inventor information is from the Harvard Business School (HBS) patent database.

Productivity: Leavers

	Treat Diff. (after-before)	Control Diff. (after-before)	DiD (treat-control)	P-value
	(1)	(2)	(3)	(4)
Patents	0.103	-1.342	1.445**	0.012
Citations/Patents	-14.134	-26.066	11.932**	0.025

Number of Leavers

	(1)	(2)	(3)	(4)
	No. of top leavers		Ln (No. of top leavers)	
	Global	Local	Global	Local
Unionization	0.182**	0.095	0.036**	0.019*
	(2.23)	(1.57)	(1.98)	(1.67)

Appendix A
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/)
Vote for union	Total number of votes for unionization 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 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 a firm in a year.	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 [#6].	Compustat
BM	The ratio of book value to market value of equity [#60/(#25 * #199)].	Compustat
ROA	Operating income before depreciation divided by total assets [#13/#6].	Compustat
PPE/Assets	Property, Plant & Equipment divided by total assets [#8/#6].	Compustat
Capx/Assets	Capital expenditure divided by total assets [#128/#6].	Compustat
Debt/Assets	Book value of debt divided by total assets [(#9+#34)/#6].	Compustat
Firm Age	Firm age is calculated by the difference between the firm's first year appeared in Compustat and the current year.	Compustat
HHI	Herfindahl index based on the firm's sales in a given 4-digit SIC industry.	Compustat
R&D/Assets	Research and Development expenditure divided by total assets [#46/#6].	Compustat
Stayers	Inventors who produce at least one patent in the firm holding union elections both three years before and after the election year.	HBS Patent and Inventor Database
New hires	Inventors who produce at least one patent within three years after the union election year in the firm holding union elections and also at least one patent within three years in a different firm before the union election year.	HBS Patent and Inventor Database
Leavers	Inventors who produce at least one patent in the firms holding union elections within three years before the election year and at least one patent in a different firm within three years after the union election year.	HBS Patent and Inventor Database
Top leavers	Leavers that are in the top 5 percentile distribution of innovation productivity three years before the election year among all inventors that depart the firm.	HBS Patent and Inventor Database

Appendix B
Patent locality

This table presents local linear regression results using the optimal bandwidth following Imbens and Kalyanaraman (2012). The dependent variable in columns (1) – (3) is the percentage of patents generated in states where union elections are held scaled by all the patents generated by the firm. In columns (4) – (6), the dependent variable is the percentage of citations received by patents generated in states where union elections are held scaled by all citations received by the patents generated by the firm. Union election results are from the National Labor Relations Board (NLRB) over 1980 to 2002. Patent data are from the NBER Patent Citation database over the 1980 to 2006 time period.

	(1)	(2)	(3)	(4)	(5)	(6)
	% of Local Patents$_{t+N}$			% of Local Citations$_{t+N}$		
	N=1	N=2	N=3	N=1	N=2	N=3
Unionization	-0.010	-0.020***	-0.025***	-0.010	-0.018***	-0.025***
	(-1.46)	(-2.72)	(-3.70)	(-1.32)	(-2.71)	(-3.93)