Internet Appendix

1 The Continuity of Vote Share Distribution

To examine whether the union elections data we use are suitable for RDD analyses, we first need to verify whether the distribution of vote share is continuous around the 50% mark. In Figure 2 of our paper, we show that the vote share distribution is continuous around the 50% cutoff using the method introduced by McCrary (2008). However, in a study comprising data from private and public firms of all sizes, Frandsen (2014) finds that union elections are less likely to be narrowly won than narrowly lost. We examine in further detail whether the union election results in our sample are biased towards union victory or defeat. Using our sample of large, public firms, we first examine such discontinuity using histograms that are similar to those proposed by Frandsen. Panel A of Figure 1 depicts the relevant histogram when we divide possible realizations of vote share for union into 20 bins (bandwidth of 0.05); panel B shows the histogram with 50 bins (bandwidth of 0.02). The patterns observed in the data suggest that elections are not manipulated at the 50% cutoff.

2 Robustness and Further Discussion

2.1 The Dynamics of Union Elections

Our focus on firm-level outcomes and cumulative bond returns could allow for potential spillover effects among sequential elections (within the same firm) to affect our estimates. The existence of subsequent elections would not bias our estimates of unionization effect as long as the outcome of the current election is not correlated with the occurrence or outcome of future elections. It could, however, inflate our estimates in case there exists intra-firm correlation in election outcomes and events (see Cellini et al. (2010)).

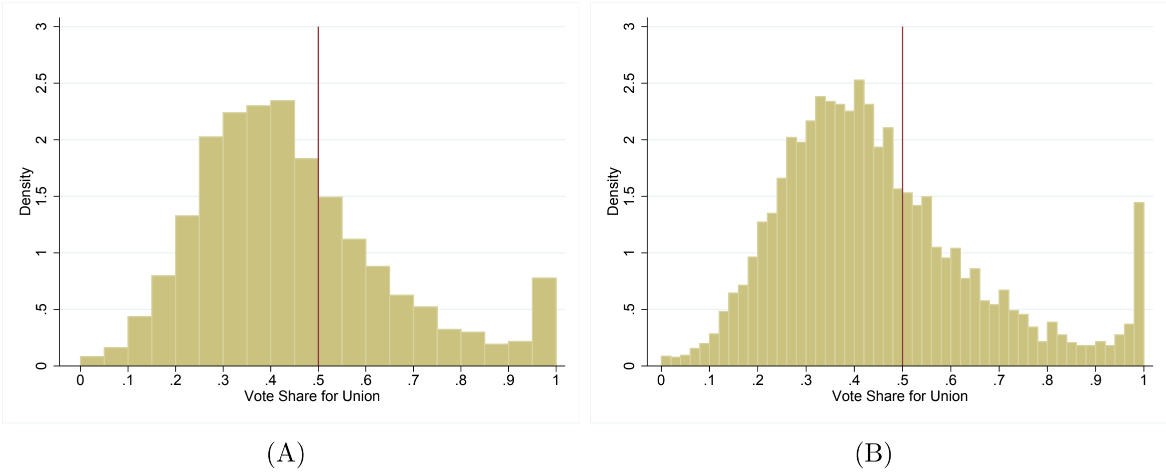

Figure 1. Histograms of the vote share distribution
This figure shows the histograms of the vote share distribution following Frandsen (2014a). The horizontal axis represents the percentage of votes in favor of unionization and the vertical axis the associated distribution density. Panel A shows the histogram with 20 bins. Panel B shows the historgram with 50 bins.

To address concerns related to how sequential elections unfold inside a firm, we examine whether the outcome of a union election is related to future union elections in the same firm. We do this following Cellini et al. (2010) and Ferreira and Gyourko (2014). For every union election in our sample, we construct indicators *FutureElection(T)* that represent whether another election would occur in the same firm within the next T months; where $T \in \{1, ..., 12\}$. We then measure whether the result from a given election (*Union Victory*) predicts the occurrence of future elections in two ways. We first adopt an OLS-based approach, regressing *FutureElection(T)* on an indicator for current election outcome (*Union Victory*), controlling for firm- and year-fixed effects. We also employ a polynomial RDD analysis, including higher orders of vote share in support of union in the regression.

Panels A (OLS-based) and B (RDD-based) of Figure A2 report the coefficients of *Union Victory* from these dynamic analyses. The coefficients indicate the extent to which current union victory can affect the likelihood that another election will take place in the same firm within the following 12 months. The horizontal axes indicate the number of months following the current election, the solid lines indicate the estimated coefficients, and the dotted lines show 90% confidence interval around the coefficients. The patterns in both panels show statistically insignificant coefficients across all horizons, with 90%

Figure A2. Current election outcome and the likelihood of future elections
This figure shows how the outcome of a current union election is related to another election occurring in the same firm within the following 12 months. Panel A shows the results from an OLS-based approach for the occurrence of future elections on the result of current elections. Panel B shows the RDD results for the occurrence of future elections. Panel C shows the results from an OLS-based approach for the outcome of future elections on the outcome *Union Victory* from current elections. Panel D shows the RDD results for the outcome of future elections. The solid lines indicate the estimated coefficients of winning a current election, and the dotted lines show 90% confidence interval around the coefficients.

confidence intervals covering zero. These results indicate that the outcome from a current representation election does not seem to lead to future elections in our sample.

We next examine whether a union victory is likely to lead to future union victories. We adopt similar OLS-based and RDD-based approaches, regressing indicators for future union victories in the following T months on current *Union Victory*, where $T \in \{1, ..., 12\}$. Panels C and D of Figure A2 reports the coefficient of *Union Victory* from these analyses. All coefficients are statistically insignificant, indicating that a current union victory does not predict future victories within our horizon.

2.2 Bond Liquidity and Speed of Adjustment

Table 4 in the main body of the paper shows a gradual drift in bond CARs over a 12-month horizon following union elections, suggesting that bondholders are slow to respond to election outcomes — corporate bonds seem "overpriced" during the event window. A comparable pattern is also observed by Lee and Mas (2012), who show that equity holders take over one year to respond to union elections. Those authors argue that the slow price reaction is not driven by the lack of information transparency, but likely due to the high risk that is inherent to arbitrage trading. Similar inefficiencies can prevent prices from immediately reflecting union elections in the corporate bond market. The high degree of illiquidity in bond trading, in particular, has been shown to intensify under-reaction to various corporate events (see Bao et al. (2011), Helwege et al. (2014), and Batta et al. (2015)).

To assess the role of trading liquidity in delaying bondholders' reactions to union elections, we quantify the liquidity of our sample bonds following Batta et al. (2015). In particular, we measure liquidity as the ratio of price uncertainty to trading volume. Given that trading volume is not available in the University of Houston database, we can only measure bond liquidity for observations after 1997. With this measure, we first verify whether our baseline findings could be driven by differences in trading liquidity for bonds of close union winners and those of close losers. To do so, we examine the distribution of bond liquidity around the vote share cutoff. Figure A3 shows that the liquidity of our sample bonds is continuous around the cutoff, with a large overlap in the confidence intervals from both sides. It seems unlikely that trading conditions in the secondary market drives the post-election declines in bond prices.

We then conduct separate RDD tests for liquid and illiquid bonds. Partitioning our sample based on whether the liquidity of a firm's bonds is above or below our sample median, we conduct local linear regressions (as in Table 4 in the paper) for each subsample over various time horizons. Figure A4 depicts the subsample results across time. The red line shows results for liquid bonds, while the blue dash line shows results for illiquid

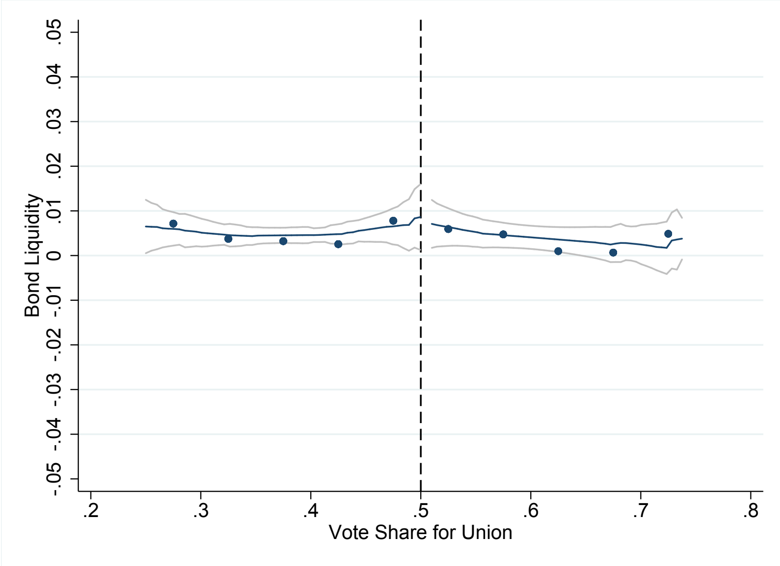

Figure A3. Bond liquidity and vote share in support of union
This figure shows the liquidity of our sample bonds around the vote share cutoff. We measure bond liquidity as the ratio of price uncertainty to trading volume (Batta et al. (2015)). The solid lines represent fitted polynomials of bond liquidity at each side of the cutoff. The dotted lines represent 90 percentile confidence intervals of the polynomials. The dots show the average bond liquidity at each 0.05 vote share interval.

ones. Bondholders in both subsamples devalue their claims by around 9.5% over the 12-month post-election window, yet the prices of liquid bonds show more than half of this devaluation (5.3%) in the first 3 months. By comparison, the prices of illiquid bonds experience a much greater delay, reflecting only around a quarter of the devaluation (2.4%) in the first 3 months. Put differently, the investors in illiquid bonds experience a drift of around 7% during the 3-month to 9-month window while those of liquid bonds only experience a 4% drift. Bond illiquidity seems to account for about half of bondholders' under-reaction to news about union election results.

3 Sample Selection

In our main analyses, we focus on non-puttable and senior bonds in order to be consistent with the existing literature in selecting bonds for our test sample (Bessembinder et al. (2009), Bao et al. (2011), and Jostova et al. (2013)). Given that our research question focuses on bondholders' value in bankruptcy court, we limit the sample to unsecured

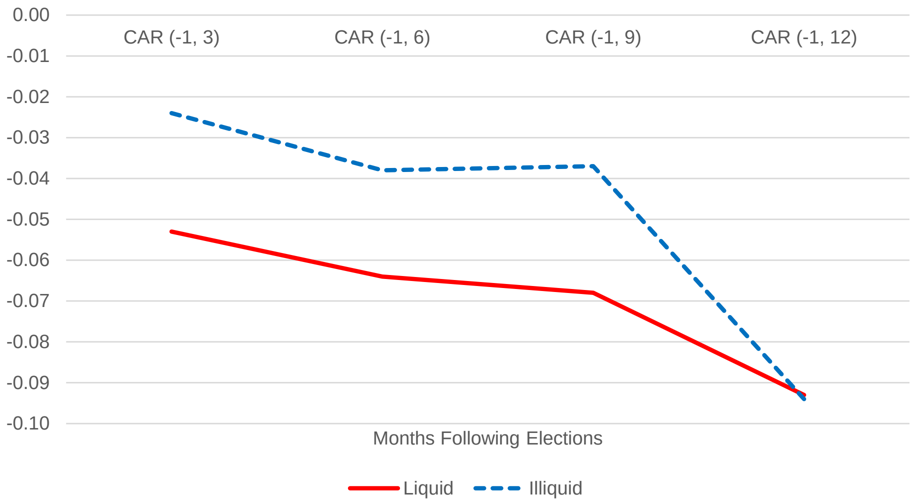

Figure A4. Liquidity and speed of adjustment
This figure shows results from separate local linear regressions for the subsamples of liquid and illiquid bonds. We measure bond liquidity as the ratio of price uncertainty to trading volume (Batta et al. (2015)). The red line shows the results for the subsample of liquid bonds, while the blue dashed line shows the results for the subsample of illiquid bonds.

bonds, which are at a similar priority level as labor claims. Notably, the percentage of junior, puttable, and secured bonds is very low (less than 5% of all bonds in our sample). Adding junior bonds to our data selection process leads to 7 more elections; further adding puttable bonds leads to 3 additional elections; adding secured bonds do not lead to additional elections. Yet, interestingly, results could potentially change by adding secured bonds since this adjustment changes the portfolio of bonds for some companies.

In the exercise below, we repeat our baseline analyses by sequentially including the above categories of bonds into the sample. Table A1 shows the results with these adjusted samples. These additional analyses yield results that are very similar to those from our baseline bond sample (displayed in Table 4 of the paper).

4 Function Form

In our main RDD analyses (shown in Table 3 of the paper), we conduct polynomial regressions allowing different polynomial coefficients on the left side and the right side of the vote share cutoff. This approach follows the recommendation by the technical literature. To wit, Lee and Lemieux (2010, *Journal of Economic Literature*, p.318) state

Table A1
Local linear regression results using adjusted samples
This table reports the results from local linear regression analyses for bond CARs following union elections. First row shows our baseline results (Table 5 in the paper). The following rows show local linear results from samples that sequentially include junior bonds, puttable bonds, and secured bonds into the sample.

Dep. Var.:	*CAR(-1, 3)*	*CAR(-1, 6)*	*CAR(-1, 9)*	*CAR(-1, 12)*
Sample Adjustments:				
Baseline sample	-0.021***	-0.022*	-0.040**	-0.047**
	(0.007)	(0.012)	(0.017)	(0.021)
Adding junior bonds to baseline	-0.020***	-0.019*	-0.038**	-0.043**
	(0.007)	(0.011)	(0.016)	(0.019)
Adding junior and puttable bonds	-0.017***	-0.020*	-0.038**	-0.043**
	(0.006)	(0.011)	(0.016)	(0.019)
Adding junior, puttable, and secured bonds	-0.016***	-0.017*	-0.029**	-0.035**
	(0.006)	(0.010)	(0.014)	(0.016)

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

that "It is recommended to let the regression function differ on both sides of the cutoff point by including interaction terms between D and X. For example, in the linear case where $f_l(X-c) = \beta_l(X-c)$ and $f_r(X-c) = \beta_r(X-c)$ (c is the cutoff point, and f_l and f_r indicate the polynomial functions on the left and right hand side of c), the pooled regression would be $Y = \alpha_l + \tau D + \beta_l(X-c) + (\beta_r - \beta_l)D(X-c) + \epsilon$. The problem with constraining the slope of the regression lines to be the same on both sides of the cutoff ($\beta_r = \beta_l$) is best illustrated by going back to the separate regressions above. If we were to constrain the slope to be identical on both sides of the cutoff, this would amount to using data on the right hand side of the cutoff to estimate α_l, and vice versa. [I]n an RD design, the treatment effect is obtained by comparing conditional expectations of Y when approaching from the left ($\alpha_l = \lim_{x \to c^-} E[Y_i|X_i = x]$) and from the right ($\alpha_r = \lim_{x \to c^+} E[Y_i|X_i = x]$) of the cutoff. Constraining the slope to be the same would thus be inconsistent with the spirit of the RD design, as data from the right of the cutoff would be used to estimate α_l, which is defined as a limit when approaching from the left of the cutoff, and vice versa."

Nonetheless, we consider a robustness analysis in which we restrict the same polynomials on both sides of the cutoff. This method facilitates the comparison of our results

Table A2
Polynomial regression results for bond CARs: Restricting the polynomials to be the same on both sides of the cutoff
This table reports the results from polynomial regression analyses for bond CARs during the three months following union elections. *Union Victory* is a dummy variable that equals 1 if the union wins the election and equals 0 if not. *Vote Share for Union* is the percentage share of votes in support of unionization in the election. *Multiple Elections* is a dummy variable that equals 1 if the firm conducts more than one elections during our sample period. Standard errors are clustered by firm.

Dep.Var.: $CAR(-1,3)$ Sample	(1) All Sample	(2) Remove 20% Tails	(3) Remove 25% Tails
Union Victory	-0.010**	-0.018***	-0.021***
	(0.006)	(0.006)	(0.007)
Vote Share for Union	0.032	0.093***	0.121**
	(0.027)	(0.034)	(0.047)
(Vote Share for Union)^2	0.029	0.05	0.044
	(0.032)	(0.067)	(0.085)
(Vote Share for Union)^3	-0.080	-0.967**	-1.587**
	(0.141)	(0.387)	(0.791)
Multiple Elections	-0.004	-0.004*	-0.005*
	(0.003)	(0.003)	(0.003)
Year FE	Yes	Yes	Yes
Observations	721	621	554
R-squared	0.14	0.18	0.20

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

to those of prior papers, such as DiNardo and Lee (2004). Table A2 reports the result. Column (1) tabulates RDD results for the entire sample. Column (2) removes the elections when the unions achieve more than 80% or less than 20% of the votes so as to focus the comparison between ex ante similar firms. Column (3) further removes elections with more than 75% or less than 25% vote share for union. This exercise confirms that extreme vote event are influential (cf. DiNardo and Lee (2004)), and as we eliminate tail outcomes, one-sided polynomial RDD estimates converge to two-sided polynomial estimates.

5 Bond Yield

Our central results are estimated using changes in bond prices (i.e., bond CARs), while some prior studies rely on bond yields (e.g., Chen et al. (2012)). While theoretically there is some degree of correspondence — albeit, not necessarily linear — between bond prices and bond yields, bond yields may incorporate information in a different way than bond prices. In particular, given that bond yield is a non-linear function of bond price, some determinants of bond prices, such as liquidity (Bao et al. (2001)), may affect changes in bond yield more strongly than they affect bond returns. In Section 2.2, we show that there is no distinguishable differences in bond liquidity between close union winners and losers. This suggests that trading illiquidity is unlikely to drive our inferences. Yet it is likely that there could be more differences between bond yield and bond prices we should consider. In particular, we recognize the possibility that bond yields could respond to unobserved pricing factors in a different way than bond returns do. It is also important to confirm our findings through tests of bond yields so as to make our inferences comparable to those in the prior literature. To do so, we compute bond yield changes around unionization and conduct RDD analyses using these measures.

We first compute abnormal yield spreads for a given corporate bond as the difference between its own yield and the weighted average yield on a benchmark portfolio that consists of all corporate bonds with the closest credit rating and time-to-maturity range. Note that subtracting the benchmark yield removes not only the common risk factors that affect corporate bond prices (i.e., credit risk premium and term structure), but also the risk-free rate from yields, as risk-free rates are already incorporated in the benchmark yield. For firms with multiple bonds outstanding, we use the weighted average of bond yields for all outstanding bonds of the firm as the measure of firm-level bond yield spreads. With the firm-level measure of bond yield spreads, we next estimate the changes in bond yields around unionization as the difference between the abnormal bond yield for the T^{th} month following the union election ($T = 3, 6, 9, 12$) and the month prior to the election. The resulting difference in bond yield spreads, or $\Delta Yield(-1, T)$, represents the changes in bond valuation surrounding unionization.

We conduct local linear regressions for bond yield spread changes during the 3-month, 6-month, 9-month, and 12-month windows following unionization. Table A3 reports the RDD results. Bondholders of close union winners experience a 43-basis-point increase in yield during 3 months following unionization relative to bonds of close union losers. This

Table A3
Effects of unionization on bond yields
This table shows the local linear RDD results for cumulative changes in bond yields following unionization. $Yield(T_1, T_2)$ denotes the changes in abnormal bond yield spreads from month T_1 to month T_2 relative to the union election month. We report the coefficient on *Union Victory* for each dependent variable. We use the optimal bandwidth defined in Imbens and Kalyanaraman (2012) for estimation. Standard errors are clustered by firm.

	Rectangular Kernel		Triangular Kernel	
	Unionization Coeff.	Standard Error	Unionization Coeff.	Standard Error
$\Delta Yield(-1, 3)$ (in bps)	42.698***	(14.960)	37.985***	(14.303)
$\Delta Yield(-1, 6)$ (in bps)	60.958**	(27.291)	63.341**	(26.249)
$\Delta Yield(-1, 9)$ (in bps)	95.419**	(35.809)	98.974***	(37.047)
$\Delta Yield(-1, 12)$ (in bps)	90.187**	(38.391)	94.682**	(40.628)

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

magnitude is economically significant compared to the level of standard deviation (343 basis points) in the sample. The estimated effect of unionization on bond yield spreads also increases along the horizon following union elections, up to a 90-basis-point discount.

It is important to note that these estimates are consistent with the baseline findings regarding bond returns in our paper. To put those numbers in perspective, one can compare the numbers reported above with our baseline finding that bondholders lose 210 basis points in the three months following unionization (please see Table 4 in the paper). These magnitudes are around 5 times as large as the estimates from bond yields. To understand the apparent differences in magnitudes, we can consider the following expression for calculating the yield of a zero-coupon bond:

$$Y = (\frac{F}{P})^{\frac{1}{T}} - 1, \tag{1}$$

where F is the face value (e.g., \$1000), P is the traded market price, and T is the time to maturity. A small change in price h will lead to a change of $-\frac{1}{T}(\frac{F}{P})^{\frac{1}{T}}\frac{h}{P}$.[1] At the same time, bond returns are directly calculated as the changes in price P, thus a small change in price h will lead to the following changes in returns $\frac{h}{P}$. Comparing the changes in yield and in returns, we can see that they differ by a magnitude of $\frac{1}{T}(\frac{F}{P})^{\frac{1}{T}}$. Given that

[1] This expression derives from the partial derivative of Y over P multiplied by h. $\partial Y/\partial P = -\frac{1}{T}(\frac{F}{P})^{\frac{1}{T}}\frac{1}{P}$.

bond price P is often close to face value, we can consider the term $(\frac{F}{P})^{\frac{1}{T}}$ to be close to 1. Returns are then approximately proportional to yield changes by time to maturity T.

We note that the analyses above are only meant to illustrate the intuition in comparing results from bond returns and bond yields. One complication one should consider is that most of our sample bonds are not zero-coupon bonds, which will add noise to the differences computed. More importantly, in our RDD analyses, we adjust all bond yields and bond returns by a benchmark level, which comprises of yields and returns of bonds with the closest maturity category. Subtracting such a benchmark level should mitigate the differences between the estimated yield changes and estimated returns. However, the benchmark cannot completely eliminate these differences, which are proportional (instead of additive) of maturity.

In all, the results from bond yield changes are consistent with the baseline finding. These findings suggest consistently that bondholders react negatively to close union victories.

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