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ABSTRACT

Using data involving customer-supplier relationships and a large sample of U.S. publicly listed firms, our study documents a negative and statistically significant relationship between economic-policy uncertainty and firms' customer-base concentration. The negative relation is predominant in firms with higher inventory efficiency and those operating in competitive, high-R&D, and nondurable industries. Customer-base diversification is further shown to enhance firm performance during periods of increasing policy uncertainty, but not when policy uncertainty decreases. Overall, our evidence suggests that firms respond to increasing policy uncertainty by diversifying their customer base and such behavior contributes positively to firm performance.

***Keywords*:** Customer-base concentration; Economic policy uncertainty; Firm performance; Customer-supplier relationships; Customer-base diversification.

1. Introduction

In product markets, firms depend on customers for revenue and often face an uncertain business environment while making significant investment in customer-supplier relationships. While prior studies have shown that size of the customer base and distribution of revenue are critical factors that drive firm performance (e.g., Patatoukas 2012, Irvine et al. 2016), the relation between customer concentration and firm performance remains unclear. Some studies suggest that firms deriving their revenue from a handful of customers are more profitable due to greater operational efficiency (e.g., Patatoukas 2012); however, others suggest that a diversified customer base is conducive to improved firm performance for firms in early stages of customer-supplier relationships, which thus have limited resources and high operating risk (Irvine et al. 2016, Saboo et al. 2017, Dhaliwal et al. 2016). Apart from firm-specific uncertainties such as those relating to supply-chain relationships, corporate decisions are subject to uncertainties in the economic environment that are driven by the timing, content, and impact of policy decisions (Gulen and Ion 2016). This study sheds light on an important question for corporate managers: When anticipating changes in economic policies, should they expand customer bases or rather focus on strengthening their relationships with existing customers?

Policy uncertainty has been one of the most widely discussed concerns among policymakers and economists over recent decades and its role in driving business cycles and impeding economic recovery has been well documented (Baker et al. 2016, Bloom et al. 2007). For instance, it was estimated that a spike in policy uncertainty following the financial crisis in 2008 resulted in a three-percent drop in GDP, accounting for one third of the total nine-percent drop (Bloom 2014). The media reported that policy uncertainty has made businesses reluctant to invest and hire. Without policy uncertainty, the labor market would have added one million jobs from 2011 to 2013.[1] At the firm level, policy uncertainty is shown to significantly reduce firms' capital investment (Gulen and Ion 2016) and M&A activities (Bonaime et al. 2018, Nguyen and Phan

[1] *Wall Street Journal*, Trying to calculate the cost of uncertainty, December 5, 2012, and Uncertainty is the enemy of recovery, April 28, 2013.

2017), and to increase managerial risk aversion (Panousi and Papanikolaou 2012). Despite this growing body of literature, the impact of policy uncertainty on how firms manage their revenue sources (i.e., their customer base) has yet to be explored. To fill this gap, our paper examines whether and how firms adjust their customer-portfolio choices following changes in policy uncertainty and whether such behavior has any significant performance implications.

Although reallocating revenue sources and developing new customer relationships are often costly and require significant resources (e.g., marketing, R&D, reallocation and investment of production capacity) as customer firms often have specific needs, diversifying the customer base can bring substantial benefits to a firm. The seminal portfolio-selection theory suggests that deriving revenues from diversified sources can decrease overall risk for the firm (Markowitz 1952). In the context of customer portfolios, serving a diversified base of customers exposes the firm less to the idiosyncratic risks of individual customer firms and reduces cash-flow volatility and vulnerability (Saboo et al. 2017, Dhaliwal et al. 2016, Srivastava et al. 1998). Furthermore, the power-dependence theory suggests that firms with a more diversified customer base have greater bargaining power vis-à-vis customer firms and, thus, are less susceptible to their power influence (Emerson 1962, Heide and John 1988).[2] In particular, when anticipating unstable economic policies, large customer firms that recognize their strong bargaining power may mitigate and pass risks upstream by requesting lower wholesale prices, demanding more lenient trade credits, forcing suppliers to hold more inventory, and offering less R&D support (Galbraith 1952).[3] Therefore, we argue that the benefits of customer-base diversification outweigh its costs during periods of increasing policy uncertainty.[4]

[2] For example, Wal-Mart is able to gain cost competitive advantage by securing low prices from its suppliers because many of the latter sell a large portion of their output to Wal-Mart, which results in strong dependencies on their relationship (Crook and Combs 2007).

[3] According to relational contract theory, supply-chain partners can engage in renegotiation over contract terms when the need arises (Baker et al. 2002, Klein et al. 1978). In the automotive industry, for example, large automakers facing a spending cut requested their suppliers to lower their prices by 2 to 3 percent (*Boston Consulting Group*, Auto Suppliers Face a Growing Financial Squeeze As Automakers Demand Both Deep Cost Cuts and Local Production, March 3, 2015).

[4] Some recent evidence suggests a positive impact of policy uncertainty on R&D (Atanassov et al. 2019, Bloom 2014).

Consequently, we hypothesize that policy uncertainty is negatively associated with firms' customer-base concentration.

To test this relationship, we measure policy uncertainty by an index (Baker-Bloom-Davis [BBD]) developed by Baker et al. (2016). The BBD index is constructed as the weighted average of four components of policy uncertainty: 1) uncertainty captured by news coverage; 2) uncertainty about future changes in federal tax policies; 3) and 4) the degree of forecasters' disagreement about future monetary and fiscal policies. Based on firms' disclosure of major customers on 10-K reports, we construct three measures of customer concentration, including a dummy for having at least one major customer, the proportion of sales made to all major customers, and a Herfindahl-Hirschman Index of customer concentration.

Based on a sample of 13,816 publicly listed firms in the U.S. over the period from 1986 to 2017, we document a negative and statistically significant relationship between economic policy uncertainty and our three measures of customer-base concentration, after controlling for various firm characteristics, macroeconomic variables, and firm and decade fixed effects. In terms of economic magnitude, a one-standard-deviation increase in policy uncertainty reduces the proportion of sales to major customer(s) by 0.31 percentage points (the HHI customer-concentration measure by 0.12 percentage points), which is equivalent to a reduction in sales of $5.81 million, given the sample-average firm sales of $1,877 million.

Our results show that firms mitigate risks through diversifying customer base when facing heightened uncertainty. Conversely, results may also suggest that firms invest in fostering stable, long-term trading relationships with major customers when uncertainty decreases. To further test these results, we examine whether the effects of increasing and decreasing policy uncertainty on customer-base concentration are asymmetric. Results from change-on-change regressions not only corroborate our baseline findings, but further show that the negative effect of policy uncertainty is large and only significant during periods when annual changes in policy uncertainty are positive (i.e., periods of increasing uncertainty); such an effect is small and insignificant during periods of decreasing uncertainty. The evidence is consistent with behavioral-economics theories positing that people often place a greater weight on downside losses relative to upside gains in their utility functions (Gul 1991, Kahneman and Tversky 1979).

A concern with our estimation is that omitted variables may codetermine policy uncertainty and customer-base concentration. To address this endogeneity concern, we adopt an instrumental variable (IV) approach and use the degree of political disagreement in the U.S., as captured by the news-based Partisan Conflict Index developed by Azzimonti (2018), to extract any plausibly exogenous variation in policy uncertainty to identify the relationship in question. The Partisan Conflict Index has been shown to measure political polarization well and to be uncorrelated with the state of the economy, making it an ideal instrumental variable in our analysis. Results from the IV estimation remain similar to our main findings.

Another concern is that the BBD index may capture general economic uncertainty unrelated to policy. To mitigate this concern, we exploit the fact that Canada and U.S. have strong economic ties and, hence, any general economic uncertainty affecting the U.S. likely also drives that of Canada. The variation in the BBD index due to general economic uncertainty is then removed by accounting for the Canadian BBD index explicitly in the model. Our results hold; measurement errors are unlikely to drive our results.

To strengthen a causal interpretation, we perform difference-in-differences tests that exploit an alternative, plausibly exogenous source of variation in policy uncertainty provided by the staggered U.S. state gubernatorial elections. State gubernatorial elections occur every four years according to laws; different state elections occur in different years. Due to their prescheduled and staggered nature, state elections represent exogenous events independent of general economic conditions that raise policy uncertainty for firms experiencing the elections relative to others in states without an election. Our tests confirm that firms in election years significantly diversify their customer base relative to those in non-election years – the impact of policy uncertainty appears causal.

To elucidate the mechanisms through which policy uncertainty affects customer-base concentration, we examine whether the negative relation in question exhibits any cross-sectional heterogeneity. First, firms with higher capability, capacity, and investment in R&D and innovation activities can more readily acquire new customers and reallocate their revenues among different customers because of a greater ability to satisfy their specific needs. Accordingly, to the extent that firms respond to rising policy uncertainty by diversifying their customer portfolios, such strategies would be more viable and evident among firms operating in high-R&D industries. Our data support this conjecture.

Second, firms operating in durable-goods industries, such as those manufacturing automobiles and heavy equipment, typically produce more unique products than do their peers in nondurable-goods industries. Durable-goods firms often invest in relationship-specific assets that have little value beyond the relationship, implying that costs for such firms to switch to alternative partners are often very high (Crawford 1990). As such, durable-goods firms place a great value on maintaining long-term relationships and would be less likely to diversify their customer base in response to increasing policy uncertainty. Consistent with our prediction, the negative association in question is shown to be less pronounced for durable-goods than for nondurable-goods firms.

Third, prior studies have found that firms with higher inventory turnover are able to respond more quickly to demand shocks by adjusting order or production quantities (Kesavan et al. 2016). Inventory theory suggests that higher inventory turnover results mainly from lower setup costs and shorter lead times (Cachon and Terwiesch 2011). Consequently, firms with higher inventory turnover may reallocate production quantities among existing and new customers in a timelier and less costly fashion and, thus, would find a customer-base-diversification strategy more viable. Supporting our argument, the negative association between customer concentration and policy uncertainty is stronger among firms with higher inventory turnover.

Fourth, according to the resource-dependency theory (Pfeffer and Salancik 1978), firms operating in competitive industries tend to have weak bargaining power vis-à-vis customer firms because of the latter's relative ease in finding a qualified substitute to replace them. Such customers often have a wide scope and considerable power in pressuring upstream firms to lower prices by threatening to switch to alternative suppliers. Because of such power disparity, firms in competitive industries have a greater need to diversify their customer base when policy uncertainty surges. The findings support our conjecture that the negative relation between policy uncertainty and customer-base concentration is more pronounced for firms operating in competitive industries.

To highlight the timeliness of our findings, we perform an event analysis for three federal budget crises – the debt ceiling (late 2011), fiscal cliff (December 2012), and shutdown of federal government (October 2013). According to Hassan et al. (2019), since the three budget crises resulted primarily from politicians' inability in reaching consensus, the increased policy uncertainty was unlikely driven by general economic conditions, thus alleviating endogeneity concerns. Our tests document significant decreases in firms' customer concentration over the three-year period (2010-2013). Among the manufacturing firms, the declines in customer-base concentration are also significantly more pronounced for non-durable-goods than durable-goods firms. Evidence from the event analysis supports our hypothesis.

To glean more insights into firms' customer-diversification strategies in response to policy uncertainty, we decompose total sales to major-customer(s) into two components using a DuPont analysis: Supply-chain sales per major customer and the number of major customers per sales (in million dollar). We find that policy uncertainty reduces the former but not the latter, suggesting that firms spread their revenue streams without terminating their existing relationships with major customers.

A final question we examine is whether diversifying the customer base in times of increasing policy uncertainty has any significant performance implications. Results from our cross-sectional tests reveal a negative and significant relation of lagged customer concentration with firm operating and gross profitability and annual sales growth during periods of increasing policy uncertainty. Little evidence of a significant relation is documented during decreasing policy uncertainty. Yet, if well-performing firms have more scope in diversifying customer bases in response to increasing uncertainty, the results may be driven by reverse causality. Further tests show that lagged firm performance fails to explain customer concentration during both uncertainty states, thus ruling this concern out. Overall, customer-base diversity during periods of increasing policy uncertainty contributes positively to firm operating and sales performance.

Our research contributes to the literature in three ways. First, studying the effect of policy uncertainty on customer concentration adds to a growing stream of finance literature examining the effect of policy uncertainty on corporate decisions. Customer concentration is an important corporate decision in the product market. Prior studies have found that policy uncertainty is damaging for short-run investment and hiring (Gulen and Ion 2016, Bonaime et al. 2018, Nguyen and Phan 2017), but some evidence also suggests that it may stimulate innovation (Atanassov et al. 2019, Bloom 2014). Our findings suggest that policy uncertainty serves as a driving force for firms to seek opportunities outside existing customer-supplier relationships and expand customer portfolios.

Second, our findings that suggest a positive association between customer concentration and firm performance when anticipating unstable economic policy contribute to a stream of accounting literature examining the link between customer concentration and firm performance. Following recent accounting studies by Patatoukas (2012) and Irvine et al. (2016), we use a sales-weighted Herfindahl-Hirschman index across major customers as a construct measuring the relative importance of each major customer in a customer portfolio. We further construct two alternative measures of customer concentration following Banerjee et al. (2008) and Dhaliwal et al. (2016). Patatoukas (2012) argues that a higher degree of customer concentration improves firm efficiency, resulting in a positive relationship between customer concentration and supplier-firm performance.[5] Irvine et al. (2016) and Dhaliwal et al. (2016), however, document a positive relation between customer concentration and supplier-firm risk, which results in a negative effect on firm performance in the early stages of customer-supplier relationships or a positive effect on cost of equity, especially for firms that are more likely to lose major customers. Supplier risk also explains a

[5] Supporting this finding, prior studies in marketing literature have argued that a concentrated customer base can help firms improve firm performance by reducing transaction costs and increasing productivity (Saboo et al. 2017), and by reducing discretionary expenses such as advertising and selling, general, and administrative expenses (Kalwani and Narayandas 1995).

negative relation between customer-base concentration and firm profitability for IPO firms (Saboo et al. 2017). Adding to this stream of literature, we document a contingency role of economic-policy uncertainty. Understanding this contingency role can help firms allocate their organizational resources more efficiently in an unstable economic environment.

Third, our study contributes to a stream of operations-management literature suggesting that a concentrated customer base benefits the firm by increasing inventory efficiency (e.g., Ak and Patatoukas 2016). We argue that a diversified customer base has the benefit of improving firms' bargaining power and, hence, may improve firm profitability in an unstable economic environment, which is consistent with prior studies showing that a concentrated customer base results in a disadvantageous position in negotiating contract terms (e.g., Crook and Combs 2007). In line with the resource-based view, we argue that large customers demand more suppliers' organizational resources, which makes the latter lose growth opportunities outside their existing relationships (Christensen and Bower 1996, Hitt et al. 2016). Such opportunity costs are even higher in periods of unstable economic policies, since large customers are more likely to appropriate value from their relationships with dependent suppliers by pressuring the latter to lower their prices. Finally, another stream of studies has examined performance differences between firms with high and low inventory turnovers (e.g., Alan et al. 2014, Chen et al. 2007, Gaur et al. 2005). In particular, Kesavan et al. (2016) find that firms with higher inventory turnovers can better manage product-market uncertainty by responding to demand shocks more quickly. We add to this stream of studies by examining policy uncertainty and demonstrating that firms with higher inventory turnover can more easily diversify their customer base when policy uncertainty increases.

The rest of the paper is structured as follows. We explain our data, sample formation, and variables in Section 2, present empirical results in Section 3, and conclude the paper in Section 4.

2. Data, sample selection, and variable construction

2.1 Data sources

We construct our sample using various databases. Our sample selection begins with all publicly listed US companies in the Compustat-CRSP merged database. To identify companies with at least one major customer and to estimate the degree of customer concentration for each sample firm, we rely on the customer-supplier relationship data that are compiled by Cen et al. (2017) using the Compustat Segments Customer File.[6] From 1975 onward, pursuant to Financial Accounting Standard No. 14 (before 1997) and No. 131 (after 1997), all publicly traded firms are required to disclose their major customers if the latter contribute 10 percent or more to the former's total revenue. Using such relationship data, we are able to identify whether a firm has any major customers as well as the amount of supply-chain transaction sales made by the firm to each of these major customers. To capture the degree of uncertainty in economic policies, we collect indexes of economic policy uncertainty from Baker et al. (2016) from 1986 onward.[7] All stock and accounting information are from CRSP and Compustat, respectively. Financial firms (SIC codes between 6,000 and 6,999) are excluded from the sample. After further excluding missing observations, our final sample consists of 13,816 firms (122,082) observations over the period from 1986 to 2017. In total, 4,986 firms have had at least one major customer at least once during the sample period. To reduce the effect of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

2.2 Measuring economic-policy uncertainty

We measure economic-policy uncertainty using an aggregate monthly index developed by Baker et al. (2016) (henceforth, referred to as the BBD index). The BBD index is constructed as the weighted average of four underlying components, each capturing a specific aspect of economic uncertainty.

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[6] We are extremely grateful to Cen et at. (2017) for making the customer-supplier relationship data available to us.
[7] The indexes are downloaded from https://www.policyuncertainty.com/. We are grateful to Professors Scott Baker, Nick Bloom, and Steven Davis for making these indexes publicly available.

The first BBD-index component is based on news coverage of policy uncertainty. From 1985 onward, in each month, a search for articles containing terms related to (1) uncertainty, (2) the economy, and (3) policy is performed on ten large US newspapers.[8] An article is defined as relating to policy uncertainty if it contains terms in all three categories. Specifically, Baker et al. (2016) searched for articles for (1) the terms "uncertainty" or "uncertain," (2) the terms "economic" or "economy," and (3) one or more of the following terms: "congress," "legislation," "White House," "regulation," "Federal Reserve," or "deficit." Since the number of articles varies over time across newspapers, the raw counts of policy-uncertainty-related articles are then divided by the total number of articles in each month in a given newspaper. The newspaper-level series are standardized to have a unit standard deviation and then summed across the ten newspapers by month. This multi-paper monthly index is then normalized to have an average value of 100.

The second index component relates to uncertainty regarding future changes in federal tax policies. To construct this component, the authors collected reports by the U.S. Congressional Budget Office (CBO) that compiles lists of temporary federal tax-code provisions. Tax-related uncertainty (regarding the path that the federal tax code will take in the future) is estimated by the annual dollar-weighted numbers of tax-code provisions scheduled to expire over the next ten years.

The third and fourth components concern the degree of forecaster disagreements about future monetary and fiscal policies, respectively. Using the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters, the authors construct forecast disagreement indexes for forecasts of CPIs, and forecasts of purchases of goods and services by federal, state, and local governments, each defined as the average of its interquartile ranges.

To construct the aggregate index of economic-policy uncertainty, each of the four component indexes is normalized by its own standard deviations. The authors then average the four components using

[8] These leading national newspapers include USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and the Wall Street Journal.

the following weights: ½ for the news-related component index, and 1/6 of the remaining three components relating to future tax changes and forecast disagreement.

Figure 1 plots the monthly policy uncertainty index over time and several political events that are accompanied by spikes in the index following Baker et al. (2016). The mean (median) index value is 107.5 (100.4).

Insert Figure 1 about here

2.3 Measuring customer concentration

Using the customer-supplier relationship information from Cen et al. (2017), we construct three measures to capture the extent of concentration of a firm's customer base. Following Dhaliwal et al. (2016), our first measure is a dummy that equals one when a firm has disclosed at least one major customer in a given year in their 10-K reports, and zero otherwise (*Major customer dummy*).

While the first measure gives an indication as to whether at least one major customer is present, however, it does not account for the number of major customers and the firm's degree of sales dependence thereon. Thus, following Banerjee et al. (2008) and Dhaliwal et al. (2016), our second measure defines customer concentration as the proportion of a firm's annual total sales to all major customers (*Major customer sales*). This measure extends the first by accounting for the importance of these customers to the firm's annual total revenue.

Nonetheless, while the second measure improves on the first, it does not account for the number of major customers and how sales are distributed across these customers. Hence, our third measure of customer concentration follows Patatoukas (2012) and applies the Herfindahl-Hirschman Index (*Major customer HHI*) to account for both the number of major customers and their importance to the firm's annual sales. Specifically, customer concentration for firm *i* in year *t* across the firm's *J* major customers is measured as follows:

$$Major\ customer\ HHI_{i,t} = \sum_{j=1}^{J} \left(\frac{Sales_{i,j,t}}{Sales_{i,t}} \right)^2, \quad (1)$$

where *Sales* $_{i,j,t}$ is the total sales disclosed by firm *i* to major customer *j* in year *t* and *Sales*$_{i,t}$ is the total sales revenue of firm *i* in year *t*. A higher value of *Major customer HHI* indicates a more concentrated customer base.

2.4 Descriptive statistics

Panel A of Table 1 presents descriptive statistics for our sample by year. As panel A shows, both the number of sample firms and the number of firms with at least one major customer increase steadily, spike in late 1990s (5,096 firms in total in 1998; 1,108 firms with major customers in 1997), and begin to decline gradually in the remaining sample period. On average, our sample comprises 3,815 firms and 850 firms have at least one major customer (22.2 percent). Moreover, the proportion of firms with major customers shows moderate time-series variation. Remaining above 20 percent for the first 13 years of our sample period, it drops to 14.5 percent in 1999, increases steadily to 26.1 percent in 2008, and thereafter starts to decline slowly.

Insert Table 1 about here

When we restrict the sample to firms with at least one major customer, we see that the average proportion of sales to major customers has increased steadily over time, from 28.1 percent in 1986 to 33.5% in 2016. Despite the upward trend in major-customer sales, the average number of major customers increases monotonically from 1.6 in the late 1980s to 2.3 in 2017, suggestive of a more diversified customer base. Apart from such apparent patterns in sales proportion and number of major customers, the average HHI of customer concentration shows relatively few fluctuations over time, increasing slowly from the early 1990s until 2007 and beginning to decline gradually towards the end of our sample period.

Panel B shows statistics by industry, defined using the Fama-French 12-industry classification (financials excluded). Firms in Business Equipment industries have the largest coverage by numbers of observations (20.6%), followed by those in Others (18.1%) and Manufacturing (12.8%). The proportion of observations of firms with at least one major customer is highest for firms in the Energy industries (34.5%), followed by those operating in the Durable Goods (32.4%) and Business Equipment (31.5%) industries. In terms of the proportion of unique firms with major customers, the top three are Energy (53.9%), Business Equipment (49.9%), and Durable Goods firms. In the subsample of firms with major customers, Healthcare (Utilities) firms, on average, have the largest (lowest) proportion of sales to major customers and HHI of customer concentration; the number of major customers (2.7) is highest among Durable Goods firms.

Insert Table 2 about here

Table 2 reports summary statistics for the customer-concentration measures. The mean values for *Major customer dummy*, *Major customer sales*, and *Major customer HHI* are 22.3%, 6.9%, and 2.1%, respectively, which are close to those reported by Dhaliwal et al. (2016). Since slightly over one-fifth of our firm-years have at least one major customer, the 25th and 75th percentiles statistics are zero for the three customer-concentration measures.

3. Empirical results

3.1 Economic-policy uncertainty and customer concentration

To examine the association between economic-policy uncertainty and customer concentration, we estimate the following baseline regression model:

$$Customer\ concentration_{i,t} = \beta_0 + \beta_1\ Policy\ Uncertainty_{t-1} + \delta \cdot X_{i,t-1} + \theta \cdot M_t + Firm\ FE + Decade\ FE + \varepsilon_{i,t}, \quad (1)$$

where i denotes a firm and t denotes a year; $Customer\ concentration_{i,t}$ is either $Major\ customer\ dummy_{i,t}$, $Major\ customer\ sales_{i,t}$, or $Major\ customer\ HHI_{i,t}$, our measures of customer concentration defined in section 2.3; $Policy\ Uncertainty_{t-1}$ is the lagged economic-policy index developed by Baker et al. (2016) and explained in section 2.2; the policy-uncertainty index measured at the end of fiscal year $t-1$ is used to explain customer concentration in fiscal year t; $X_{i,t-1}$ is a vector of lagged firm-level control variables, including log sales revenue (*ln(Sale)*), log firm age (*ln(Age)*), financial leverage (*Leverage*), R&D expenses scaled by total sales (*R&D/Sale*), return on assets (*ROA*), monthly return volatilities over the fiscal year (*Risk*), growth opportunities (*Tobin's q*), property, plant, and equipment scaled by total assets (*Asset tangibility*), and selling, general, and administrative expenses scaled by total assets (*SG&A/TA*). For a more detailed definition of variables, please refer to the Appendix, Table A.1. Summary statistics are reported in Table 2.

Since the economic-policy-uncertainty index is a time-series variable, we are unable to include time fixed effects in equation (1). To account for the effect of unobserved marketwide shocks on customer concentration, we include four macroeconomic variables (M_t), including the annual growth rates in real GDP (*GDP growth*) and the consumer price index (*CPI growth*), spreads between AAA and BAA corporate-bond yields by Moody's (*Default spread*), and the three-month U.S. Treasury Bill rate (*T3bill*). An election indicator (*Election indicator*) is also included to account for the effect of presidential elections on customer concentration. Moreover, since summary statistics given earlier show that customer concentration may have slowly evolved over time, we further include three dummy variables for years in the 1990s, 2000s, and 2010s (D_{1990}, D_{2000}, and D_{2010}) to account for any systematic differences in customer concentration across decades.

Firm fixed effects (*Firm FE*) are included in the models to account for the effect of time-invariant unobserved firm heterogeneity on customer concentration. As such, identification of the relation in question relies on within-firm variation, or time-series variation, in policy uncertainty and customer concentration. Standard errors are double-clustered at the firm and year levels.

It is important to note that the amount of time-series variation differs across our three customer-concentration measures. In particular, the binary nature of *Major customer dummy* suggests that it likely exhibits the least intertemporal variation (among the three measures) because such variation arises only when firms switch from having at least one major customer to none, or vice versa.[9] Hence, although it has

[9] As Table OA.1 (online appendix) shows, mean *ΔMajor customer dummy*, *ΔMajor customer sales*, and *ΔMajor customer HHI* are -0.34, -0.12, and -0.06 percentage points, respectively. Table OA.2 (online appendix) reports their distribution by year, dividing them into three groups: Positive changes, no change, and negative changes. Regarding *ΔMajor customer dummy*, there are 3,477 firm-years (3.3%) with a negative change (i.e., from having at least one major customer to none) and 3,120 (3.0%) firm-years with a positive change (i.e., from none to having at least one major customer), whereas the rest of the firm-years (93.7%) exhibit no change. On the contrary, the other two

been used in prior studies (e.g., Dhaliwal et al. 2016), *Major customer dummy* is a rather crude and noisy measure of customer concentration that does not capture the within-firm changes in customer concentration for firms without a switch in the presence of major customers in our model with firm fixed effects. Readers should exercise caution when interpreting the results for *Major customer dummy*. This also highlights the importance for us to report and discuss results based on *Major customer sales* and *Major customer HHI*.

Insert Table 3 about here

Table 3 reports results from estimating equation (1). Column (1) presents the estimation of the linear probability model where *Major customer dummy* is the dependent variable.[10] We find that the coefficient estimate on the economic-policy-uncertainty index is negative and statistically significant (at the five-percent level), controlling for firm characteristics, macroeconomic factors, and decade and firm fixed effects. A one-standard-deviation increase in *Policy uncertainty* (0.31) is associated with a decrease in the probability of having at least one major customer by approximately 0.7 percentage points.

In column (2), where *Major customer sales* is the dependent variable, we find that *Policy uncertainty* enters negatively and significantly (at the one-percent level) in the model. A one-standard-deviation increase in *Policy uncertainty* reduces the proportion of sales to major customers by (0.308 × -0.0099) 0.31 percentage points. Considering sample-average sales of $1,877 million, the 0.31-percentage-point decline is equivalent to a $5.81 million reduction in sales to major customers. Column (3) presents the estimation results for our third measure of customer concentration in the form of HHI. The estimate for *Policy uncertainty* is negative and significant at the one-percent level. Economically, a one-standard-deviation increase in the economic policy uncertainty index is associated with a 0.12-percentage-point decline in *Major customer HHI*.

customer-concentration measures have more intertemporal variation; 13.3% and 11.6% of *ΔMajor customer sales* (13.2% and 11.7% of *ΔMajor customer HHI*) are negative and positive changes, respectively.

[10] The linear probability model is applied here because the inclusion of firm fixed effects in probit or logit models leads to the incidental-parameter problem (for a survey regarding this problem, please see Lancaster (2000)).

Overall, the evidence supports our hypothesis that firms diversify their customer base when economic-policy uncertainty increases.

3.2 Subcomponent analysis

As discussed in section 2.2, the economic-policy-uncertainty index comprises four components (weighting in brackets) relating to news coverage (1/2), tax policy (1/6), and forecaster dispersions in government purchases (1/6) and in the consumer price index (1/6). In this section, we report baseline tests that replace the aggregate index with four subcomponent indexes in Table 4.

Insert Table 4 about here

In columns (1) to (4) where the dependent variable is *Major customer dummy*, we find that the news-coverage-based policy-uncertainty index (*Policy uncertainty (News)*) is associated with a significantly lower likelihood of having a major customer, whereas the other three indexes are insignificant. Results for *Major customer sales* and *Major customer HHI* in columns (5) to (12) show a similar pattern: *Policy uncertainty (News)* is negatively and significantly associated with customer concentration, whereas little evidence of significant explanatory power is documented for the other three subindexes. This finding suggests that firms respond significantly to policy uncertainty reflected in the major newspapers outlets, but not to policy uncertainty driven by future tax changes, government purchases, or inflation.

3.3 Robustness tests

This section presents robustness results for both the aggregate and news-based indexes. To save space, while firm and macroeconomic controls and fixed effects are included in each model, only the estimates for the policy-uncertainty indexes are reported in Table 5.

Insert Table 5 about here

First, in rows (1) and (2), we replace firm fixed effects with industry fixed effects (based on the Fama-French 49-industry classification), finding that our results are similar. Second, firms with and without major customers may differ systematically and our estimates might be biased if such differences affect their exposure to economic-policy uncertainty and customer base. To address this concern, in rows (3) and (4), we reestimate the tests for *Major customer sales* and *Major customer HHI* on a subsample of firms with at least one major customer in a given year. Our results remain qualitatively similar, albeit being slightly less significant.

Third, rows (5) and (6) apply alternative standard errors, double-clustered at the industry and year levels, showing that our results remain robust. Fourth, since time fixed effects are not accounted for in our baseline models, and if negative shocks from financial crises lead to surges in policy uncertainty that simultaneously affect firms' customer base, our results may be driven by inadequate control for these omitted negative shocks. To show that this is not the case, we follow Bekaert et al. (2014) in defining years 1998, 2008, and 2009 as crisis years and find that our results are intact after excluding observations during the crisis years, suggesting that this concern is unlikely to be severe.

Instead of using the policy uncertainty index at the end of fiscal year *t-1*, rows (9) and (10) alternatively apply the average policy-uncertainty index over the three months before the end of fiscal year *t-1* to explain customer concentration of fiscal year *t*. Our results hold. Finally, in rows (11) and (12), we natural-logarithm transform the policy uncertainty indexes in the baseline tests, finding that our results hold.

3.4 Change-on-change regressions

Results thus far show that economic-policy uncertainty negatively associates with customer concentration, consistent with firms mitigating risks associated with uncertainty by diversifying their customer base. Conversely, these results may also suggest that firms narrow their customer base and focus on developing more stable, long-term trading relationships when uncertainty clears. While both interpretations may be equally feasible, behavioral economic theories suggest that the effect of policy uncertainty on customer concentration may be asymmetric between states of increasing and decreasing uncertainty.

Economists have long recognized that people care differently about downside losses than about upside gains. For instance, in the behavioral decision-making model under risk by Kahneman and Tversky (1979) and the axiomatic model of decision making under uncertainty by Gul (1991), the preferences for loss aversion and disappointment aversion allow agents to place greater weight on losses relative to gains in their utility functions. Likewise, early studies in portfolio management advocate the use of semi-variance as opposed to total variance to better capture downside losses than upside gains (Markowitz 1952). Ang et al. (2006) extend the capital asset-pricing model (CAPM) to allow the treatment of risk to be asymmetric by estimating downside and upside market beta separately, documenting a significant, positive premium for downside-risk exposure.

Accordingly, corporate managers who are averse to losses and disappointment are likely more concerned with potential losses arising from increasing uncertainty than on potential gains that can be achieved through strengthening trading relationships with customers when uncertainty decreases. If this behavioral view is true, the documented negative relation between economic-policy uncertainty and customer concentration should cluster in periods of rising uncertainty, and such a relationship should be weak during other periods.

To test this conjecture, we estimate an alternative change-on-change regression model that replaces the dependent variable and the firm and macroeconomic variables of equation (1) with their respective yearly changes. Results from the alternative-change model help ensure robustness. The change-on-change regression model is specified as follows:[11]

[11] The change-on-change regression (or the "first differencing method" or "first-difference estimator" referred to by Wooldridge (2010, p.316)) differences time-invariant firm heterogeneity out. Due to the first-differencing, the first time period for each firm in our sample is lost, resulting in fewer observations. Results can be interpreted in a similar manner as a firm fixed effects regression, i.e., a within-firm relationship between policy uncertainty and customer concentration. As pointed out by Wooldridge (2020, pp. 467-468) and Wooldridge (2010, pp.321-326), when there are only two time periods, the application of firm fixed effects and first-differencing would yield identical estimates. However, when there are more than two periods, the estimates and efficiency of the approaches may differ depending on whether assumptions regarding the disturbance terms hold. Our finding that estimation results are consistent under both approaches enhance the credibility of our results. The change-on-change regressions are applied in prior studies, e.g., Lee et al. (2014), Heider and Ljungqvist (2015), Griffin et al. (2019), among others.

$$\Delta Customer\ concentration_{i,t} = \beta_0 + \beta_1\ \Delta Policy\ Uncertainty_{t\text{-}1} + \delta \cdot \Delta X_{i,\ t\text{-}1} + \theta \cdot \Delta M_t + Firm\ FE + Decade\ FE + \varepsilon_{i,t}. \quad (2)$$

Firm fixed effects and decade dummies are controlled for in the model;[12] standard errors are double-clustered at the firm and year levels. *ΔCustomer concentration* represents yearly changes in *Major customer dummy*, *Major customer sale*, or *Major customer HHI.*

Insert Table 6 about here

Panels A, B, and C of Table 6 report estimation results of equation (2) for *Major customer dummy*, *Major customer sales,* and *Major customer HHI*, respectively. Across the panels, in columns (1) and (2) where the full sample is used, we find that yearly changes in the aggregate and news-based economic-policy indexes enter the models negatively and mostly significantly (at the ten-percent level or better). Results based on *ΔMajor customer dummy* in panel A are slightly weaker than those for the other two customer-base measures, perhaps due to a lack of time-series variation as discussed previously. The evidence suggests that changes in policy uncertainty are negatively associated with changes in customer concentration, corroborating the negative within-firm relation documented in our baseline tests.

To test for asymmetric effects of policy uncertainty on customer concentration, we partition our sample into two groups according to whether the yearly changes in policy uncertainty are positive. We then estimate equation (2) on the two subsamples. Across the panels, columns (3) to (6) show that coefficient estimates for the yearly changes in policy uncertainty are negative, considerably larger in absolute magnitude, and are statistically significant only in the subsample of firms experiencing positive changes in policy uncertainty. Among firms experiencing decreasing uncertainty, however, yearly changes in policy uncertainty do not significantly explain changes in customer concentration.

Overall, our findings are robust to using alternative change-on-change regressions. Importantly, consistent with a behavioral explanation, the documented negative effect is shown to be asymmetric and only significant during periods of rising uncertainty. While we document little evidence that managers

[12] Results are similar if the firm fixed effects are omitted from the change model.

narrow their customer base when uncertainty decreases, our evidence suggests that they mitigate risk arising from policy uncertainty by diversifying their customer base.

3.5 The instrumental variable approach

Although we account for a wide array of firm and macroeconomic controls and fixed effects in our estimation, the endogeneity concern regarding omitted variables remains. In this section, we apply an instrumental-variable (IV) approach and use the plausibly exogenous extracted variation in policy uncertainty to identify the relationship in question. A valid instrument should ideally be significantly correlated with policy uncertainty (the relevance criterion) and affect customer concentration only through this relationship (the exclusion criterion).

The instrument proposed in our study is the degree of political disagreement in the U.S., captured by the news-based Partisan Conflict Index (*Partisan Conflict Index*) developed by Azzimonti (2018).[13] Azzimonti (2018) adopts a semantic search approach and measures the degree of partisan conflict using the frequency of newspaper coverage of articles reporting political disagreement about government policy in each month from 1981 onward. In her analysis, the *Partisan Conflict Index* is shown to closely mirror the historical evolution of the political-polarization measure by McCarty et al. (2006) and is driven by elections, fiscal-policy debates, and other political events. Importantly, little relationship with the state of the economy, such as recessions and periods of high unemployment rates, is documented for the Partisan Conflict Index. A growing body of studies (e.g., McCarty et al. 2006; McCarty and Shor, 2016) argues that partisan polarization and political disagreement hinder the formation of legislative coalitions and lead to greater variation in policy. We argue that partisan conflict increases the degree of uncertainty in economic policy (thus satisfying the relevance criterion), in turn influencing the private sector and customer-base concentration. Apart from its weak empirical relation with the state of the economy, it is not immediately apparent how the degree of partisan disagreement on government policies could drive a firm’s decisions on

[13] We thank Professor Marina Azzimonti for making this data publicly available.

customer base in a manner other than through its effect on policy uncertainty. Thus, we are reasonably confident that the exclusion criterion is likely to be satisfied.

Since economic-policy-uncertainty indexes and the instrument are both invariant across firms, the usual two-stage least-squares methodology is inappropriate, since the repeated values in the instrument would inflate its correlation with the endogenous variable. Following Gulen and Ion (2016), we address this problem by estimating a time-series regression in the first stage at the monthly-frequency level and a panel regression with bootstrapped standard errors in the second stage.[14] Specifically, the first-stage monthly time-series regression is written as follows:

$$\textit{Policy uncertainty}_t = \beta_0 + \beta_1 \textit{ Partisan conflict index}_t + \delta \cdot X_t + \theta \cdot M_t + \textit{Decile FE} + \varepsilon_t. \quad (3)$$

where *Policy uncertainty* is either the aggregate policy-uncertainty index or the news-based uncertainty index; X_t is a vector consisting of the same set of firm controls, averaged cross-sectionally, as in our baseline tests of equation (1);[15] M_t is a vector containing the same set of macroeconomic time-series control variables as in equation (1), but measured at different frequencies, including quarterly real GDP growth, monthly growth rates in the consumer price index, monthly levels of default spreads and three-month Treasury Bill rates, and a presidential-election indicator. Decade dummy variables for the 1990s, 2000s, and 2010s are included. The fitted value from estimating equation (3) captures the portion of variation in policy uncertainty that is plausibly exogenous to firms' customer concentration.

In untabulated first-stage results, we find that the partisan-conflict index is positively and significantly (at the five-percent level or better) associated with both the aggregate policy-uncertainty index and the news-based subindex. The *F*-statistics for the coefficient estimate for *Partisan Conflict index* are

[14] We bootstrap the double-clustered standard errors at the firm and year levels 100 times to address the potential bias due to the use of an estimated regressor in the second stage.
[15] The firm controls, except for firm age (*Age*) and stock-return volatilities (*RISK*), are averaged for each calendar quarter, based on quarterly firm data from the Compustat Quarterly database, and assigned to all three months in that quarter. Firm age is averaged for each calendar year from the Compustat Annual database and assigned to all months in a calendar year. Monthly stock-return volatilities are averaged for each month and matched by month.

5.3 and 10.78 for the aggregate and news-based indexes, respectively, suggesting that the instrument likely satisfies the relevance criterion.

In the second-stage analysis, we estimate the following panel regression:

$$Customer\ concentration_{\ i,t} = \beta_0 + \beta_1\ Policy\ uncertainty\ (fitted)_{\ t-1} + \delta \cdot X_{\ i,\ t-1} + \theta \cdot M_{\ t} + Firm\ FE + Decade\ FE + \varepsilon_{\ i,t}, \quad (4)$$

Policy Uncertainty (fitted) is the fitted value from estimating equation (3); specifically, the fitted indexes measured at fiscal year *t-1* are used to explain customer concentration of fiscal year *t*.

Insert Table 7 about here

Panels A and B of Table 7 report the estimation results for equation (4) on the firm-year panel for both the aggregate and news-based indexes, respectively. As both panels show, similar to our baseline results, the fitted policy-uncertainty indexes enter negatively and significantly in all models.

Overall, results from our IV estimation suggest that endogeneity is unlikely to fully explain our results. Given that our estimation is consistent between the aggregate and news-based uncertainty indexes and that the majority of variation in the aggregate index comes from the news-based index, in subsequent sections we mainly report tests using the news-based uncertainty index, unless otherwise stated.

3.6 Canadian economic-policy-uncertainty index

A potential concern is that the economic-policy-uncertainty index is measured with errors and thus it may in part capture general economic uncertainty that is somewhat unrelated to policies. To address this concern, we follow Gulen and Ion (2016) and include the Canadian economic-policy-uncertainty index in our analysis. The rationale is that, since Canada and U.S. have strong economic ties with each other through extensive trade and investments, shocks that drive general economic uncertainty in the U.S. likely also affect general economic uncertainty in Canada, albeit to a lesser extent, and vice versa. If the BBD policy-uncertainty index (Baker et al. 2016) in part captures general economic uncertainty unrelated to policy, the

Canadian index would be driven, to some extent, by the same sources of general economic uncertainty that impacts the U.S., which can thus be removed by explicitly controlling for the Canadian index in the analysis.

Insert Table 8 about here

As a first test, panel A of Table 8 puts the U.S. news-based policy-uncertainty index and the Canadian aggregate policy uncertainty index to a "horse race." Our results consistently show that estimates for the U.S. policy-uncertainty index remain negative and statistically significant, whereas those for the Canadian index are small in magnitude and insignificant. This evidence reassures us that firms do not respond to uncertainty in Canadian economic policies as well as any general economic uncertainty that is commonly experienced by both countries but captured in the Canadian index.

To offer a more formal test, we formulate a two-stage analysis. In the first stage, we eliminate the part in the U.S. index that constitutes general economic uncertainty commonly experienced by both countries by extracting the index component that is orthogonal to the Canadian index using the following monthly time-series regression:

$$\textit{Policy uncertainty (News)}_t = \beta_0 + \beta_1 \textit{ Canadian policy uncertainty index}_t + \delta \cdot X_t + \theta \cdot M_t + \textit{Decile FE} + \varepsilon_t . \quad (5)$$

Equation (5) is identical to equation (3), except that we replace the Partisan Conflict Index with the Canadian aggregate policy-uncertainty index. The regression residual from equation (5) represent the part of U.S. news-based policy-uncertainty index that is orthogonal to the Canadian index. The residual-based index, measured at fiscal year *t-1*, is used to explain customer concentration in fiscal year *t* in the second-stage panel regression. Panel B shows that the residual-based index remains negatively and significantly (at the one-percent level) associated with the three measures of customer concentration.

3.7 An alternative identification strategy based on state gubernatorial elections

To further strengthen a causal interpretation of our findings, we perform an additional endogeneity test that exploits an *alternative* source of variation in policy uncertainty, which is plausibly exogenous, provided by the staggered U.S. state gubernatorial elections (i.e., state governor elections), for identification. Data of state gubernatorial elections are collected from the Congressional Quarterly (CQ) Press Electronic Library.

There are two main advantages of using the state gubernatorial elections as proxy for the variation in policy uncertainty. First, the timing of the gubernatorial elections is prescheduled and fixed by law. All state elections except Louisiana are held on the first Tuesday following the first Monday in November. All states except Vermont and New Hampshire hold gubernatorial elections every four years. As such, the state elections can be viewed as exogenous events that increase policy uncertainty independent of the general economic conditions, the latter may drive firms' decisions in relation to their customer base or revenue streams, thereby resolving endogeneity concerns.

Second, elections of different states take place in different years, i.e., staggered across states and years, and, hence, considerable variation in policy uncertainty between- and within-state is available for identifying the relation in question. Elections for five states are held in odd-numbered years, i.e., prior to a presidential election; elections for other states are held in even-numbered years, coinciding with mid-term or presidential elections. Besides, the number of state elections is large compared to presidential elections. There are in total 418 state elections over the period from 1986 to 2017.

Our hypothesis is that firms are likely to face heightened economic-policy uncertainty before or during a state gubernatorial election and significantly diversify their customer base as a result. To test this hypothesis, we formulate a first-difference model as follows:

$$\Delta \mathit{Customer\ concentration}_{i,s,t} = \beta_0 + \beta_1\, \mathit{State\ election\ dummy}_{s,t} + \delta \cdot \Delta X_{i,\,t-1} + \mathit{Firm\ FE} + \mathit{Industry} \times \mathit{Year\ FE} + \varepsilon_{i,s,t}. \quad (6)$$

where s denotes a headquarter state. *State election dummy* is a dummy that equals one when a firm experiences a state gubernatorial election in a given year, and zero otherwise. The estimated β_1 is a difference-in-differences estimate because it captures how customer concentration of the treated firms (i.e., those receiving the state elections) changes in the election years relative to the control firms in non-election years.

Figure 2 illustrates how we define whether a firm is affected (or "treated") by a state election. Suppose there is a state election in November of calendar year *t*. If a firm has a fiscal year ending in months between January and April of calendar year *t,* customer concentration measured at the end of the next fiscal year is deemed affected by the election. If a firm's fiscal year ends in months between May and December in calendar year *t*, customer concentration measured at the end of the current fiscal year is affected by the election. The rationale is that within a one-year period before an election (i.e., from December in calendar year *t*-1 to November in calendar year *t*), a firm is considered as experiencing an election year and thus increased policy uncertainty (treated) when there are at least six months of the selected fiscal year preceding the election.

Firm fixed effects and industry-year (Fama-French 49-industry classification) interacted fixed effects are included in the model to control for time-invariant firm heterogeneity and industry-specific time trends. Standard errors are double-clustered at the state and year levels. In the analysis, we further exclude firm-years that are headquartered in Vermont, New Hampshire, and Louisiana which either have two-year election cycles or non-fixed election timing.

Insert Table 9 about here

Panel A reports summary statistics for the state elections. After excluding the three states, there are in total 378 state elections across 47 states. Panel B reports the difference-in-differences estimates. Columns (1) to (3) report the estimation results for equation (6) without firm fixed effects. Consistent with our hypothesis, we find that firms in election years significantly reduce their customer concentration relative to those in non-election years; results are consistent across the three measures of customer concentration. In columns (4) to (6) where firm fixed effects are included, results are quantitatively similar. Based on the estimates from columns (4) to (6), for firms experiencing a state-election year, their *Major customer dummy*, *Major customer sales*, and *Major customer HHI* decline by 0.61, 0.28, and 0.09 percentage points, respectively; the economic magnitude is similar to that of our baseline results based on the policy uncertainty index.

Overall, our tests exploiting an alternative state-level source of variation in policy uncertainty corroborate our baseline results, suggesting that endogeneity is unlikely to drive our results.

3.8 Cross-sectional heterogeneity

To provide further evidence in support of our risk-mitigating hypothesis, in this section we explore cross-sectional heterogeneity in the effect of economic-policy uncertainty on customer concentration and report the estimation results in Table 10.

Insert Table 10 about here

First, firms with greater investment in R&D and innovation activities are more capable of acquiring new customers and reallocating their revenues among different customers and, hence, we expect such firms to find a customer-base-diversification strategy to be less costly and more viable. While firm-level R&D intensity is likely to be endogenous to various corporate decisions and outcomes, we measure R&D intensity at the industry level, since we believe it to be less volatile and driven by covariates at the firm level than the firm-level measure. Specifically, to identify firms with high R&D intensity, in each year we calculate the average *R&D/Sale* for each 2-digit SIC industry. We construct *High industry R&D* as a dummy that equals one for those firms in the top quartile of industry-average *R&D/Sale,* and zero otherwise, and interact it with the news-based policy-uncertainty index to explain the three measures of customer-base concentration. As panel A shows, the estimates for policy uncertainty remain negative and highly significant and, importantly, the estimates for the interaction terms are negative and significant at the five-percent level or better. This evidence suggests that firms operating in high-R&D industries respond significantly more negatively to increases in policy uncertainty than those in low-R&D industries, which is consistent with our hypothesis.

Second, longer-term trading relationships in durable-goods industries are often maintained and valued more (compared to those in nondurable-goods industries) because firms operating in such industries typically produce more unique products. Hence, we expect such firms to be reluctant to pursue a customer-base-diversification strategy when policy uncertainty increases. Following Titman and Wessels (1988), manufacturing industries are defined as those with SIC codes between 2,000 and 4,000; those manufacturing industries with SIC codes lower than 3,400 (3,400 or above) produce nondurable (durable) products. *Durable* is a dummy that equals one for firms operating in manufacturing industries that produce durable goods, and zero otherwise. Similarly, we interact *Durable* with the news-based policy-uncertainty index to explain the three measures of customer-base concentration. To sharpen the test that compares the relationship between durable- and nondurable-goods manufacturers, we perform it only on a subsample of manufacturing firms. As shown in panel B, the interaction terms between *Durable* and the policy-uncertainty index yield positive and significant (at the five-percent or better) coefficient estimates, suggesting that the negative association in question is less pronounced among firms manufacturing durable goods compared to their peers manufacturing nondurable goods. This finding is consistent with our hypothesis.

Third, inventory turnover, which measures the number of times inventory is sold or replaced in a given time period, is shown to be an important indicator of operational efficiency. Firms with higher operational efficiency can respond to rising policy uncertainty more quickly by reallocating production quantities and diversifying customer bases. Inventory turnover is computed as cost of goods sold divided by average inventory; we calculate the average inventory turnover for each 3-digit SIC industry in each year. *High industry inventory turnover* is a dummy that equals one for firms with above-median industry-average inventory turnover, and zero otherwise. In panel C, we find that *High industry inventory turnover* interacts negatively and significantly with the news-based policy-uncertainty index. This finding is consistent with the hypothesis that firms with high operational efficiency have a greater ability to diversify their customer base when policy uncertainty increases.

Finally, the resource-dependency theory (Pfeffer and Salancik 1978) suggests that firms operating in more competitive product markets tend to have weaker bargaining power vis-à-vis their customers because of the latter's relative ease in finding qualified substitutes. When opportunities arise, customers often threaten to switch to alternative suppliers and can exercise their power to pressure upstream firms to lower prices and offer better contract terms. The disparity in power within the supply chain thus suggests that firms in more competitive industries have a greater need to diversify their customer base during mounting policy uncertainty. Product market competition is measured by the HHI of market concentration (*HHI*), which is constructed based on 3-digit SIC industry sales. A higher value of *HHI* indicates a more concentrated product market in general and thus proxies for lower competition. *HHI (top quartile)* is a dummy that equals one for firms in the top quartile of *HHI*, and zero otherwise. Panel D presents estimation results that support our hypothesis. Specifically, the positive coefficient estimates for the interaction term between *HHI (top quartile)* and the policy-uncertainty index are statistically significant in the models of *Major customer sale* and *Major customer HHI*. This finding is consistent with the view that firms operating in more competitive product markets have a greater need to diversify their customer base to mitigate the adverse impact of rising uncertainty in economic policies.

3.9 Case studies based on three federal budget crises

Our estimation results, which are based on the full sample spanning many years, reveals that firms prefer customer diversity when policy uncertainty is high. To confirm that our results are not spurious and are relevant to today's fast-changing political and business landscapes, we follow Hassan et al. (2019), present three case studies of extremely high policy uncertainty in the early 2010s, and examine their implications for customer concentration.[16]

According to Hassan et al. (2019), due to the inability of politicians in reaching consensus, three federal budget crises occurred in the early 2010s had significantly increased policy uncertainty. The first occurred in the third quarter of 2011 when the federal government reached its "debt ceiling"; the default of federal debts was prevented only by a final-minute budget deal between the President and Congress. The

[16] We are extremely grateful for the anonymous reviewer for suggesting this empirical test that traces customer concentration over a period of dramatic policy uncertainty.

second was the threat of going over the "fiscal cliff" in December 2012 when expiring tax cuts coincided with reduced government spending. The third refers to the 16-day shutdown of the federal government in October 2013 after Congress failed to pass a budget before reaching a final compromise.

As shown in Figure 1, the Baker et al. (2016)'s policy-uncertainty index is high between January 2011 and December 2013. The index has its peak (over the entire sample period) in August 2011 (index value=245.1). The mean (median) index value is 153.4 (157.5) over the 2011-2013 period, considerably higher than the full-sample mean of 107.5 (100.4). Motivated by these statistics showing that policy uncertainty was extraordinarily high during the 2011-2013 period, we examine how customer concentration evolved between 2010 and 2013.

Insert Table 11 about here

In panel A of Table 11, columns (1) to (3) report the full-sample average customer-concentration measures in 2010 and 2013 and their cumulative changes over the 2010-2013 period. Consistent with our hypothesis and earlier results, we find that the three-year changes in customer concentration are negative and significant at the ten-percent level or better. Columns (1) to (3) of panel B report the conditional means (i.e., the estimated intercepts) of the three-year changes in the three customer-concentration measures, controlling for the firm controls (as of 2010) and industry fixed effects. The negative changes in *Major customer sales* and *Major customer HHI* remain significant at the ten-percent level or better in the multivariate analysis.

In panel A, columns (4) to (9) reports the average customer-concentration measures for the manufacturing durable-goods and non-durable-goods firms. Consistent with the notion that durable-goods industries place a greater value on long-term trading relationships and our results from Table 10, we find that non-durable-goods firms reduced customer concentration considerably more (about twice as much) than the durable-goods ones. Panel B presents multivariate tests estimated on a subsample of manufacturing firms, regressing the three-year changes on a durable-goods dummy (*Durable*), firm controls (as of 2010), and industry fixed effects (Fama-French 12-industry classification). We find that *Durable* enter positively and significantly in two of the three customer-concentration models.

Together, while there is little plausibly exogenous variation in policy uncertainty in the event analysis, our results show that firms reduce customer concentration significantly amidst the federal crises; such reduction is also more pronounced among non-durable-goods firms. Evidence from this section is entirely consistent with our main findings.

3.10 Further discussions on customer-diversification strategies

Intuitively speaking, when diversifying revenue streams, firms can seek to either (1) increase the number of customers they are dealing with, (2) spread out their revenue flows across their existing customer portfolio, or (3) both. The former strategy cannot be tested reliably because data of non-major customers are unavailable. Nonetheless, we shed some light on the second strategy by applying a DuPont decomposition on *Major customer sales*:

$$\frac{Sale_{SC\,i,t}}{Sale_{i,t}} = \frac{Sale_{SC\,i,t}}{\#\,major\ customers_{it}} \times \frac{\#\,major\ customers_{it}}{Sale_{it}} \tag{7}$$

where $Sale_{SC}$ is a firm's total sales made to its major customers; *Sale* is the firm's total sales in a given year. *# major customers* is the number of major customers of a firm in a given year. The first decomposed term captures the amount of supply-chain sale per major customer; the second decomposed term is the number of major customers per one million dollar sales. Because of high skew, we natural-logarithm transform the two decomposed components (plus one), regressing them on the policy uncertainty index and the baseline firm and macroeconomic controls and fixed effects; these panel regressions are performed on a subsample of firms with at least one major customer.[17] The estimation results are reported in Table 12.

Insert Table 12 about here

[17] The decomposition can only be applied for the subsample of firms with at least one major customer, since the first decomposed term would be undefined when the number of major customers is zero.

Columns (1) to (2) and (3) to (4) report results based on the overall and news-based policy-uncertainty indexes, respectively. As columns (1) and (2) show, policy uncertainty significantly reduces supply-chain sale per major customer but does not drive the number of major customers per million dollar sales. Results based on the news-based index in columns (3) to (4) are similar but more significant.

Together, while it is uncertain as to whether firms may have acquired new non-major customers, our evidence suggests that firms with at least one major customer shift their sales to non-major customers without terminating their existing relationships with major customers.

3.11 Economic policy uncertainty, customer concentration, and firm performance

Does diversifying the customer base in times of surging policy uncertainty enhance or impede firm performance? To answer this question, we adopt the Fama-MacBeth approach (Fama and MacBeth 1973) to examine the cross-sectional relationship between customer concentration and firm performance, and we test whether such a relationship varies between periods of increasing and decreasing policy uncertainty. Specifically, we estimate the following model:

$$\textit{Firm performance}_{i,t} = \beta_0 + \beta_1\, \textit{Customer concentration}_{i,t-1} + \delta \cdot X_{i,t-1} + \textit{Industry FE} + \varepsilon_t\,, \quad (8)$$

where *Customer concentration* $_{i,t-1}$ is the concentration of major customers of firm *i* in year *t*-1; it is either *Major customer sales* or *Major customer HHI. Firm performance* $_{i,t}$ is either the firm's *ROA*, gross profits to total assets (*Gross profit/TA*), or annual sales growth (*Sales growth*). The same set of lagged control variables ($X_{i,t-1}$) excluding *Tobin's q* and *ROA* is included in the model. Under the Fama-MacBeth approach, a cross-sectional regression is estimated in each year and the time-series average coefficient estimates, standard errors, and R-squared are computed and reported.

Insert Table 13 about here

Panel A of Table 13 reports the estimation of equation (8) for *ROA*. As columns (1) and (2) show, firms with a higher degree of customer concentration have significantly higher operating profitability.

Economically, on average, a one-standard-deviation higher *Major customer sales* (*Major customer HHI*) is associated with a 34.9 basis-point (42.0 basis-point) decline in *ROA*.

In columns (3) to (6), our sample is partitioned into two groups according to whether the previous year was characterized by an increase in *Policy uncertainty*, i.e., whether the lagged changes (from *t*-2 to *t*-1) in *Policy uncertainty* are positive. In other words, in columns (3) and (4) [(5) and (6)], the reported coefficient estimates are computed by averaging the estimates from cross-sectional regressions across the years during which the lagged changes in policy uncertainty are positive (negative). As the columns show, the negative average coefficient estimates for customer concentration are considerably larger in magnitude and only statistically significant in the subsample of firms experiencing an increase in policy uncertainty.

The results for *Gross profit/TA* and *Sales growth* reported in panels B and C are remarkably similar. As columns (1) and (2) show, the two measures of customer concentration each enter negatively and significantly in the models. Specifically, a one-standard-deviation increase in *Major customer sales* (*Major customer HHI*) is associated with a 28.2 basis-point (40.6 basis-point) decrease in *Gross profit/TA* and with a 1.4 percentage-point (1.4 percentage-point) decline in *Sales growth*. Importantly, the significant negative association of customer concentration with gross profit to total assets and with annual sales growth is noticeably larger in magnitude and *only* significant during periods of increasing policy uncertainty.

A potential concern is that causality may operate in the opposite direction if more profitable firms have a greater capacity and a wider scope in finding alternative customers and diversifying their customer base. To rule out the reverse causality concern, we perform Fama-MacBeth cross-sectional tests using the two measures of customer concentration as dependent variables and the one-year lagged *ROA*, *Gross profit/TA*, and *Sales growth* as explanatory variables, estimated separately on the two subsamples of increasing and decreasing policy uncertainty. The results reported in the online appendix, Table OA.3 show that lagged firm performance fails to explain customer concentration regardless of whether policy uncertainty is increasing or decreasing. Our evidence suggests that the reverse causality concern is unlikely to be severe.

Overall, our evidence is consistent with the view that diversifying the customer base in times of increasing policy uncertainty likely improves firm and sales performance.

4. Conclusions

Uncertainty in U.S. economic policy is an important factor that firms must consider when managing their revenue sources. Hence, shocks to policy uncertainty can lead firms to adjust their customer portfolios. Using the BBD economic-policy-uncertainty index developed by Baker et al. (2016) and three measures of customer-base concentration constructed using customer-supplier relationship data compiled by Cen et al. (2017), we find robust evidence that policy uncertainty is negatively associated with customer concentration, consistent with the intuition of the modern portfolio theory (Markowitz 1952). The economic magnitude of the effect is also significant. A one-standard-deviation increase in policy uncertainty reduces the proportion of sales to major customer(s) by 0.31 percentage points, which is equivalent to a reduction of $5.81 million.

Interestingly, we find that the effect of policy uncertainty is asymmetric between states of increasing and decreasing policy uncertainty. The negative effect is significant only during periods of increasing uncertainty, while it is insignificant during periods of decreasing uncertainty, consistent with behavioral-economics theories suggesting a loss-aversion effect (Kahneman and Tversky 1979). Moreover, our results are robust to several endogeneity tests, including an instrumental variable estimation, difference-in-differences tests exploiting the plausibly exogenous variation in policy uncertainty given by the staggered U.S. state gubernatorial elections, and an event-type analysis based on three federal budget-crisis events in the early 2010s.

Our findings have three important implications. First, our study offers evidence that policy uncertainty may induce firms to diversify their revenue sources. From a policymaker's perspective, this finding is important because it shows that policy uncertainty can encourage firms to diversify their revenue sources to reduce their revenue risk and/or to build new customer relationships as a real option for future growth, even though it may be detrimental to short-term investment.

Second, while prior studies have suggested that customer-base diversification can hurt operating efficiency, our findings suggest that customer-base diversification improves firm profitability and sales growth during periods of increasing policy uncertainty. This finding is especially important for corporate managers, because it can help firms optimize their allocation of organizational resources between strengthening stronger trading relationships with a few major customers for high efficiency and seeking new opportunities outside existing customer-supplier relationships for reduced risk.

Third, our contingency results suggest that firms' customer-concentration levels will be affected to different degrees. Firms that are more dependent on their trading partners (e.g., those operating in low-R&D, nondurable, and competitive industries) are less able to appropriate the joint value created in existing customer-supplier relationships and thus would seek greater diversity in their customer base when facing heightened uncertainty. Moreover, firms with higher operational efficiency can respond more rapidly to environmental shocks and, hence, have a wider scope and greater ability to diversify their customer base when policy uncertainty increases.

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Figure 1. Baker et al. (2016)'s policy uncertainty index

This figure plots the monthly policy uncertainty index from Baker et al. (2016).

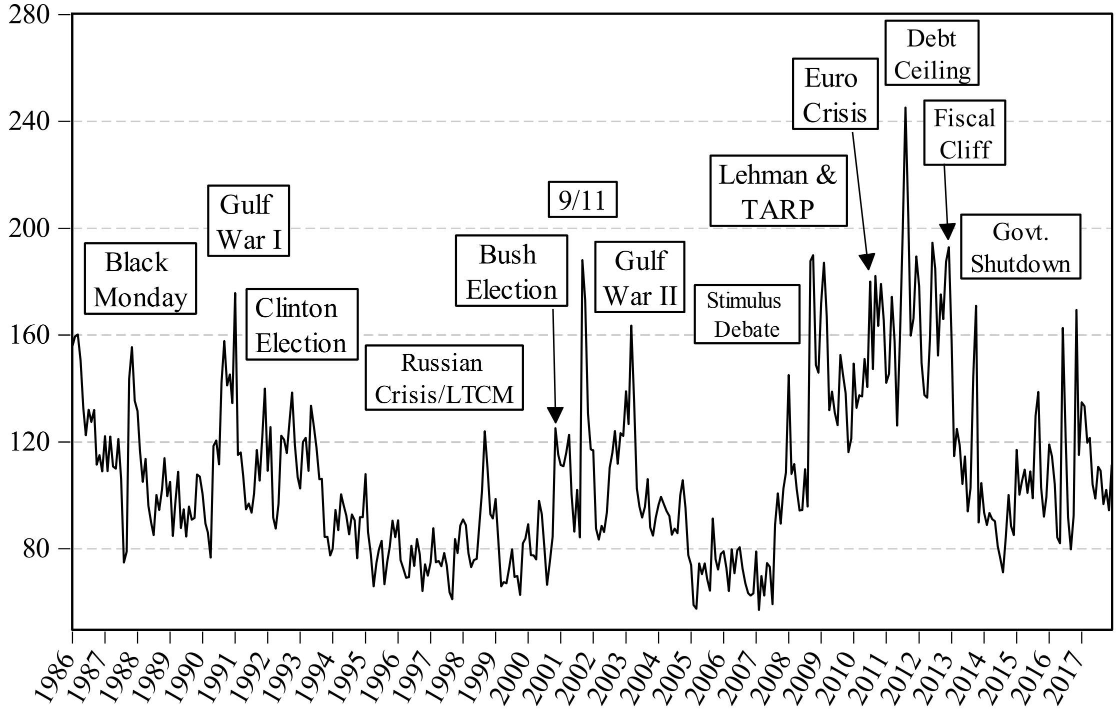

Figure 2. Measuring the election years for state gubernatorial elections

This figure shows how we define a firm-year as coinciding with a state gubernatorial election. All gubernatorial elections except those in Louisiana are held on the first Tuesday following the first Monday in November. States except Vermont and New Hampshire hold gubernatorial elections every four years, five in odd-numbered years while the others in even-numbered years.

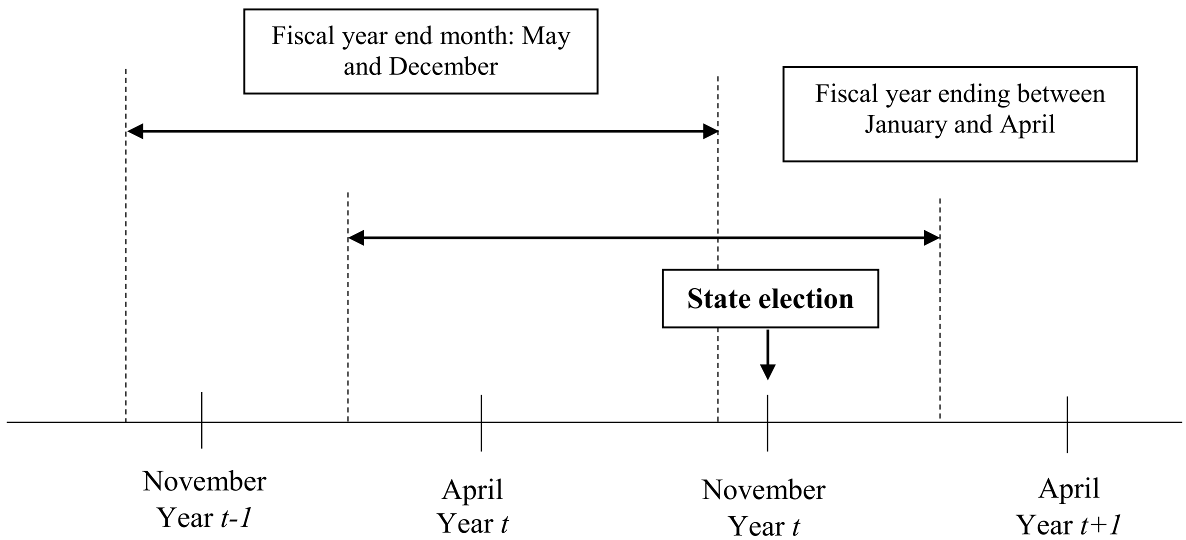

Table 1. Descriptive statistics

This table reports descriptive statistics by year (panel A) and by industry according to the Fama-French 12-industry classification (panel B; financials are excluded). Panel A reports the number of observations, number of unique firms with major customers disclosed, and proportion of major customers for the full sample. In the last three columns, we report the average proportion of transaction sales, number of major customers, and the HHI index of customer concentration for the subsample of firms with major customers. Panel B reports similar statistics by industry. Industry number denotes: 1. Non-durables, 2. Durables, 3. Manufacturing, 4. Energy, 5. Chemical, 6. Business equipment, 7. Telecom, 8. Utilities, 9. Shops, 10. Healthcare, 12. Others.

Panel A. By year

				Firms with major customers		
Year	Obs.	Unique firms with major customers	%	Avg. proportion of sales	Number of customers	HHI
1986	3,596	726	20.2%	28.11%	1.6	0.087
1987	3,608	742	20.6%	27.26%	1.6	0.084
1988	3,821	806	21.1%	27.12%	1.6	0.082
1989	3,788	793	20.9%	27.58%	1.6	0.087
1990	3,787	807	21.3%	27.88%	1.6	0.089
1991	3,808	841	22.1%	27.80%	1.6	0.088
1992	3,803	855	22.5%	27.66%	1.6	0.085
1993	4,042	954	23.6%	28.23%	1.6	0.090
1994	4,261	982	23.0%	28.36%	1.6	0.090
1995	4,607	1040	22.6%	28.80%	1.6	0.090
1996	4,786	1084	22.6%	28.76%	1.6	0.089
1997	4,998	1108	22.2%	29.79%	1.6	0.093
1998	5,096	1066	20.9%	30.70%	1.6	0.095
1999	4,913	713	14.5%	31.73%	1.8	0.095
2000	4,582	856	18.7%	31.93%	1.9	0.091
2001	4,504	954	21.2%	31.94%	1.8	0.090
2002	4,409	1043	23.7%	33.18%	1.9	0.098
2003	4,136	985	23.8%	32.74%	1.9	0.096
2004	3,938	912	23.2%	32.64%	1.9	0.096
2005	3,762	916	24.3%	32.26%	2.0	0.093
2006	3,648	910	24.9%	33.15%	2.0	0.099
2007	3,514	923	26.3%	33.54%	2.0	0.103
2008	3,429	895	26.1%	32.83%	2.0	0.099
2009	3,402	886	26.0%	32.89%	2.1	0.100
2010	3,226	826	25.6%	32.52%	2.1	0.099
2011	3,114	755	24.2%	32.40%	2.2	0.097
2012	3,131	759	24.2%	32.15%	2.3	0.091
2013	3,061	736	24.0%	31.90%	2.3	0.091
2014	3,059	695	22.7%	32.15%	2.4	0.092
2015	3,073	691	22.5%	33.10%	2.3	0.099
2016	3,120	694	22.2%	33.49%	2.3	0.104
2017	2,060	254	12.3%	30.55%	2.3	0.084

Panel B. By industry

Industry	Obs.	Unique firms	Obs. with major customers	%	Unique firms with major customers	%	Firms with major customers: Avg. proportion of sales	Number of Customers	HHI
1	8,167	781	2,161	26.5%	325	41.6%	26.1%	1.7	0.066
2	3,866	368	1,252	32.4%	166	45.1%	36.9%	2.7	0.100
3	15,606	1,445	3,605	23.1%	605	41.9%	26.3%	1.7	0.072
4	6,982	811	2,410	34.5%	437	53.9%	33.2%	1.9	0.099
5	3,162	291	641	20.3%	104	35.7%	25.3%	1.6	0.070
6	25,157	2,935	7,919	31.5%	1,464	49.9%	29.0%	1.8	0.079
7	4,228	558	595	14.1%	135	24.2%	29.2%	1.9	0.077
8	4,741	321	532	11.2%	96	29.9%	15.4%	1.9	0.039
9	15,022	1,643	1,693	11.3%	323	19.7%	29.6%	1.8	0.084
10	13,093	1,477	3,035	23.2%	549	37.2%	44.0%	1.9	0.173
12	22,058	3,186	3,364	15.3%	782	24.5%	31.2%	1.9	0.104
Total	122,082	13,816	27,207	22.3%	4,986	36.1%	30.8%	1.8	0.093

Table 2. Summary statistics

This table reports summary statistics for our final sample. The sample period covers 1986-2016. Our final firm-year panel dataset consists of 13,816 firms and 122,082 observations, of which 4,986 firms (27,207 observations) have major customers.

Variables	Obs.	Mean	Stdev	25%	Median	75%
Major customer dummy $_t$	122,082	0.223	0.416	0.000	0.000	0.000
Major customer sales $_t$	122,082	0.069	0.166	0.000	0.000	0.000
Major customer HHI $_t$	122,082	0.021	0.070	0.000	0.000	0.000
Policy uncertainty $_{t-1}$	122,082	1.074	0.308	0.843	1.004	1.222
Policy uncertainty (News) $_{t-1}$	122,082	1.110	0.387	0.826	1.037	1.390
Policy uncertainty (Fed) $_{t-1}$	122,082	0.965	0.451	0.625	0.858	1.196
Policy uncertainty (CPI) $_{t-1}$	122,082	0.969	0.283	0.748	0.884	1.113
Policy uncertainty (Tax) $_{t-1}$	122,082	2.083	3.883	0.135	0.189	2.236
Sale (million) $_{t-1}$	122,082	1,877	5,551	38	190	963
ln(Sale) $_{t-1}$	122,082	5.221	2.394	3.649	5.249	6.870
Firm age $_t$	122,082	15.997	12.971	6.000	12.000	22.000
ln(Firm age) $_t$	122,082	2.444	0.838	1.792	2.485	3.091
Leverage $_{t-1}$	122,082	0.231	0.209	0.036	0.201	0.362
R&D/Sale $_{t-1}$	122,082	0.228	1.145	0.000	0.000	0.058
ROA $_{t-1}$	122,082	0.063	0.205	0.035	0.107	0.164
Risk $_{t-1}$	122,082	0.147	0.092	0.083	0.123	0.182
Tobin's q $_{t-1}$	122,082	1.959	1.625	1.054	1.406	2.162
Asset tangibility $_{t-1}$	122,082	0.300	0.245	0.100	0.226	0.449
SG&A/TA $_{t-1}$	122,082	0.277	0.269	0.070	0.212	0.398
GDP growth $_t$	122,082	0.027	0.015	0.019	0.029	0.038
CPI growth $_t$	122,082	0.027	0.012	0.019	0.028	0.034
Default spread $_t$	122,082	0.010	0.003	0.007	0.009	0.011
T3bill $_t$	122082	0.035	0.024	0.010	0.042	0.054
Election indicator $_t$	122,082	0.252	0.434	0.000	0.000	1.000
D_{1990}	122,082	0.361	0.480	0.000	0.000	1.000
D_{2000}	122,082	0.322	0.467	0.000	0.000	1.000
D_{2010}	122,082	0.195	0.396	0.000	0.000	0.000

Table 3. Economic policy uncertainty and customer concentration

This table reports results from regressions examining the relationship between economic-policy uncertainty and the degree of customer concentration. The dependent variables are a dummy for the presence of major customers (*Major customer dummy*), the proportion of sales to major customers (*Major customer sales*), and the HHI index of major customer concentration (*Major customer HHI*). The main variable of interest is the overall economic-policy-uncertainty index (*Policy uncertainty*), constructed by and downloaded from Baker et al. (2016). Lagged firm controls include: natural log of firm total sales (*ln(Sale)*), natural log of firm age in year *t* (*ln(Firm age)*), financial leverage (*Leverage*), R&D intensity (*R&D/Sale*), return on assets (*ROA*), firm monthly return volatilities (*Risk*), Tobin's q (*Tobin's q*), plants, property, and equipment to total assets (*Asset tangibility*), and selling, general, and administrative expenses to total assets (*SG&A/TA*). Macroeconomic control variables include real GDP annual growth rates (*GDP growth*), CPI annual growth rates (*CPI growth*), and spread between Moody's BAA and AAA corporate bond yield (*Default spread*). Firm fixed effects and decade dummies (for the 1990s, 2000s, and 2010s) are accounted for in all models. Standard errors are double-clustered at the firm and year levels. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Major customer dummy $_t$	*Major customer sales $_t$*	*Major customer HHI $_t$*
	(1)	(2)	(3)
Policy uncertainty $_{t-1}$	-0.024**	-0.0099***	-0.0039***
	(-2.396)	(-2.8672)	(-3.5676)
ln(Sale) $_{t-1}$	0.009**	0.0028*	-0.0000
	(2.455)	(1.7630)	(-0.0618)
ln(Firm age) $_t$	-0.037***	-0.0134***	-0.0048***
	(-3.319)	(-3.6604)	(-3.5955)
Leverage $_{t-1}$	-0.029**	-0.0073	-0.0008
	(-2.142)	(-1.1893)	(-0.2752)
R&D/Sale $_{t-1}$	-0.012***	-0.0062***	-0.0030***
	(-4.237)	(-3.3195)	(-3.1220)
ROA $_{t-1}$	0.010	0.0102	0.0055
	(0.655)	(1.3754)	(1.6584)
Risk $_{t-1}$	-0.055**	-0.0145	-0.0041
	(-2.470)	(-1.5792)	(-0.9788)
Tobin's q $_{t-1}$	0.000	0.0011	0.0005
	(0.190)	(1.5472)	(1.5434)
Asset tangibility $_{t-1}$	0.031	0.0197**	0.0086**
	(1.480)	(2.3156)	(2.3971)
SG&A/TA $_{t-1}$	-0.032**	-0.0170***	-0.0069**
	(-2.343)	(-2.9568)	(-2.5913)
GDP growth $_t$	-0.737	-0.1847	-0.0752
	(-1.302)	(-1.1420)	(-1.4420)
CPI growth $_t$	0.222	-0.0142	-0.0117
	(1.029)	(-0.1872)	(-0.4550)
Default spread $_t$	-0.131	0.2432	0.0742
	(-0.050)	(0.3136)	(0.2911)
T3bill $_t$	-0.796**	-0.2432**	-0.0749**
	(-2.535)	(-2.2961)	(-2.2217)
Election indicator $_t$	0.004	0.0001	0.0002
	(0.635)	(0.0652)	(0.3239)

D_{1990}	-0.010	-0.0013	-0.0006
	(-0.529)	(-0.2323)	(-0.3181)
D_{2000}	0.008	0.0106	0.0017
	(0.343)	(1.3528)	(0.6924)
D_{2010}	0.026	0.0164*	0.0034
	(0.990)	(1.9052)	(1.1864)
Firm FE	Yes	Yes	Yes
Observations	122,082	122,082	122,082
Adjusted R-squared	0.557	0.607	0.534

Table 4. Subcomponents

This table reports results that use the subcomponents of the overall economic-policy-uncertainty index. The dependent variables are a dummy for the presence of major customers (*Major customer dummy*), the proportion of sales to major customers (*Major customer sales*), and the HHI index of major customer concentration (*Major customer HHI*). *Policy uncertainty (News)* is the news-coverage component index of economic-policy uncertainty. *Policy uncertainty (Fed)* is the component index based on the forecaster disagreement regarding the forecasts of purchases of goods and services by federal, state, and local governments. *Policy uncertainty (CPI)* is the component index based on the dispersion on CPI forecast. *Policy uncertainty (Tax)* is the component index of policy uncertainty concerning future changes in federal tax policies. Firm controls, firm fixed effects, and decade dummies (for the 1990s, 2000s, and 2010s) are accounted for in all models. Standard errors are double-clustered at the firm and year levels. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Major customer dummy $_t$				*Major customer sales $_t$*				*Major customer HHI $_t$*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Policy uncertainty (News) $_{t-1}$	-0.032***				-0.0109***				-0.0039***			
	(-3.270)				(-3.5626)				(-4.0507)			
Policy uncertainty (Fed) $_{t-1}$		0.003				0.0008				0.0002		
		(1.632)				(1.6006)				(1.2046)		
Policy uncertainty (CPI) $_{t-1}$			0.009				0.0001				-0.0001	
			(0.830)				(0.0262)				(-0.1101)	
Policy uncertainty (Tax) $_{t-1}$				0.021				0.0050				0.0017
				(1.334)				(0.9822)				(1.0730)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122,082	122,082	122,082	122,082	122,082	122,082	122,082	122,082	122,082	122,082	122,082	122,082
Adjusted R-squared	0.558	0.557	0.557	0.557	0.534	0.534	0.534	0.534	0.535	0.534	0.534	0.534

Table 5. Robustness tests

This table reports robustness test results. The dependent variables are a dummy for the presence of major customers (*Major customer dummy*), the proportion of sales to major customers (*Major customer sales*), and the HHI index of major customer concentration (*Major customer HHI*). In each set of tests, we report results for both *Policy uncertainty* and *Policy uncertainty (News)*. Columns (1) and (2) replace firm fixed effects with industry fixed effects, constructed using the Fama-French 49-industry classification. Columns (3) and (4) estimate the tests on the subsample of firms with at least one major customer. Columns (5) and (6) alternatively double-cluster standard errors at the industry and year levels (industry defined using the Fama-French 49-industry classification). Columns (7) and (8) exclude crisis years, including 1998, 2008, and 2009. Columns (9) and (10) apply alternative economic-policy-uncertainty indexes. Instead of using the fiscal year end index values, we average the indexes over the latest three months before a firm's fiscal year end. Columns (11) and (12) use log-transformed economic policy uncertainty indexes. Firm controls, firm fixed effects, and decade dummies (for 1990s, 2000s, and 2010s) are accounted for in all models. Standard errors are double-clustered at the firm and year levels, unless stated otherwise. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

			Major customer dummy $_t$		*Major customer sales $_t$*		*Major customer HHI $_t$*	
			Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
(1)	Industry FE	*Policy uncertainty $_{t-1}$*	-0.023*	(-1.981)	-0.0117**	(-2.5082)	-0.0046***	(-3.0288)
(2)	Industry FE	*Policy uncertainty (News) $_{t-1}$*	-0.030***	(-3.056)	-0.0122***	(-3.6279)	-0.0047***	(-4.1115)
(3)	Customer major customers only	*Policy uncertainty $_{t-1}$*			-0.0108*	(-1.9306)	-0.0053*	(-2.0170)
(4)	Customer major customers only	*Policy uncertainty (News) $_{t-1}$*			-0.0059*	(-1.6949)	-0.0037**	(-2.1421)
(5)	Alternative S.E.	*Policy uncertainty $_{t-1}$*	-0.024*	(-2.031)	-0.0099**	(-2.3226)	-0.0039**	(-2.2652)
(6)	Alternative S.E.	*Policy uncertainty (News) $_{t-1}$*	-0.032***	(-2.932)	-0.0109***	(-2.8158)	-0.0039**	(-2.6263)
(7)	Remove crisis windows	*Policy uncertainty $_{t-1}$*	-0.027**	(-2.175)	-0.0113**	(-2.5437)	-0.0045***	(-3.0844)
(8)	Remove crisis windows	*Policy uncertainty (News) $_{t-1}$*	-0.034***	(-2.923)	-0.0118***	(-3.2268)	-0.0043***	(-3.6771)
(9)	Alternative uncertainty measure	*3-month Policy uncertainty $_{t-1}$*	-0.034***	(-2.839)	-0.0121***	(-3.1631)	-0.0044***	(-3.3403)
(10)	Alternative uncertainty measure	*3-month Policy uncertainty (News) $_{t-1}$*	-0.041***	(-3.471)	-0.0131***	(-3.4100)	-0.0044***	(-3.4422)
(11)	Natural log transformation	*ln(Policy uncertainty) $_{t-1}$*	-0.040***	(-3.151)	-0.0155***	(-3.7066)	-0.0057***	(-4.2585)
(12)	Natural log transformation	*ln(Policy uncertainty (News)) $_{t-1}$*	-0.044***	(-3.964)	-0.0148***	(-4.2052)	-0.0051***	(-4.4878)

Table 6. Change-on-change regressions

This table reports results from change-on-change regressions that replace the firm and macroeconomic variables in the baseline model with their respective yearly first differences. The dependent variables are the yearly changes (from year *t*-1 to *t*) in the major-customer dummy (*ΔMajor customer dummy*) (panel A), the proportion of sales to major customers (*ΔMajor customer sales*) (panel B), and the HHI index of major customer concentration (*ΔMajor customer HHI*) (panel C). In each panel, columns (1) and (2) present full-sample results; columns (3) and (4) [(5) and (6)] analyze a subsample of firms in which *ΔPolicy uncertainty* $_{t-1}$ is positive [negative]. In each panel, we report results for both *Policy uncertainty* and *Policy uncertainty (News).* Yearly changes in the firm and macroeconomic controls are included. Decile and firm fixed effects are included in each model. Standard errors are double-clustered at the firm and year levels. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. ***Major customer dummy***

	ΔMajor customer dummy $_t$					
Sample	Full sample		*+ve ΔPolicy uncertainty* $_{t-1}$		*-ve ΔPolicy uncertainty t-1*	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ*Policy uncertainty* $_{t-1}$	-0.0173		-0.0285		0.0040	
	(-1.6307)		(-1.5812)		(0.5019)	
Δ*Policy uncertainty (News)* $_{t-1}$		-0.0132*		-0.0304**		-0.0007
		(-1.6981)		(-2.3043)		(-0.0844)
ΔControls	Yes	Yes	Yes	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,313	105,313	55,837	56,144	49,476	49,169
Adjusted R-squared	-0.044	-0.044	-0.017	-0.019	-0.033	-0.037

Panel B. ***Major customer sales***

	ΔMajor customer sales $_t$					
Sample	Full sample		*+ve ΔPolicy uncertainty* $_{t-1}$		*-ve ΔPolicy uncertainty* $_{t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ*Policy uncertainty* $_{t-1}$	-0.0075**		-0.0100*		-0.0018	
	(-2.1233)		(-1.7787)		(-0.4281)	

	(1)	(2)	(3)	(4)	(5)	(6)
Δ*Policy uncertainty (News)* $_{t-1}$		-0.0057**		-0.0112***		-0.0026
		(-2.3541)		(-2.7887)		(-0.9006)
ΔControls	Yes	Yes	Yes	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,313	105,313	55,837	56,144	49,476	49,169
Adjusted R-squared	-0.024	-0.023	0.0024	0.0034	0.0018	0.0067

Panel C. ***Major customer HHI***

	ΔMajor customer HHI $_t$					
Sample	Full sample		*+ve ΔPolicy uncertainty* $_{t-1}$		*-ve ΔPolicy uncertainty* $_{t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ*Policy uncertainty* $_{t-1}$	-0.0032**		-0.0039*		-0.0002	
	(-2.5898)		(-1.9704)		(-0.1367)	
Δ*Policy uncertainty (News)* $_{t-1}$		-0.0024***		-0.0041***		-0.0016
		(-3.2578)		(-2.9600)		(-1.5363)
ΔControls	Yes	Yes	Yes	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,313	105,313	55,837	56,144	49,476	49,169
Adjusted R-squared	-0.024	-0.024	-0.0008	0.0007	0.030	0.020

Table 7. The instrumental variable approach

This table reports estimation results under the instrumental variable (IV) approach. Following Gulen and Ion (2016), we perform a first-stage monthly time-series regression to extract the variation in policy uncertainty that is plausibly exogenous. The proposed instrument is the monthly Partisan Conflict Index, developed by Azzimonti (2018) based on semantic searches in major U.S. newspapers. In the second stage, the fitted values from the first-stage time-series regression are then used to explain our three measures of customer concentration in the firm-year panel dataset. The dependent variables in the second-stage analysis are a dummy for the presence of major customers (*Major customer dummy*), the proportion of sales to major customers (*Major customer sales*), and the HHI index of major customer concentration (*Major customer HHI*). Since the fitted policy-uncertainty variable is estimated, we bootstrap the double-clustered (by firm and year) standard errors 100 times. The controls and fixed effects in the second-stage regressions are identical to those in the baseline tests. Panels A and B report the second-stage results for the aggregate and news-based policy uncertainty indexes, respectively. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Major customer dummy $_t$	*Major customer sales* $_t$	*Major customer HHI* $_t$
	(1)	(2)	(3)
Panel A. ***Policy uncertainty***			
Policy uncertainty (fitted)	-0.032***	-0.0106***	-0.0029***
	(-5.147)	(-4.9220)	(-2.8742)
Controls	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	122,082	122,082	122,082
Adjusted R-squared	0.557	0.607	0.534
Panel B. ***Policy uncertainty (News)***			
Policy uncertainty (News) (fitted)	-0.047***	-0.0140***	-0.0039***
	(-9.088)	(-7.6369)	(-4.3981)
Controls	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	122,082	122,082	122,082
Adjusted R-squared	0.557	0.607	0.534

Table 8. Using the Canadian policy uncertainty index to mitigate endogeneity concerns

This table reports results from further tests to mitigate potential endogeneity concerns using the Canadian policy-uncertainty index. The dependent variables are a dummy for the presence of major customers (*Major customer dummy*), the proportion of sales to major customers (*Major customer sales*), and the HHI index of major customer concentration (*Major customer HHI*). In panel A, we estimate baseline tests, controlling for the Canadian policy-uncertainty index. In panel B, we first run a first-stage time-series regression that regresses the news-based policy uncertainty index on the Canadian policy-uncertainty index, firm and macroeconomic controls, and decade fixed effects. The estimated residuals from this first-stage regression thus represent the part of news-based policy uncertainty index that is orthogonal to the Canadian policy uncertainty index (*Orthogonalized policy uncertainty (News)*). Firm controls, firm fixed effects, and decade dummies (for the 1990s, 2000s, and 2010s) are accounted for in all models. Double-clustered standard errors at the firm and year levels are reported in panel A. Panel B reports t-statistics based on double-clustered standard errors bootstrapped for 100 times. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Major customer dummy $_t$	*Major customer sales $_t$*	*Major customer HHI $_t$*
	(1)	(2)	(3)
Panel A. Controlling for Canadian economic policy uncertainty index			
Policy uncertainty (News) $_{t-1}$	-0.029**	-0.0099***	-0.0037***
	(-2.738)	(-3.0713)	(-3.6290)
Policy uncertainty (Canada) $_{t-1}$	-0.003	-0.0012	-0.0003
	(-0.305)	(-0.3518)	(-0.2744)
Controls	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	122,082	122,082	122,082
Adjusted R-squared	0.558	0.607	0.535
Panel B. Orthogonalized policy uncertainty			
Orthogonalized policy uncertainty (News) $_{t-1}$	-0.024***	-0.0084***	-0.0035***
	(-6.420)	(-5.8793)	(-5.1690)
Controls	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	122,082	122,082	122,082
Adjusted R-squared	0.557	0.607	0.534

Table 9. Identification using state gubernatorial elections

This table reports difference-in-differences tests that exploit the plausibly exogenous variation in policy uncertainty provided by the U.S. state gubernatorial elections for identification. Data for state gubernatorial elections are collected from the Congressional Quarterly (CQ) Press Electronic Library. Firms headquartered in Vermont, New Hampshire, and Louisiana are dropped since in the former two states, elections are held every two years, while the election timing varied over time for Louisiana. Panel A gives the total number state elections over our sample period (1986-2017), the number of states involved, and the number of firm-year observations that coincide with the election years. Panel B report results from difference-in-differences tests. The dependent variables are the yearly changes in the major-customer dummy (*ΔMajor customer dummy*), the proportion of sales to major customers (*Major customer sales*), and the HHI index of major customer concentration (*Major customer HHI*). *State election dummy* is a dummy variable that equals one during a state election year, and 0 otherwise. The yearly changes in firm and macroeconomic controls, firm fixed effects, and industry-year interacted fixed effects are included in the model. Standard errors are double-clustered at the state and year levels; *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary statistics for the state gubernatorial elections

Number of elections	378
Number of states	47
Firm-years coinciding with elections	26,719

Panel B. Difference-in-differences tests

	ΔMajor customer dummy	*ΔMajor customer sales*	*ΔMajor customer HHI*	*ΔMajor customer dummy*	*ΔMajor customer sales*	*ΔMajor customer HHI*
	(1)	(2)	(3)	(4)	(5)	(6)
State election dummy	-0.0055***	-0.0024***	-0.0008***	-0.0061***	-0.0028***	-0.0009***
	(-3.1150)	(-3.0209)	(-2.3978)	(-4.3180)	(-3.8300)	(-2.5139)
ΔControls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,337	94,337	94,337	94,337	94,337	94,337
Adjusted R-squared	0.0089	0.0071	0.0020	-0.039	-0.020	-0.026

Table 10. Cross-sectional heterogeneity

This table examines the cross-sectional heterogeneity in the relation between policy uncertainty and customer concentration. The dependent variables are a dummy for the presence of major customers (*Major customer dummy*), the proportion of sales to major customers (*Major customer sales*), and the HHI index of major customer concentration (*Major customer HHI*). *High industry R&D* is a dummy variable that equals one when a firm operates in a 2-digit SIC industry in the top quartile in terms of industry-average *R&D/Sale*, and zero otherwise. *Durable* is a dummy variable that equals one for firms operating in manufacturing industries specializing in making durable goods (SIC code: 3,400 to 4,000), and zero for those operating in manufacturing industries producing nondurable goods (SIC code: 2,000 to 3,399). The tests reported in panel B are estimated on a subsample of manufacturing industries (SIC code: 2,000 to 4,000). *High industry inventory turnover* is a dummy variable that equals one when a firm operates in a 3-digit SIC industry with above-median industry-average inventory turnover, and zero otherwise. Inventory turnover is computed as cost of goods sold divided by average inventory. *High HHI* is a dummy variable that equals one when a firm's HHI of market concentration (constructed based on 3-digit SIC codes) is in the top quartile, and zero otherwise. Firm and macroeconomic controls, firm fixed effects, and decade dummies (for the 1990s, 2000s, and 2010s) are accounted for in all models. Standard errors are double-clustered at the firm and year levels. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Major customer dummy $_t$	*Major customer sales* $_t$	*Major customer HHI* $_t$
	(1)	(2)	(3)
Panel A. Industry R&D			
Policy uncertainty (News) $_{t-1}$	-0.027***	-0.0080***	-0.0026***
	(-3.109)	(-3.1348)	(-3.4075)
Policy uncertainty (News) $_{t-1}$ × *High industry R&D* $_{t-1}$	-0.014**	-0.0108***	-0.0050***
	(-2.106)	(-3.1843)	(-3.2651)
High industry R&D $_{t-1}$	-0.027	0.0216	0.0231**
	(-0.652)	(0.9708)	(2.2466)
Controls	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	122,082	122,082	122,082
Adjusted R-squared	0.558	0.607	0.535
Panel B. Durable vs Non-durable (manufacturing firms only)			
Policy uncertainty (News) $_{t-1}$	-0.054***	-0.0186***	-0.0074***
	(-4.705)	(-4.6443)	(-4.4319)
Policy uncertainty (News) $_{t-1}$ × *Durable*	0.030***	0.0089**	0.0044***
	(3.174)	(2.5143)	(2.7753)
Durable	-0.067	-0.0440	-0.0347**
	(-0.796)	(-1.1685)	(-2.1325)
Controls	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	58,525	58,525	58,525
Adjusted R-squared	0.549	0.605	0.525
Panel C. Industry inventory turnover			

Policy uncertainty (News) $_{t-1}$	-0.029***	-0.0085***	-0.0024***
	(-2.785)	(-3.0963)	(-2.9249)
Policy uncertainty (News) $_{t-1}$ × *High industry inventory turnover*	-0.005	-0.0046*	-0.0028***
	(-0.859)	(-1.9679)	(-3.1498)
High industry inventory turnover	0.011	0.0102	0.0122**
	(0.263)	(0.7985)	(2.2844)
Controls	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	120,128	120,128	120,128
Adjusted R-squared	0.559	0.610	0.538
Panel D. Market concentration (3-digit SIC HHI)			
Policy uncertainty (News) $_{t-1}$	-0.036***	-0.0121***	-0.0046***
	(-3.513)	(-3.7301)	(-4.2607)
Policy uncertainty (News) $_{t-1}$ × *High HHI* $_{t-1}$	0.016**	0.0047**	0.0029***
	(2.196)	(2.0405)	(2.8627)
High HHI $_{t-1}$	-0.107**	-0.0259**	-0.0086*
	(-2.264)	(-2.0783)	(-1.8489)
Controls	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	122,082	122,082	122,082
Adjusted R-squared	0.558	0.607	0.535

Table 11. Evidence from three federal budget crises

This table presents an event analysis examining how customer concentration evolved during a period (between 2010 and 2013) of high policy uncertainty due to three federal budget crises in the U.S. Panel A reports the three measures of customer concentration in 2010 and 2013 and their cumulative changes over the three-year period. Columns (1) to (3) report the measures and their changes for the full sample; columns (4) to (9) report these measures for manufacturing durable (SIC code: 3,400 to 4,000) and non-durable goods (SIC code: 2,000 to 3,399) firms. Columns (1) to (3) of panel B reports the conditional means of the three-year cumulative changes of the customer concentration measures (i.e., estimated intercepts), controlling for lagged firm controls (in 2010) and industry (Fama-French 49-industry classification) fixed effects. Using only manufacturing firms, columns (4) to (6) regress the three-year changes in the customer concentration measures on *Durable*, a dummy variable that equals one for durable-goods firms and zero for non-durable-goods firms, lagged firm controls (in 2010), and industry (Fama-French 12-industry classification) fixed effects. Standard errors are clustered at the industry level. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary statistics

				Manufacturing firms only					
	Full sample			Durable			Non-Durable		
	2010	2013	Diff.	2010	2013	Diff	2010	2013	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Major customer dummy $_t$	0.254	0.243	-0.011*	0.339	0.328	-0.011	0.329	0.303	-0.026*
Major customer sales $_t$	0.045	0.041	-0.005***	0.053	0.049	-0.005*	0.066	0.056	-0.010**
Major customer HHI $_t$	0.023	0.020	-0.003**	0.024	0.022	-0.002	0.035	0.028	-0.007*
Observations		2522			658			493	

Panel B. Multivariate analysis

	Full sample			Manufacturing firms only		
	ΔMajor customer dummy	*ΔMajor customer sales*	*ΔMajor customer HHI*	*ΔMajor customer dummy*	*ΔMajor customer sales*	*ΔMajor customer HHI*
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.033	-0.019**	-0.013*	Suppressed	Suppressed	Suppressed
	(-1.094)	(-2.250)	(-1.865)			
Durable				0.040**	0.007***	0.005
				(2.664)	(4.490)	(1.554)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,522	2,522	2,522	1,151	1,151	1,151
Adjusted R-squared	0.004	-0.001	0.000	0.006	0.006	0.016

Table 12. Decomposing *Major customer sales*

In this table, we decompose *Major customer sales* into two components. The first is total supply-chain transaction sales divided by the number of major customers; the second is the number of major customers divided by the firm's total sales. Due to high skew, the decomposed variables (added one) are natural-logarithm transformed and then used as dependent variables. The model is estimated on a subsample of firms with at least one major customer in a given year. The main variables of interest are the overall and news-based economic-policy-uncertainty indexes (*Policy uncertainty* and *Policy uncertainty (News)*). The baseline controls and fixed effects are included in the models. Standard errors are double-clustered at the firm and year levels. *T*-statistics are reported in parentheses; symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Sample	At least one major customer			
	$ln\left(1+\frac{Sale_{SC}}{\#\ major\ customer}\right)_t$	$ln\left(1+\frac{\#\ major\ customers}{Sale}\right)_t$	$ln\left(1+\frac{Sale_{SC}}{\#\ major\ customer}\right)_t$	$ln\left(1+\frac{\#\ major\ customers}{Sale}\right)_t$
	(1)	(2)	(3)	(4)
Policy uncertainty $_{t-1}$	-0.0673*	0.0001		
	(-1.9535)	(0.0461)		
Policy uncertainty (News) $_{t-1}$			-0.0471**	0.0002
			(-2.0759)	(0.2157)
Controls	Yes	Yes	Yes	Yes
Decile FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	27,207	27,207	27,207	27,207
Adjusted R-squared	0.9192	0.8345	0.9192	0.8345

Table 13. Economic policy uncertainty, customer concentration, and firm performance

This table reports results from Fama-MacBeth cross-sectional regressions examining the relation between economic-policy uncertainty, customer concentration, and firm performance. The dependent variables are returns on assets (*ROA*) (panel A), gross profits to total assets (*Gross profit/TA*) (panel B), and annual sales growth (*Sales growth*) (panel C). The main independent variables of interest are the one-year lagged *Major customer sales* and *Major customer HHI*. The same set of one-year-lagged controls, excluding *Tobin's q* and *ROA,* as in the baseline model is included in each model. In columns (3) to (6), we divide our sample into two groups according to whether the yearly changes in lagged *Policy uncertainty* are positive. Industry dummy variables are included in each model. The average coefficients, corresponding *t*-statistics (reported in parentheses), and R-squared are reported for each model. Symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. *ROA*

	ROA_t					
	Full sample		+Δ*Policy uncertainty* $_{t-1}$		-Δ*Policy uncertainty* $_{t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Major customer sales $_{t-1}$	-0.021***		-0.017**		-0.013	
	(-5.307)		(-2.300)		(-0.922)	
Major customer HHI $_{t-1}$		-0.060***		-0.050***		-0.021
		(-5.549)		(-2.919)		(-0.590)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120,723	120,723	71,777	71,777	48,946	48,946
Average R-squared	0.370	0.349	0.405	0.405	0.397	0.397

Panel B. *Gross profit/TA*

	Gross profit/TA $_t$					
	Full sample		+Δ*Policy uncertainty* $_{t-1}$		-Δ*Policy uncertainty* $_{t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Major customer sales $_{t-1}$	-0.017***		-0.013**		-0.005	
	(-5.169)		(-2.247)		(-0.407)	
Major customer HHI $_{t-1}$		-0.058***		-0.050***		-0.008
		(-8.081)		(-2.797)		(-0.253)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120,720	120,720	71,775	71,775	48,945	48,945

Average R-squared	0.664	0.664	0.659	0.659	0.692	0.693

Panel C. ***Sales growth***

	Sales growth $_t$					
	Full sample		*+ΔPolicy uncertainty $_{t-1}$*		*-ΔPolicy uncertainty $_{t-1}$*	
	(1)	(2)	(3)	(4)	(5)	(6)
Major customer sales $_{t-1}$	-0.084***		-0.104***		-0.051	
	(-5.988)		(-5.275)		(-1.321)	
Major customer HHI $_{t-1}$		-0.205***		-0.258***		-0.138
		(-6.099)		(-5.635)		(-1.254)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120,767	120,767	71,803	71,803	48,964	48,964
Average R-squared	0.131	0.131	0.171	0.171	0.185	0.186

Appendix A.1. Variable Definition

Variable	Definition	Source
Major customer dummy	A dummy that equals one for firms with major customers, and zero otherwise.	Compustat Segments Customer File, Cen et al. (2017)
Major customer sales	A firm's fraction of sales to its major customers. Takes a value of zero for firms with no major customers.	Compustat Segments Customer File, Cen et al. (2017)
Major customer HHI	Herfindahl-Hirschman index of a firm's concentration in sales to major customers, computed as the sum of squared proportion of transaction sales.	Compustat Segments Customer File, Cen et al. (2017)
Policy uncertainty	An overall measure of economic-policy uncertainty, computed as the weighted averages (weights in brackets) of the four individual components: (1/2) News-based policy-uncertainty index, (1/6) tax code expiration-based uncertainty index, (1/6) CPI forecast disagreement measure, and (1/6) the federal/state/local purchases disagreement measure.	Baker et al. (2016)
Policy uncertainty (News)	News-coverage-based policy-uncertainty index.	Baker et al. (2016)
Policy uncertainty (Fed)	Federal/state/local purchases disagreement measure.	Baker et al. (2016)
Policy uncertainty (CPI)	CPI forecast disagreement measure.	Baker et al. (2016)
Policy uncertainty (Tax)	Tax code expiration-based uncertainty index	Baker et al. (2016)
ln(Sale)	Natural log of sales (in million US dollars).	Compustat
ln(Firm age)	Natural log of firm age.	Compustat
Leverage	Financial leverage, computed as the sum of short- and long-term debts divided by total assets.	Compustat
R&D/Sale	The ratio of R&D expenditure to total sales.	Compustat
ROA	Return on assets, computed as operating income before depreciation divided by total assets.	Compustat
Risk	Monthly return volatilities estimated over the 12-month period in a given fiscal year.	CRSP

Tobin's q	Market value of equity plus total assets minus book value of equity, all divided by total assets. Market value of equity is calculated by multiplying the year-end closing price by the number of shares outstanding.	Compustat/CRSP
Asset tangibility	Plant, property, and equipment divided by total assets.	Compustat
SG&A/TA	Selling, general, and administrative expenses to total assets.	Compustat
GDP growth	Annual GDP growth.	Federal Reserve Bank of St. Louis
CPI growth	Annual CPI growth.	Federal Reserve Bank of St. Louis
Default spread	Spread between the Moody's seasoned Baa corporate bond yield and the Moody's seasoned AAA corporate bond yield.	Federal Reserve Bank of St. Louis
T3bill	The three-month U.S. Treasury Bill rate.	Federal Reserve Bank of St. Louis
Election indicator	Dummy that equals one for years with a presidential election.	Compustat
D_{1990}	Dummy that equals one for fiscal years between 1990 and 1999, and zero otherwise.	Compustat
D_{2000}	Dummy that equals one for fiscal years between 2000 and 2009, and zero otherwise.	Compustat
D_{2010}	Dummy that equals one for fiscal years after 2009, and zero otherwise.	Compustat
Inventory turnover	Inventory turnover, computed as cost of goods sold divided by average inventory.	Compustat
Market concentration (3-digit SIC HHI)	Market concentration, computed as firm sales divided by the total 3-digit SIC code industry sales.	Compustat
Durable	Indicator variable equal one for firms operating in the durable goods industry and zero otherwise. Durable goods industries are defined as those with two-digit-SIC codes between 3,400 and 3,999.	Compustat
Industry R&D	Industry-average R&D-to-sales ratio.	Compustat
Sales growth	Annual sales growth.	Compustat
Gross profit/TA	Gross profit to total assets ratio.	Compustat

$\frac{Sale_{SC}}{\# \ major \ customer}$	Supply-chain total sales divided by the number of major customers.	Compustat, Compustat Segments Customer File, Cen et al. (2017)
$\frac{\# \ major \ customers}{Sale}$	The number of major customers divided by firm total sales.	Compustat, Compustat Segments Customer File, Cen et al. (2017)