Operational Risk Management of Political Risk: Evidence from Customer Concentration*

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Abstract

This study investigates the impact of a firm's political risk on its customer concentration. Using firm-level political risk measures, we find that greater political risk for suppliers leads to lower customer concentration. Firms with higher default risk, higher volatility, less product differentiation, and shorter customer relationships respond more to political risk by reducing their customer concentration. We address the challenge of causal interpretation of these findings by utilizing the exogenous increases in political risk induced by the redrawing of electoral district boundaries following the 2010 U.S. Census. Overall, our empirical evidence indicates that political risk significantly impacts firms' operational risk strategy in terms of management of customer concentration risk.

Keywords: Operational Risk, Political Risk, Customer Concentration, Supply Chain

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1. Introduction

Significant increases in political risk in the past decade (Baker and Bloom, 2016) has meant that its importance in the determination of economic outcomes has risen substantially. Since political risk is often difficult to hedge, it would be reasonable to assume that companies try to mitigate it via operational risk management. Consistent with this, Giambona, Graham, Harvey, and Bodnar (2019) find that 83% of the global firms surveyed manage their operational risks in this way.

We focus on the interaction between political risk and one specific dimension of operational risk - that on account of customer concentration. The link between customer concentration and political risk is suggested by a Wharton–EY survey that focused on political risk management. It found that increased political risk highly impacted overall strategy as well as sales for over 50% of the respondents.[1] Additionally, the survey found that supply chain and sourcing were rated as highly or very highly impacted by political risk by 33% of managers. Thus, an implication of the above survey is that customer concentration (which is closely related to overall strategy, sales as well as supply chain) and political risk are both linked and firms may change concentration risk in response to changes in political risk.

An earnings call by Analog Devices provides an example of such a change. Vincent Roche, the CEO, said: "So we have pretty much discounted our top—what used to be our number one customer in China—to pretty much zero in our long-term planning thinking. It has been a low single-digit customer over the past few quarters. *So, we have factored also by the way the latest regulatory upheaval into our numbers*."[2] The above example may be more broadly applicable as past papers suggest that there is a risk-return tradeoff in terms of higher returns versus higher risk for firms with concentrated customers.[3] This implies that firms have an incentive to manage

[1] As per the survey, the top three functions that were impacted by political risk were mergers and acquisitions, overall strategy, and sales and revenue, with 59%, 53%, and 53% of managers rating these functions to be highly or very highly impacted. See "Geostrategy in Practice 2020" at the Wharton Risk Center.

[2] Sources: Analog Devices Third Quarter 2020 Earnings Call. The regulatory upheaval mentioned for Analog devices was, in fact, political risk. Italics emphasis of the last sentence added by authors.

[3] Dhaliwal, Judd, Serfling, and Shaikh (2016) and Campello and Gao (2017) establish that the risk on account of customer concentration results in a higher cost of capital. In contrast, Patatoukas (2012) and Irvine, Park, and Yildizhan (2016) highlight the positive value of customer concentration in terms of firm profitability. This implies that there is a trade-off between higher returns and higher risk on account of customer concentration.

concentration risk especially when the external environment changes. Furthermore, Cen et al. (2016) finds that 1/3rd of buyer-customer relationships last for one year, which provides evidence consistent with management of customer concentration.

Motivated by the Wharton-EY survey evidence as well as past academic literature that suggests that supplying firms may be actively managing customer concentration, we examine the link between firm-specific political risk and customer concentration. The measure of political risk that we use is developed by Hassan, Hollander, Lent, and Tahoun (2019) who use textual analysis of earnings call transcripts to derive their measure. They find that firm-specific political risk accounts for over 90% of the total political risk faced by firms. Therefore, this measure allows for a much better analysis of the impact of firm-level political risk on corporate behavior. In addition, use of a firm specific measure also allows for analysis of the complementarity of various modes of operational risk management – a topic that is usually investigated in the context of substitution of financial versus operational risk (Allayanis, Ihrig and Weston, 2001; Hoberg and Moon, 2017). This would be harder to analyze with the aggregate economy-wide measure of political uncertainty of Baker and Bloom (2016) as the impact can differ significantly across firms and firms may be subject to a large degree of additional uncertainty not captured by the above measure.

We construct six measures of customer concentration, specifically an indicator of having at least one major customer, the number of major customers, the Herfindahl-Hirschman Index (HHI) of customer concentration, the proportion of sales made to all major customers, the average percentage of sales to major customers, and the percentage of sales to the largest major customer. We document a negative and statistically significant relationship between firm-specific measures of political risk and measures of customer concentration. Our baseline controls for a variety of firm characteristics as well as firm- and year-fixed effects. In terms of economic magnitude, a one standard deviation increase in political risk is associated with a 3.6 percentage point decrease in the number of major customers and a 2.8 percentage point decrease in the proportion of sales to the major customers, which is equivalent to an $18 million reduction in sales to those customers. Note that these effects are in addition to any aggregate

political risk effects that are accounted for by year-fixed effects.

One possible confounding effect that may drive the above results is that firm-specific political risk and customer concentration are co-determined by another unobserved variable. To address whether this possibility impacts the results, we exploit the redrawing of U.S. electoral districts as a source of exogenous variation in firm political risk. Redistricting followed the 2010 decennial U.S. census and changed many firms' political exposure, as they were placed in a new district with the potential for a new member of the U.S. House of Representatives. Denes, Fisman, Schulz, and Vig (2017) use this setting and find that redistricting reduces firm returns and increases firm uncertainty. Thus, firms affected by redistricting are likely to have increased political risk.

Using a difference-in-differences design based on the redistricting event described above, we estimate the causal effect of political risk on firms' customer concentration. Specifically, we compare the customer concentration of firms represented by a new House member with that of firms that are geographically proximate to the treated firms but not subject to redistricting. We document that treated firms experience a statistically and economically significant decline in customer concentration. The economic magnitude of the impact is sizable—redistricting results in an 8.3% reduction in the likelihood of having a major customer and a 13.7% reduction in the percentage of sales to the largest major customer.

Another concern is that the change in customer concentration may be due to customers rather than suppliers. One channel for such a reduction is that customers reduce their purchases from suppliers who experience an increase in political risk. A second channel may arise due to positively correlated political risks in the supply chain. An increase in the customer's own political risk may cause it to reduce purchases from suppliers who face correlated political risks to reduce the impact of the given political risk event on its operations. We conduct tests of both channels and find that our results are unlikely to be due either of these factors.

Next, we conduct cross-section analyses of potential differences in the response to political risk along three dimensions – (1) Other measures of firm risk, (2) duration of supplier-customer relationship and (3) Product market competition. Operational risk management principles

suggest that supplying firms with higher risk should respond to a larger extent to an increase in political risk. Using a firm's standard deviation as a measure of total risk and its Altman Z score as a measure of default risk, we find that responses are higher for firms with higher total risk and higher default risk.

The next cross-sectional investigation is motivated by the work of Irvine, Park, and Yidizham (2016) and Chen, Levy, Martin, and Shalev (2021). Customers with long-standing relationships may have developed more firm-specific capital, either hard capital such as fixed investments or soft capital such as ease of coordination or trust. Therefore, it might be costlier to diversify away from these customers than from others. We partition the sample into two groups based on the median relationship duration and find that the reduction in customer concentration is more pronounced for firms with shorter relationships. Irvine, Park, and Yidizham (2016) find that supply firms with customers with shorter relationship durations have lower operating profits, which is consistent with our results that suppliers are more likely to reduce sales and/or terminate relationships with these customers.

The third cross-sectional investigation is motivated by the work of Hoberg and Phillips (2016). Firms with more differentiated products should be less concerned about the composition of their customer base because they have greater bargaining power in the product market. Thus, a large customer may not be a large source of risk to a supplying firm with unique products as such customers are unlikely to be able to find substitutes. We measure product differentiation using a similarity score developed by Hoberg and Phillips (2016). Firms with a lower similarity score with their closest competitors have more differentiated products. Consistent with our conjecture, firms with more differentiated products respond less to political risk in terms of changing customer concentration.

In the last section of the paper, we examine what actions firms take to achieve lower concentration. One option is to acquire more small customers.[4] This would imply an increase

[4] An example of focusing on smaller customers is found in the 10K filing of Ciena Corporation. It stated: "The company's business, particularly, the size of its revenue growth potential has been historically dependent on two major customers, Sprint and MCI Worldcom. … The company's sales efforts are focused on a greater number of smaller opportunities."

in marketing costs. Consistent with this, we find that an increase in political risk indeed leads to increased selling, general and administrative expenses (SG&A). The increases in costs are larger for firms with more cash as well as less leverage, suggesting that financial constraints can limit the extent to which firms can secure alternative customers as they try to reduce customer concentration.

We make several contributions to the literature. First, using firm-specific political risk as the empirical setting for identification, we demonstrate unambiguously that customer concentration is a significant operational risk that companies actively manage. There are parallels to our study in other dimensions of operational risk. For example, in the literature on the management of foreign exchange risk, Allayannis, Ihrig, and Weston (2001) address whether firms manage exchange-rate risk by using financial contracts or operational adjustments. More recently, Hoberg and Moon (2017) have used textual analysis to show that operational hedging is an important dimension of risk management for multinational firms. In the context of mergers and merger waves, Garfinkel and Watson-Hankins (2011) find that operational risk management influences the decision to vertically integrate. Similarly, Hamm, Jung, Lee, and Yang (2021) find that companies manage operational risks by maintaining excess inventory when dealing with labor unions. Thus, the above suggests that there are many ways to manage operational risk. We add to this by showing that reduction in customer concentration is an alternative risk management mechanism.

Fisman, Knill, Mityakov, and Portnykh (2022) also study political uncertainty at the firm level but in a different setting. They derive a firm-specific political beta value for Russian firms, based on a voting record of the given country with Russa in the UN, and find that Russian firms' exports respond more to countries where the firm has a higher political beta value. Our cross-sectional tests also document results that mirror their political beta effect for exports—firms for whom customer concentration risk matters more respond more to firm-specific political risk.

Second, most studies have examined the effect of aggregate policy and political

uncertainty on firm actions and outcomes.[5] In contrast, we use firm-level political uncertainty. One advantage of using firm-level uncertainty over aggregate uncertainty is that the former is less likely to have general equilibrium effects, meaning that some of the measured effects in prior studies may be due to the response of one firm to the actions of another in the supply chain. In fact, the model by Pastor and Veronesi (2013) predicts such effects and finds them to be significant using stock market data. As mentioned earlier, the use of firm level political uncertainty allows us to examine cross-sectional variation in reaction to political risk at a granular level and the differences across other firm specific attributes such as the duration of the buyer-supplier relationship and product uniqueness.

Third, we add to the literature on the propagation of supply chain risks between suppliers and customers. Several studies in finance have focused on the propagation of credit risk along the supply chain (See Hertzel, Li, Officer and Rodgers, 2008 as an early example and more recently Agca, Babich, Birge and Wu, 2022). In contrast, the propagation impact of political risk is not well studied. Charoenwong, Han and Wu (2022) study the propagation of political risk with international data and find that aggregate trade policy uncertainty can result increased on-shoring or increased offshoring of suppliers by US firms. We show that policy uncertainty can result in decreased reliance on major customers by suppliers; thus providing evidence that suppliers can also react to policy uncertainty in addition to customers. Further, we demonstrate that all types of policy uncertainty can affect supply chain relationships on account of risk management motives. Lastly, we demonstrate that policy uncertainty is important even in domestic supply chain relationships.

The rest of the paper is structured as follows. We explain our data, sample, and variables in Section 2. We present the main empirical results in Section 3 and additional cross-sectional tests in Section 4. We conclude in Section 5.

[5] Studies that measure the impact of political risk typically use measures at the economy level. See, for example, Bonaime, Gulen, and Ion (2017); Gulen and Ion (2016); Julio and Yook (2012); Leung and Sun (2021); Nguyen and Phan (2017).

2. Sample Selection and Variables

2.1 Measuring firm-level political risk

Hassan Hollander, Lent, and Tahoun (2019) construct a time-varying metric of firm-specific political risk by analyzing quarterly conference calls of publicly listed companies, where financial analysts and other market participants engage in discussions with senior management regarding current events. The authors utilize a machine-learning algorithm to assess the transcripts of these conference calls and identify the proportion of the conversation that pertains to political matters. Their algorithm distinguishes between the topics being discussed by extracting all two-word combinations (bigrams) from training libraries containing comprehensive sets of political topics, $\mathbb{P}$, and nonpolitical ones, $\mathbb{N}$. The authors construct the political risk measure by counting the number of exclusively political bigrams near a synonym of risk or uncertainty and dividing it by the total number of bigrams in the transcript, adjusting for the transcript's length.

$$PRisk_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \left(1[b \in \mathbb{P} \backslash \mathbb{N}] \times 1[|b - r| < 10] \times \frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \right), \quad (1)$$

where r is the position of the nearest synonym of risk or uncertainty and $b = \{0,1, \ldots, B_{it}\}$ indexes bigrams in firm i's call at time t. Each bigram is assigned a score based on its political association, where the score is proportional to the frequency of bigram b in the political training library (f_b) and the total number of bigrams in the training library ($B_{\mathbb{P}}$). Hassan et al. (2019) thoroughly validate this metric through a series of rigorous checks. Firstly, they verify whether the algorithm correctly identifies conversations related to political risk by human inspection. Secondly, they examine how the measure aligns with political events over time and with sectors that have a high susceptibility to political risk. Thirdly, they conduct tests to determine the correlation between political risk and firm outcomes that are likely to be influenced by political risk, such as planned investments and hiring. Fourthly, they ensure that the measure does not reflect news about the mean of political exposure, i.e., it does not reflect sentiment about political events in a firm's conference call. Finally, they establish that political risk differs from nonpolitical risk through a set of tests.

Since $PRisk_{it}$ is computed at the firm-quarter level and firm characteristics are only available at the firm-year level, we use the average of $PRisk_{it}$ for a given firm-fiscal year to generate annual standardized firm-level political risk (denoted as $zPRisk_{it}$). Hassan et al. (2019) also construct an index of firm-level political sentiment. This variable is constructed by counting the use of political bigrams based on their proximity to positive and negative sentiment words using the Loughran and McDonald (2011) sentiment dictionary and then scaling the resulting counts with the total number of bigrams in that transcript. Since our study focuses on changes in risk, we use political sentiment as a control variable to ensure that the results are not driven by directional changes in political news affecting the firm.

2.2 Measuring customer concentration and customer political risk

To identify the major customers of the firms, we utilize Compustat's Segment Customer database. Since 1976, the Financial Accounting Standard Board's (FASB) Statement of Financial Accounting Standards No. 14 (SFAS 14) has mandated that suppliers disclose external customers responsible for at least 10% of their revenues. Although SFAS 131 replaced SFAS 14 in 1997, public companies are still obligated to report such customers under SEC Regulation S-K Item 101.[6]

In accordance with prior research, we develop six metrics to gauge the degree of concentration in a supplier's customer base. Firstly, we generate an indicator variable that equals one if a supplier discloses at least one corporate customer responsible for 10% or more of its yearly revenue, and zero otherwise (*Major Customer*). Secondly, we calculate the total number of a firm's major corporate customers (*Number of Major Customers*). Thirdly, we employ an adaptation of the Herfindahl-Hirschman Index to quantify customer concentration (*Customer HHI*). We measure the customer concentration of supplier *i* in year *t* across the supplier's *J* major customers as:

[6] Suppliers sometimes voluntarily report customers that account for less than 10% of sales. As these disclosures are voluntary, we do not use these to reduce concerns of a potential selection bias. See Chen, Su, Tian, and Su (2021) for a discussion of potential biases that might arise if such firms were included.

$$Customer\ HHI_{it} = \sum_{j=1}^{J} \left(\frac{Sales_{ijt}}{Sales_{it}}\right)^2, \quad (2)$$

where $Sales_{ijt}$ refers supplier *i*'s sales to major customer *j* in year *t* and $Sales_{it}$ refers supplier *i*'s total sales in year *t*. *Customer HHI* varies between 0 and 1, with larger values indicating a more concentrated customer base. The variable is equal to 0 when a supplier does not report sales to any major customers and 1 when a supplier relies solely on a single major customer for all of its yearly revenues.

Fourth, we define *Total Major Customer Sales* as the percentage of a firm's sales to all major corporate customers that account for at least 10% of total sales. Fifth, we define *Average Major Customer Sales*, which is *Total Major Customer Sales* divided by *Numbers of Major Customer*. Our last measure is *Largest Major Customer Sales,* which is the percentage of a firm's sales to its largest corporate customers.[7]

Similar to *PRisk* and its standardized value, we also compute standardized measures of customer political risk. Since each firm may have multiple major customers and since, for most of our empirical tests, the unit of observation is a firm-year per supplier firm, we first compute the standardized political risk for each customer firm of a given supplier firm for a fiscal year based on the average of quarterly values. Next, we compute the average of each of these annual customer political risk values to derive the average of the political risk for all major customers of the supplier firm for a given firm-year.

2.3 Sample construction

We use Compustat for data on firm characteristics and CRSP for return data. Political risk data is obtained from Hassan et al. (2019).[8] We start with all U.S. firm-year observations in Compustat for the period 2002–2019. We use observations from 2002 onward because, after the introduction of Regulation FD, U.S. public firms have been required to make conference

[7] Studies typically use a single measure of customer concentration, which is labeled CC and is identical in definition to the customer HHI that we compute. See, for example, Dhaliwal, Judd, Serfling, and Shaikh (2016); Irvine, Park, and Yildizhan (2016); Campello and Gao (2017); and Crawford, Huang, Li, and Yang (2020).
[8] https://www.firmlevelrisk.com/

call scripts publicly available, which is needed for the construction of the Hassan et al. (2019) measure. Firms from the financial services and utilities industries are excluded (SICs 4900–4999 and 6000–6999). We then match the customer concentration data to the financial data in Compustat to obtain the basic sample of supplier firms. We further match it to the Hassan et al. (2019) political risk dataset to obtain political risk data for both suppliers and customers. We exclude observations with unavailable information from Compustat for calculating our key variables of interest or from the political risk dataset. This final sample consists of 6762 firm-year observations, with 1,187 distinct firms. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the potential impact of outliers.

Note that our sample is smaller than those used in prior papers (Dhaliwal, Judd, Serfling, and Shaikh, 2016; Chen et al., 2022).[9] This is because we require political risk measures for customers and suppliers. However, this implies that firm-year observations where only foreign firms or domestic unlisted firms are listed as major customers are not included in the sample, as these are unavailable in the Hassan et al. (2019) dataset. To the extent that supplying to foreign firms is in itself riskier than domestic activities, this implies that our measure may underestimate the true effects of firm political risk on changes in customer concentration, as changes in political risk may result in a larger response by a supplier to their foreign customers.[10] Another difference in empirical design is that we use firm fixed effects, which allows for much more precise quantification of the effects of political risk, as all time-invariant time heterogeneity is taken into account.[11]

3. Baseline empirical results

3.1 Descriptive statistics

Table 1 shows the descriptive statistics for our sample of supplier firms. The average

[9] For example, in Chen et al. (2021), there are 8,738 firm-year observations with major customers.
[10] Using the EPU political risk measure, which measures economy-wide political risk, Charoenwong, Han, and Wu (2022) find that increases in political risk can result in a significant increase in the likelihood of on-shoring of suppliers for U.S. firms with a high degree of domestic sales.
[11] In robustness tests, we will fill in the median industry values for customer political risk where it is missing. Likewise, consistent with some past studies, we will use industry-year fixed effects, instead of firm fixed effects, in our robustness tests

number of major customers is 1.21. The mean of Customer HHI is 0.06. On average, sales to all major customers account for 25% of total revenue. These figures are comparable to those of Dhaliwal, Judd, Serfling, and Shaikh (2016) and Campello and Gao (2017).

To understand the relationship between political risk and customer concentration, we plot the five measures of customer concentration across different level of relationship between political risk (excluding the dummy variable for a major customer). Since there are too many observations to plot in a single graphic, we divide the *PRisk* variable into deciles and compute the average customer concentration for each decile. Figure 1 shows the plots. For all five concentration measures, a negative pattern is clearly visible—thus higher political risk is associated with lower customer concentration. In the next subsection, we test whether this pattern continues to hold when controlling for other determinants of customer concentration and whether the relationship can be considered causal.

3.2 Baseline results

Our baseline model uses multivariate panel regressions to study whether the supplier's political risk affects its customer concentration. Specifically, we run the following regression:

$$Customer\ Concentration_{i,t+1} = \beta_0 + \beta_1 zPRisk_{i,t} + \beta_2 Controls_{i,t} + FirmFE + YearFE + \varepsilon_{it}, \quad (3)$$

where *Customer Concentration* is one of the six dependent variables described in Section 2.2 (*Major Customer*, *Number of Major Customers*, *Customer HHI*, *Total Major Customer Sales*, *Average Major Customer Sales*, and *Largest Major Customer Sales*).

Note that our empirical specification examines the impact of an increase in political risk (subscript *t*) on future customer concentration (subscript *t+1*). The rationale is that it is difficult for supplying firms to change the amounts they supply to their major customers contemporaneously. The firm-level controls are also measured in year *t* to account for the possibility that the firms may change some of these variables in year *t+1* in response to increases in political risk.

The key independent variable is the standardized measure of political risk from *PRisk*

defined in Section 2.1. In addition to this, we include other measures related to the textual analysis in the work of Hassan et al. (2019). The first is *PSentiment*, which is a signed variable that measures the positive or negative sentiment embedded in the textual analysis. The reason for using sentiment is that we want to isolate the impact of risk increases, rather than the effect of negative or positive sentiment. Additionally, CEOs may strategically attribute negative news about economic performance or prospects to political events (Gad et al., 2020).

We also include *Customer PRisk* in the baseline to account for the fact that customer political risk may also impact the supplying firm's decision to engage with a particular customer as a major customer. To the extent that a customer's political risk increases, suppliers may be reluctant to make relationship-specific investments that are often part of the customer-supplier relationships. Lastly, we also include the political sentiment at the customer firm (*Customer PSentiment*) to account for the fact that positive (negative) political sentiment in a customer firm may impact a given supplier's decision to engage with it to a greater or lesser extent.

Following the literature, we control for a list of firm characteristics that may impact the level of sales to a major customer (Dhaliwal, Judd, Serfling, and Shaikh, 2016; Irvine, Park, and Yidizham, 2016; Chen et al., 2022). We control for firm size as measured by the natural logarithm of sales (*Log Asset*); firm leverage (*Leverage*); cash flow (*Cash*); profitability as measured by return on assets (*ROA*); market value of equity divided by book value of equity (*MTB*); property, plant, and equipment divided by total assets (*PPE*); net sales minus cost of goods sold divided by net sales (*Gross Margin*), and return volatility (*ROA Volatility*). Variable definitions are provided in the appendix.

We include firm fixed effects to control for the potential impact of time-invariant unobservable firm characteristics and cluster standard errors at the firm level to allow for correlations of residuals in the time series at the firm level. We also include year-fixed effects to control for common macroeconomic effects as well as the political risks at the level of the overall economy that are highly significant in prior studies (Julio and Yook, 2012; Gulen and Ion, 2016). Thus, our results should be interpreted as the additional impact of firm-level political risk on customer concentration over and above the effect on account of economy-wide

political risk.

Table 2 presents the results of the baseline regressions. The coefficients of the supplier's political risk are negative and statistically significant in all six models. One standard deviation increase in *PRisk* leads to a 1.3% reduction in the likelihood of having a major customer. At the intensive margin, sales to the largest major customer reduce by 0.4% of firm sales. Using the overall sample mean value of the largest major customer sales, which is 19%, this corresponds to a reduction of 2.11%. Likewise, in terms of total sales to major customers, one standard deviation increase in political risk leads to a reduction of 0.7% of sales, which corresponds to a reduction of 2.8% of total major customer sales, relative to the total major customer sales mean value of 25% for our sample. These results suggest a negative and economically significant relation between suppliers' political risk and customer concentration, i.e., the higher the firm's political risk, the lower the customer concentration.

Among the firm-specific controls, leverage is highly significant in all specifications, which confirms the results of Banerjee, Dasgupta, and Kim (2008), who used a much earlier sample period. Additionally, *Customer PSentiment* is positive in several specifications, suggesting that firms respond positively to positive political news about their customers by increasing the sales and concentration of these customers.

3.3 Difference-in-Differences regression—using redistricting as an exogenous shock

A potential concern with our estimation is that omitted variables may jointly determine political uncertainty and future customer-based concentration. Some variation in a firm's political exposure may arise from management's choices of product markets. These unobservable factors may simultaneously impact a firm's current year's political risk as well as customer concentration in future years.

We follow Denes, Fisman, Schulz, and Vig (2017) to estimate the causal effect of political uncertainty on customer concentration using redistricting. In a series of rulings in the 1960s, the U.S. Supreme Court decided that legislative districts require roughly equal populations. Consequently, district boundaries are periodically readjusted to take into account new

population data, which becomes available after the decennial census.

Denes, Fisman, Schulz, and Vig (2017) argue that redistricting increases political uncertainty in several ways—it disturbs the connection between the firm and its representative and requires time to build a connection with a new representative, and it entails dealing with the differing power of the new representative to voice company concerns at the state and federal levels and the potentially different ideology of that representative. Using the announcement dates, they find evidence that stock prices react around redistricting announcement dates. They also find an increase in implied volatility for the treated firms, which is consistent with a rise in political risk.

For our sample period, the relevant event was the redistricting following the 2010 decennial U.S. Census. This redistricting changed many firms' exposure to Congress by potentially placing them in a new district with a new House representative. Therefore, for an individual firm, the redrawing of district boundaries after the census is a plausibly exogenous event that significantly influences its political risk over which the firm has very little control.

We collect data on political boundaries from the UCLA's United States Congressional District Shapefiles (Lewis, Devine, Pitcher, and Martis 2013). This dataset provides the exact boundaries of every U.S. Congressional District from 1789 to 2016. Using ArcGIS, we intersect the longitude and latitude of each firm headquarters location with the related shapefile of United States Congressional Districts. Our approach is to match firms affected by the redistricting with nearby firms *not* affected by redistricting.

The actual release date of the U.S. Census was December 21, 2010 (Source: U.S. Census Bureau News Release). After the results are released, each state legislature or state-level commission determines new districts based on whether the state gained or lost districts as well as changes in population density within the state. The following website (balletopedia.org) provides data on the actual data of states that enacted congressional district changes. A total of 31 states enacted legislation with the new district borders in 2011 with the earliest redistricted map being passed by Arkansas on April 13, 2011. An additional 12 states passed redistricting legislation in 2012, and seven states did not have any redistricting. Based on this timeline, for

firms with headquarters in states that passed the redistricting maps in 2011, we define the post-treatment period from 2012 onward. For firms with headquarters in states that passed the redistricting law in 2012, we define the post-treatment period as 2013 onward.

We define a company as a treated firm if its most recent (pre-redistricting) congressional representative continues to run for election post-redistricting but runs in a district whose boundaries no longer include the current headquarters location of the firm. We restrict the control group to firms located within a radius of 200 kilometers of the treated firm. If a control firm is matched with multiple treated firms, we use it only once.

We use an event window starting three years prior to the redistricting date and ending three years afterward as the estimation window. The rationale is that Denes, Fisman, Schulz, and Vig (2017) find that firms sometimes change their headquarters in response to redistricting.[12] Choosing a narrower time window allows us to minimize the effect of other possible confounding events and focus solely on the political risk effect. Thus, for firms with a redistricting in 2011, we form a panel from years 2009 to 2014, with years 2012 to 2014 being the post-treatment years for these firms. For firms with redistricting in 2012, we form a panel from 2010 to 2015, with the post-treatment years being 2013 to 2015.

Additionally, we restrict our sample to only those firms that appeared in our sample in 2011 or earlier. The rationale is that firms entering the sample after 2011 into the redistricted areas or the control areas may differ from firms already present in the area prior to redistricting. The above criteria result in a total of 67 treated firms and 297 control firms, which constitute the base sample for this test. Out of the treated firms, 55 are subject to redistricting in 2011 and 12 in 2012.

Our main specification to examine the effects of changed political boundaries on customer concentration employs a difference-in-differences approach as follows:

$$Customer\ Concentration_{it+1} = \beta_0 + \beta_1 Post_t * Treat_i + \beta_2 Controls_{it} + Firm + Year + \varepsilon_{it}, \quad (4)$$

[12] They use a two-year window when they study corporate responses to the redistricting. Our results are robust to using a two-year window (results available on request).

where the dependent variable *Customer Concentration* is a list of concentration measures, *Treat* indicates whether firm *i*'s congressional representatives changed as a result of congressional redistricting, and *Post* indicates the period following the redistricting event. *Treat* and *Post* are absorbed as we include firm and year-fixed effects in the model and therefore are not included as separate control variables in the regressions.

Table 3 shows the results. The coefficients of *Treat*Post* are negative and statistically significant in four out of the six specifications. The coefficient estimate of *Post*Treat* has a negative 8.3% effect on the likelihood of having a major customer. Likewise, *Post*Treat* has a significantly negative effect on the largest major customer sales (-2.6%), which corresponds to a 13.68% decrease in the largest major customer sales.

Customer PSentiment has a significantly positive effect on customer concentration, with a one standard deviation increase in customer sentiment increasing the likelihood of a major customer by 5.9%. All other models also suggest customer political sentiment has a very important effect. This suggests that firms increase their sales to customers with positive political news, which implies that firms react to the political risk in their customers' supply chains.

In Table 4, we test for parallel trends as well as long-run effects by including dummy variables in the pre-treatment period, as suggested by Angrist and Pischke (2009). Since we have a six-year window, all effects are measured relative to the first year. The pre-treatment coefficients for all models are insignificant for one and two years prior to the treatment (*Treat -1* and *Treat -2*). Incidentally, we also study the long-run effects and find that firms change their customer concentration in the treatment year, with no further change in customer concentration after this year. In fact, using this specification, the treatment year effects are much larger relative to Table 3.

3.4 Correlated supply chain risk

As mentioned in the introduction, a decrease in sales to a major customer may be due to correlated risks across the supply chain. This may result in a confounding problem—whether a supplier's increased political risk may proxy for a customer's increased political risk and is

measuring its effect better. As a first test of whether this impacts our result, we exclude supplier political risk and supplier sentiment from the baseline and estimate this using only customer political risk. This specification avoids any possible confounding effect of a supplier's political risk acting as a proxy for its customer's political risk. Panel A of Table 5 presents the results of this regression. We find that the exclusion of supplier political risk does not make the customer political risk a significant determinant of customer concentration, suggesting that a confounding problem on account of supply chain linkages does not drive our results.

As a second test of correlated supply chain risk causing our results, we estimate *Residual Political Risk of Suppliers* by regressing the supplier's political risk on the customers' political risk and aggregate economic policy uncertainty (Baker and Bloom 2016). We run the following regression:

$$zPRisk_{i,t} = zCustomerPRisk_{i,t} + EPU_t + \epsilon_{i,t}, \quad (5)$$

where $zPRisk$ is the supplier's political risk, $zCustomerPRisk$ is the customer's political risk, and EPU is the economic policy uncertainty index from Baker and Bloom (2016). We then use the residual ($\epsilon_{i,t}$) from the regression as a measure of supplier political risk. This residual is orthogonal to customer political risk as well as to any aggregate policy risk by construction. We find that the *Residual Political Risk of Suppliers* has a similar effect, relative to the non-orthogonalized *PRisk* that is used in the baseline (Table 5 Panel B).

A customer and supplier's political risk may also have some common components on account of risks that impact both of their industries. Orthogonalizing a supplying firm's political risk with regard to its customers may not necessarily completely capture the interdependence of supplier and customer's political risk. To alleviate this potential problem, we add industry-level supplier political risks in the empirical specification of Equation (5). Specifically, we compute an industry-level *PRisk* using the sales-weighted average *PRisk* of firms in the supplier's industry (using two-digit SIC codes for the industry).

We also construct a similar industry-level *Customer PRisk* for customers. As the unit of observation is the firm-year for a supplier with firms possibly having multiple customers, we

use the sales percentage of each customer as the weight to construct the weighted average industry-level *Customer PRisk* for each firm-year observation.

$$zPRisk_{i,t} = zCustomer\ PRisk_{i,t} + zPRisk_{Ind\,i,t} + zCustomer\ PRisk\_Ind_{i,t} + EPU_t + \epsilon_{i,t}. \quad (6)$$

Panel C of Table 5 shows that the *Residual Political Risk of Suppliers* from Equation (6) is significant in most specifications when it is used in place of *zPRisk* in the baseline specification, indicating that the correlation of supply chain risks does not impact our results. In other settings, correlated supply chain risks that have been demonstrated to be important by Charoenwong, Han, and Wu (2022) and Agca, Babich, Birge, and Wu (2022). In our setting, the use of firm political risk measures may minimize the effect of supply chain correlations.

3.5 Customers' decision to reduce supplier concentration

Another potential concern is that the decrease in customer concentration on account of increased political risk may be driven by customers rather than suppliers, i.e., when customers observe an increase in political risk to their suppliers, they choose to reduce their purchases from the supplier.

To investigate whether this impacts our results, we construct an empirical specification where we use a sample of firm-year observations based on the customer firms in our sample. To do so, we calculate the customer's purchase concentration measures similar to those for the supplying firm's customer concentration, except that these are computed using the customer's cost of goods sold rather than sales, and we don't set 10% cutoffs for the ratio of the supplier's sales to the customer' cost of goods, which is much smaller than sales percentage of revenue of suppliers. Table 6 presents the results. We find that the political risk of a supplier does not affect its customer's purchase concentration. Therefore, we conclude that the diversification in firms' customer concentration is more likely to be driven by a reduction in supplying firms rather than customer firms.[13]

[13] The supplying firm need not be a major supplier to the customer. Hence the political risk of the supplier may not materially impact the customer much. However, as noted earlier, using the same data set, Barrot and Sauvagnat (2016) document large effects in terms of sales, even when the supplier is small, relative to the customer.

As a second test of whether the decision is driven by customers, we stratify industries into those with higher supplier bargaining power and those with higher customer bargaining power. To measure relative bargaining power, we use the ratio of the mean profit margin of suppliers' industry to the mean profit margin of their customers' industry.[14] The use of this variable is motivated by several studies on the profit margins of customers vis-à-vis their suppliers. According to Ravenscraft (1983), Balakrishnan et al. (1996), Gosman et al. (2004), and Piercy and Lane (2006), major customers often leverage their bargaining power to coerce suppliers into reducing their prices, offering more relaxed credit terms, and providing more frequent deliveries in smaller quantities, resulting in a decrease in inventory levels for the significant customers. These inequitable arrangements exert pressure on suppliers' profitability. Therefore, the ratio of the profit margin of the supplier's industry to the customer should reflect the supplier's bargaining power.

If the decision to reduce sales is customer-driven, we should observe that firms in industries with high customer bargaining power should have a larger response to supplier political risk, since such firms are inherently more powerful in their relationships with suppliers. On the other hand, if the decision to reduce sales is supplier-driven, we should observe a larger reduction in major customer sales and customer concentration for firms with high supplier bargaining power and low customer bargaining power.

Panels A and B of Table 7 report cross-sectional results, conditional on the relative profit margin for larger and smaller supplier bargaining power, where the high and low bargaining power samples are based on the sample median values for the industry-level relative profit margin, i.e., the ratio of the mean profit margin of suppliers' industry to the mean profit margin of their customers' industry. The results in both panels A and B show that the coefficient on *zPRisk* is significantly negative only for the subsample of suppliers with greater bargaining power. This is consistent with the reduction in sales being done by suppliers and inconsistent

[14] When there are multiple major customers, we compute the industry mean profit margin for each customer's industry and then compute the overall average profit margin for all major customers. Then we take the ratio of the mean supplier industry profit margin to its average customer industry profit margin as computed above.

with customer-driven reductions in purchases from their suppliers.

4 Cross-Sectional Tests

4.1 Interaction of political risk and other firm risks

First, we examine whether firms' responses to changes in political risk are influenced by their total and default risk. To the extent that the firms have higher values for both risks, we expect that they should have a reduction in larger customer concentration in response to an increase in political risk.

To measure the total risk, we compute the annual standard deviation of stock prices based on daily returns and divide our sample into high and low volatility values based on the median of each year. Using this, we examine the responses of these two subsamples in Table 8. We find that high-volatility stocks react strongly to *PRisk*, while low-volatility stocks do not react at all to it. The one exception is the number of major customers used as the dependent variable (Model 2), where both types of firms show a reduction of around 4%.

In a similar spirit, we use the Altman Z-score to divide the sample into firms with high and low default risk. Note that Z-score is likely to be lower in recessions and higher in expansions, reflecting changes in the aggregate likelihood of default. Thus, we use the full distribution of Z-scores (rather than the annual values) to classify firms into high and low default firms. Panel A of Table 9 reports the results for low Z-score (high default risk) firms, and Panel B reports the results for high Z-score (low default risk) firms. We find that firms with higher default risk reduce their customer concentration, while those with lower default risk do not.

4.2 Long-standing major customer versus new major customer

Firms that have long-standing relationships with customers may have developed more firm-specific capital, either in the form of hard capital (e.g., fixed investment) or soft capital (e.g., ease of coordination or trust). Therefore, it might be costlier to diversify away from such customers, compared to those without long-term relationships. Thus, we expect that firms with

long-standing relationships with customers should respond less to changes in political risk.

To test this, we construct relationship duration by tracking a firm's transaction history for each of its major customers. Using this, we calculate the average duration of the relationship between a firm and its major customers. We partition the sample into two groups based on the median relationship duration, which in our sample is four years.

Table 10 presents the results. We find that the reduction in customer concentration in response to changes in political risk is statistically significant for firms with shorter relationship duration but not for firms with long-standing customer relationships. In fact, the impact is much larger, relative to the baseline. For example, a one standard deviation increase in political risk leads to a 3% reduction in the likelihood of a major customer, whereas this number was 1.3% in the baseline in Table 2. Likewise, the number of major customers reduces by 7.4% for the short-duration sample, whereas, in the baseline, this is 3.6%. The sales of the largest major customers decrease by 1.1% for the short-duration sample, which corresponds to a 4.4% reduction for the largest customer.[15]

4.3 Product differentiation

Firms with more differentiated products in the market should be less concerned about the customer base, due to their greater bargaining power in the product markets. Thus, for these firms, a large customer should not represent a concentration risk, as the customers cannot easily replace the supplier's products. This also relates to the notion of the specificity of a firm's inputs to its customers, as defined by Barraot and Sauvagnot (2016). However, note that input specificity may arise on account of relationship-specific investment by a supplier tailoring an input for the customer. On the other hand, product differentiation relates to fewer alternatives available for a firm's products, regardless of any relationship-specific investments. Thus, we expect a firm with more differentiated products to respond less to changes in its own political

[15] Model 1 of Table 9 Panel A cannot be estimated, as there is no observation where a firm with a long-standing relationship drops all major customers. With firm fixed effects, the model requires at least one firm in the subsample to drop all major customers.

risk in terms of customer concentration.

An alternative interpretation of product differentiation is that it inversely relates to a firm's product market risk. In this case, a firm with more differentiated products is less risky, and therefore, similar to the arguments made in Section 4.1 on total and default risk, we should expect firms with more differentiated products to respond less to changes in political risk.

We obtain the differentiation of product offerings between two firms based on the TNIC3 similarity score, defined by Hoberg and Phillips (2016) from the Hoberg Phillips data library. They define a product similarity score, a real number in the interval [0,1], which describes the similarity of a firm's product offering to those of other firms. A higher score indicates that the firm more resembles its peers in the product market, which implies more competition. The firm-by-firm pairwise similarity scores are calculated by forming word vectors for each firm to compute continuous measures of product similarity.

We define a firm's similarity score as the average of the top five similarity scores that a firm has with all other firms in Compustat. A firm with unique products will have a lower similarity score even with its closest competitors. As we seek to find firms with more differentiated products and consequently greater product market power, we define uniqueness as (1 – firm similarity score). We sort the firms into quartiles based on their scores from low to high. We create a rank variable, Rank(unique), which equals 1 for firms with the lowest uniqueness score (highest similarity score) and 4 for firms with the highest uniqueness score (lowest similarity score). We further interact this rank variable with the political risk measure to capture the marginal effect of product differentiation on the effect of political risk on customer concentration.

Table 11 presents the results of adding the rank and its interaction with *PRisk* to the baseline model. The interaction is positively significant for five out of the six models, suggesting that firms with more differentiated products respond less to the political risk in their customer concentration. This confirms our intuition that lower operational risk in terms of product markets makes firms respond less to political risk in terms of changes in customer concentration.

4.4 Political risk effect on sales and expenses

So far we have focused exclusively on the impact of increased political risk on a firm's choices of customer concentration. In this last subsection prior to the robustness tests, we examine the impact on sales growth and selling expenses. To the extent that firms diversify away from a major customer, this implies that they should seek out new customers, which should increase their SG&A expenses. Using SG&A normalized by sales, we find that *PRisk* increases expenses (Panel A of Table 12), suggesting that firms incur costs of diversifying away from their large customers. The magnitude of the coefficient is large—a one standard deviation increase in political risk results in a 3.6% increase in SG&A. In Panel B of Table 12, we also find that the increases in SG&A are larger for firms with more cash, and for firms with less leverage, suggesting that financial constraints can limit the extent to which firms can secure alternative customers as they try to reduce customer concentration.

5 Robustness Tests

5.1 Government customers

First, we examine whether the effects we document are valid when we examine firms with major government customers. Cohen and Li (2020) suggest that government customers have unique characteristics that make them different from major corporate customers. In particular, they argue that firms with major customers have lower demand uncertainty, more stable customer relationships, and less product market competition. Motivated by this, we recompute our measures of concentration using only sales to government entities as the concentration measure. The results, presented in Panel A of Table 13, show that there is no response to an increase in political risk on customer concentration measured using only government customers. Thus, we provide further evidence of the uniqueness of major government customers, as these customers do not contribute to increased operational risk.

5.2 Industry median customer values

We lose some observations due to the requirement that data for political risk and political sentiment for customer firms be available. As an augmented sample, we replace all missing values of customer risk and customer sentiment with median industry values and re-estimate the regression. We continue to find highly significant results for the five of six models in Panel B of Table 13. However, a counterintuitive finding for this sample is that customer political risk has a positive effect on customer concentration—an artifact perhaps of using median industry values rather than actual values.

5.3 Industry-year fixed effects

Some papers on customer concentration have used industry-year fixed effects as opposed to firm-fixed effects—partly because there is less variation in firm-level customer concentration (Dhaliwal, Judd, Serfling, and Shaikh, 2016; Chen et al., 2021). Thus, using firm fixed effects is a more stringent test of the effect of customer concentration. To test this alternative, we replace firm fixed effects with industry-year fixed effects. We also drop customer political risk and sentiment variables as control variables to obtain a larger sample. Table 13 Panel C presents the results. For this sample, we find highly significant results for all six specifications. However, a drawback of this model is that its overall fit is much lower. For models 2 to 6, the R^2 in Table 13 Panel C ranges from 6.5% to 7.3%. In contrast, the corresponding models in the baseline in Table 2 have R^2 from 39.7% to 60.3%. Even model (1), where the two values are somewhat comparable, has an R^2 of 9.7% compared to 7.4% for industry-year fixed effects in Table 2. We continue to find highly significant results by adding both industry-year fixed effects and filling in missing customer political risk values in Panel D of Table 13.

5.4 Exclusion of trade risk

Political risk can arise on account of several factors. In addition to the total political risk measure, Hassan et al. (2019) also create training libraries for eight political topics: economic policy and budget, environment, trade, institutions and political process, healthcare, security

and defense, tax policy, and technology and infrastructure. One concern may be that recent headline-grabbing political events, such as Donald Trump's trade frictions with China as well as several other countries, may drive our results.

For example, during the earnings conference call for the first quarter of 2011 by Procter & Gamble, the CEO stated: "The risks moving forward is what happens with the state of government intervention around the world as it pertains to free trade." In this case, the trade risk could lead to the sudden termination of a major customer in some specific geographic area, so firms would be incentivized to diversify their customer base.

In Panel E of Table 13, we regress the total political risk measure on the sub-measure of Trade created by Hassan et al. (2019).[16] We use the residual from this regression as the measure of political risk unrelated to trade wars, i.e., *re_PRiskT_Trade*. We find that this residual continues to have an effect of a similar magnitude to the original Hassan et al. index, suggesting that trade wars per se are not the main driver of our results.

5.5 Effect of increasing sales as the larger denominator

If the increased political risk is somehow associated with higher sales to nonmajor customers in subsequent years, then the results we observe might be driven by a larger denominator, not by a conscious action by a firm to reduce its customer concentration but rather due to a higher growth in the market for small customers. If so, we should observe that *PRisk* in year *t* is positively associated with sales growth between years *t* and *t+1*. We examine this and do not find any significant effect, as reported in Panel F of Table 13. This implies that the reduction in major customer concentration is not due to an increase in its denominator, i.e., an increase in total sales.

6. Conclusion

Political risk affects firms' operations because of its role in driving business cycles and

[16] The total index is not a simple summation of the subindices, and thus one cannot subtract the trade index from the total index.

impeding economic recoveries (Baker et al., 2016). Survey evidence suggests that firms engage in active management of political risk and customer concentration is an important dimension of that can be impacted. However, academic evidence on this is sparse and we fill this important gap in the literature using a new measure of firm-specific political risk derived by Hassan et al. (2019). We find that firms reduce customer concentration when faced with increased political risk, which is consistent with the management of overall operational risk as well as customer concentration risk.

Past work in finance on supply chain risk has largely focused on propagation of credit risk. However, our work builds on the work by Chaorenwong, Han and Wu (2022) shows that political risk can also have supply chain effects. In contrast to their work, we show that these effects can manifest due to supplier actions whereas their work showed effects due to customer actions. Further, we show that domestic policy uncertainty can also have supply chain impact.

Our work adds to prior literature on operational risk where the focus is often on the substitution of financial versus operational risk (Allayanis, Ihrig and Weston (2001); Hoberg and Moon (2017)). We add to the nascent literature that demonstrates the interaction of different dimensions of operational risk such as Garfinkel and Hankins (2011) and Hamm, Jung, Lee and Yang (2022). Thus, our work implies that customer concentration is an important dimension that would need to be controlled for when evaluating other risk management functions.

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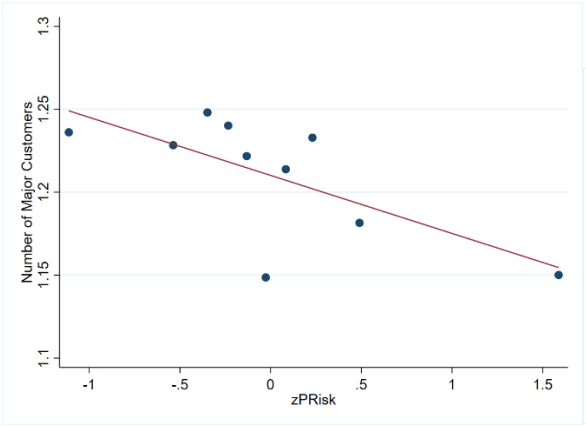
Appendix: Variable Definitions

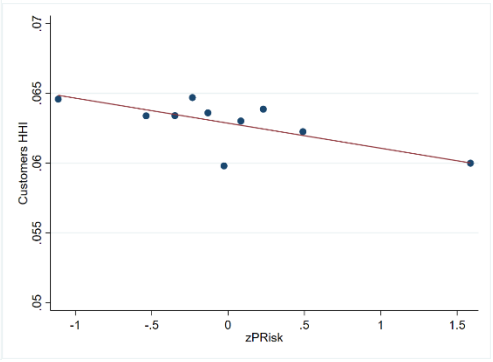
Variable	Description
Customer concentration measures	
Major Customer	An indicator variable is set to 1 if a firm has at least one corporate customer that accounts for at least 10% of its total sales, and 0 otherwise.
Number of Major Customers	The total number of a firm's major corporate customers.
Customer HHI	The customer sales-based Herfindahl-Hirschman Index is calculated by summing the squares of the ratios of major corporate customer sales to the supplier's total sales.
Total Major Customer Sales	The total fraction of a firm's total sales to all corporate customers account for at least 10% of total sales.
Average Major Customer Sales	The average fraction of a firm's total sales to all corporate customers account for at least 10% of total sales.
Largest Major Customer Sales	The largest fraction of a firm's total sales to all corporate customers account for at least 10% of total sales.
Firm-level political risk and sentiment measures	
PRisk	Standardized average of the quarterly values firm-level political risk as defined in HHLT for a given supplier and fiscal year.
PSentiment	Standardized average of the quarterly values of firm-level political sentiment as defined in HHLT for a given supplier and fiscal year.
Customer PRisk	For each supplier, the average of all of its major customers' Individual Customer PRisk for that year.
Customer PSentiment	For each supplier, the average of all of its major customer's Individual Customer PSentiment for that year.
Residual Political Risk of Suppliers	Residual from the regression of supplier's political risk on customers' political risk (and supplier's industry-level political risk and customers' industry-level political risk) and economic policy uncertainty.
re_PRiskT_Trade	Residual from the regression of total political risk on sub-measure of *Trade* political risk created by HHLT.
Other variables	
Asset (Log Asset)	Total Assets in $ million (Natural logarithm of one plus total assets in $ million)
Leverage	The sum of debt in current liabilities plus long-term debts divided by total assets.
Cash	Cash and short-term investments divided by total assets.
ROA	Earnings before interest and taxes divided by total assets.
Market to Book	Market to book value of assets.
PPE	Property, plant, and equipment divided by total assets.
Gross Margin	Net sales minus cost of goods sold divided by net sales.
ROA Volatility	The standard deviation of ROA over the two years.
Treat	An indicator variable is set to 1 if a firm changed its district because of the redistricting after the 2010 census, and 0 otherwise.
Post	An indicator variable is set to 1 after the congressional map enactment date, and 0 otherwise.
Treat – 2	An indicator variable is set to 1 in the year that is two years before the treatment and 0 otherwise.
Treat – 1	An indicator variable is set to 1 in the year that is one year before the treatment, and 0 otherwise.
Treat	An indicator variable is set to 1 in the treatment year, and 0 otherwise
Treat + 1	An indicator variable is set to 1 in the year that is one year after the treatment, and 0 otherwise.
Treat + 2	An indicator variable is set to 1 in the year that is two years after the treatment and 0 otherwise.
Major Supplier	An indicator variable is set to 1 if a firm is its supplier's major customer, and zero otherwise.

Number of Major Supplier	The number of major suppliers with which the customer interacts based on the definition of *Major Supplier*.
Supplier HHI	Supplier purchases-based Herfindahl-Hirschman Index calculated by summing the squares of the ratios of corporate supplier purchases to the supplier's total COGS for all suppliers that list the given firm as a major customer.
Total Major Supplier purchases	The total fraction of a firm's total purchases from all corporate suppliers that list the firm as a major customer.
Average Major Supplier purchases	The average fraction of a firm's total purchases from all corporate suppliers that list the firm as a major customer.
Largest Major Supplier purchases	The largest fraction of a firm's total purchases from all corporate suppliers that list the firm as a major customer
Stock Volatility	Annual stock price standard deviation.
AltmanZ	AltmanZ=1.2(working capital/total assets)+1.4(retained earnings/total assets)+3.3(EBIT/total assets)+0.6(market value of equity/total liabilities)+0.999(sales/total assets)
CASH_change	The change of cash divided by last year's cash.
LINKAGE	Duration of the relation between the supplier and customer.
Rank (unique)	A ranked variable based on the average of the product similarity (Hoberg and Phillips, 2016), which equals 1 if firms with the lowest uniqueness score and 4 if firms with the highest uniqueness score.
Rank(unique)	Ranked variable based on the average of the product similarity (Hoberg and Phillips, 2016), which equals 1 if firms with the lowest uniqueness score and 5 if firms with the highest uniqueness score.
Sales Growth	The change in sales divided by last year's sales.
SG&A	Selling, general, and administrative expenses divided by sales.
Cash Flow	Income before extraordinary items plus depreciation and amortization minus preferred and common dividends, scaled by total assets.

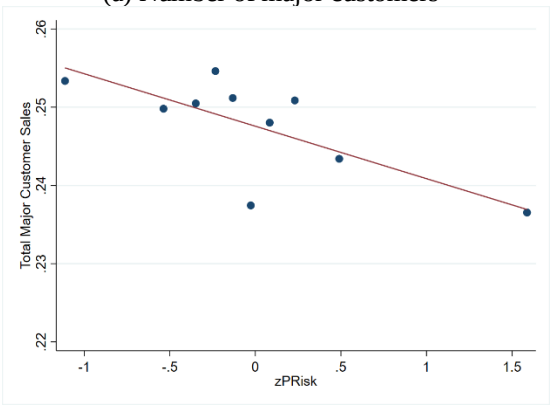
Figure 1
Customer Concentration and Political Risk



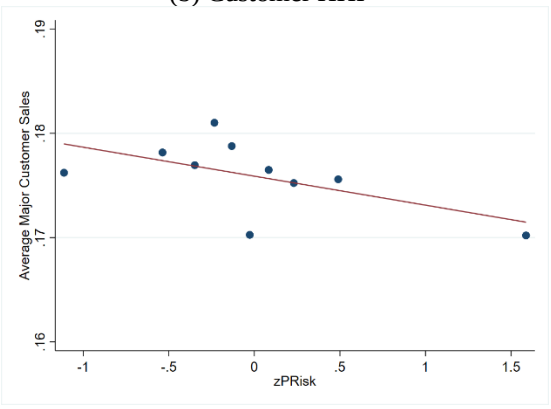
(a) Number of major customers



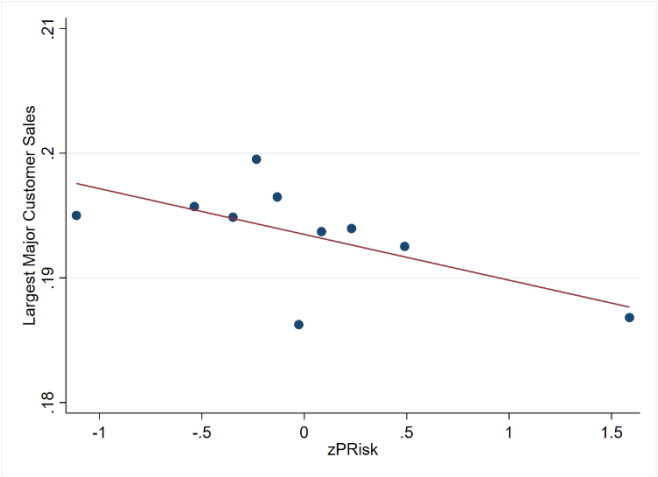
(b) Customer HHI



(c) Total major customer sales ratio



(d) Average major customer sales ratio



(e) Largest major customer sales

Table 1: Summary Statistics

This table reports summary statistics for the variables used in our baseline analysis. For each variable, we report the number of observations, mean, standard deviation, 25th percentile, median, and 75th percentile. Continuous variables are winsorized at their 1st and 99th percentiles. All variables are defined in Appendix.

	N	mean	Standard deviation	p25	Median	p75
Major Customer	6762	0.85	0.36	1.00	1.00	1.00
Number of Major Customers	6762	1.21	0.81	1.00	1.00	2.00
Customer HHI	6762	0.06	0.06	0.02	0.04	0.10
Total Major Customer Sales	6762	0.25	0.17	0.12	0.21	0.39
Average Major Customer Sales	6762	0.18	0.11	0.12	0.16	0.24
Largest Major Customer Sales	6762	0.19	0.12	0.12	0.17	0.27
PRisk	6762	-0.00	1.00	-0.61	-0.29	0.24
PSentiment	6762	-0.00	1.00	-0.63	-0.06	0.57
Customer PRisk	6762	-0.00	1.00	-0.60	-0.31	0.19
Customer PSentiment	6762	-0.00	1.00	-0.59	-0.06	0.52
Total Assets ($ million)	6757	4426	13632	223	823	3082
Leverage	6743	0.24	0.30	0.02	0.20	0.37
Cash	6757	0.24	0.23	0.05	0.16	0.37
ROA	6752	-0.05	0.34	-0.06	0.03	0.07
Market to Book	6753	1.55	1.61	0.64	1.11	1.85
PPE	6757	0.23	0.24	0.06	0.14	0.30
Gross Margin	6743	0.08	2.56	0.24	0.40	0.59
ROA Volatility	6752	0.10	0.30	0.02	0.04	0.10

Table 2: Focal Firms' Political Risk, Customers' Political Risk, and Customer Concentration

This table presents the effect of suppliers' firm-level political risk on customer concentration. The dependent variable in Column 1 is a major customer indicator, which takes the value of one if a firm has at least one customer that accounts for at least 10% of the firm's annual revenues and zeroes otherwise. The dependent variable in Column 2 is the number of major customers with which the supplier interacts. The dependent variable in Column 3 is the corporate customer sales-based Herfindahl-Hirschman Index. The dependent variables in Columns 4, 5, and 6 are the sum/average/largest of a firm's sales to all of its major customers divided by its total sales, respectively. The main independent variable is the standardized firm-level political risk (*PRisk*) as defined in HHLT. *PSentiment* is the standardized firm-level political risk sentiment as defined in HHLT. *Customer PRisk* and *Customer PSentiment* are the corresponding political risk for customers. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.013**	-0.036***	-0.002**	-0.007***	-0.003*	-0.004**
	(-2.143)	(-3.369)	(-2.195)	(-2.955)	(-1.893)	(-2.208)
PSentiment	-0.005	-0.001	0.000	-0.000	-0.001	-0.001
	(-0.758)	(-0.106)	(0.012)	(-0.004)	(-0.429)	(-0.380)
Customer PRisk	0.001	0.006	-0.000	-0.001	-0.001	-0.001
	(0.141)	(0.532)	(-0.549)	(-0.312)	(-0.819)	(-0.667)
Customer PSentiment	0.007	0.019	0.002**	0.006**	0.003	0.004*
	(0.892)	(1.362)	(2.157)	(2.107)	(1.561)	(1.916)
Log Asset	0.028**	0.056*	-0.002	0.002	-0.001	-0.002
	(2.095)	(1.811)	(-0.788)	(0.255)	(-0.246)	(-0.346)
Leverage	-0.104***	-0.183**	-0.018***	-0.057***	-0.036***	-0.041***
	(-2.731)	(-2.327)	(-2.657)	(-3.143)	(-2.991)	(-2.937)
Cash	-0.041	0.080	0.016*	0.040	0.016	0.026
	(-0.735)	(0.611)	(1.683)	(1.507)	(0.944)	(1.339)
ROA	0.003	0.015	-0.003	-0.005	-0.004	-0.005
	(0.141)	(0.375)	(-0.686)	(-0.381)	(-0.554)	(-0.514)
Market to Book	-0.002	0.013	-0.001	-0.001	-0.002	-0.002
	(-0.328)	(1.311)	(-0.890)	(-0.325)	(-1.179)	(-1.008)
PPE	-0.061	0.471*	0.023	0.083	0.007	0.020
	(-0.600)	(1.934)	(1.206)	(1.551)	(0.235)	(0.534)
Gross Margin	0.001	0.003	0.000	0.000	0.000	0.000
	(0.383)	(0.674)	(0.106)	(0.147)	(0.157)	(0.038)
ROA Volatility	0.033*	0.019	0.007**	0.019*	0.013**	0.014**
	(1.781)	(0.583)	(2.013)	(1.949)	(2.275)	(2.104)
Constant	0.712***	0.726***	0.071***	0.219***	0.187***	0.204***
	(7.041)	(3.107)	(3.767)	(4.266)	(5.849)	(5.459)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6762	6762	6762	6762	6762	6762
Adjusted R^2	0.097	0.416	0.603	0.511	0.397	0.457

Table 3: Redistricting as An Exogenous Shock to Political Risk

This table reports the coefficient estimates for difference-in-difference regression on customer concentration, with control firms located within 200 km of the treated firms, including customers' firm-level political risk. *Treat* is an indicator that takes on a value of 1 if a firm's Congressional representative changed as a result of congressional redistricting and 0 otherwise. *Post* indicates the three years following the redistricting, and is 0 in the three years prior. Detailed variable definitions are in the Appendix. The specification includes firm-year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
Post_Treat	-0.083*	-0.045	-0.009*	-0.027	-0.027**	-0.026*
	(-1.716)	(-0.566)	(-1.663)	(-1.502)	(-2.208)	(-1.899)
PSentiment	-0.013	-0.015	-0.001	-0.003	-0.003	-0.004
	(-1.011)	(-0.661)	(-0.815)	(-0.605)	(-1.093)	(-1.159)
Customer	0.004	-0.012	-0.001	-0.003	-0.001	-0.001
PRisk	(0.312)	(-0.544)	(-0.752)	(-0.722)	(-0.328)	(-0.423)
Customer	0.059***	0.079**	0.004*	0.015**	0.012***	0.013***
Psentiment	(3.354)	(2.578)	(1.855)	(2.462)	(2.943)	(2.921)
Log Asset	0.027	0.049	-0.005	-0.006	-0.009	-0.007
	(0.648)	(0.684)	(-0.985)	(-0.370)	(-0.828)	(-0.539)
Leverage	-0.295***	-0.312*	-0.054***	-0.143***	-0.113***	-0.132***
	(-3.193)	(-1.934)	(-3.810)	(-3.768)	(-4.468)	(-4.862)
Cash	-0.184	-0.058	0.011	0.002	-0.022	-0.004
	(-1.251)	(-0.226)	(0.618)	(0.043)	(-0.611)	(-0.113)
ROA	0.007	-0.024	-0.000	-0.002	0.001	-0.000
	(0.158)	(-0.335)	(-0.029)	(-0.092)	(0.085)	(-0.024)
Market to	0.008	0.007	-0.000	-0.001	0.002	0.001
Book	(0.915)	(0.492)	(-0.293)	(-0.268)	(0.880)	(0.408)
PPE	-0.093	-0.109	0.056	0.084	0.069	0.076
	(-0.426)	(-0.240)	(1.408)	(0.810)	(0.946)	(0.939)
Gross	-0.003	-0.007	-0.000	-0.002	-0.001	-0.001
Margin	(-0.453)	(-0.935)	(-0.342)	(-0.441)	(-0.396)	(-0.378)
ROA	-0.033	-0.131*	-0.002	-0.011	-0.010	-0.008
Volatility	(-0.664)	(-1.734)	(-0.239)	(-0.412)	(-0.555)	(-0.413)
Constant	0.818***	0.981*	0.093**	0.296***	0.251***	0.249***
	(2.878)	(1.875)	(2.485)	(2.770)	(3.301)	(2.977)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1635	1635	1635	1635	1635	1635
Adjusted R^2	0.137	0.494	0.672	0.589	0.489	0.538

Table 4
Parallel trend tests

This table reports the parallel trend of the DID test. The dependent variables in Columns (1) to (6) are measures of firms' customer concentration. *Treat – 2* is a dummy variable that takes a value of 1 in the year that is two years before the treatment and 0 otherwise. *Treat – 1* is a dummy variable that takes a value of 1 in the year that is one year before the treatment and 0 otherwise. *Treat* is a dummy variable that takes a value of 1 in the treatment year and 0 otherwise. *Treat + 1* is a dummy variable that takes a value of 1 in the year that is one year after the treatment and 0 otherwise. *Treat + 2* is a dummy variable that takes a value of 1 in the year that is two years after the treatment and 0 otherwise. Detailed variable definitions are in the Appendix. The specification includes firm-year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
Treat – 2	0.032	-0.019	-0.006	-0.017	-0.005	-0.010
	(0.502)	(-0.183)	(-1.008)	(-0.854)	(-0.349)	(-0.613)
Treat – 1	-0.004	0.045	-0.003	-0.012	-0.009	-0.009
	(-0.050)	(0.393)	(-0.462)	(-0.561)	(-0.609)	(-0.532)
Treat	-0.200**	-0.204	-0.022**	-0.076**	-0.059***	-0.061***
	(-2.264)	(-1.389)	(-2.230)	(-2.562)	(-3.048)	(-2.778)
Treat + 1	-0.045	0.045	-0.011	-0.026	-0.029	-0.027
	(-0.566)	(0.280)	(-1.061)	(-0.783)	(-1.468)	(-1.148)
Treat + 2	0.009	0.034	-0.008	-0.019	-0.017	-0.018
	(0.109)	(0.239)	(-0.867)	(-0.665)	(-0.889)	(-0.822)
Psentiment	-0.013	-0.015	-0.001	-0.003	-0.004	-0.004
	(-1.058)	(-0.667)	(-0.969)	(-0.746)	(-1.282)	(-1.338)
Customer	0.005	-0.012	-0.001	-0.003	-0.001	-0.001
PRisk	(0.407)	(-0.543)	(-0.731)	(-0.675)	(-0.249)	(-0.367)
Customer	0.060***	0.079**	0.004*	0.016**	0.012***	0.013***
Psentiment	(3.408)	(2.568)	(1.871)	(2.484)	(3.001)	(2.959)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1635	1635	1635	1635	1635	1635
Adjusted R^2	0.142	0.495	0.672	0.590	0.491	0.540

Table 5: Correlated supply chain risks

Panel A: Exclusion of Supplier Political Risk

This table presents the results of excluding supplier political risk. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
Customer PRisk	0.001	0.005	-0.000	-0.001	-0.001	-0.001
	(0.095)	(0.453)	(-0.593)	(-0.374)	(-0.853)	(-0.707)
Customer PSentiment	0.007	0.019	0.002**	0.006**	0.003	0.004*
	(0.874)	(1.367)	(2.145)	(2.099)	(1.539)	(1.891)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6762	6762	6762	6762	6762	6762
Adjusted R^2	0.096	0.415	0.602	0.510	0.397	0.456

Panel B: Residual Political Risk of Suppliers after adjusting for customer political risk

This table presents the estimates of *Residual Political Risk of Suppliers*, which is from the regression of the supplier's political risk on the customers' political risk and economic policy uncertainty. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
Residual Political Risk of Suppliers	-0.013**	-0.037***	-0.002**	-0.007***	-0.003*	-0.004**
	(-2.101)	(-3.377)	(-2.155)	(-2.922)	(-1.802)	(-2.135)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6762	6762	6762	6762	6762	6762
Adjusted R^2	0.097	0.416	0.603	0.511	0.397	0.457

Table 5 (continued)

Panel C: Residual Political Risk of Suppliers after adjusting for customer, supplier industry, and customer industry political risk

This table presents the estimates of the *Residual Political Risk of Suppliers*, which is from the regression of the supplier's political risk on the customers' political risk, supplier's industry-level political risk, customers' industry-level political risk, and economic policy uncertainty. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
Residual Political Risk of Suppliers	-0.012**	-0.035***	-0.002*	-0.006***	-0.002	-0.003*
	(-2.009)	(-3.275)	(-1.951)	(-2.721)	(-1.604)	(-1.924)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6688	6688	6688	6688	6688	6688
Adjusted R^2	0.097	0.418	0.604	0.515	0.398	0.458

Table 6: Customers' Purchase Concentration

This table presents the effect of suppliers' political risk on supplier concentration. The dependent variable in Column 1 is a major supplier indicator, which takes the value of one if a firm is its supplier's major customer and zeroes otherwise. The dependent variable in Column 2 is the number of major suppliers with which the customer interacts. The dependent variable in Column 3 is the corporate supplier purchases-based Herfindahl-Hirschman Index. The dependent variables in Columns 4, 5, and 6 are the sum/average/largest of a firm's sales to all of its major suppliers divided by its total cogs, respectively. The main independent variable is the standardized firm-level political risk (*PRisk*) as defined in HHLT. Suppliers' political risk, *Supplier PRisk*, is lagged and standard annual mean of *PRisk*. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Supplier	(2) Number of Major Supplier	(3) Supplier HHI	(4) Total Major Supplier purchases	(5) Average Major Supplier purchases	(6) Largest Major Supplier purchases
Supplier PRisk	-0.008	-0.038	-0.000	-0.000	-0.000	-0.000
	(-1.490)	(-1.118)	(-0.426)	(-0.510)	(-1.451)	(-0.767)
Supplier PSentiment	-0.008	0.033	-0.000	-0.001	-0.000	-0.001
	(-1.270)	(0.910)	(-1.215)	(-1.202)	(-1.619)	(-1.440)
Log Asset	0.053***	1.746***	0.000	0.006**	-0.001	0.001
	(3.067)	(5.284)	(0.608)	(2.172)	(-1.107)	(0.835)
Leverage	0.033	-0.106	-0.001*	-0.015*	-0.004	-0.009
	(0.624)	(-0.192)	(-1.865)	(-1.921)	(-1.237)	(-1.637)
Cash	-0.064	-0.427	0.001	0.009	0.002	0.007
	(-0.836)	(-0.376)	(0.780)	(0.632)	(0.501)	(0.845)
ROA	0.091	-0.164	-0.000	-0.000	0.001	0.000
	(1.213)	(-0.217)	(-0.249)	(-0.030)	(0.203)	(0.008)
Market to Book	0.006	0.227**	0.000	0.000	-0.000	-0.000
	(0.617)	(2.467)	(0.378)	(0.360)	(-1.009)	(-0.067)
PPE	0.053	3.588**	0.001	0.017	0.003	0.009
	(0.511)	(2.248)	(1.132)	(1.198)	(0.603)	(1.066)
Gross Margin	0.028***	0.064**	0.000	0.001*	0.001*	0.001*
	(5.237)	(2.353)	(1.273)	(1.691)	(1.813)	(1.852)
ROA Volatility	0.075	1.861*	0.001	0.014	0.001	0.009
	(0.730)	(1.660)	(0.362)	(0.436)	(0.095)	(0.393)
Constant	0.389**	-12.723***	0.001	-0.020	0.026**	0.010
	(2.259)	(-3.972)	(0.376)	(-0.729)	(2.401)	(0.586)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4894	4894	4894	4894	4894	4894
Adjusted R^2	0.207	0.910	0.594	0.645	0.618	0.601

Table 7: Relative bargaining Power of Suppliers versus Customer

This table presents the effect of the relative profit margin of the supplier to the customer on the main results. Panel A presents the result of samples with higher relative profit margins compared to their customers, and Panel B presents that of samples with lower ones. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Higher Relative Profit Margin of the Supplier to the Customer

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.023**	-0.056***	-0.004***	-0.013***	-0.007***	-0.008***
	(-2.364)	(-3.292)	(-2.888)	(-3.388)	(-2.802)	(-2.763)
PSentiment	-0.001	-0.000	0.001	0.002	0.001	0.001
	(-0.125)	(-0.025)	(0.798)	(0.617)	(0.394)	(0.434)
Customer	-0.002	0.017	0.001	0.004	0.001	0.002
PRisk	(-0.245)	(0.910)	(1.328)	(1.308)	(0.369)	(0.682)
Customer	0.004	0.022	0.002	0.006	0.003	0.004
PSentiment	(0.330)	(0.971)	(1.164)	(1.440)	(0.937)	(1.046)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3119	3119	3119	3119	3119	3119
Adjusted R^2	0.110	0.400	0.602	0.494	0.392	0.450

Panel B: Lower Relative Profit Margin of the Supplier to the Customer

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.004	-0.014	-0.000	-0.002	-0.000	-0.001
	(-0.458)	(-0.911)	(-0.288)	(-0.595)	(-0.145)	(-0.399)
PSentiment	-0.004	0.018	-0.001	0.000	-0.002	-0.002
	(-0.447)	(1.013)	(-0.541)	(0.127)	(-0.984)	(-0.845)
Customer	0.010	0.005	-0.002	-0.003	-0.002	-0.002
PRisk	(1.098)	(0.288)	(-1.167)	(-0.895)	(-0.694)	(-0.685)
Customer	0.009	-0.008	0.002	0.002	0.003	0.004
PSentiment	(0.792)	(-0.410)	(1.030)	(0.413)	(1.107)	(1.321)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3119	3119	3119	3119	3119	3119
Adjusted R^2	0.087	0.434	0.621	0.534	0.428	0.486

Table 8: Cross-sectional Analysis: Stock Volatility

This table presents the results of our cross-sectional analyses based on the stock volatility subsamples. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Higher Stock Volatility

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.013	-0.044***	-0.003**	-0.010***	-0.004*	-0.006**
	(-1.522)	(-2.962)	(-2.346)	(-2.812)	(-1.826)	(-2.135)
PSentiment	-0.008	-0.005	0.000	0.001	-0.001	-0.001
	(-0.809)	(-0.236)	(0.133)	(0.257)	(-0.214)	(-0.233)
Customer PRisk	-0.002	-0.006	-0.001	-0.002	-0.003	-0.003
	(-0.209)	(-0.312)	(-0.937)	(-0.598)	(-1.135)	(-1.033)
Customer PSentiment	0.016	0.033	0.002	0.006	0.003	0.004
	(1.103)	(1.257)	(0.936)	(1.033)	(0.672)	(0.966)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3050	3050	3050	3050	3050	3050
Adjusted R^2	0.101	0.398	0.545	0.457	0.351	0.410

Panel B: Lower Stock Volatility

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.012	-0.043**	-0.001	-0.005	-0.001	-0.001
	(-1.246)	(-2.269)	(-0.618)	(-1.496)	(-0.456)	(-0.608)
PSentiment	-0.003	0.003	-0.001	-0.002	-0.002	-0.002
	(-0.276)	(0.195)	(-0.587)	(-0.548)	(-0.684)	(-0.720)
Customer PRisk	0.002	0.013	0.000	0.001	-0.000	-0.000
	(0.202)	(0.862)	(0.170)	(0.244)	(-0.043)	(-0.001)
Customer PSentiment	0.000	-0.002	0.002*	0.005	0.004	0.004
	(0.046)	(-0.135)	(1.834)	(1.338)	(1.585)	(1.555)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3058	3058	3058	3058	3058	3058
Adjusted R^2	0.105	0.470	0.665	0.573	0.443	0.504

Table 9: Cross-sectional Analysis: Default Risk

This table presents the results of our cross-sectional analyses based on the default risk subsamples. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Higher Default Risk

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.016*	-0.041**	-0.002*	-0.008**	-0.004*	-0.005*
	(-1.814)	(-2.522)	(-1.859)	(-2.216)	(-1.756)	(-1.801)
PSentiment	-0.001	0.002	0.000	0.001	-0.000	-0.000
	(-0.062)	(0.125)	(0.034)	(0.277)	(-0.115)	(-0.086)
Customer PRisk	-0.009	-0.004	-0.001	-0.004	-0.004	-0.004
	(-1.036)	(-0.259)	(-1.266)	(-1.145)	(-1.624)	(-1.461)
Customer PSentiment	0.007	0.020	0.002	0.007	0.002	0.004
	(0.584)	(0.994)	(1.592)	(1.497)	(0.836)	(1.189)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3170	3170	3170	3170	3170	3170
Adjusted R^2	0.116	0.414	0.600	0.507	0.396	0.456

Panel B: Lower Default Risk

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.006	-0.017	-0.001	-0.005	-0.002	-0.003
	(-0.643)	(-1.057)	(-1.220)	(-1.586)	(-0.872)	(-1.157)
PSentiment	-0.003	-0.006	-0.001	-0.002	-0.001	-0.001
	(-0.277)	(-0.318)	(-0.526)	(-0.428)	(-0.494)	(-0.514)
Customer PRisk	0.012	0.008	0.000	0.001	0.001	0.001
	(1.201)	(0.482)	(0.325)	(0.405)	(0.556)	(0.468)
Customer PSentiment	0.004	0.017	0.001	0.003	0.001	0.001
	(0.338)	(0.867)	(0.383)	(0.813)	(0.360)	(0.402)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3158	3158	3158	3158	3158	3158
Adjusted R^2	0.082	0.452	0.639	0.550	0.423	0.486

Table 10: Duration of Customer-supplier Relationship

This table presents the results of our cross-sectional analyses based on the long-duration subsample (*LINKAGE* larger than 4). All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Longer Duration

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	na	-0.007	-0.001	-0.002	-0.001	-0.001
	(na)	(-0.741)	(-1.005)	(-1.014)	(-0.471)	(-0.819)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3644	3644	3644	3644	3644	3644
Adjusted R^2	.	0.605	0.775	0.741	0.716	0.757

Panel B: Shorter Duration

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.030**	-0.074***	-0.002	-0.011***	-0.005*	-0.006**
	(-2.433)	(-3.970)	(-1.622)	(-2.711)	(-1.880)	(-2.029)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2740	2740	2740	2740	2740	2740
Adjusted R^2	0.082	0.307	0.485	0.386	0.294	0.342

Table 11: Uniqueness of Firms' Products

This table presents the results of our cross-sectional analyses of the uniqueness of firms' products. *Rank (unique)* is a ranked variable based on the average of the product similarity (Hoberg and Phillips, 2016), which equals 1 if firms with the lowest uniqueness score and 4 if firms with the highest uniqueness score. *PRisk*Rank(unique)* is the interaction of *PRisk* and *Rank (unique)*. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.038**	-0.056**	-0.005***	-0.017***	-0.011***	-0.012***
	(-2.578)	(-2.296)	(-3.195)	(-3.372)	(-3.105)	(-3.254)
Rank(unique)	0.002	-0.009	-0.000	0.000	0.001	0.001
	(0.276)	(-0.704)	(-0.147)	(0.099)	(0.608)	(0.347)
*PRisk*Rank(unique)*	0.010**	0.008	0.001**	0.004**	0.003***	0.003***
	(2.000)	(0.953)	(2.400)	(2.354)	(2.703)	(2.671)
PSentiment	-0.005	-0.002	-0.000	-0.000	-0.001	-0.001
	(-0.782)	(-0.132)	(-0.020)	(-0.032)	(-0.452)	(-0.408)
Customer PRisk	0.001	0.006	-0.000	-0.001	-0.001	-0.001
	(0.104)	(0.529)	(-0.579)	(-0.347)	(-0.865)	(-0.709)
Customer PSentiment	0.007	0.019	0.002**	0.006**	0.003	0.004*
	(0.913)	(1.382)	(2.188)	(2.132)	(1.585)	(1.944)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6762	6762	6762	6762	6762	6762
Adjusted R^2	0.097	0.416	0.603	0.512	0.398	0.458

Table 12: Selling and General Administration Expenses

Panel A

This table presents the effect of suppliers' firm-level political risk on SG&A expenses. The dependent variable is SG&A expenses, calculated as selling, general, and administrative expenses divided by sales. All other variables are defined in Appendix. All specifications include firm controls and firm and year fixed effects. Panel B also includes Psentiment, Customer PRisk and Customer Psentiment as additional controls that are not reported. All these controls are insignificant for all models as is the case with Panel A. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) SG&A
PRisk	0.039**
	(2.158)
PSentiment	-0.015
	(-1.063)
Customer PRisk	-0.010
	(-0.923)
Customer PSentiment	-0.008
	(-0.700)
Firm_FE	Yes
Firm Controls	Yes
Year_FE	Yes
N	6762
Adjusted R^2	0.544

Panel B

	Cash		Leverage	
	High	Low	Low	High
PRisk	0.061*	0.011	0.055*	0.011
	(1.769)	(0.631)	(1.729)	(0.631)
Firm_FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes
N	3257	3272	3276	3272
Adjusted R2	0.544	0.452	0.567	0.452

Table 13: Robustness

Panel A: Major government customers

This table presents the effect of suppliers' firm-level political risk on customer concentration. The dependent variables are customer concentration measures defined in Table 2 while using only sales to the US Government to compute the measures. The main independent variable is the standardized firm-level political risk (*PRisk*) as defined in HHLT. *PSentiment* is the standardized firm-level political risk sentiment as defined in HHLT. All other variables are defined in Appendix. All specifications include firm and year fixed effects. Continuous variables are winsorized at their 1st and 99th percentiles. Standard errors are corrected for heteroskedasticity and clustering at the firm level (t-statistics are in parentheses). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Major Government Customer Number	(3) Total Major Government Customer Sales
PRisk	0.003	-0.000
	(0.851)	(-0.073)
PSentiment	-0.001	-0.001
	(-0.309)	(-0.519)
Firm_FE	Yes	Yes
Firm Controls	Yes	Yes
Year_FE	Yes	Yes
N	6762	6762
Adjusted R^2	0.757	0.737

Panel B: Industry median customer values

This table presents the baseline results with the missing Customer *PRisk* and *Customer PSentiment* replaced with the industry-level median values.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.003*	-0.006**	-0.000*	-0.001**	-0.001	-0.001*
	(-1.648)	(-2.565)	(-1.733)	(-2.195)	(-1.484)	(-1.672)
PSentiment	-0.002	-0.002	0.000	0.000	-0.000	-0.000
	(-0.934)	(-0.779)	(0.560)	(0.087)	(-0.119)	(-0.093)
Customer PRisk	0.013***	0.017***	0.001***	0.003***	0.002***	0.002***
	(5.302)	(4.717)	(2.644)	(3.921)	(4.072)	(3.969)
Customer PSentiment	0.003	0.008*	0.000	0.002*	0.001	0.001
	(0.860)	(1.785)	(1.396)	(1.714)	(1.083)	(1.285)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	40070	40070	40070	40070	40070	40070
Adjusted R^2	0.632	0.650	0.656	0.679	0.657	0.669

Table 13 (continued)

Panel C: Industry-year fixed effects

This table presents the baseline results without *Customer PRisk* and *Customer PSentiment* and includes the Industry-Year fixed effect.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.012***	-0.018***	-0.001***	-0.003***	-0.002***	-0.003***
	(-4.762)	(-4.854)	(-2.930)	(-3.931)	(-4.052)	(-4.040)
Ind_Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	44179	44179	44179	44179	44179	44179
Adjusted R^2	0.074	0.065	0.065	0.073	0.071	0.072

Panel D: Industry-year fixed effects and Industry Median Customer Values

This table presents the Panel B results with the Industry-Year fixed effect.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
PRisk	-0.014***	-0.020***	-0.001***	-0.004***	-0.003***	-0.003***
	(-5.353)	(-5.355)	(-3.364)	(-4.451)	(-4.607)	(-4.591)
Ind_Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	40061	40061	40061	40061	40061	40061
Adjusted R^2	0.094	0.079	0.082	0.092	0.093	0.093

Panel E: Exclusion of Trade Risk

This table presents the baseline results using the residual measure of political risk which is unrelated to trade wars, *re_PRiskT_Trade*.

	(1) Major Customer	(2) Number of Major Customers	(3) Customer HHI	(4) Total Major Customer Sales	(5) Average Major Customer Sales	(6) Largest Major Customer Sales
re_PRiskT_Trade	-0.012**	-0.035***	-0.002**	-0.007***	-0.003*	-0.004**
	(-2.047)	(-3.117)	(-2.213)	(-2.881)	(-1.792)	(-2.138)
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6762	6762	6762	6762	6762	6762
Adjusted R2	0.097	0.416	0.603	0.511	0.397	0.457

Table 13 (continued)

Panel F: Sales Growth Effect

This table presents the effect of suppliers' firm-level political risk on sales growth. The dependent variables are *SalesGrowth*, calculated as the change in sales divided by last year's sales.

	(1) SALESGROWTH
PRisk	0.014
	(1.376)
PSentiment	0.017
	(1.471)
Customer PRisk	-0.001
	(-0.080)
Customer PSentiment	0.003
	(0.296)
Firm_FE	Yes
Firm_Controls	Yes
Year_FE	Yes
N	6750
Adjusted R2	0.269