Uncertainty, Stock Prices, and Debt Structure*

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Abstract

Despite the recognized importance of debt structure in transmitting economic shocks, we know little about its role in transmitting uncertainty. We find that bank debt reduces stock price sensitivity to policy uncertainty, unlike non-bank debt. This mitigating effect comes from cash-flow insolvent firms, consistent with the idea that they particularly value renegotiability of bank debt. Using high-frequency methods, we address challenges in identifying policy uncertainty shocks, focusing on the 2018-2019 U.S.-China trade policy uncertainty and on monetary-policy-related uncertainty around FOMC announcements. Our results suggest that bank debt provides insurance and flexibility for shareholders of distressed firms, especially during uncertain times.

Keywords: policy uncertainty; trade policy; monetary policy; asset prices; debt structure
JEL Codes: E44, F13, G12, G20, G30

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1 Introduction

Uncertainty has been at the forefront of discussions among policymakers, academics, and investors for at least the past two decades. The literature has extensively studied the wide-ranging effects of policy uncertainty on financial markets and business cycles (Pastor and Veronesi 2012; Baker, Bloom, and Davis 2016). Nevertheless, the difficulty of distinguishing policy uncertainty from broader macroeconomic fluctuations has often complicated efforts to identify the response of firm fundamentals (Kelly, Pastor, and Veronesi 2016). Similarly, significant gaps remain in our understanding of the transmission mechanism of these shocks.

Our paper makes two key contributions. First, we introduce a novel identification strategy that isolates exogenous policy uncertainty shocks using high-frequency financial data from events such as the 2018-2019 U.S.-China trade war and monetary policy announcements. This approach addresses the long-standing difficulty of separating policy uncertainty from broader economic fluctuations. By focusing on specific, identifiable shocks, we provide a clearer and more precise measure of the impact of policy uncertainty on financial markets.

Second, we study how policy uncertainty moves stock prices through firms' debt structure, focusing on the dichotomy between the two main forms of corporate debt, bank debt and non-bank debt. Previous literature has studied the importance of bank vs. non-bank debt in the transmission of *first-moment* policy shocks to stock prices (Ippolito et al. 2018, Gurkaynak et al. 2022). Analogously, we explain how debt structure shapes the transmission of policy *uncertainty* shocks to stock prices. Therefore, our research complements recent work suggesting that capital structure (debt vs. equity) influences the impact of economic uncertainty (Alfaro, Bloom, and Lin 2024).

Our findings confirm the theoretical prediction of Pastor and Veronesi (2012) that higher policy uncertainty lowers stock prices. Moreover, we find that bank debt and non-bank debt make sharply different contributions to the transmission of policy uncertainty. Specifically, using bank debt exclusively mitigates a firm's stock price response to policy uncertainty

shocks by about one-third, whereas non-bank debt usage does not affect this response. This result suggests that bank debt can provide insurance for shareholders during uncertain times, which may explain why firms are willing to pay higher rates on bank debt (Schwert 2020).

The mitigating effect of bank debt we document is not obvious ex ante. In general, bank debt can influence the transmission of policy uncertainty through two non-mutually exclusive channels. On the one hand, adverse shocks can reduce bank lending, amplifying the negative effects on borrowers heavily reliant on bank debt. This is known as the bank balance-sheet channel (Jimenez et al. 2012). On the other hand, a financial flexibility channel, as discussed in Ai et al. (2021), arises from banks' unique ability to renegotiate debt contracts. The informational advantage of banks and their close relationships with borrowers allow them to provide better flexibility, which helps insulate bank-dependent borrowers from adverse shocks (Boot et al. 1993; Hadlock and James 2002; De Fiore and Uhlig 2011, 2015). While the two channels are not mutually exclusive, the mitigating effect of bank debt when facing policy uncertainty is more in line with the financial flexibility channel.

As a further refinement of the mechanism, our additional findings emphasize the role of renegotiation over the broader concept of borrower-bank relationship, as the relationship is a necessary but not sufficient condition for renegotiation. Although one would expect relationships to benefit all borrowers, our findings show that the mitigating effect of bank debt is concentrated among cash-flow insolvent firms – firms unable to meet their debt obligations without renegotiation.[1] This distinction underscores that renegotiation, rather than relationship, is the primary mechanism. Firms that cannot make timely payments are more likely to bring both themselves and their banks to the negotiation table, whereas banks have little incentive to renegotiate with firms that can meet their obligations. Moreover, banks may have additional incentives to renegotiate with cash-flow insolvent firms to avoid

[1]These firms have recently attracted growing attention from academic and policy circles (Favara, Minoiu, and Perez-Orive 2021) as well as public media, which calls these firms "zombie firms." Bloomberg (Lee and Contiliano 2020) reports that 739 firms of the Russel 3000 index with around $1.98 trillion debt could not cover their interest expenses by the end of 2020 based on the trailing 12-month operating income, in an article called "America's Zombie Companies Rack Up $2 Trillion of Debt."

recognizing loan losses, which can be costly due to agency problems (Bonfim et al. 2022) or regulatory constraints (Caballero et al. 2008; Blattner et al. 2019). Even in the absence of such frictions, an unconstrained bank may prefer to renegotiate rather than liquidate, as the firm may be more valuable as a going concern (Faria-e-Castro, Paul, and Sanchez 2024). We provide further evidence for renegotiation using balance sheet variables by showing that higher policy uncertainty leads to both longer debt maturity and lower per-period debt repayments for cash-flow insolvent firms that use more bank debt, consistent with debt maturity extension and reduced debt burden thanks to renegotiation by such firms.

Our analysis begins with a direct approach, examining the relation between the monthly economic policy uncertainty (EPU) index from Baker et al. (2016) and firm-level monthly stock returns. Our analysis highlights the identification challenge of separating economic policy uncertainty from the uncertainty in the macroeconomic environment that influences policy decisions (Kelly, Pastor, and Veronesi, 2016). In particular, during the 2007–2009 Global Financial Crisis (GFC), a significant source of policy uncertainty was arguably the uncertainty originating from the banking crisis. The direction of the financial uncertainty stemming from a banking crisis would, by construction, counteract any mitigating effect of bank debt. Accordingly, we find an ambiguous effect of bank debt on the relationship between the EPU index and stock returns. However, the mitigating effect of bank debt becomes clear once we take out the GFC period. In particular, we find that a firm that uses only bank debt would be shielded from about one third of the impact of the EPU index on the stock value compared with a firm that does not use any bank debt.

Nevertheless, we cannot definitely argue that removing the GFC period resolves the identification problem completely. For better identification, we need a setting where stock prices are affected primarily by economic policy uncertainty, rather than uncertainty in macroeconomic environment that the economic policy may be reacting to. We address this challenge by first focusing on the exogenous changes in trade policy uncertainty during the 2018-2019 U.S.-China trade war period.

The trade war is ideal for our study because the significant financial market fluctuations during this period are widely attributed to increased policy uncertainty (Carney 2019). While trade policy changes can affect the economy through numerous channels other than uncertainty, their total expected impact was small compared to financial markets' strong reaction during the trade war.[2] Nevertheless, policy uncertainty associated with trade war can raise risk premia (Bianconi, Esposito, and Sammon 2021), thereby tightening financial conditions as argued by Bank of England Governor Mark Carney.[3] This emphasis on uncertainty in the context of U.S.-China trade war is also consistent with Rogers, Sun, and Sun (2024) who find that U.S.-China tensions' economic transmission over the last three decades primarily operates through the uncertainty channel.

We identify the impact of exogenous changes in trade policy uncertainty with a high-frequency event study approach. We systematically collect a series of trade-war-related news, the precise timing of which is unexpected. The event dates associated with the trade war news explain three quarters of the increase in high-yield spreads and about half of the decline in yields on long-term Treasury debt during our sample period. Since news about the trade war is quickly reflected in market prices, we are able to identify the effect of the exogenous uncertainty shocks due to trade war news by using the heteroskedasticity-based estimator of Rigobon and Sack (2003, 2004, 2005) with high-frequency financial market data. This estimator addresses the two big identification challenges that (i) trade-war-related uncertainty is not directly observable, in that the trade war news on any given day cannot be precisely quantified, and (ii) other factors are continuously influencing asset prices in addition to trade war uncertainty.

[2]For example, an August 2019 report by Goldman Sachs predicted that the total peak effect from these macroeconomic channels will amount to 0.2 percent of GDP (Hatzius et al. 2019), which is in line with the estimates reported by Amiti et al. (2019) and Fajgelbaum et al. (2020, 2021). Accordingly, former U.S. Treasury Secretary Lawrence Summers commented that the large gyrations in financial markets attributed to the trade war are puzzling (Summers 2019).

[3]Hatzius et al. (2019) predicted an additional 0.6 percent drop in GDP due to financial conditions and policy uncertainty. While Fajgelbaum et al. (2020) and Amiti et al. (2019) do not consider the impacts of trade policy uncertainty, the latter acknowledges that "higher uncertainty may be reflected in the substantial falls in equity markets around the time of some of the most important trade policy announcements."

We find that the increased uncertainty due to the trade war has a significant negative impact on financial markets. Trade war news that raises the Chicago Board Options Exchange's Volatility Index (VIX) by 2 percentage points per annum (one standard deviation) increases high-yield spreads by 7 basis points, decreases the 10-year Treasury rate by 2.6 basis points, and lowers stock prices by 0.9 percent.[4] This effect is quantitatively significant as it is equivalent to the Federal Reserve increasing the federal funds target rate by 25 basis points (Bernanke and Kuttner 2005, Gurkaynak et al. 2005a). Although our paper is not the first to document an adverse impact of the trade war on U.S. asset prices, our paper is, to the best of our knowledge, the first to establish and quantify the causal impact of exogenous trade uncertainty shocks on U.S. financial markets.

Using this empirical framework, we confirm that the impact is less negative for stocks of firms that heavily rely on bank debt whereas non-bank debt does not have a mitigating effect, consistent with the financial flexibility channel. Specifically, a one standard deviation increase in bank debt usage, defined as the ratio of bank debt to total assets, can mitigate around 6% of the impact on a firm's stock value. We find that this effect is in line with those obtained from the EPU index in that a firm fully financed with bank debt is shielded from about a third of the average total impact.

Next, we shed more light on the mechanism through which the financial flexibility channel operates. Intuitively, borrowers that have trouble servicing their debt are more likely to value the option to renegotiate their debt. These cash-flow insolvent firms have recently attracted growing attention from academic and policy circles (Favara, Minoiu, and Perez-Orive 2021) as well as public media, which calls these firms "zombie firms."[5] Accordingly, we use the

[4]Our choice of VIX as the uncertainty measure is consistent with previous literature, such Bloom (2009) and Basu and Bundick (2017). Uncertainty indices calculated using news articles and economic data are also highly correlated with VIX at monthly level, and the economic reactions to changes in these indices closely resemble the economic reactions to VIX, e.g. Baker et al. (2016) and Scotti (2016). For our high-frequency approach, daily VIX has the additional advantage of reacting to macroeconomic news very quickly, whereas a daily EPU index may react with a delay depending on how synchronized news organizations are in reporting.

[5]Associated Press (Condon 2024) reports "Zombies are commonly defined as companies that have failed to make enough money from operations in the past three years to pay even the interest on their loans."

terms *cash-flow insolvent* and (potential) *zombie* for such firms interchangeably throughout the paper, notwithstanding the fact that the definition of zombie firms has been evolving in the academic literature.[6] We find that a cash-flow insolvent firm that derives half of its capital from bank debt shows no negative stock price reaction to increased uncertainty, highlighting bank debt's role in insulating such firms against uncertainty shocks.[7]

Our results about cash-flow insolvent firms also rule out other potential explanations for the mitigating effect of bank debt. For example, one might argue that banks are more risk-averse due to regulations or better at picking winners due to informational advantages, lending to firms less sensitive to macroeconomic news. This would suggest that firms insulated from shocks use more bank debt, rather than bank debt insulating firms. However, if this were true, higher bank debt usage would be associated with weaker reaction to uncertainty for all firms, including cash-flow solvent firms, which is not the case in the data.

Our findings regarding the role of bank debt usage become more striking when compared with non-bank debt usage. In particular, since the financial flexibility channel stems from ease of renegotiation of bank debt, we expect to not observe similar results for non-bank debt. Indeed, in contrast to bank debt usage, higher non-bank debt usage is associated with greater responsiveness to trade war news, and cash-flow solvency status does not have any effect on this association. Therefore, the results regarding non-bank debt usage provide a falsification test of our main results about bank debt. Finally, while the notion of a zombie firm is relevant in our context only due to its relation to cash-flow insolvency as a transmission

[6]The earlier literature focused on zombie lending as a mechanism for avoiding the recognition of a loan loss by a financially weak bank, thereby worsening inefficient allocation of funds, e.g., Caballero et al. (2008) and Acharya et al. (2019, 2020). Recent research puts a more positive spin on this issue, suggesting that it may be optimal for even a financially strong bank to evergreen the loan when the bank has market power and internalizes the effect of its choices on the borrowing firm's policies (Faria-e-Castro, Paul, and Sanchez 2024). Other recent research suggests that relationship lending mitigates the impact of a downturn on firm growth and does not constitute evergreening of loans (Beck et al. 2018). Regardless of the net impact of zombie firms and the characteristics of the banks that support them, it is clear that bank debt plays a special role for such firms, which makes them a natural candidate to study the mechanism underlying our results.

[7]We emphasize cash-flow insolvency, rather than balance-sheet insolvency, because the latter is more difficult to resolve through renegotiation, which reduces the value and importance of the option to renegotiate. We discuss and compare the two types of insolvency in more detail in Section 4.5.2.

mechanism, our results are unique in the zombie literature which typically does not include data on non-bank debt.

Our results are robust to controlling various firm-level characteristics that have been shown to affect the responsiveness of stock prices to macroeconomic shocks, including Tobin's Q, firm size, and balance sheet liquidity, along with firm and industry-date fixed effects. We further show that our results are not driven by endogenous changes in firms' debt structure in anticipation of a trade war, using the firm-level debt structure before Donald Trump's presidency as an instrument. The results also remain very similar after accounting for Fama-French risk factors. Additionally, our results remain consistent when we restrict our sample to firms with a zero revenue share from China, suggesting that the revenue exposure to China does not explain our results. Our findings also cannot be explained by the differential usage of bank debt and non-bank debt between the cash-flow insolvent and other firms because the two groups' utilization of both types of debt turn out to be similar. Finally, we show that our results are robust after creating matched samples of cash-flow insolvent and other firms based on their firm-level characteristics.

We use trade war news to identify economic policy uncertainty shocks since the effect of trade war on financial markets is widely attributed to increased policy uncertainty (Carney 2019). Nevertheless, an unexpected increase in tariffs could reduce stock values by reducing cash flow expectations, which increases market leverage and, through the leverage effect, the VIX. In such a case, the fluctuations in the VIX on the event days are not driven by fluctuations in uncertainty but by fluctuations in expected cash flows. To address this concern, we follow the Bharath and Shumway (2008) method to "unlever" the VIX. We find that this unlevering exercise leads to practically no change in our results.

As an additional analysis, we focus on the scheduled FOMC announcements to study whether our results can be generalized to monetary-policy-related uncertainty. The timing of these announcements is known well in advance and investors pay close attention to it. This approach provides an advantage if one may still be concerned that high-frequency events that

increase uncertainty coincidentally carry news of negative first-moment shocks even though first-moment and uncertainty shocks are not causally linked. Specifically, the first-moment shocks on scheduled FOMC announcement dates are well identified because there has been a long literature studying the impact of monetary policy shocks based on the movements in short-term interest rate derivatives and longer-term Treasury yields, starting with Bernanke and Kuttner (2005) and Gurkaynak, Sack, and Swanson (2005a). These properties allow us to clean the movements that can be attributed to the first-moment shocks instead of policy uncertainty.[8]

Using the FOMC announcement dates, we first confirm that our main results regarding the impact of policy uncertainty remain very similar. Then we show that purging the first-moment shocks on FOMC announcement dates does not materially change our coefficient estimates. This result holds even after using intraday data in a narrow event window around the FOMC announcements, which allows us to rule out that the results may be driven by news other than FOMC announcements on the same day (Gurkaynak, Sack, and Swanson 2005a and Nakamura and Steinsson 2018) or by pre-FOMC drift (Lucca and Moench 2015). Therefore, we conclude that, even in an environment where we can directly control for the first-moment shocks, our main results hold: Stock prices react negatively to increased policy uncertainty. Higher bank debt reduces the stock price sensitivity to uncertainty whereas non-bank debt does not have a similar effect. The mitigating effect of bank debt is concentrated among firms experiencing cash-flow insolvency. Overall the evidence from this exercise is also consistent with the argument that bank debt can provide insurance and flexibility during uncertain times.

Related Literature – Our paper is related to the literature that uses high-frequency data to identify the effects of policy news on asset prices. Bernanke and Kuttner (2005)

[8]The flip side of using FOMC announcements is that monetary policy uncertainty may reduce banks' willingness to lend by affecting the uncertainty of their costs and revenues as both are based on interest-earning assets. Therefore, we may see the mitigating effect of bank debt to be somewhat weaker for the impact of monetary policy uncertainty.

use daily stock prices and fed funds futures on FOMC announcement days to study the effect of unanticipated monetary policy changes on stock prices. Gurkaynak et al. (2005b) study how various asset prices react to unexpected changes in macroeconomic variables on the days of macroeconomic data releases, such as output, employment, and inflation. More recent papers refine this approach to study the cost of nominal frictions and associated risk premia, e.g. Gorodnichenko and Weber (2016) and Weber (2015), or transmission of monetary policy shocks through financial frictions and bank lending, e.g. Ippolito et al. (2018) and Gurkaynak et al. (2022). Our paper contributes to this literature by studying, for the first time to the best of our knowledge, the effect of policy uncertainty shocks and trade tensions.

Our work also pertains to the recent literature studying the effects of uncertainty shocks. This literature finds that increased uncertainty can generate countercyclical markups and depress output, consumption, and investment (e.g. Bloom 2009, Julio and Yook 2012, Basu and Bundick 2017). We contribute to the literature by studying the reaction of financial markets using well-identified uncertainty shocks with high-frequency data and by documenting evidence consistent with the theoretical predictions of finance literature (Pastor and Veronesi 2012). Finally, we contribute to the recent event studies that investigate the effect of the U.S.-China trade war through macroeconomic spillovers and trade networks (Egger and Zhu 2020, Huang et al. 2023, Amiti et al. 2021). We differ from these papers not only in terms of our focus on uncertainty and debt structure, but also in terms of our empirical approach that addresses potential identification concerns in event studies.

Last but not least, while our results are consistent with the financial flexibility channel, they do not imply that the bank balance sheet channel is shut off during periods of heightened policy uncertainty. For example, Correa et al. (2024) find that banks that are more exposed to trade uncertainty reduce their credit supply more. Our work differs from theirs because we are comparing bank financing to other sources of financing rather than making a comparison across different banks. The ability to renegotiate plays a role in both settings because

we know from previous work that weaker banks, on average, are less likely to renegotiate (Chodorow-Reich and Falato 2022). Taken together, the two papers imply that bank debt provides more financial flexibility than other sources of debt but this benefit is reduced for weaker banks and cash-flow solvent borrowers.

2 Suggestive Evidence

We examine the negative effect of uncertainty shocks through the lens of capital structure. Specifically, we investigate whether firms' debt structure matters in the transmission of policy uncertainty to stock prices. The central premise of our paper is based on the natural experiment in the next section. In this section, we present some suggestive evidence that establishes the link between economic policy uncertainty, stock prices, and debt structure.

We expect that higher economic policy uncertainty leads to lower stock prices. This theoretical link has been established in the previous literature (Pastor and Veronesi, 2012). However, we do not know how debt structure, specifically bank vs. non-bank debt, contributes to this relationship. We focus on studying the usage of bank debt vs. non-bank debt in this paper because bank debt can play two important roles with opposing effects.

On the one hand, worsened economic conditions caused by higher uncertainty can deteriorate banks' balance sheets, leading to a sharp reduction in loan supply and thereby amplifying the negative effect of uncertainty on bank-dependent borrowers. This is the so-called bank balance-sheet channel (Jimenez et al. 2012). On the other hand, banks specialize in acquiring private information about borrowing firms and typically enjoy concentrated creditor rights. As a result, bank debt is easier to renegotiate compared to public debt, especially during periods of distress (Boot et al 1993, Chemmanur and Fulghieri 1994, Berlin and Mester 1992, Hadlock and James 2002, Denis and Mihov 2003, De Fiore and Uhlig 2011). With higher uncertainty, the option value of renegotiation rises, which can help counteract the negative effect of uncertainty shocks on stock prices of bank-dependent borrowers. We dub this mechanism the financial flexibility channel. These two channels are

not mutually exclusive and their prominence is an empirical question.

2.1 Data

Our first two data sources include monthly stock returns from the Center for Research in Security Prices (CRSP) and the EPU index from Baker, Bloom, and Davis (2016). The EPU index captures news coverage frequency for policy-related economic uncertainty and has been a popular measure in the literature. The index is originally designed to reflect the frequency of articles in 10 leading U.S. newspapers that contain the following trio of terms: "economic" or "economy"; "uncertain" or "uncertainty"; and one or more of "Congress," "deficit," "Federal Reserve," "legislation," "regulation," or "White House." It has gone through various improvements since then and is readily available online.[9]

Our third source of data is Compustat and Capital IQ for debt structure. Public firms in the U.S. report detailed information on their capital and debt structure, thanks to the disclosure requirements by the Regulations S-X and S-K of the Securities Act of 1933. Capital IQ has been systematically compiling the relevant information from firms' regulatory filings, including financial footnotes. After 2002, the coverage by Capital IQ is comprehensive (Colla, Ippolito, and Li 2013, Gurkaynak, Karasoy-Can, and Lee 2022). Based on Capital IQ, we are able to decompose a firm's total debt into bank debt and non-bank debt. This then allows us to compute $BankLeverage$ as the ratio of total bank debt to total assets (Compustat item AT) and $NonBankLeverage$ as the ratio of total non-bank debt to total assets, where the total non-bank debt is defined as total debt (Compustat items DLC+DLTT) minus the total bank debt.[10]

Following Colla, Ippolito, and Li (2013), we clean our sample by removing firms in the financial sector (SIC codes 6000-6999) and utility sector (SIC codes 4900-4949), firms with missing or zero values for total assets, firms with missing or zero values for total debt, and

[9] See https://www.policyuncertainty.com/categorical_epu.html.

[10] We use the annual files because debt structure data is not as well populated in the quarterly files. Accordingly, we match the stock market data with the last available annual balance sheet data.

firms for which the difference between Compustat total debt and the sum of Capital IQ debt types exceeds 10% of the Compustat total debt.[11]

The return sample starts with January 2004, because comprehensive debt structure data from Capital IQ starts in 2003 and we use lagged firm characteristics in our empirical regressions, and goes to the end of 2019.

2.2 Suggestive Evidence

We estimate the following regression

$$\begin{aligned} r_{i,t} &= \alpha_i + \beta \times \Delta EPU_t + \gamma \times \Delta EPU_t \times BankLeverage_{i,t-1} \\ &\quad + \delta \times \Delta EPU_t \times NonBankLeverage_{i,t-1} \\ &\quad + Controls + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

The dependent variable, $r_{i,t}$, is the monthly return on firm i's stock in month t. The explanatory variables include the change in the monthly EPU index, ΔEPU_t, and its interaction with the ratio of bank debt to total assets for firm i, $BankLeverage_i$, and the ratio of non-bank debt to total assets for firm i, $NonBankLeverage_i$. $Controls$ include standalone $BankLeverage_i$ and $NonBankLeverage_i$, as well as industry-time fixed effects.

Table 1 shows the results for regression (1). We begin with a univariate panel regression of stock returns on changes in the monthly EPU index over the full sample. The result, shown in column (1), confirms the theoretical negative relationship between economic policy uncertainty and stock returns predicted by Pastor and Veronesi (2012). In particular a one standard deviation (26 units) increase in the EPU index is associated with a decline in stock value of 1.82 ($= 0.07 * 26$) percent, which is both economically and statistically significant. As the next step, we control for industry-month fixed effects and look at the effect of debt structure in column (2) and use Fama-French three-factor excess returns in column (3), both

[11] In addition to bank debt, the Capital IQ debt types include commercial paper, senior bonds and notes, subordinated bonds and notes, capital leases, and other debt.

of which present an ambiguous result. In particular, while the coefficient of the impact through non-bank leverage (δ) is negative the impact from bank debt (γ) is economically small and statistically insignificant.

This pattern illustrates an identification problem using the EPU index. It is very difficult to disentangle economic policy uncertainty from macroeconomic uncertainty (Kelly, Pastor, and Veronesi, 2016). While there are certainly exogenous changes in policy uncertainty (for example, due to changes in government policy and political landscape), policy is also a function of the macroeconomic environment and an uncertainty in the macroeconomic environment would be by construction translated into a policy uncertainty. As a particular example, in the context of 2007–2009 GFC, the source of both the macroeconomic and policy uncertainty was due to a banking crisis. Therefore, even though the banking relationships may in general protect a borrower against the impact of policy uncertainty, we would not be able to see the effect in the data using an index or proxy for policy uncertainty, such as the EPU index, because the direction of the financial uncertainty stemming from a banking crisis would, by construction, have the opposite effect on firms that rely more on bank debt.

In order to circumvent this issue, we study regression (1) separately for the 2007–2009 GFC period in columns (4)–(6).[12] Columns (5) and (6) of Table 1 show that both the bank and non-bank debt had an amplifying effect during the GFC period, with a much larger change for the influence of bank debt compared to columns (2) and (3). This result is consistent with the argument that this period was a period of high financial uncertainty that particularly hit the banking sector, making separate identification of the impact of policy and macroeconomic uncertainty difficult.

Finally, columns (7)–(9) shows the results for regression (1) for the whole sample excluding GFC. Arguably, this period is devoid of any banking-related recessions and hence

[12]We are defining this period as starting in April 2007, when New Century, an American real estate investment trust specializing in subprime lending and securitization, filed for Chapter 11 bankruptcy protection, which propagated the subprime mortgage crisis. We take the end date as the passage of Dodd-Frank Act in December 2009.

provides a cleaner identification regarding how debt structure influences the impact of economic policy uncertainty on stock values. For this period, we see that bank debt usage actually reduces, rather than amplifies, the impact of economic policy uncertainty, consistent with the financial flexibility channel. In particular, a firm that uses only bank debt would be shielded from about one third of the impact of the EPU index on its stock value compared with a firm that does not use any bank debt.

Although taking out the GFC period is a good first step in better identification, we cannot definitely argue that this approach completely resolves the identification problem. For this purpose, we need a setting where stock prices are affected primarily by economic policy uncertainty, rather than uncertainty regarding macroeconomic variables that the economic policy may be reacting to. The next section addresses this challenge by focusing on the 2018-2019 U.S.-China trade war period in a daily setting. This setting also allows us to study the economic mechanisms underlying the empirical patterns.

3 Measuring the Effect of Policy Uncertainty on Financial Markets using the U.S.-China Trade War

Our study uses the U.S.-China trade war as a natural experiment to identify uncertainty shocks through trade-war-related news. The fundamental premise of this approach is that these pieces of news have a significant effect on the financial markets. Anecdotal evidence suggests that this is indeed the case. For example, Figure 1 shows how the S&P 500 index was flat until Friday, August 23, 2019, and reacted immediately when President Trump tweeted that he "hereby ordered" American companies to "immediately start looking for an alternative to China," although "it was not immediately clear how, or under what authority, the president could implement these declared orders."[13] That day, the stock market closed down about 2.5 percent. Obviously, a single event isn't sufficient evidence to assert

[13] https://www.cnbc.com/2019/08/23/trump-says-hes-ordering-american-companies-to-immediately-start-looking-for-an-alternative-to-china.html

a systematic importance. In order to measure the effect of policy uncertainty on financial markets via our approach we need two ingredients: (i) a list of trade-war-related news and (ii) a method of identifying the effect of exogenous uncertainty shocks on financial markets.

3.1 Identifying Trade-War-Related News

We systematically search for news related to the trade war from public sources and construct a complete timeline of the trade-war-related news events. We also utilize Factiva to confirm whether the timing of each news arrival falls within the trading hours of the same day. If the earliest timestamp of a news event is after the trading hours, we shift the event window to the next trading day to capture the relevant impact on the financial markets. Our timeline identifies 28 event days during the period from January 2018 to August 2019. Internet Appendix A includes the details of our timeline construction.

During the period from January 2018 through August 2019, these news events related to the trade war account for an increase of 50 basis points (of the total 70 basis points rise) in the high-yield spread, and about 55 basis points of the 90 basis points decline in the 10-year Treasury yield (Table 2, Panel A). Overall, the trade-war-related news appears to significantly impact the financial markets.

3.2 Identifying the Effect of Uncertainty Shocks via Heteroskedasticity

The news events alone are insufficient to identify the effect of the uncertainty shocks on U.S. financial markets because various factors can affect the financial markets simultaneously. To address this challenge, we utilize the heteroskedasticity-based estimator of Rigobon and Sack (2003, 2004, 2005).[14]

The framework of the heteroskedasticity-based estimator assumes that daily changes of

[14]We base our analysis on daily events, consistent with the approach of Rigobon and Sack (2003, 2004, 2005). One could alternatively use intraday events for identification. However, it is difficult to pinpoint the exact minute of the arrival of each trade-war-related news, except for the timing of the President's tweets. Even if one focuses on using these tweets, they do not always reveal new information about the trade war, meaning the identification is weak at best.

financial variables can be characterized by a system of linear equations. If we let z_1 be trade-war-induced uncertainty shocks, z_2 be the vector of all other shocks, and Δy_1 and Δy_2 be the daily changes of two financial market variables, we can write the equations for Δy_1 and Δy_2 as:

$$\Delta y_1 = \alpha_1 z_1 + \alpha_2 z_2 + e_1 \tag{2}$$

$$\Delta y_2 = \beta_1 z_1 + \beta_2 z_2 + e_2, \tag{3}$$

where e_1 and e_2 are idiosyncratic shocks.

This system of equations reveals two identification challenges. First, the variable z_1 is unobservable, in that on any given event day, the uncertainty shock from the trade-war-related news cannot be precisely quantified. However, we can let y_1 be a financial variable that is known for representing changes in uncertainty, such as the Chicago Board Options Exchange's Volatility Index (VIX), which measures the 30-day implied volatility on the S&P 500 index.[15] We can let y_2 be a financial variable, such as stock prices, which reacts to uncertainty shocks and whose reaction we want to estimate. We can then answer the question: "What is the effect of a change in uncertainty induced by the trade war that moves VIX by one percentage point per annum on stock values?" In other words, although one cannot directly measure z_1, and hence its effect β_1, it is possible to identify β_1/α_1 to gauge the impact of the uncertainty shock on the financial markets.

The second identification challenge is that, even during the event days, financial variables can be affected by shocks unrelated to the trade war. Therefore, if we were to simply regress the daily change of a financial variable on the daily change of VIX on event days, the resulting

[15]This choice conforms with the existing literature that extensively uses VIX as an uncertainty measure, such as Basu and Bundick (2017) and Bloom (2009). Uncertainty indices calculated using news articles and economic data are also highly correlated with VIX, and the economic reactions to changes in these indices closely resemble the economic reactions to VIX, e.g. Baker et al. (2016) and Scotti (2016). For our high-frequency approach, daily VIX has the additional advantage of reacting to policy news very quickly, whereas a daily EPU index may react with a delay depending on how synchronized news organizations are in reporting.

coefficient estimates could be influenced by confounding factors.[16] To address this challenge, we follow Rigobon and Sack (2003, 2004, 2005) and start with a set of event and non-event days and two identification assumptions: (i) the variance of the trade-war-induced shocks (z_1) is higher on event dates, (ii) the variance of other news and the variance of the idiosyncratic shocks on event dates are equal to their counterparts on non-event dates. Intuitively, this identification strategy allows for all types of news to be present on any given day but assumes that any difference in the volatility of the movements in the financial variables and VIX occurring on event dates, relative to non-event days, is attributable to news about the trade war.[17]

Under the identification assumptions, we can then consistently estimate β_1/α_1 by running the following regression over a set of event days (ED) and non-event days (NED)

$$\Delta y = \beta \times \Delta VIX + \varepsilon, \tag{4}$$

where $\Delta y = (\Delta y_{ED}, \Delta y_{NED})'$ and $\Delta VIX = (\Delta VIX_{ED}, \Delta VIX_{NED})'$, and instrumenting ΔVIX with $IV = (\Delta VIX_{ED}, -\Delta VIX_{NED})'$.

To see this mathematically, note that the instrumental variables estimate of β satisfies

$$\operatorname{plim} \widehat{\beta}_{IV} = \frac{cov(\Delta y, IV)}{cov(\Delta VIX, IV)} = \frac{cov(\Delta y_{ED}, \Delta VIX_{ED}) - cov(\Delta y_{NED}, \Delta VIX_{NED})}{var(\Delta VIX_{ED}) - var(\Delta VIX_{NED})}. \tag{5}$$

Once we replace ΔVIX in equation (5) with Δy_1 in equation (2) and Δy in equation (5) with Δy_2 in equation (3), it is relatively straightforward to show that $\operatorname{plim} \widehat{\beta}_{IV} = \beta_1/\alpha_1$ under

[16] In the context of equations (2) and (3), this would be a regression of Δy_2 on Δy_1. The associated OLS estimator would be $\beta_{OLS} = cov(\Delta y_1, \Delta y_2)/var(\Delta y_1) = [\beta_1\alpha_1 var(z_1) + \beta_2\alpha_2 var(z_2)]/[\alpha_1^2 var(z_1) + \alpha_2^2 var(z_2) + var(e_1)] \neq \beta_1/\alpha_1$ due to omitted variables, $var(z_2) \neq 0$, and measurement error, $var(e_1) \neq 0$.

[17] This assumption could fail if the trade-war-related news is somehow systematically driven by other shocks that influence the financial markets. For example, it might be the case that the trade-war-related news is strategically revealed to divert public attention from other news events. Nevertheless, we deem it unlikely that the majority of our trade-war-related news fits this category, especially considering that we focus on high-frequency (daily) event windows. In addition, controlling for lagged changes of the financial variables in our regressions does not alter our results.

the identification assumptions.[18] The intuition for our regression is simple: Since only the variance of trade-war-induced shocks is different on event dates when compared to non-event dates, all the other sources of variance in Δy and ΔVIX on event dates get cleaned out, leading to a consistent estimate of β_1/α_1.

Our identification strategy requires a set of non-event days in addition to our event days. Figure 2 presents the VIX series since January 2018, along with our 28 event days. For each event day, we choose the non-event day as the same weekday two weeks earlier.[19] We choose to separate each event and non-event day by a two-week interval to ensure an adequate time gap between event and non-event days; our results are robust to using alternative intervals.

Table 2, Panels A and B compare the summary statistics of major financial variables on the event and non-event days. Consistent with the identification assumptions, the standard deviations, as well as the minimum and maximum values, indicate that the financial variables are indeed substantially more volatile on the event days. While the heteroskedasticity-based estimator has been popular in studying the effect of monetary policy on asset prices (Rigobon and Sack 2003, Nakamura and Steinsson 2018), our paper, to the best of our knowledge, is the first to implement such approach to study the effect of uncertainty shocks on financial markets.

3.3 Aggregate Effect of Uncertainty Shocks on Financial Markets

We start our analysis by studying the effect of the trade-war-induced uncertainty shocks on aggregate variables in the U.S. financial markets. For this exercise, we use the data on VIX, the two-year Treasury yields, the 10-year Treasury yields, high-yield spreads, and the

[18] Under the identification assumptions, we have $var(z_{2,ED}) = var(z_{2,NED})$. As a result, the numerator in equation (5) will become $\beta_1\alpha_1 [var(z_{1,ED}) - var(z_{1,NED})]$, while the denominator in equation (5) will become $\alpha_1^2 [var(z_{1,ED}) - var(z_{1,NED})]$, leading to $\text{plim}\, \widehat{\beta}_{IV} = \beta_1/\alpha_1$.

[19] For the event day of August 23, 2019, the candidate for the non-event day two weeks prior overlaps with the event day of August 9, 2019. We therefore add an additional week and choose August 2, 2019 as the corresponding non-event day.

S&P 500 index from the Federal Reserve Economic Data (FRED).[20] Table 3 summarizes the estimated effect of the trade-war-induced uncertainty shocks that drive up VIX by one unit, equivalent to a one-percentage-point or roughly half-a-standard-deviation increase in the annualized implied volatility during our sample period. Table 3 shows such an uncertainty shock lowers the two-year and 10-year Treasury yields by about 1.5 basis points and increases the high-yield spreads by about 3.5 basis points, consistent with our expectations based on the arguments by policymakers and previous academic literature (Carney 2019, Pastor and Veronesi 2012). We further observe such an uncertainty shock reduces the S&P 500 index by about 0.46 percent. These estimates are quantitatively important, as they suggest that the impact of an uncertainty shock driving up VIX by one standard deviation aligns with the effect of the Federal Reserve raising the federal funds target rate by 25 basis points (Bernanke and Kuttner 2005, Gurkaynak et al. 2005a). Our results on the aggregate variables thus lead to the conclusion that the trade-war-induced uncertainty has a significant impact on the U.S. financial markets.

We also check if our results may be heavily influenced by an outlier event day. We do so by excluding one event day at a time and re-estimating the coefficients in Table 3. Figure 3 reports the histogram resulting from this exercise. As the figure suggests, all of our estimates remain stable, being less than one standard deviation away from the original estimates in Table 3. We therefore alleviate the concern that our results are affected by outlier event days.

3.4 Trade Exposure and the Effect of Trade-War-Related Uncertainty Shocks on Stock Prices

So far, we have established the causal effect of the uncertainty shocks on aggregate variables in the financial markets. A natural extension of our method is studying whether trade-war-related uncertainty shocks affect different stocks differently, based on companies'

[20]The high-yield spreads are measured as the Bank of America Merrill Lynch U.S. High Yield Master II Option-Adjusted Spread. See Table 2 for additional details on variable definitions.

revenue exposure to China. This question is not only interesting in its own right but it also provides a sanity check to confirm that our heteroskedasticity-based identification approach indeed captures the uncertainty shocks specific to the U.S.-China trade war. If this is the case, we should observe that (i) firms that derive a larger share of their revenue from China are more negatively affected, while (ii) the share of non-U.S. revenue from foreign countries other than China does not play a significant role in the shock transmission. In addition to confirming these expectations, this section shows that the uncertainty shocks significantly decrease the stock prices of U.S. firms, even for firms that do not have a direct revenue exposure to China.

The daily stock return data for our cross-sectional analysis comes from the CRSP, where we can compute the daily stock returns for U.S. firms during our sample period. We also calculate the revenue share of each firm from China and other countries using the geographic segment data from Compustat Historical Segments.[21] As firms can endogenously respond to the trade war during our sample period, we utilize the revenue share in 2017, the year preceding the trade war, to account for each firm's geographic exposure. We remove financial (SIC codes 6000-6999) and utility (SIC codes 4900-4949) firms from our sample due to their distinct capital structures and demand, making them difficult to compare to other businesses. We further exclude firms from our sample if a firm reports sales to the Asia-Pacific regions, but does not explicitly delineate its sales to China, to avoid measurement errors.

Using the cross-sectional data and our sets of event days (ED) and non-event days (NED), we estimate the following fixed-effects instrumental variable regression:

$$r_{i,t} = \alpha_i + \beta \times \Delta VIX_t + \gamma \times \Delta VIX_t \times ChinaShare_i + \delta \times \Delta VIX_t \times X_i + \varepsilon_{i,t} \qquad (6)$$

by instrumenting ΔVIX with $IV = (\Delta VIX_{ED}, -\Delta VIX_{NED})'$, consistent with Section 3.2. The dependent variable, $r_{i,t}$, is the daily return of firm i's stock on date t. $ChinaShare_i$

[21] Another popular dataset used in the literature is FactSet. We have spot checked our Compustat data with FactSet and verified that the information matches in both datasets.

measures firm i's revenue share from China in 2017. X_i includes two additional variables: firm i's revenue share from non-U.S. sources other than China and a dummy variable that indicates if firm i derives all of its revenue domestically from the U.S.

Table 4 presents the main findings from our cross-sectional analysis. Similar to Section 3.3, Table 4 summarizes the estimated effect of the uncertainty shocks that drive up VIX by one unit, equivalent to a one-percentage-point or roughly half-a-standard-deviation increase in the annualized implied volatility during our sample period. Column (1) of the table shows that such an uncertainty shock reduces the stock prices by around 0.4 percent on average, in line with the results related to the S&P 500 index in Table 3. This effect remains consistent after we control for firms' revenue shares from China in column (2). In addition, column (2) indicates that the negative effect on stock prices is significantly stronger for firms with a larger revenue exposure to China. Specifically, a 10 percentage point increase in the revenue share from China ($ChinaShare$) leads to an additional 0.04 percent decline in stock prices. These results remain very similar when we restrict our sample to firms that have revenue from any foreign region, thereby excluding domestic firms, in column (3). These findings are also stable when we further restrict our sample in column (3) to firms with revenues from China in column (4). Our results from columns (1) to (4) therefore demonstrate two insights: (i) the uncertainty shocks significantly decrease stock prices of U.S. firms on average, regardless of their revenue exposure to China, and (ii) firms with a higher revenue exposure to China experience a significantly more negative impact.

Building on our findings from columns (1) to (4), we next investigate if a firm's revenue exposure to non-U.S. sources other than China influences our results. Since our identification strategy should capture uncertainty shocks specifically from the U.S.-China trade war and not other sources, our results should not depend on a firm's foreign revenue exposure from non-U.S. sources. Consistent with this argument, column (5) confirms that our main estimates remain almost unchanged after controlling for a firm's revenue share from non-U.S. sources other than China ($ForeignNonChinaShare$) and the dummy variable that indicates if a firm

derives all of its revenue domestically from the U.S. ($USonly$). Moreover, the coefficients of these two additional variables are economically and statistically insignificant. Our results are also robust when we add industry-date fixed effects in column (6) to address the possibility that some industries may react substantially differently to the trade-war-induced uncertainty shocks, such as those that heavily rely on inputs from China. Together, columns (5) and (6) provide evidence that our findings do not depend on firms' foreign revenue shares from non-U.S. sources other than China, which supports the validity of our identification strategy.

4 Policy Uncertainty, Stock Prices, and Debt Structure: Evidence from the U.S.-China Trade War

Section 3 demonstrates the significant causal impact of uncertainty shocks on financial markets, using the U.S.-China trade war as a natural experiment. It also shows that the trade-war-induced uncertainty shocks substantially lower the stock prices of U.S. firms, regardless of their revenue exposure to China. In this section, we examine the effect of uncertainty shocks through the lens of firm's debt structure. We confirm our suggestive evidence from Section 2 that debt structure matters, in that the usage of bank debt mitigates the negative effect of uncertainty shocks on stock prices, while such mitigating effect does not exist for non-bank debt, consistent with the financial flexibility channel.

We then study the economic mechanism behind this finding. Intuitively, among two borrowers with the same debt structure, the one that has trouble servicing its debt with its cash flows is more likely to value the option to renegotiate its debt following a policy uncertainty shock. Moreover, the renegotiation may be more likely to happen for these firms for two reasons. First, the inability of such firms to make timely payments induces both the firm and the bank to come to the table whereas the bank does not have any incentive to renegotiate the debt if the firm can generate enough income to make its payments in a timely manner. Therefore, cash-flow insolvency activates the option to renegotiate by the firm. Second, the bank may have incentives to renegotiate with such firms. When a

cash-flow insolvent firm depends on bank debt for survival, a reduction in loan supply may imply the recognition of a loan loss. This can be undesirable for the lending bank due to agency problems (Bonfim et al. 2022) or regulatory constraints (Caballero et al. 2008, Blattner et al. 2019) and induce the bank to keep the firm alive by evergreening, which has helped such firms earn the moniker "zombie firms." Even in the absence of such frictions, an unconstrained bank may have an incentive to evergreen the loan because the firm is more valuable as a going concern rather than being liquidated (Faria-e-Castro, Paul, and Sanchez 2024).[22] Some recent research even suggests that bank lending mitigates the impact of a downturn on firms facing financial hardship and does not constitute evergreening of loans (Beck et al. 2018).

Overall, regardless of social desirability of keeping such firms afloat or the financial health status of these firms' banks, it is clear that the ability to renegotiate bank debt plays a special role for these firms, which makes these firms a natural candidate to study the mechanism underlying our results. In particular, we expect that the mitigating effect of bank debt should be stronger for such firms. Since the moniker of "zombie" for these firms stuck in the literature and public media, we use the terms "cash-flow insolvent" and (potential) "zombie" interchangeably throughout the paper, notwithstanding the evolving definition of zombies and their perceived contribution to the economy in the academic literature.

We find that the mitigating effect of bank debt is concentrated among firms that persistently lack sufficient earnings to cover their interest expenses, consistent with the notion that such firms are more likely to benefit from the option to renegotiate. Furthermore, we show evidence that the mitigating effect is indeed driven by these firms' lack of sufficient cash-flows (cash-flow insolvency) rather than lack of sufficient assets (balance-sheet insolvency), consistent with the argument that bank debt offers negotiation flexibility to avoid

[22]Early research on zombies includes an evergreened firm paying a lower interest rate on loans than non-evergreened firms do as a criterion of being a zombie firm (Caballero et al. 2008). However, recent research argues that it can be optimal for banks to evergreen bank-dependent distressed firms even when the bank is healthy and there is no friction from recognizing loan losses; moreover, these firms pay higher interest rates than non-evergreened firms (Faria-e-Castro, Paul, and Sanchez 2024).

inefficient liquidation of an otherwise balance-sheet solvent firm.

4.1 Data: Cash-Flow Insolvency and Additional Firm-Level Characteristics

For cash-flow insolvency, we focus on firms that could not service their debt with their earnings, which have been also the recent focus of policymakers, academics, investors, and public media concerned with zombie firms.[23] We therefore adopt the definition from the recent studies that directly captures this idea (McGowan et al. 2018, Banerjee and Hofmann 2018, 2022). Accordingly, we define cash-flow insolvent (potential zombie) firms as mature firms that consistently have an interest coverage ratio (ICR) below one for three years (2015-2017) leading to 2017.[24] Since the age of a firm is not directly observable for many U.S. public companies, we consider a firm as mature if it has been publicly traded for at least five years by the end of 2017.[25] To improve comparability between cash-flow insolvent and other firms, we include only mature firms in our sample. The resulting share of zombie firms in our study is around 7%, which is broadly consistent with the figure for U.S. public firms reported in Favara, Minoiu, and Perez-Orive (2021).

For firm-level debt structure, we follow our practice in Section 2.1 and utilize Compustat and Capital IQ to measure firms' $BankLeverage$ and $NonBankLeverage$. On top of $BankLeverage$ and $NonbankLeverage$, which were introduced in Section 2, we include additional control variables in our main analysis that are known to influence the responsiveness of stock prices to macroeconomic shocks as well as the performance of zombie firms (e.g.

[23] See, for example, The Economist (2020), Bloomberg (Lee and Contiliano 2020), Fortune (Daniel 2022) for public media, Goldman (2022) for investors, and McGowan et al. (2018), Banerjee and Hofmann (2018, 2022) for academic research and policy institutions.

[24] This definition is also consistent with the accounts in public media. For example, Associated Press (Condon 2024) writes "zombies are commonly defined as companies that have failed to make enough money from operations in the past three years to pay even the interest on their loans." We define the ICR as the ratio of EBITDA from Compustat over interest expenses (Compustat item XINT). Our results are robust when we define the ICR as EBIT over interest expenses instead.

[25] The literature tends to use a 10-year age restriction to define mature firms (McGowan et al. 2018, Banerjee and Hofmann 2018). Meanwhile, Ritter (2021) documents that the median age of U.S. public firms at their initial public offering during 2001–2020 is 11 years. Therefore, our definition of mature firms is more conservative, helping to avoid misclassifying young, high-growth firms with low ICRs as zombie firms. Our results are also robust when we change the age restriction to a range of values around five years or remove the age restriction completely.

Ippolito, Ozdagli, and Perez-Orive 2018, Favara, Minoiu, and Perez-Orive 2021, Banerjee and Hofmann 2018). These variables include Tobin's Q ($TobinQ$), firm size ($LogAssets$), and the quick ratio ($QuickRatio$) as a measure for firms' balance sheet liquidity. $TobinQ$ is computed as (MVE+DLC+DLTT)/AT, where MVE is the market value of equity, calculated as the common shares outstanding (CSHO) multiplied by the annual close price (PRCC_F) from Compustat. $LogAssets$ is the natural logarithm of total assets. $QuickRatio$ is defined as the ratio of cash and cash equivalents to current liabilities (Compustat CHE/LCT).[26] Since firms may change their debt structure in response to the trade war, we anchor all firm-level characteristics in 2017, the year before the trade war, in our analysis, in line with our practice in Section 3.4.

Table 5, Panel A presents the summary statistics for the full sample, the sample of cash-flow insolvent firms (potential zombie firms), and the sample of cash-flow solvent firms (non-zombie firms). Since we are interested in the role of debt structure in the transmission of uncertainty shocks to stock prices, it is reassuring to observe that the distribution of $BankLeverage$ and $NonBankLeverage$ is similar for the cash-flow insolvent firms and other firms. Consistent with Favara, Minoiu, and Perez-Orive (2021), we do detect significant differences in Tobin's Q, firm size, and the quick ratio between the two groups, as can be seen in the last column of Table 5, Panel A. To account for these differences, we first explicitly control these variables in our regressions. In addition, we also match our cash-flow insolvent and other firms using various techniques to alleviate remaining concerns regarding confounding factors associated with firm-level characteristics before the trade war.

4.2 Econometric Framework

To test the role of debt structure in the transmission of uncertainty shocks to stock prices, we use our sets of event days (ED) and non-event days (NED) and estimate the following

[26] Tobin's Q and firm size are also closely related to the characteristics underlying the Fama-French book-to-market and size factors. Accordingly, Daniel and Titman (1997) and Ferson and Harvey (1999) suggest that directly controlling for firm characteristics subsumes the effect of the Fama and French (1992) risk factors. Nevertheless, we also study the Fama-French excess returns explicitly and find robust outcomes.

fixed-effects instrumental variable regression:

$$\begin{aligned} r_{i,t} &= \alpha_i + \beta_0 \times \Delta VIX_t + \gamma_0 \times \Delta VIX_t \times BankLeverage_i + \delta_0 \times \Delta VIX_t \times NonBankLeverage_i \\ &\quad + \beta_1 \times \Delta VIX_t \times CFInsolvent_i + \gamma_1 \times \Delta VIX_t \times BankLeverage_i \times CFInsolvent_i \\ &\quad + \delta_1 \times \Delta VIX_t \times NonBankLeverage_i \times CFInsolvent_i + Controls + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

by instrumenting ΔVIX with $IV = (\Delta VIX_{ED}, -\Delta VIX_{NED})'$, following our practice in Section 3. The dependent variable, $r_{i,t}$, is the daily return of firm i's stock on t. $BankLeverage_i$ measures the ratio of bank debt to total assets for firm i. $NonBankLeverage_i$ measures the ratio of non-bank debt to total assets for firm i. $CFInsolvent_i$ is a dummy variable indicating whether a firm is cash-flow insolvent. $Controls$ include the interaction terms of these variables that do not involve ΔVIX_t plus the additional firm-level characteristics, together with their interaction terms with ΔVIX_t and $CFInsolvent_i$. All firm-level characteristics are calculated using 2017 data, the year preceding the trade war.

4.3 Main Results

Table 6 presents our main results. Similar to the interpretation in Section 3, Table 6 summarizes the estimated effect of the uncertainty shocks that drive up VIX by one unit, equivalent to a one-percentage-point or roughly half-a-standard-deviation increase in the annualized implied volatility during our sample period. We begin our estimation by focusing on the first two terms in equation (7) only. Table 6, column (1) shows that the uncertainty shocks lower the stock prices by about 0.425 percent on average for firms without bank debt, in line with our estimates from Section 3. In addition, column (1) reveals that a one standard deviation (0.17) increase in the 2017 value of $BankLeverage_i$ can mitigate around 6% ($= 0.17 * 0.15/0.425$) of the negative effect of the uncertainty shocks.

A natural concern for column (1) is that firms with more bank debt simply borrow more in general and the mitigating effect is associated with a firm's total debt rather than bank debt. To address this concern, we control for the usage of non-bank debt in column (2). As

the column indicates, the mitigating effect of bank debt remains stable, whereas a higher usage of non-bank debt seems to amplify, rather than attenuate, the negative effect of the uncertainty shocks. Our results so far thus lend support to the financial flexibility channel over the bank balance-sheet channel.

In order to provide further evidence for the economic mechanism underlying the financial flexibility channel, namely the ability to renegotiate, we study whether the effect is primarily driven by the natural beneficiaries of the renegotiation, i.e. the cash-flow insolvent firms, as discussed in Section 4.2. Table 6, column (3) demonstrates that this is indeed the case. In fact, the mitigating effect of bank debt can be completely attributed to the cash-flow insolvent firms. A one-standard-deviation increase (0.2) in the bank leverage for an average cash-flow insolvent firm can mitigate around 45% ($= 0.2 * 0.89/0.39$) of the negative effect of the uncertainty shocks on their stock prices. For other firms, the mitigating effect of bank debt is economically small (0.038 vs 0.89) and statistically insignificant. Furthermore, the coefficient of a firm's cash-flow insolvency status (-0.082) is also small and statistically insignificant, suggesting that our results are not driven by a firm's cash-flow insolvency itself, but its interaction with the usage of bank debt. Our findings in column (3) are robust after controlling for additional firm-level characteristics in column (4) that are known to influence the responsiveness of stock prices to macroeconomic shocks as well as the performance of zombie firms (e.g. Ippolito, Ozdagli, and Perez-Orive 2018, Favara, Minoiu, and Perez-Orive 2021, Banarjee and Hoffman 2018). Column (5) further validates the robustness of our results by including the industry-date fixed effects.[27]

Our benchmark regressions thus far utilize firm-level characteristics in 2017, the year preceding the U.S.-China trade war. Although this alleviates the concern that firms can

[27]Since bank debt consists of term loans and revolving credit, we decompose it in the internet appendix to examine their roles separately. We also include undrawn revolving credit to assess whether the associated liquidity insurance, rather than renegotiation flexibility, explains the mitigating effect of bank debt. Table A1 shows that both term loans and outstanding revolving credit provide a significant mitigating effect. However, the effect of undrawn credit is not statistically significant, suggesting that our results are not driven by its liquidity insurance.

endogenously respond to the trade war during our sample period, it may still be possible that firms have already adjusted their debt structure in 2017 in anticipation of future trade-war-induced uncertainty shocks, especially considering that Donald Trump's presidency began in January 2017. To address this concern, we instrument the bank leverage and non-bank leverage in 2017 with their counterparts in 2016. Using lagged debt structure as instruments is not only common in the literature (Ippolito, Ozdagli, and Perez-Orive 2018, Gurkaynak, Karasoy-Can, and Lee 2022), but also suitable in our case since Trump's election victory at the end of 2016 came mostly as a surprise. As can be seen from column (6), our results from this exercise closely align with those in column (5).

Next, we repeat our analysis using Fama-French three-factor excess returns in column (7) to ensure that our results are not driven by risk factors in the cross-sectional asset pricing literature. As an additional analysis, we restrict the sample in column (8) to firms with a zero revenue share from China to ensure that our results are not driven by revenue exposure to China we have studied in Section 3. In both cases, we find that our main result holds in that the mitigating effect of bank debt originates from cash-flow insolvent firms.[28]

To the best of our knowledge, we provide the first empirical evidence on the role of debt structure in the transmission of uncertainty shocks to stock prices. Our findings show that firms' debt structure matters, in that the usage of bank debt mitigates the negative effect of uncertainty shocks on stock prices, while such mitigating effect does not exist for non-bank debt. We further illustrate that the mitigating effect of bank debt is concentrated among mature firms that persistently lack sufficient earnings to cover their interest expenses. Overall, our results are consistent with the financial flexibility channel of bank debt, especially for cash-flow insolvent firms.

[28]We also note that the coefficient of $\Delta VIX \times BankLeverage$ in these two columns are negative and statistically significant at 10% level. This may suggest that the bank balance sheet channel dominates the financial flexibility channel for at least some cash-flow solvent firms. Nevertheless, this result is neither robust across every specification in Table 6, nor would it invalidate our main result that the mitigating effect of bank debt in the overall sample, documented in columns (1) and (2), originates from cash-flow insolvent firms.

Our findings on cash-flow insolvent firms are also useful to rule out other explanations for the mitigating effect of bank debt. For instance, one may be concerned that the positive coefficient of bank leverage can be caused by endogenous selection by the banks. In particular, banks may face additional scrutiny from the regulators and therefore be more risk-averse than other investors. Banks can also be better at picking "winners" due to their informational advantage. As a result, banks can lend to firms that are less sensitive to macro uncertainty shocks. In this case, our result would be interpreted not as "bank debt is special" but as "firms that rely more on bank debt are special." Though a reasonable concern, it is unlikely that our findings can be explained by such arguments. If our results were driven by the endogenous lending decisions because banks are more risk averse or are good at picking "winners," the bank leverage should display a similar, if not stronger, effect for the cash-flow solvent firms, which is not the case in the data.[29]

4.4 Matching Analyses

Our results so far are unlikely to be driven by the differential usage of bank debt and non-bank debt between the cash-flow insolvent and other firms because the debt structure of these firms turn out to be similar (Table 5, Panel A). Moreover, our regressions so far control for confounding factors by adding the relevant firm characteristics as control variables. Nevertheless, one can argue that this approach is not enough since the cash-flow insolvent firms and other firms in our sample are fundamentally different in terms of their characteristics. An alternative approach to address this concern is pruning observations from the data so that the remaining cash-flow insolvent and solvent firms are similar (matched) to each other. We therefore conduct further robustness checks by performing two such matching exercises.

We start our matching analyses with Mahalanobis matching in Section 4.4.1, a widely used matching method belonging to a class of matching methods known as equal percent bias

[29]It should also be noted that other large investors in the non-bank debt market, such as insurance companies, are also regulated. This further decreases the likelihood that our results can be explained by the endogenous lending decisions of banks because they are more risk averse due to regulatory reasons.

reducing (EPBR). Despite its popularity, we acknowledge that an EPBR matching method has shortcomings in achieving balance between the treatment and control groups, which, in our case, corresponds to the cash-flow insolvent and other firms (e.g. Mielke and Berry 2007). In fact, an EPBR matching method does not guarantee any level of imbalance reduction in any given data set (Iacus, King, and Porro 2012). We therefore use the Mahalanobis matching as a robustness check and address the associated concerns by implementing an alternative matching method known as coarsened exact matching (CEM) in Section 4.4.2.

4.4.1 Mahalanobis Matching

To construct our matched sample with Mahalanobis matching, we first calculate the Mahalanobis distance between each cash-flow insolvent firm and cash-flow solvent firm using all firm-level characteristics in Table 6. The matched sample is then created by pairing each cash-flow insolvent firm with cash-flow solvent firms based on their Mahalanobis distance. To improve the matching quality, we implement the pairing with replacement. That is, the selections of cash-flow solvent firms for cash-flow insolvent firms are independent of each other. Because this requirement reduces the size of the matched cash-flow solvent group, we pair each cash-flow insolvent firm with the top three cash-flow solvent firms based on the shortest Mahalanobis distance to ensure a sufficiently large sample size.

Table 5, Panel B reports the summary statistics for the matched sample. Compared with the summary statistics for the full sample (Table 5, Panel A), there are notable improvements in the balance between the two groups of firms across firm-level characteristics. The regression outcomes based on the matched sample are presented in Table 6, column (9). As the column indicates, our results remain robust, despite the large reduction in the sample size caused by the matching procedure.

Though the Mahalanobis matching notably improves the balance between the two groups, we can still detect a statistically significant difference in Tobin's Q, firm size, and the quick ratio. To overcome this problem and further improve the quality of the matching, we now

discuss our robustness check based on the CEM.

4.4.2 Coarsened Exact Matching

To address the concerns associated with Mahalanobis matching, we construct a matched sample using CEM as a further robustness check. The basic idea of CEM is to coarsen each variable of interest into bins, before exactly matching the coarsened data according to the bins to prune unmatched units. After the matching, the coarsened data are discarded and the original (uncoarsened) values of the matched data are retained. As shown by Iacus, King, and Porro (2009, 2011), CEM dominates commonly used existing (EPBR and other) matching methods in its ability to reduce imbalance, model dependence, estimation error, bias, and other criteria. Particularly, as a member of the class of matching methods known as monotonic imbalance bounding (MIB), CEM guarantees to eliminate all imbalances beyond the chosen levels of coarsening, which bounds the maximum level of imbalance in the data ex ante. In comparison, an EPBR matching method, such as Mahalanobis matching, does not guarantee any level of imbalance reduction. Moreover, the coarsening choice for any given variable has no effect on the imbalance bound for any other variables under CEM. In comparison, an EPBR matching method can reduce the imbalance for some variables ex post, while worsening the imbalance for some other variables. It is also worth noting that CEM satisfies the congruence principle, which requires congruence between the data space and analysis space. An EPBR matching method violates the congruence principle, leading to less robust inferences with sub-optimal properties (Mielke and Berry 2007).[30] Finally, CEM has the practical advantage that it tends to produce a well-matched sample with a reasonably large sample size.

We perform the CEM by coarsening each of the firm-level characteristics that display a significant difference between the cash-flow insolvent and cash-flow solvent firms. Concretely, we coarsen Tobin's Q and the quick ratio into 4 bins defined by their 25th, 50th, and 75th

[30]Specifically, Mahalanobis matching violates the congruence principle by projecting covariates from the natural n-dimensional data space to a different space defined by the Mahalanobis distance.

percentiles in the main sample (the sample of Table 5, Panel A). We coarsen firm size, as measured by the natural logarithm of the total assets, into 6 bins defined by its 10th, 25th, 50th, 75th, and 90th percentiles to address the concern that firm size is the dimension in which we observe the largest difference between the two groups of firms.[31] To adjust for the different stratum sizes caused by different numbers of observations of the cash-flow solvent firms that are matched to the observations of the cash-flow insolvent firms, we weigh our matched sample following Iacus, King, and Porro (2012).

The summary statistics for our matched sample based on the 96 strata are reported in Table 5, Panel C. Compared with the matched sample from the Mahalanobis matching (Table 5, Panel B), we can now achieve a better balanced sample without a statistically significant difference across all of the firm-level characteristics, as shown by the last column of Table 5, Panel C. The improvement of the matched sample also comes with a larger sample size.

Table 6, column (10) presents the regression outcomes of the CEM matching. As the column demonstrates, our results remain robust. Overall, we have conducted matching analyses based on different classes of matching methods. The fact that we are able to obtain estimates consistent with the main findings relieves the concern that our results are driven by confounding factors associated with the firm-level characteristics included in the analysis.

4.5 Additional Insights on the Economic Mechanism

Our analysis so far has demonstrated that firms' debt structure matters for the effect of uncertainty shocks. Specifically, we have shown that bank debt can mitigate the negative effect of uncertainty shocks on shareholders in terms of stock prices, while such mitigating effect does not exist for non-bank debt. We have also illuminated the mechanism underlying this result by showing that the mitigating effect of bank debt is concentrated among cash-flow insolvent firms.

[31] Our results are robust to alternative ways of coarsening, including coarsening using all of the firm-level characteristics in Table 6 including the bank and non-bank leverage.

In this section, we provide additional insights on the economic mechanisms underlying the mitigating effect. We first present evidence against the possibility that the mitigating effect is driven by mergers and acquisitions (M&As). We then elucidate that the mitigating effect is primarily driven by firms' insolvency associated with their cash flows, instead of their balance sheet positions, consistent with the argument that bank debt offers renegotiation flexibility.

4.5.1 Controlling for Mergers and Acquisitions

A potential mechanism behind the mitigating effect that originates from cash-flow solvent firms is mergers and acquisitions (M&As). In particular, a bank may be more willing to renegotiate if the bank believes that the firm's zombie status makes it a more likely target for M&As, which can improve the firm's financial health because its liabilities will be taken over by the acquiring firm.[32]

To see if M&As play a role in our main results, we exclude firms that are delisted during our sample period due to M&As (having a CRSP delisting code of 2XX) from our sample. We also exclude firms that underwent significant M&As in 2017 based on the footnote of the Compustat sales item (SALE_FN = AA and AB), following previous studies (Kashyap, Lamont, and Stein 1994, Anantharaman and Lee 2014, and Ozdagli 2018.)

Table 7, column (1) reports our results after dropping the M&As.[33] Compared with Table 6, column (5), the mitigating effect of bank debt remains almost unchanged. We thus conclude that M&As are unlikely to explain our results.

4.5.2 Cash Flow Insolvency vs. Balance Sheet Insolvency

Our analysis focuses on cash-flow insolvency rather than balance-sheet insolvency. According to the Uniform Fraudulent Conveyance Act and the Uniform Commercial Code,

[32] Around 19% of zombie firms in the world's 20 largest economies end up being acquired (Altman, Dai, and Wang, 2024).

[33] We omit some variables in the table for brevity. See Table A3 for the full table.

cash flow insolvency occurs when a debtor cannot make payments due to the debtor's lack of financial liquidity, but not lack of assets. According to the Bankruptcy Code, balance sheet insolvency occurs when a debtor's liabilities exceed its assets at fair values.[34]

Our focus on cash-flow insolvency stems from the fact that it is an easier problem to resolve through renegotiation because it often involves addressing immediate liquidity issues and requires an agreement on cash-flow estimates. Balance-sheet insolvency, on the other hand, can be more complex to resolve through renegotiation because it requires an estimation of fair value. The U.S. courts typically determine fair value "as estimating what the debtor's assets would realize if sold in a prudent manner in current market conditions" (Matter of Lamar Haddox, 1994). Therefore, renegotiation on the fair value depends not only on estimates of cash-flows but also on the estimates of the discount factor by the market, as well as the timing of the sale. The matter is further complicated whether this assessment should be made at going-concern value or liquidation value.[35]

Nevertheless, although the resolution of balance-sheet insolvency is very complex, the bank may still prefer to support a balance-sheet insolvent firm if the firm's going-concern value is sufficiently higher than the liquidation value (Faria-e-Castro, Paul, and Sanchez 2024). Therefore, a robustness test regarding balance-sheet vs cash-flow insolvency can tell us whether the results are driven by the increased value of the renegotiation option, which is available to cash-flow insolvent firms regardless of their balance-sheet insolvency status, or driven by balance-sheet-insolvent firms that also happen to be cash-flow insolvent.

To form a measure on balance-sheet insolvent firms, we utilize the Altman's Z score and define mature firms that consistently have an Altman's Z score below zero for three years

[34]For details, see: https://www.law.cornell.edu/wex/insolvency.

[35]From https://www.law.cornell.edu/wex/insolvency: "The Seventh Circuit in In re Taxman Clothing Co., Inc. provides a useful example of this thinking. The principal issue was the proper valuation of a clothing company's inventory. At an auction, the inventory was liquidated for $110,000, but there was strong evidence that the inventory would net $215,000 if sold as a going concern. The court chose the latter value for solvency purposes because the court concluded that the firm's inventory's proper value was the profit that it could have obtained through a sale in the usual course of business, rather than the value resulting from a quick and harsh liquidation."

leading to 2017 as balance-sheet insolvent firms in our sample.[36] We choose the Altman's Z score to measure a firm's balance sheet insolvency because of its accuracy, popularity, and simplicity in making balance-sheet-based default predictions.[37] Following Altman et al. (2017), we use the Z"-score model in our main analysis, which is applicable for both privately and publicly held firms and for both manufacturing and non-manufacturing firms. Our results are robust when we use the original Z-score model developed in Altman (1968) based on publicly held manufacturing firms.[38]

Table 7, column (2) repeats the analysis in column (1) by replacing cash-flow insolvency with balance-sheet insolvency. Compared with column (1), column (2) shows that the mitigating effect of bank debt is much weaker for the balance-sheet insolvent firms, though it is still statistically significant. To further verify the dominance of cash-flow insolvency in our results, we further check the mitigating effect for the cash-flow insolvent firms, conditioning on a firm's balance-sheet insolvency status. Specifically, we perform our regression analysis in column (3) with dummy variables that indicate whether a firm is cash-flow insolvent, balance-sheet insolvent, or both cash-flow and balance-sheet insolvent. As column (3) suggests, the mitigating effect is primarily driven by a firm's cash flow insolvency (the coefficient ΔVIX $\times$ BankLeverage $\times$ CF Insolvent), whereas the balance-sheet insolvent firms do not display a significant difference relative to the benchmark group (the coefficient ΔVIX $\times$ BankLeverage $\times$ BS Insolvent). In addition, though the coefficient for the firms that are both cash-flow and balance-sheet insolvent is negative (the coefficient ΔVIX $\times$ BankLeverage $\times$ Both Insolvent), it is statistically insignificant and does not completely offset the mitigating effect from the cash-flow insolvent firms. As a result, our findings

[36] The choice of zero as the cutoff threshold for balance-sheet insolvency is motivated by Altman (2023) and Altman, Dai, and Wang (2024).

[37] For example, the Altman's Z score outperforms other models in explaining CDS spreads and indicating corporate resilience (Das et al. 2009, McKinsey 2020).

[38] The Altman's Z score from the Z"-score model is computed as $3.25+6.56\times\frac{\text{Current Assets}-\text{Current Liabilities}}{\text{Total Assets}}+3.26\times\frac{\text{Retained Earnings}}{\text{Total Assets}}+6.72\times\frac{\text{EBIT}}{\text{Total Assets}}+1.05\times\frac{\text{Book Value of Equity}}{\text{Total Liabilities}}$. The Altman's Z score from the original Z-score model is computed as $1.2\times\frac{\text{Current Assets}-\text{Current Liabilities}}{\text{Total Assets}}+1.4\times\frac{\text{Retained Earnings}}{\text{Total Assets}}+3.3\times\frac{\text{EBIT}}{\text{Total Assets}}+1.4\times\frac{\text{Market Value of Equity}}{\text{Total Liabilities}}+1\times\frac{\text{Sales}}{\text{Total Assets}}$.

from columns (1), (2), and (3) provide evidence that the mitigating effect of bank debt is primarily driven by a firm's cash flow insolvency. This is consistent with the argument that bank debt offers negotiation flexibility and that the option value of renegotiation rises amidst heightened uncertainty.

Given the association of the mitigating effect with cash-flow insolvency, we conduct one final robustness test by replacing the ICR with the debt service coverage ratio (DSCR) in our definition of cash-flow insolvent firms. The DSCR is defined as EBITDA/(Interest Expenses + Previous Year's Debt in Current Liabilities), which is a more inclusive and less popular measure for cash-flow insolvency (Demerjian and Owens 2016).[39] The results for the robustness check are displayed in columns (4) and (5). As the columns suggest, despite a more generalized definition for cash flow insolvency, our findings remain robust.

5 Policy Uncertainty versus First-Moment Shocks

We use trade war news to identify economic policy uncertainty shocks since the effect of trade war on financial markets is widely attributed to increased policy uncertainty (Carney 2019). Nevertheless, one may still be concerned about whether our approach confounds the effects of uncertainty with first-moment shocks. In this section, we provide two separate analyses that accounts for potential confounding effects that can stem from first-moment shocks. In both cases, the coefficient estimates remain practically identical.

5.1 Unlevering VIX

An unexpected increase in tariffs could reduce stock values by reducing cash flow expectations, which increases market leverage and, through the leverage effect, the VIX. In such a case, the fluctuations in the VIX on event days are not driven by fluctuations in uncertainty but by fluctuations in expected cash-flows.

[39] Using the DSCR to define cash flow insolvent firms could be overinclusive. Consider a solvent firm that is expected to use liquid assets to cover its principals and EBITDA to only cover its interest expenses. The firm can have a DSCR consistently below one and thus be classified as a cash flow insolvent firm, though the firm is solvent from both the cash flow and balance sheet perspectives.

To illustrate the issue mathematically, if we let V denote the total market value of the firm (or index) and E denote the market value of equity, the following equation describes the relation of the standard deviation of equity value (i.e. VIX) to the standard deviation of total market value:

$$\sigma_E = \frac{V}{E}\sigma_V \tag{8}$$

under the assumption that debt is risk-free.[40] This is a reasonable assumption for our case since the VIX is based on returns on S&P 500 index, which emphasizes large firms that are far from default. For levered firms with risk-free debt, a negative shock to expected cash flows would (in percentage terms) reduce E more than it would reduce V, thereby increasing V/E. In this scenario, σ_E would increase without any change in macroeconomic uncertainty (and hence σ_V).

The illustration of the problem above also shows us how to solve the problem. In particular, we follow the Bharath and Shumway (2008) method to "unlever" the VIX. We sum up the market value of equity for all companies in the S&P 500 index to capture E in equation (8), add up on top of it all these companies' book value of debt, which is equal to market value when debt is risk free, to capture V. We use the VIX for σ_E. Then, equation (8) allows us to calculate σ_V, which is an uncertainty measure clear of any first-moment effects.

We find that this unlevering exercise leads to negligible changes in our results throughout the paper; all coefficients and standard errors were the same up to the second decimal point. As an illustrative example, Table A2 in the internet appendix reproduces the full-sample results in Table 6 using the unlevered VIX.

Still, one may be concerned that trade war events that increase uncertainty are, by chance, also events that carry news of negative expected cash flow shocks. In this case, although first-moment shocks are not causally linked to uncertainty shocks, they just happen to be correlated. In the following section, we take this concern seriously, regardless of how

[40] See equation (4) in Bharath and Shumway (2008).

unlikely it appears, by using scheduled FOMC monetary policy announcements as a separate laboratory.

5.2 Monetary-policy-related uncertainty

In this section, we use the reaction of stock prices to the movements in the VIX on scheduled FOMC announcement dates to study the impact of monetary-policy-related uncertainty. The timing of these announcements is known well in advance and investors pay close attention to it. The first-moment shocks are well identified because there has been a long literature studying the impact of monetary policy shocks based on the movements in short-term interest rate derivatives and longer-term Treasury yields, starting with Bernanke and Kuttner (2005) and Gurkaynak, Sack, and Swanson (2005). These properties allow us to clean from the changes in VIX on FOMC announcement dates the movements that can be attributed to the first-moment shocks instead of policy uncertainty. The flip side of this approach is that monetary policy uncertainty may reduce banks' willingness to lend by affecting the uncertainty of their costs and revenues as both are based on interest-earning assets. Therefore, the mitigating effect of bank debt may be somewhat weaker for the impact of monetary policy uncertainty.

Table 8 presents the results when we use the same regression specification in our trade war analysis, this time using scheduled FOMC announcement dates starting 2004.[41] The first five columns show that the results are (at least qualitatively) very similar to our previous results: Higher bank debt reduces the stock price sensitivity to uncertainty whereas the non-bank debt does not have a similar effect (columns (1)-(3)). The mitigating effect of bank debt is concentrated among firms experiencing cash-flow insolvency (columns (4) and (5)).

Columns (6) and (7) purge the first-moment shocks using different methods. For column (6), we first run a regression of change in the VIX on monetary policy target and path

[41] Accordingly all balance sheet variables are the latest available numbers from Compustat and Capital IQ files as of the date of an FOMC announcement. Consistent with our previous analysis, we use the annual files because debt structure data is not as well populated in the quarterly files. We also omit some variables in the table for brevity. See Table A4 for the full table.

surprises (Gurkaynak, Sack, and Swanson 2005 and Nakamura and Steinsson 2018) using the data from Gurkaynak et al. (2022). We then take the residual to replace the VIX in the regression from column (5). For column (7), we first run a regression of change in the VIX on target and path surprises as well as on 2-, 5-, 10-, and 30-year Treasury yields (which are commonly used in the literature to capture the effect of quantitative easing) and then take the residual to replace the VIX in the regression from column (5). The coefficients remain practically unchanged. Finally, column (8) shows the result that the mitigating effect of bank debt originates from cash-flow insolvent firms remain when using Fama-French excess returns in the model in column (7) as well.

Last but not least, we use intraday asset price data to alleviate any remaining concerns that the results in this section may be driven by news other than FOMC announcements that occur on the same day. Following, previous literature (e.g. Gurkaynak et al, 2005a; Gorodnichenko and Weber, 2016; Nakamura and Steinnson 2018; Ozdagli and Velikov 2020) we use intraday stock returns in a tight window around FOMC announcements. This approach also addresses the concern that our results may be driven by the pre-FOMC announcement drift reported by Lucca and Moench (2015).[42] Column (9) shows the same analysis as in column (7) using intraday returns, intraday VIX, as well as intraday interest rate changes for orthogonalization, in the same event window. We see that the mitigating effect of bank debt usage is still concentrated among cash-flow insolvent firms. Indeed, the coefficient of $\Delta VIX \times BankLeverage \times CFInsolvent$ is practically identical to that in column (7).

This analysis confirms that our main results still hold in an environment where we can directly control for the first-moment shocks: Stock prices react negatively to increased policy uncertainty. Higher bank debt reduces the stock price sensitivity to uncertainty whereas the non-bank debt does not have a similar effect. The mitigating effect of bank debt is

[42]We note that even if our daily return results were driven by pre-FOMC drift, they would sill be informative regarding the effect of resolution in uncertainty on FOMC announcement days in the framework proposed by Ai and Bansal (2018) and Ai et al. (2022) to the extent that such resolution of uncertainty is also reflected in changes in daily VIX.

concentrated among firms experiencing cash-flow insolvency.

6 Evidence of Renegotiation from Firms' Balance Sheets

Our results thus far are consistent with the argument that bank debt can mitigate the impact of economic policy uncertainty due to banks' ability to provide flexibility in renegotiating with borrowers. While our results on stock prices and cash-flow insolvency support this argument, we further examine balance sheet data for a more direct evidence of renegotiation following increased policy uncertainty. As balance sheet data is available at a lower frequency than that of stock prices, we utilize the quarterly data from Compustat. Accordingly, we take the quarterly average of the monthly EPU index from Baker et al. (2016).

To examine whether firms can successfully renegotiate to relieve their debt burden, we check if their debt maturity has been extended and if their per-period debt payments relative to total debt have been reduced. Accordingly, we are interested in the following two balance-sheet items. The first one is the ratio of short-term debt to total debt, measured by DLCQ/(DLCQ+DLTTQ) from Compustat, to detect changes in debt maturity.[43] The second one is the debt payment ratio, defined as the sum of short-term debt payments and interest expense divided by total debt, (DLCQ+XINTQ)/(DLCQ+DLTTQ) from Compustat, to detect changes in the per-period debt payments relative to total debt.

We then estimate the following regression to test for evidence of renegotiation:

$$\begin{aligned}\Delta LnY_{i,t} \;=\; & \alpha_i + \beta_0 \times \Delta LnEPU_{t-1} + \gamma_0 \times \Delta LnEPU_{t-1} \times BankLeverage_{i,t-1} \\ & + \delta_0 \times \Delta LnEPU_{t-1} \times NonBankLeverage_{i,t-1} + \beta_1 \times \Delta LnEPU_{t-1} \times CFInsolvent_{i,t-1} \\ & + \gamma_1 \times \Delta LnEPU_{t-1} \times BankLeverage_{i,t-1} \times CFInsolvent_{i,t-1} \\ & + \delta_1 \times \Delta LnEPU_{t-1} \times NonBankLeverage_{i,t-1} \times CFInsolvent_{i,t-1} + Controls + \varepsilon_{i,t}. \quad (9)\end{aligned}$$

The dependent variable, $\Delta LnY_{i,t}$, is our balance-sheet-based measure of renegotiation for

[43] We use this variable because the maturity data in Compustat Fundamentals Quarterly is limited, unlike Compustat Fundamentals Annual, which reports long-term debt maturing in up to five years separately.

firm i at quarter t. $\Delta LnEPU_{t-1}$ is the quarterly average of the monthly EPU index. Both the dependent variables and the uncertainty measure are in logs so that the results can be interpreted as elasticities. For firms' bank leverage ($BankLeverage$), non-bank leverage ($NonBankLeverage$), the dummy variable for cash-flow insolvent firms ($CFInsolvent$), and the additional firm-level characteristics in $Controls$, including Tobin's Q, firm size, and the quick ratio, we use the same definitions as before based on the annual data and measure them at the end of the last year. We also include only mature firms that have been publicly traded for at least five years by the end of the last year, consistent with our earlier analysis.

Table 9 presents the results of our analysis.[44] We begin by examining the relation between the EPU index and debt maturity. Column (1) shows that, on average, higher economic policy uncertainty increases the short-term debt ratio. This is consistent with the argument that policy uncertainty tends to make long-term debt riskier and more expensive, which can raise firms' reliance on short-term debt. However, this effect is mitigated for cash-flow insolvent firms with more bank debt, as indicated by the significantly negative coefficients of $\Delta Ln(EPU) \times BankLeverage \times CFInsolvent$ in column (2). These firms experience an extension of debt maturity, consistent with the premise of our earlier analysis that they are more likely to successfully renegotiate their debt thanks to bank debt's flexibility. In line with our earlier findings, a similar pattern does not exist for cash-flow solvent firms or non-bank debt usage. Our results are robust after controlling for the additional firm-level characteristics in column (3) and the additional time fixed effects in column (4).

The remaining columns of Table 9 repeat the analysis with the debt payment ratio as the dependent variable. The results from columns (5)–(8) complement those from columns (1)–(4), demonstrating that the debt burden relief comes through a reduction of per-period debt payments, in addition to an extension of debt maturity. Overall, our findings support the argument that bank debt can mitigate the impact of economic policy uncertainty because of banks' ability to provide flexibility in renegotiating with borrowers.

[44] We omit some variables in the table for brevity. See Table A5 for the full table.

7 Conclusion

This paper provides new evidence on the effect of uncertainty on financial markets and the role debt structure plays in the transmission of changes in uncertainty. Our analysis uses not only low-frequency (monthly) stock returns and the EPU index from Baker et al. (2016) based on news articles, but also high-frequency (daily and intraday) identification exploiting U.S.-China trade policy uncertainty and monetary-policy-related uncertainty on scheduled FOMC announcement dates as natural laboratories. We find that a rise in policy uncertainty decreases stock prices. In addition, there are significant cross-sectional differences in the sensitivity of stock prices to policy uncertainty. In particular, the usage of bank debt helps stabilize the negative effect of uncertainty shocks, but this effect is concentrated among cash-flow insolvent, a.k.a. zombie, firms. The usage of non-bank debt, on the other hand, does not have a similar mitigating effect.

Our findings have practical implications for policymakers, firms, and investors. Understanding how bank debt can provide a buffer against policy uncertainty can inform decisions on policy implementation, financial regulation, debt management, and portfolio allocation. Moreover, although the focus of our paper is the U.S., our findings can be applicable to other regions, especially Europe, where bank debt tends to weight heavier in the corporate debt structure and zombie firms are increasingly prevalent in the post-pandemic economic landscape. Furthermore, our approach and results can help us better understand the more recent events, such as the effect of uncertainty associated with COVID-19, global supply chain disruptions, and the Russia-Ukraine conflict. We hope our paper can stimulate future research in today's uncertain economic environment.

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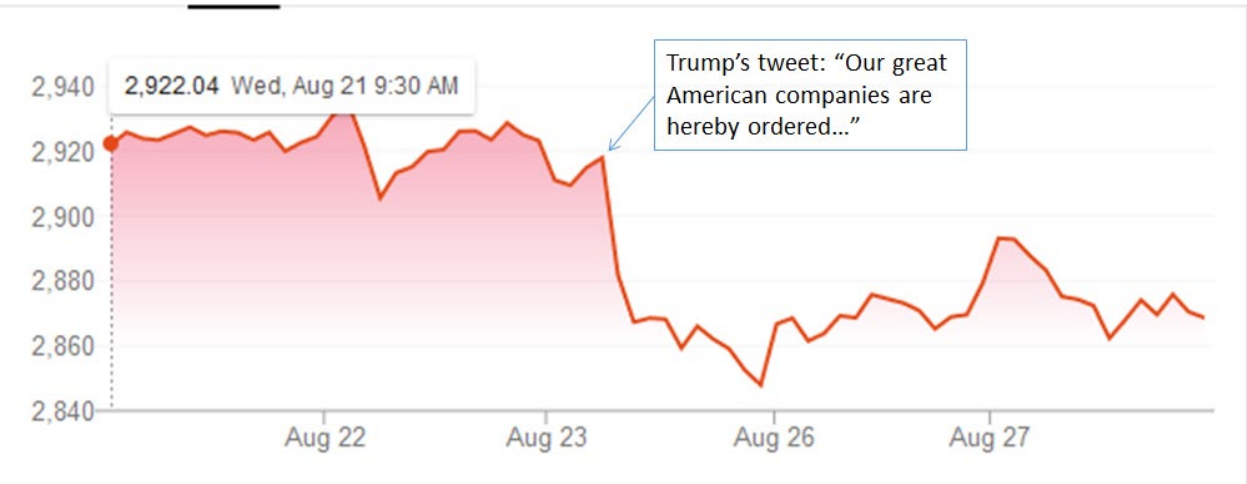
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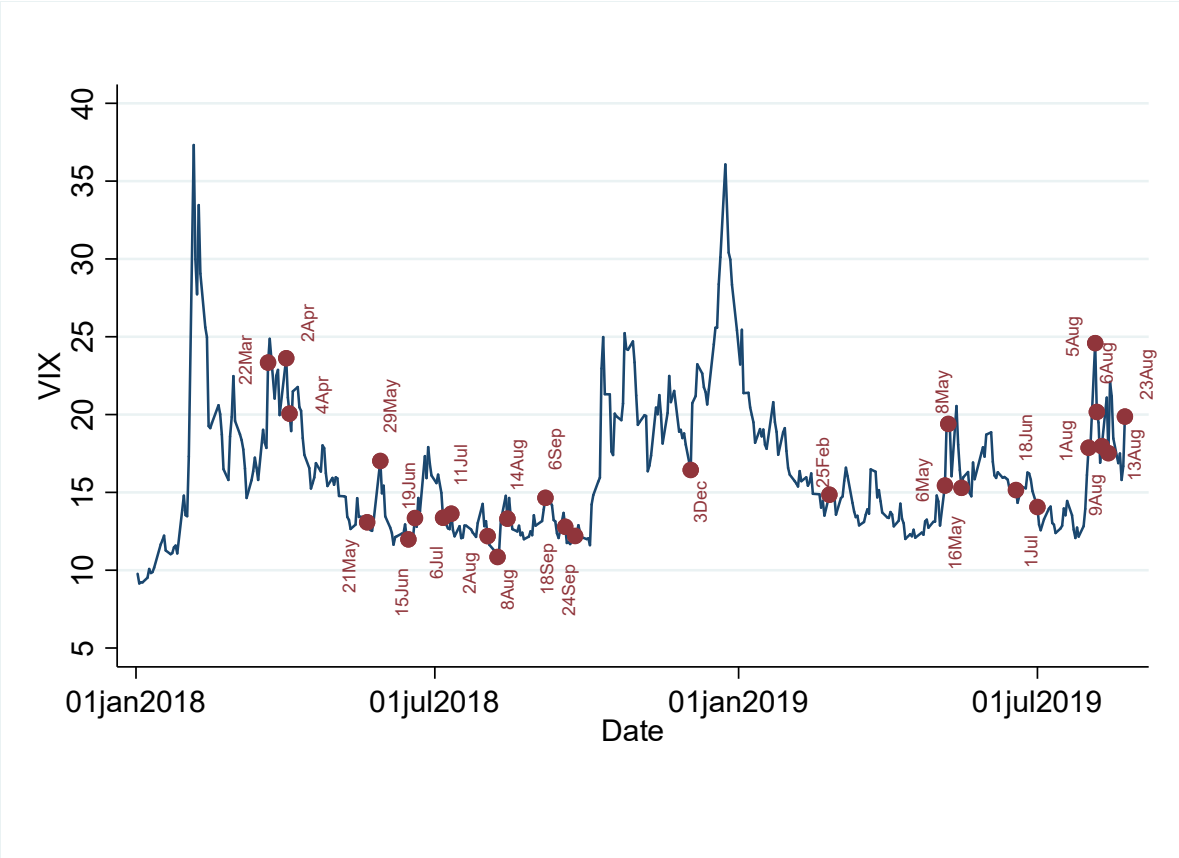
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Figure 1: S&P 500 Index around Trump's Tweet on August 23, 2019



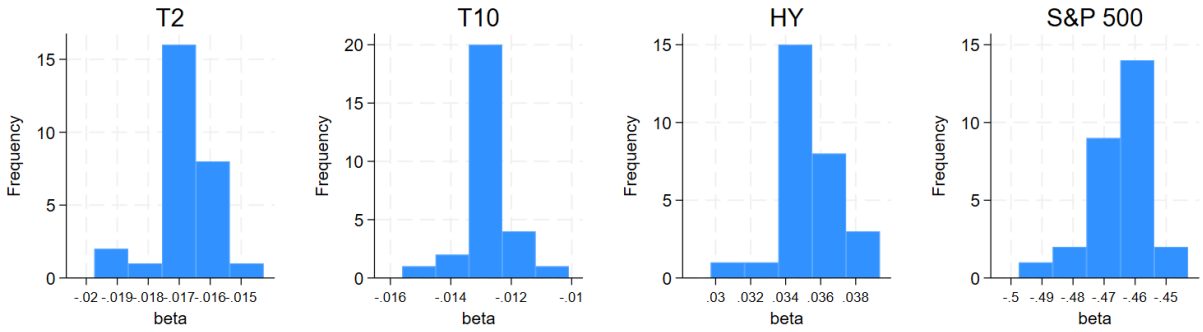
Alt Text: Figure 1 shows how the S&P 500 index was flat until Friday, August 23, 2019, and reacted immediately when President Trump tweeted that he "hereby ordered" American companies to "immediately start looking for an alternative to China."

Figure 2: VIX and the Trade-War-Related News



Alt Text: Figure 2 plots the VIX series during our sample period, along with our 28 event days, represented by red dots.

Figure 3: Robustness to Outlier Events



This figure reports the distribution of the coefficient estimates in Table 2 after we exclude one event day at a time from the estimation and re-estimating the coefficients. The dropping of one event day implies the dropping of a pair of the event day and the associated non-event day in the estimation. T2 (T10) refers to the two-year (10-year) Treasury yields, HY refers to high-yield spreads, measured as the Bank of America Merrill Lynch U.S. High Yield Master II Option-Adjusted Spread, and SP500 refers to the S&P 500 index.

Alt Text: Figure 3 plots the distribution of the coefficient estimates from Table 2 in histograms and shows that they remain stable after excluding one event day at a time from the estimation and re-estimating the coefficients.

Table 1: Baker et al. (2016) Economic Policy Uncertainty (EPU) Index and Stock Returns

	Full Sample (01/2004-12/2019)			GFC (04/2007-12/2009)			Non-GFC (01/2004-03/2007 & 01/2010-12/2019)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Monthly Ret	Monthly Ret	FF3	Monthly Ret	Monthly Ret	FF3	Monthly Ret	Monthly Ret	FF3
ΔEPU	-0.0705***			-0.154***			-0.0351*		
	(0.0213)			(0.0463)			(0.0184)		
ΔEPU*BankLeverage		0.00176	0.00403		-0.0791**	-0.0650*		0.0128**	0.0132***
		(0.0113)	(0.00841)		(0.0381)	(0.0355)		(0.00514)	(0.00326)
ΔEPU*NonBankLeverage		-0.0201*	-0.0102		-0.0672**	-0.0446*		0.000829	0.00446
		(0.0120)	(0.00931)		(0.0312)	(0.0231)		(0.00930)	(0.00785)
BankLeverage		1.703***	1.455***		13.84***	12.83***		1.290***	1.081***
		(0.369)	(0.343)		(3.370)	(3.351)		(0.234)	(0.246)
NonBankLeverage		1.474***	0.943***		5.929**	4.426**		1.363***	1.009***
		(0.372)	(0.359)		(2.170)	(1.971)		(0.377)	(0.373)
Observations	351,859	351,859	351,121	66,285	66,285	66,197	285,574	285,574	284,923
R-squared	0.030	0.200	0.086	0.087	0.267	0.118	0.026	0.178	0.085
Stock FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Month FEs	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

This table presents the results of our general analysis using the monthly EPU index from Baker et al. (2016). Columns (1)-(3) report the results based on our full sample, where columns (1) and (2) show the results for the monthly stock returns, and column (3) shows the results for the Fama-French excess returns. Columns (4)-(6) report the results for the GFC period, where columns (4) and (5) show the results for the monthly stock returns, and column (6) shows the results for the Fama-French excess returns. Finally, columns (7)-(9) report the results for the non-GFC period, where columns (7) and (8) show the results for the monthly stock returns, and column (9) shows the results for the Fama-French excess returns. The factor loadings for the Fama-French excess returns are estimated using monthly returns in the last 36 months. BankLeverage is the total bank debt from Capital IQ divided by the total assets (AT) from Compustat. NonBankLeverage is book leverage ((DLC+DLTT)/AT from Compustat) minus BankLeverage. Following Colla, Ippolito, and Li (2013), we exclude firms in the utility sector (SIC 4900-4949) and the financial sector (SIC 6000-6999), firm-year observations with missing or zero values for total assets or total debt, and firm-year observations where the difference between the total debt from Compustat and the sum of debt types in Capital IQ exceeds 10% of the total debt from Compustat. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Summary Statistics of Financial Variables on Event and Non-Event Dates

Panel A: Event Dates

Variables	Obs.	Mean	Std. Dev.	Min	Max
ΔVIX	28	0.524	2.505	–4.420	6.980
ΔT2	28	–0.014	0.058	–0.160	0.080
ΔT10	28	–0.020	0.051	–0.160	0.060
ΔHY	28	0.017	0.104	–0.150	0.340
ΔSP500	28	–0.162	1.232	–2.978	1.513

Panel B: Non-Event Dates

Variables	Obs.	Mean	Std. Dev.	Min	Max
ΔVIX	28	–0.420	0.920	–1.970	1.850
ΔT2	28	0.004	0.031	–0.060	0.070
ΔT10	28	0.000	0.029	–0.040	0.060
ΔHY	28	–0.001	0.054	–0.170	0.100
ΔSP500	28	0.222	0.561	–0.728	2.143

The data is from Federal Reserve Economic Data (FRED) by Federal Reserve Bank of St. Louis. VIX refers to the Chicago Board Options Exchange's Volatility Index, T2 (T10) refers to the two-year (10-year) Treasury yields, HY refers to high-yield spreads, measured as the Bank of America Merrill Lynch U.S. High Yield Master II Option-Adjusted Spread, and SP500 refers to the S&P 500 index. The unit for VIX is percent per annum. The units for T2, T10, and HY are percentage points. Changes in SP500 represent percentage changes in the S&P500 index.

Table 3: Aggregate Effect of Uncertainty Shocks on Financial Markets

	(1) ΔT2	(2) ΔT10	(3) ΔHY	(4) ΔSP500
ΔVIX	–0.017***	–0.013***	0.035***	–0.465***
	(0.005)	(0.004)	(0.007)	(0.045)
Observations	56	56	56	56

T2 (T10) refers to the two-year (10-year) Treasury yields, HY refers to high-yield spreads, measured as the Bank of America Merrill Lynch U.S. High Yield Master II Option-Adjusted Spread, and SP500 refers to the S&P 500 index. Heteroskedasticity-robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Cross-Sectional Effect of Uncertainty Shocks on Stocks Prices

	(1) All	(2) All	(3) Non-U.S.	(4) China-Only	(5) All	(6) All
ΔVIX	-0.392***	-0.383***	-0.378***	-0.411***	-0.386***	
	(0.0715)	(0.0720)	(0.0689)	(0.0759)	(0.0721)	
ΔVIX*ChinaShare		-0.400***	-0.415***	-0.327**	-0.419***	-0.522***
		(0.150)	(0.151)	(0.164)	(0.151)	(0.156)
ΔVIX*ForeignNonChinaShare					0.0227	0.00312
					(0.0380)	(0.0358)
ΔVIX*USonly					-0.00614	-0.00450
					(0.0233)	(0.0233)
Observations	84,784	84,784	52,951	10,363	84,784	84,504
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-date FEs	No	No	No	No	No	Yes

This table presents the results of our cross-sectional analysis for U.S. firms. Our sample excludes firms in the financial sector (SIC codes 6000-6999) and utility sector (SIC codes 4900-4949). All regression models include firm-level fixed effects. ChinaShare is the ratio of a firm's sales to China over its total sales. ForeignNonChinaShare is the ratio of a firm's sales to foreign countries other than China over its total sales. USonly is a dummy variable that indicates if a firm derives all of its sales domestically from the U.S. Columns (1), (2), (5), and (6) include all (1587) firms, for which there is sufficient information to calculate ChinaShare. Column (3) includes only firms (990) with sales to a foreign country outside of the U.S. Column (4) includes only firms (191) with sales to China. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Summary Statistics: Cash-Flow Solvent vs. Cash-Flow Insolvent Firms

Panel A: The Full Sample

	Full Sample (N = 72,037)		CF Solvent (N = 67,154)		CF Insolvent (N = 4,883)		T-Test CF Solvent=CF Insolvent
	Mean	SD	Mean	SD	Mean	SD	P-value
Daily Returns	.01	3.34	-.003	3.06	.21	5.95	0.000
BankLeverage	.14	.17	.14	.17	.14	.20	0.588
NonBankLeverage	.17	.22	.17	.22	.16	.26	0.658
TobinQ	1.83	1.63	1.73	1.34	3.23	3.48	0.000
LnTA	7.34	2.00	7.55	1.87	4.55	1.58	0.000
QuickRatio	.88	2.14	.76	1.96	2.59	3.38	0.000

Number of cash-flow insolvent firms: 95. Number of firms in total: 1,316.

Panel B: The Matched Sample based on Mahalanobis Matching

	Full Sample (N = 13,388)		CF Solvent (N = 8,505)		CF Insolvent (N = 4,883)		T-Test CF Solvent=CF Insolvent
	Mean	SD	Mean	SD	Mean	SD	P-value
Daily Returns	.11	4.63	.04	3.67	.21	5.95	0.043
BankLeverage	.16	.20	.17	.21	.14	.20	0.567
NonBankLeverage	.15	.25	.15	.24	.16	.26	0.723
TobinQ	2.65	2.85	2.32	2.35	3.23	3.48	0.022
LnTA	5.14	1.73	5.48	1.72	4.55	1.58	0.000
QuickRatio	1.83	2.72	1.40	2.14	2.59	3.38	0.002

Number of cash-flow insolvent firms: 95. Number of firms in total: 254.

Panel C: The Matched Sample based on Coarsened Exact Matching

	Full Sample (N = 22,997)		CF Solvent (N = 18,114)		CF Insolvent (N = 4,883)		T-Test CF Solvent=CF Insolvent
	Mean	SD	Mean	SD	Mean	SD	P-value
Daily Returns	.10	4.41	.08	3.90	.21	5.95	0.054
BankLeverage	.14	.20	.14	.19	.14	.20	0.554
NonBankLeverage	.17	.39	.18	.42	.16	.26	0.830
TobinQ	2.89	2.37	2.80	1.96	3.23	3.48	0.176
LnTA	4.75	1.49	4.80	1.46	4.55	1.58	0.148
QuickRatio	2.22	3.36	2.13	3.34	2.59	3.38	0.350

Number of cash-flow insolvent firms: 95. Number of firms in total: 427.

This table presents the summary statistics of our analysis using the U.S.-China trade war as a natural experiment. We include only mature firms that have been publicly traded for at least five years by the end of 2017. A cash-flow insolvent (potential zombie) firm is defined as a firm that consistently has an interest coverage ratio (Compustat EBITDA/XINT) below one for three years leading to 2017. BankLeverage is the ratio of total bank debt from Capital IQ to total assets (AT) from Compustat. NonBankLeverage is defined as book leverage (Compustat (DLC+DLTT)/AT) minus the BankLeverage. TobinQ, LogAssets, and QuickRatio are based on Compustat. TobinQ is computed as (MVE+DLC+ DLTT)/AT, where MVE is the market value of equity, calculated as the common shares outstanding (CSHO) multiplied by the annual close price (PRCC_F). LogAssets is the natural logarithm of total assets. QuickRatio is defined as CHE/LCT. Following Colla, Ippolito, and Li (2013), we exclude firms in the utility sector (SIC 4900-4949) and the financial sector (SIC 6000-6999), firm-year observations with missing or zero values for total assets or total debt, and firm-year observations where the difference between the total debt from Compustat and the sum of debt types in Capital IQ exceeds 10% of the total debt from Compustat.

Table 6: Debt Structure, Cash-Flow Insolvent Firms, and the Effect of Uncertainty Shocks on Daily Stock Returns

	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Full Sample	(5) Full Sample	(6) Leverage IV	(7) FF3	(8) ChinaShare=0	(9) Mahalanobis	(10) CEM
ΔVIX	-0.425***	-0.400***	-0.393***	-0.106						
	(0.0692)	(0.0682)	(0.0706)	(0.105)						
ΔVIX*CF Insolvent			-0.0817	0.115	0.0544	0.256	0.169	-0.162	-0.0541	-0.164
			(0.121)	(0.257)	(0.243)	(0.274)	(0.294)	(0.308)	(0.259)	(0.311)
ΔVIX*BankLeverage	0.150***	0.117**	0.0376	-0.0296	-0.0708	-0.0733	-0.121*	-0.122*	0.0954	-0.128
	(0.0554)	(0.0536)	(0.0376)	(0.0387)	(0.0441)	(0.0610)	(0.0698)	(0.0680)	(0.137)	(0.202)
ΔVIX*BankLeverage*CF Insolvent			0.888***	1.002***	1.127***	1.056**	1.093***	1.641***	0.943***	1.148***
			(0.258)	(0.261)	(0.308)	(0.522)	(0.381)	(0.456)	(0.311)	(0.374)
ΔVIX*NonBankLeverage		-0.113*	-0.102	0.0341	0.0113	-0.0513	0.0316	-0.0241	-0.159	0.0471
		(0.0625)	(0.0619)	(0.0582)	(0.0485)	(0.0664)	(0.0453)	(0.0700)	(0.128)	(0.151)
ΔVIX*NonBankLeverage*CF Insolvent			-0.0441	0.0115	0.0852	0.270	0.362	0.375	0.237	0.0199
			(0.183)	(0.189)	(0.200)	(0.330)	(0.295)	(0.244)	(0.236)	(0.294)
ΔVIX*TobinQ				-0.0129	-0.0190**	-0.0174*	-0.00450	-0.0197**	-0.0122*	-0.0348
				(0.00975)	(0.00825)	(0.00955)	(0.00788)	(0.00951)	(0.00709)	(0.0286)
ΔVIX*TobinQ*CF Insolvent				-0.00725	-0.000392	-0.0325	0.00810	-0.00152	-0.00461	0.0157
				(0.00511)	(0.00641)	(0.0253)	(0.0132)	(0.00412)	(0.00862)	(0.0344)
ΔVIX*LogAssets				-0.0373***	-0.0357***	-0.0339***	0.00298	-0.0369***	-0.0568**	-0.0551**
				(0.00954)	(0.0105)	(0.0109)	(0.00907)	(0.0126)	(0.0276)	(0.0240)
ΔVIX*LogAssets*CF Insolvent				-0.0626*	-0.0580	-0.0883*	-0.0772*	-0.0373	-0.0418	-0.0429
				(0.0364)	(0.0352)	(0.0525)	(0.0453)	(0.0547)	(0.0398)	(0.0436)
ΔVIX*QuickRatio				0.00428	0.00427*	0.00403**	0.00341	0.0109	0.00539	-0.00450
				(0.00275)	(0.00231)	(0.00197)	(0.00317)	(0.0131)	(0.0116)	(0.00729)
ΔVIX*QuickRatio*CF Insolvent				-0.00400	-0.00750	-0.00561	-0.00916	-0.0339	-0.00342	0.00685
				(0.0138)	(0.0141)	(0.0163)	(0.0198)	(0.0554)	(0.0131)	(0.0174)
Observations	72,037	72,037	72,037	72,037	72,037	65,447	72,026	37,183	13,388	22,997
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-date FEs	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of our analysis using the U.S.-China trade war as a natural experiment. Columns (1)-(5) report the main results. Column (6) shows the results after instrumenting the bank and non-bank leverages in 2017 with their counterparts in 2016. Column (7) shows the results for the Fama-French excess returns, where the factor loadings are estimated using daily returns in calendar year 2017. Column (8) shows the results by using only firms with no sales to China. Columns (9) and (10) show the results based on the Mahalanobis matching and coarsened exact matching, respectively. We include only mature firms that have been publicly traded for at least five years by the end of 2017. A cash-flow insolvent (potential zombie) firm is defined as a firm that consistently has an interest coverage ratio (Compustat EBITDA/XINT) below one for three years leading to 2017. BankLeverage is the total bank debt from Capital IQ divided by the total assets (AT) from Compustat. NonBankLeverage is book leverage ((DLC+DLTT)/AT from Compustat) minus BankLeverage. TobinQ, LogAssets, and QuickRatio are based on Compustat. TobinQ is computed as (MVE+DLC+ DLTT)/AT, where MVE is the market value of equity, calculated as the common shares outstanding (CSHO) multiplied by the annual close price (PRCC_F). LogAssets is the natural logarithm of total assets. QuickRatio is defined as CHE/LCT. Following Colla, Ippolito, and Li (2013), we exclude firms in the utility sector (SIC 4900-4949) and the financial sector (SIC 6000-6999), firm-year observations with missing or zero values for total assets or total debt, and firm-year observations where the difference between the total debt from Compustat and the sum of debt types in Capital IQ exceeds 10% of the total debt from Compustat. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Economic Mechanisms – M&As, Cash-Flow Insolvency, and Balance-Sheet Insolvency

	(1) ICR	(2) Altman Z	(3) ICR & Altman Z	(4) DSCR	(5) DSCR & Altman Z
ΔVIX*BankLeverage	-0.0693	0.0821	-0.0410	-0.0768	-0.0567
	(0.0493)	(0.0906)	(0.0572)	(0.0491)	(0.0583)
ΔVIX*BankLeverage*CF Insolvent	1.365***		1.804***	0.698**	1.007**
	(0.306)		(0.359)	(0.292)	(0.451)
ΔVIX*BankLeverage*BS Insolvent		0.323**	-0.215		-0.176
		(0.159)	(0.447)		(0.561)
ΔVIX*BankLeverage*Both Insolvent			-0.660		-0.303
			(0.999)		(0.842)
ΔVIX*NonBankLeverage	0.0429	0.0379	0.0647	0.0523	0.0684
	(0.0584)	(0.0426)	(0.0482)	(0.0535)	(0.0476)
ΔVIX*NonBankLeverage*CF Insolvent	0.137		0.191	-0.209	0.0226
	(0.218)		(0.157)	(0.141)	(0.146)
ΔVIX*NonBankLeverage*BS Insolvent		-0.414	-0.0112		0.0946
		(0.251)	(0.362)		(0.468)
ΔVIX*NonBankLeverage*Both Insolvent			-0.379		-0.776
			(0.655)		(0.625)
Observations	53,801	53,801	53,801	53,801	53,801
Firm FEs	Yes	Yes	Yes	Yes	Yes
Industry-date FEs	Yes	Yes	Yes	Yes	Yes

This table compares our results based on cash-flow insolvency and balance-sheet insolvency after dropping firms that are delisted during our sample period due to M&As or underwent significant M&As in 2017. We include only mature firms that have been publicly traded for at least five years by the end of 2017. The cash-flow insolvent firms in columns (1) and (3) are defined as firms that consistently have an interest coverage ratio (Compustat EBITDA/XINT) below one for three years leading to 2017. The cash-flow insolvent firms in columns (4) and (5) are defined as firms that consistently have a debt service coverage ratio (Compustat EBITDA/(XINT+L.DLC)) below one for three years leading to 2017. The balance-sheet insolvent firms in columns (2), (3), and (5) are defined as firms that consistently have an Altman's Z score (the Z''-score model) below zero for three years leading to 2017. BankLeverage is the total bank debt from Capital IQ divided by the total assets (AT) from Compustat. NonBankLeverage is book leverage ((DLC+DLTT)/AT from Compustat) minus BankLeverage. Table A2 displays the full version of this table including TobinQ, LogAssets, and QuickRatio based on Compustat. TobinQ is computed as (MVE+DLC+ DLTT)/AT, where MVE is the market value of equity, calculated as the common shares outstanding (CSHO) multiplied by the annual close price (PRCC_F). LogAssets is the natural logarithm of total assets. QuickRatio is defined as CHE/LCT. Following Colla, Ippolito, and Li (2013), we exclude firms in the utility sector (SIC 4900-4949) and the financial sector (SIC 6000-6999), firm-year observations with missing or zero values for total assets or total debt, and firm-year observations where the difference between the total debt from Compustat and the sum of debt types in Capital IQ exceeds 10% of the total debt from Compustat. Our sample includes 974 firms with 82 cash-flow insolvent firms and 63 balance-sheet insolvent firms for columns (1), (2), and (3), among which 39 firms are both cash-flow and balance-sheet insolvent. There are 132 cash-flow insolvent firms and 63 balance-sheet insolvent firms for columns (4) and (5), among which 47 firms are both cash-flow and balance-sheet insolvent. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Effect of Monetary-Policy-Related Uncertainty on Stock Prices during Scheduled FOMC Announcement Dates

	(1) Daily Ret	(2) Daily Ret	(3) Daily Ret	(4) Daily Ret	(5) Daily Ret	(6) Daily Ret Orth Target+Path	(7) Daily Ret Orth Full	(8) Daily FF3 Orth Full	(9) Intraday Ret Orth Full
ΔVIX	-0.546***	-0.559***	-0.536***	-0.264***					
	(0.0681)	(0.0675)	(0.0638)	(0.0530)					
ΔVIX*CF Insolvent				0.526***	0.541***	0.575***	0.579***	0.268	0.293*
				(0.133)	(0.127)	(0.147)	(0.163)	(0.170)	(0.159)
ΔVIX*BankLeverage		0.122***	0.0985**	0.0287	0.0128	-0.00279	-0.00123	0.0808	-0.0874**
		(0.0381)	(0.0404)	(0.0526)	(0.0471)	(0.0537)	(0.0577)	(0.0528)	(0.0344)
ΔVIX*BankLeverage*CF Insolvent				0.205**	0.235***	0.210**	0.256***	0.191***	0.253**
				(0.0855)	(0.0731)	(0.0963)	(0.0865)	(0.0578)	(0.111)
ΔVIX*NonBankLeverage			-0.136**	0.00300	0.0123	0.0158	0.0306	0.0906	-0.0553**
			(0.0595)	(0.0577)	(0.0603)	(0.0678)	(0.0676)	(0.0734)	(0.0241)
ΔVIX*NonBankLeverage*CF Insol.				0.0872	0.0624	0.00865	-0.108	-0.250*	0.0773
				(0.0953)	(0.121)	(0.112)	(0.108)	(0.135)	(0.0810)
ΔVIX*TobinQ				-0.00944	-0.0193**	-0.0187*	-0.0137	-0.0131	-0.00179
				(0.0172)	(0.00899)	(0.00973)	(0.0114)	(0.0104)	(0.00701)
ΔVIX*TobinQ*CF Insolvent				-0.0357**	-0.0308**	-0.0279**	-0.0333**	-0.00689	-0.0152**
				(0.0158)	(0.0129)	(0.0133)	(0.0140)	(0.0126)	(0.00734)
ΔVIX*LogAssets				-0.0410***	-0.0389***	-0.0390***	-0.0361***	0.00130	-0.0248***
				(0.00829)	(0.00824)	(0.00844)	(0.00801)	(0.00559)	(0.00801)
ΔVIX*LogAssets*CF Insolvent				-0.112***	-0.115***	-0.123***	-0.118***	-0.0500	-0.0497**
				(0.0239)	(0.0241)	(0.0279)	(0.0299)	(0.0316)	(0.0234)
ΔVIX*QuickRatio				0.00736	0.00584	0.00369	0.000254	0.00453	-0.00214
				(0.00530)	(0.00425)	(0.00414)	(0.00541)	(0.00638)	(0.00575)
ΔVIX*QuickRatio*CF Insolvent				-0.00367	-0.00237	-0.00199	0.00311	-0.00156	-0.00551
				(0.0103)	(0.00997)	(0.00997)	(0.0103)	(0.0116)	(0.00858)
Observations	174,784	174,784	174,784	174,784	174,784	174,784	174,784	174,666	127,851
Stock FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Date FEs	No	No	No	No	Yes	Yes	Yes	Yes	Yes

This table presents the results of our analysis on monetary-policy-rated uncertainty. We skip some rows of the table for brevity and report the full version of the table in Table A3. Columns (1)-(5) report our main results. Column (6) shows the results after orthogonalizing daily VIX using the monetary policy target and path surprises following Gurkaynak et al. (2005, 2022) and Nakamura and Steinsson (2018). Column (7) shows the results after orthogonalizing daily VIX using the target and path surprises as well as changes in the 2-, 5-, 10-, and 30-year Treasury yields. Column (8) shows the results of column (7) after replacing the dependent variable with the Fama-French excess returns, where the factor loadings are estimated using daily returns in the previous calendar year. Column (9) shows our results after using intraday returns, intraday VIX, and the orthogonalization based on the target and path surprises as well as the intraday changes in the 2-, 5-, 10-, and 30-year Treasury yields. The sample of our analysis stops at the end of 2018, which is the end of the target and path surprise series from Gurkaynak et al. (2022). We include only mature firms that have been publicly traded for at least five years by the end of the previous year for each day. All other firm-level characteristics have an equivalent one-year lag. A cash-flow insolvent (potential zombie) firm is defined as a firm that consistently has an interest coverage ratio (Compustat EBITDA/XINT) below one for three years. BankLeverage is the total bank debt from Capital IQ divided by the total assets (AT) from Compustat. NonBankLeverage is book leverage ((DLC+DLTT)/AT from Compustat) minus BankLeverage. TobinQ, LogAssets, and QuickRatio are based on Compustat. TobinQ is computed as (MVE+DLC+ DLTT)/AT, where MVE is the market value of equity, calculated as the common shares outstanding (CSHO) multiplied by the annual close price (PRCC_F). LogAssets is the natural logarithm of total assets. QuickRatio is defined as CHE/LCT. Following Colla, Ippolito, and Li (2013), we exclude firms in the utility sector (SIC 4900-4949) and the financial sector (SIC 6000-6999), firm-year observations with missing or zero values for total assets or total debt, and firm-year observations where the difference between the total debt from Compustat and the sum of debt types in Capital IQ exceeds 10% of the total debt from Compustat. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Evidence of Renegotiation from Firms' Balance Sheets

	(1) ΔLn(STDebt)	(2) ΔLn(STDebt)	(3) ΔLn(STDebt)	(4) ΔLn(STDebt)	(5) ΔLn(DebtPayment)	(6) ΔLn(DebtPayment)	(7) ΔLn(DebtPayment)	(8) ΔLn(DebtPayment)
ΔLn(EPU)	0.0417*	0.0297	0.0425		0.0237	0.0258	-0.0226	
	(0.0241)	(0.0267)	(0.0766)		(0.0195)	(0.0241)	(0.0592)	
ΔLn(EPU)*CF Insolvent		-0.0251	0.172	0.155		-0.0373	0.115	0.0959
		(0.0697)	(0.181)	(0.185)		(0.0527)	(0.160)	(0.159)
ΔLn(EPU)*BankLeverage		0.0848	0.0959	0.0831		0.0116	0.0349	0.0242
		(0.101)	(0.107)	(0.100)		(0.0608)	(0.0648)	(0.0647)
ΔLn(EPU)*BankLeverage*CF Insolvent		-0.560**	-0.540**	-0.535**		-0.336***	-0.261**	-0.256*
		(0.246)	(0.237)	(0.230)		(0.123)	(0.129)	(0.132)
ΔLn(EPU)*NonBankLeverage		0.0490	0.0656	0.0588		0.00810	-0.0121	-0.00890
		(0.112)	(0.0996)	(0.0977)		(0.0663)	(0.0756)	(0.0750)
ΔLn(EPU)*NonBankLeverage*CF Insolvent		0.0947	0.121	0.111		0.0497	0.112	0.101
		(0.159)	(0.176)	(0.175)		(0.126)	(0.141)	(0.136)
ΔLn(EPU)*TobinQ			-0.0159	-0.0224			-0.00715	-0.0162
			(0.0137)	(0.0137)			(0.0134)	(0.0131)
ΔLn(EPU)*TobinQ*CF Insolvent			-0.00157	0.00581			-0.0213	-0.0121
			(0.0223)	(0.0226)			(0.0204)	(0.0209)
ΔLn(EPU)*LogAssets			-0.000290	-0.00173			0.00791	0.00571
			(0.0107)	(0.00920)			(0.00838)	(0.00795)
ΔLn(EPU)*LogAssets*CF Insolvent			-0.0328	-0.0308			-0.0187	-0.0175
			(0.0341)	(0.0341)			(0.0356)	(0.0349)
ΔLn(EPU)*QuickRatio			0.0126	0.0137			0.00561	0.00621
			(0.0132)	(0.0145)			(0.0119)	(0.0125)
ΔLn(EPU)*QuickRatio*CF Insolvent			-0.0248	-0.0272			-0.00497	-0.00594
			(0.0193)	(0.0205)			(0.0142)	(0.0148)
Observations	69,619	69,619	69,619	69,619	75,476	75,476	75,476	75,476
R-squared	0.018	0.018	0.019	0.022	0.016	0.016	0.017	0.020
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	No	No	No	Yes	No	No	No	Yes

This table presents balance-sheet evidence on the renegotiation flexibility of bank debt in response to policy uncertainty shocks. Columns (1)-(4) report the results for the short-term debt ratio (STDebt), which is debt due within one year divided by total debt (DLCQ/(DLCQ+DLTTQ)) from Compustat Fundamentals Quarterly. Columns (5)-(8) report the results for the debt payment ratio (DebtPayment), which is the sum of debt due within one year and interest expenses divided by total debt ((DLCQ+XINTQ)/(DLCQ+DLTTQ)) from Compustat Fundamentals Quarterly. Our uncertainty measure is the quarterly average of the monthly EPU index from Baker et al. (2016), lagged by one quarter. Both the dependent variables and the uncertainty measure are in logs so that the results can be interpreted as elasticities. The dependent variables are also winsorized at 1% to remove outliers. For the cash-flow insolvent firms and firms' debt structure, we follow the same definitions with the rest of our analysis using Compustat Fundamentals Annual and Capital IQ. These variables are measured at the end of the previous year for each quarter. We also include only mature firms that have been publicly traded for at least five years by the end of the previous year for each quarter, consistent with our earlier analysis. A cash-flow insolvent (potential zombie) firm is defined as a firm that consistently has an interest coverage ratio (Compustat EBITDA/XINT) below one for three years. BankLeverage is the total bank debt from Capital IQ divided by the total assets (AT) from Compustat. NonBankLeverage is book leverage ((DLC+DLTT)/AT from Compustat) minus BankLeverage. TobinQ, LogAssets, and QuickRatio are based on Compustat. TobinQ is computed as (MVE+DLC+ DLTT)/AT, where MVE is the market value of equity, calculated as the common shares outstanding (CSHO) multiplied by the annual close price (PRCC_F). LogAssets is the natural logarithm of total assets. QuickRatio is defined as CHE/LCT. Following Colla, Ippolito, and Li (2013), we exclude firms in the utility sector (SIC 4900-4949) and the financial sector (SIC 6000-6999), firm-year observations with missing or zero values for total assets or total debt, and firm-year observations where the difference between the total debt from Compustat and the sum of debt types in Capital IQ exceeds 10% of the total debt from Compustat. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

INTERNET APPENDIX

Appendix A: U.S.-China Trade War Timeline

To construct our timeline of news events related to the U.S.-China trade war, we systematically search for news from public sources including AP News, BBC, CNBC, CNN, and Reuters. Unless indicated otherwise, the source of our news events below is the Reuters/CNBC timeline of the U.S.-China trade war, which covers milestone dates and associated key events.[1] Our results are robust if we use only the events from the Reuters/CNBC timeline. We also check all events in Factiva to confirm whether the timing of each news arrival falls within the trading hours of the same day. If the earliest timestamp of a news event is after the trading hours, we shift the event window to the next trading day to capture the relevant impact on the financial markets. The detailed list of our news events is presented below.

March 22, 2018: Trump asked the United States trade representative (USTR) to investigate applying tariffs on $50–60 billion worth of Chinese goods. (Source: CNN, https://www.cnn.com/2018/03/22/politics/donald-trump-china-tariffs-trade-war/.)

April 2, 2018: China imposes tariffs of up to 25 percent on 128 U.S. products.[2]

April 4, 2018: On April 3 (after trading hours), Trump unveils plans for 25 percent tariffs on about $50 billion of Chinese imports. On April 4, China responds with plans for retaliatory tariffs on about $50 billion of U.S. imports.

May 19/20, 2018 (weekend): Chinese officials agreed to "substantially reduce" America's trade deficit with China by committing to "significantly increase" its purchases of American goods. As a result, Treasury Secretary Steven Mnuchin announced that "We are putting the

[1] See https://www.reuters.com/article/us-usa-trade-china-timeline-idUSKCN1UZ24U or https://www.cnbc.com/2019/08/23/reuters-america-timeline-key-dates-in-the-u-s-china-trade-war.html. We omit the events that are not exclusively related to the trade between China and the U.S., such as accusations of intellectual property theft or tariffs on all imported goods regardless of origin.

[2] On March 8, 2018, Trump orders 25% tariffs on steel imports and 10% on aluminum from all suppliers - not just China. Since this was not explicitly related to China, it has been eliminated.

trade war on hold". (Source: AP News, https://www.apnews.com/41443aaca704426b9f35b16607271a60).

May 29, 2018: The White House announced that it would impose a 25 percent tariff on $50 billion of Chinese goods with "industrially significant technology." The full list of products affected to be announced by June 15, 2018. (CNN, https://money.cnn.com/2018/05/29/news/economy/china-tariffs/index.html).

June 15, 2018: The United States sets an effective date of July 6 for 25 percent levies on $34 billion of Chinese imports. It says 25 percent tariffs will also kick in on an additional $16 billion of goods after a public comment period. China responds in kind with tariffs on $34 billion of U.S. goods.

June 18, 2018 (after trading hours): The White House declared that the United States would impose additional 10 percent tariffs on another $200 billion worth of Chinese imports if China retaliated against these U.S. tariffs. China retaliates, threatening its own tariffs on $50 billion of U.S. goods, and stating that the United States had launched a trade war. (CNN, https://money.cnn.com/2018/06/18/news/economy/trump-china-tariffs-retaliation/)

July 6, 2018: American tariffs on $34 billion of Chinese goods came into effect. China imposed retaliatory tariffs on U.S. goods of a similar value. (Source: BBC, https://www.bbc.com/news/business-44707253).

July 10, 2018 (after trading hours): The United States unveils plans for 10 percent tariffs on $200 billion of Chinese imports.

August 1, 2018 (after trading hours): Trump orders the USTR to increase the tariffs on $200 billion of Chinese imports to 25 percent from the originally proposed 10 percent.

August 7, 2018 (after trading hours): The United States releases the list of $16 billion of Chinese goods to be subject to 25 percent tariffs. China retaliates with 25 percent duties on $16 billion of U.S. goods.

August 14, 2018: China filed a complaint with the World Trade Organization (WTO), stating that U.S. tariffs on foreign solar panels clash with WTO ruling and have destabilized the international market for solar PV products. (Source: Reuters, https://www.reuters.com/article/us-usa-trade-china-solar/china-says-u-s-solar-tariffs-violate-trade-rules-lodges-wto-complaint-idUSKBN1L001K)

September 6, 2018: Trump threatens tariffs on $200 billion more of Chinese imports. (Originally reported as September 7 by Reuters, corrected using Factiva.)

September 18, 2018: On September 17 (after trading hours): the United States announced its 10 percent tariff on $200 billion worth of Chinese goods would begin on September 24, 2018, increasing to 25 percent by the end of the year. China promptly responded with 10 percent tariffs on $60 billion of U.S. imports. (Source: CNBC, https://www.cnbc.com/2018/09/18/china-says-new-tariffs-on-us-goods-worth-60-billion-effective-sept-24.html)

September 24, 2018: The United States implements 10 percent tariffs on $200 billion of Chinese imports. The administration says the rate will increase to 25 percent on Jan. 1, 2019. China answers with duties of its own on $60 billion of U.S. goods.

December 1, 2018 (Saturday): The United States and China agree on a 90-day halt to new tariffs. Trump agrees to put off the Jan. 1 scheduled increase of tariffs on $200 billion of Chinese goods until early March while talks between the two countries take place. China agrees to buy a "very substantial" amount of U.S. products.

February 24, 2019 (Sunday): Trump extends the March 1 deadline, leaving the tariffs on $200 billion of Chinese goods at 10 percent on an open-ended basis.

May 5, 2019 (Sunday): Trump tweets that he intends to raise the tariff rate on $200 billion of Chinese goods to 25 percent on May 10.

May 8, 2019: The Trump administration gives formal notice of its intent to raise tariffs on $200 billion of Chinese imports to 25 percent from 10 percent, effective May 10. Earlier,

Reuters reported that China had backtracked on almost all aspects of a draft trade pact with the United States.

May 15, 2019 (after trading hours): President Trump signed an executive order Wednesday that allows the U.S. to ban telecommunications network gear and services from foreign adversaries, in a measure widely believed to be aimed at China and telecom companies including Huawei Technologies Co. and ZTE Corp. (Source: CNBC, https://www.cnbc.com/video/2019/05/15/trump-signs-executive-order-targeting-huawei.html).

June 18, 2019: Trump and Xi speak by phone, and the two sides agree to rekindle trade talks ahead of a planned meeting between the two leaders scheduled for the Group of 20 (G20) summit in Japan at the end of June.

June 29, 2019 (Saturday): At the G20 meeting in Osaka, the United States and China formally agree to restart trade talks after concessions from both sides. Trump agrees to no new tariffs and an easing of restrictions on Chinese telecom powerhouse Huawei Technologies Co Ltd. China agrees to unspecified new purchases of U.S. farm products.

August 1, 2019: After two days of trade talks with little progress and complaints by Trump that China has not followed through on a promise to buy more U.S. farm products, he announces 10 percent tariffs on $300 billion worth of Chinese imports, in addition to the 25 percent tariffs already levied on $250 billion worth of Chinese goods. Trump says the talks between Washington and Beijing would continue despite the new tariffs, and that the rate could be increased above 25 percent in stages.

August 5, 2019: China's Commerce Ministry responds to the latest U.S. tariffs by halting purchases of U.S. agricultural products, and the Chinese currency, the yuan, weakens past the seven yuan per one dollar level, sending equity markets sharply lower. After U.S. markets close, the U.S. Treasury says it has determined for the first time since 1994 that China is manipulating its currency, knocking the U.S. dollar sharply lower and sending gold prices to a six-year high.

August 6, 2019: China's central bank, the People's Bank of China, says Beijing has not and will not use the yuan to respond to trade frictions. A senior Trump aide says U.S.-China trade talks are still planned in Washington in September, and the latest tariffs could still be changed if talks go well, a message that helps calm markets.

August 9, 2019: Trump says he is not ready to make a deal with Beijing and suggests he may cancel in-person trade talks with China scheduled for Washington in September.

August 13, 2019: Trump delayed some of the tariff increases that he had announced earlier. Trump and his advisors, Peter Navarro, Wilbur Ross and Larry Kudlow, conceded that the higher tariffs were postponed to avoid harming American consumers during the Christmas shopping season. (Source: CNBC, https://www.cnbc.com/2019/08/13/trump-says-he-delayed-tariffs-because-of-concerns-over-christmas-shopping-season.html)

August 23, 2019: China announced that it will impose additional retaliatory tariffs against about $75 billion worth of U.S. goods. Trump tweeted that he "hereby ordered" American companies to "immediately start looking for an alternative to China." Furthermore, tariffs are to be raised from 25 percent to 30 percent on the existing $250 billion worth of Chinese goods beginning on October 1, 2019, and from 10 percent to 15 percent on the remaining $300 billion worth of goods beginning on December 15, 2019.

Table A1: Trade War Analysis with the Decomposition of Bank Debt

	(1) Daily Ret	(2) Daily Ret	(3) Daily Ret	(4) Daily Ret	(5) Daily Ret
ΔVIX	-0.403***	-0.375***	-0.365***	-0.0571	
	(0.0684)	(0.0672)	(0.0708)	(0.111)	
ΔVIX*CF Insolvent			-0.160	-0.0172	-0.0545
			(0.115)	(0.241)	(0.234)
ΔVIX*TermLoanRatio	0.158**	0.130**	0.0453	-0.0133	-0.0438
	(0.0616)	(0.0626)	(0.0386)	(0.0415)	(0.0528)
ΔVIX*TermLoanRatio*CF Insolvent			0.848***	0.985***	1.089***
			(0.289)	(0.288)	(0.330)
ΔVIX*RevolverRatio	0.148	0.0871	0.0300	-0.0985	-0.176*
	(0.107)	(0.0943)	(0.0942)	(0.0904)	(0.0901)
ΔVIX*RevolverRatio*CF Insolvent			2.336*	2.085*	2.310*
			(1.242)	(1.170)	(1.165)
ΔVIX*NonBankLeverage		-0.122*	-0.111*	0.0215	-0.00376
		(0.0611)	(0.0603)	(0.0548)	(0.0448)
ΔVIX*NonBankLeverage*CF Insolvent			-0.000328	0.0767	0.142
			(0.183)	(0.202)	(0.208)
ΔVIX*UndrawnRatio	-0.187	-0.200	-0.221*	-0.258*	-0.190
	(0.136)	(0.135)	(0.129)	(0.131)	(0.114)
ΔVIX*UndrawnRatio*CF Insolvent			1.094	1.256	0.964
			(1.011)	(0.821)	(0.671)
ΔVIX*TobinQ				-0.00961	-0.0159**
				(0.00972)	(0.00792)
ΔVIX*TobinQ*CF Insolvent				-0.00622	-0.000191
				(0.00667)	(0.00797)
ΔVIX*LogAssets				-0.0395***	-0.0375***
				(0.00987)	(0.0107)
ΔVIX*LogAssets*CF Insolvent				-0.0603*	-0.0555
				(0.0347)	(0.0336)
ΔVIX*QuickRatio				0.00191	0.00269
				(0.00316)	(0.00245)
ΔVIX*QuickRatio*CF Insolvent				0.00494	-9.42e-05
				(0.0145)	(0.0145)
Observations	72,037	72,037	72,037	72,037	72,037
Firm FEs	Yes	Yes	Yes	Yes	Yes
Industry-date FEs	No	No	No	No	Yes

This table presents the results of our trade war analysis by comparing the effect of term loans, outstanding balance for revolving credits, and the undrawn portion of revolving credits. In line with the main analysis, we include only mature firms that have been publicly traded for at least five years by the end of 2017. A cash-flow insolvent (potential zombie) firm is defined as a firm that consistently has an interest coverage ratio (Compustat EBITDA/XINT) below one for three years leading to 2017. TermLoanRatio is the outstanding balance for term loans from Capital IQ divided by the total assets (AT) from Compustat. RevolverRatio is the outstanding balance for revolving credits from Capital IQ divided by the total assets (AT) from Compustat. NonBankLeverage is book leverage ((DLC+DLTT)/AT from Compustat) minus BankLeverage, which is the sum of TermLoanRatio and RevolverRatio. UndrawnRatio is the undrawn credit portion of revolving credits from Capital IQ divided by the total assets (AT) from Compustat. TobinQ, LogAssets, and QuickRatio are based on Compustat. TobinQ is computed as (MVE+DLC+ DLTT)/AT, where MVE is the market value of equity, calculated as the common shares outstanding (CSHO) multiplied by the annual close price (PRCC_F). LogAssets is the natural logarithm of total assets. QuickRatio is defined as CHE/LCT. Following Colla, Ippolito, and Li (2013), we exclude firms in the utility sector (SIC 4900-4949) and the financial sector (SIC 6000-6999), firm-year observations with missing or zero values for total assets or total debt, and firm-year observations where the difference between the total debt from Compustat and the sum of debt types in Capital IQ exceeds 10% of the total debt from Compustat. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Trade War Analysis using "Unlevered" VIX

	(1) Daily Ret	(2) Daily Ret	(3) Daily Ret	(4) Daily Ret	(5) Daily Ret
ΔVIX	-0.425***	-0.401***	-0.393***	-0.106	
	(0.0690)	(0.0682)	(0.0704)	(0.106)	
ΔVIX*CF Insolvent			-0.0823	0.110	0.0504
			(0.120)	(0.258)	(0.244)
ΔVIX*BankLeverage	0.152***	0.118**	0.0379	-0.0296	-0.0703
	(0.0563)	(0.0546)	(0.0379)	(0.0391)	(0.0445)
ΔVIX*BankLeverage*CF Insolvent			0.901***	1.016***	1.140***
			(0.263)	(0.267)	(0.314)
ΔVIX*NonBankLeverage		-0.114*	-0.103	0.0329	0.00987
		(0.0631)	(0.0626)	(0.0587)	(0.0492)
ΔVIX*NonBankLeverage*CF Insolvent			-0.0380	0.0184	0.0916
			(0.185)	(0.193)	(0.205)
ΔVIX*TobinQ				-0.0126	-0.0187**
				(0.00987)	(0.00838)
ΔVIX*TobinQ*CF Insolvent				-0.00739	-0.000580
				(0.00543)	(0.00658)
ΔVIX*LogAssets				-0.0374***	-0.0358***
				(0.00954)	(0.0105)
ΔVIX*LogAssets*CF Insolvent				-0.0621*	-0.0575
				(0.0368)	(0.0356)
ΔVIX*QuickRatio				0.00424	0.00423*
				(0.00276)	(0.00233)
ΔVIX*QuickRatio*CF Insolvent				-0.00358	-0.00704
				(0.0138)	(0.0141)
Observations	72,037	72,037	72,037	72,037	72,037
Firm FEs	Yes	Yes	Yes	Yes	Yes
Industry-date FEs	No	No	No	No	Yes

This table presents the results of our trade war analysis using the "unlevered" VIX following Bharath and Shumway (2008). In line with the main analysis, we include only mature firms that have been publicly traded for at least five years by the end of 2017. A cash-flow insolvent (potential zombie) firm is defined as a firm that consistently has an interest coverage ratio (Compustat EBITDA/XINT) below one for three years leading to 2017. BankLeverage is the total bank debt from Capital IQ divided by the total assets (AT) from Compustat. NonBankLeverage is book leverage ((DLC+DLTT)/AT from Compustat) minus BankLeverage. TobinQ, LogAssets, and QuickRatio are based on Compustat. TobinQ is computed as (MVE+DLC+ DLTT)/AT, where MVE is the market value of equity, calculated as the common shares outstanding (CSHO) multiplied by the annual close price (PRCC_F). LogAssets is the natural logarithm of total assets. QuickRatio is defined as CHE/LCT. Following Colla, Ippolito, and Li (2013), we exclude firms in the utility sector (SIC 4900-4949) and the financial sector (SIC 6000-6999), firm-year observations with missing or zero values for total assets or total debt, and firm-year observations where the difference between the total debt from Compustat and the sum of debt types in Capital IQ exceeds 10% of the total debt from Compustat. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Full Version of Table 7

	(1) ICR	(2) Altman Z	(3) ICR & Altman Z	(4) DSCR	(5) DSCR & Altman Z
ΔVIX*CF Insolvent	-0.0826		-0.205	-0.244	-0.385***
	(0.233)		(0.183)	(0.159)	(0.141)
ΔVIX*BS Insolvent		0.264	0.937**		1.131**
		(0.296)	(0.452)		(0.507)
ΔVIX*Both Insolvent			-0.577		-0.709
			(0.573)		(0.593)
ΔVIX*BankLeverage	-0.0693	0.0821	-0.0410	-0.0768	-0.0567
	(0.0493)	(0.0906)	(0.0572)	(0.0491)	(0.0583)
ΔVIX*BankLeverage*CF Insolvent	1.365***		1.804***	0.698**	1.007**
	(0.306)		(0.359)	(0.292)	(0.451)
ΔVIX*BankLeverage*BS Insolvent		0.323**	-0.215		-0.176
		(0.159)	(0.447)		(0.561)
ΔVIX*BankLeverage*Both Insolvent			-0.660		-0.303
			(0.999)		(0.842)
ΔVIX*NonBankLeverage	0.0429	0.0379	0.0647	0.0523	0.0684
	(0.0584)	(0.0426)	(0.0482)	(0.0535)	(0.0476)
ΔVIX*NonBankLeverage*CF Insolvent	0.137		0.191	-0.209	0.0226
	(0.218)		(0.157)	(0.141)	(0.146)
ΔVIX*NonBankLeverage*BS Insolvent		-0.414	-0.0112		0.0946
		(0.251)	(0.362)		(0.468)
ΔVIX*NonBankLeverage*Both Insolvent			-0.379		-0.776
			(0.655)		(0.625)
ΔVIX*TobinQ	-0.0220**	-0.0183**	-0.0213**	-0.0224***	-0.0224**
	(0.00856)	(0.00845)	(0.00869)	(0.00839)	(0.00839)
ΔVIX*TobinQ*CF Insolvent	0.00829		0.0114	0.00931	0.0139
	(0.00873)		(0.0112)	(0.0131)	(0.0119)
ΔVIX*TobinQ*BS Insolvent		0.00182	-0.0611		0.00206
		(0.0254)	(0.125)		(0.169)
ΔVIX*TobinQ*Both Insolvent			0.0580		-0.00529
			(0.108)		(0.167)
ΔVIX*LogAssets	-0.0379***	-0.0322**	-0.0351***	-0.0415***	-0.0392***
	(0.0108)	(0.0130)	(0.0121)	(0.0113)	(0.0126)
ΔVIX*LogAssets*CF Insolvent	-0.0470		-0.0366*	0.0199	0.0205
	(0.0375)		(0.0215)	(0.0194)	(0.0155)
ΔVIX*LogAssets*BS Insolvent		-0.0474	-0.135*		-0.181**
		(0.0533)	(0.0781)		(0.0839)
ΔVIX*LogAssets*Both Insolvent			0.0947		0.144
			(0.143)		(0.131)
ΔVIX*QuickRatio	0.00303	0.000606	0.00382	0.00225	0.00296
	(0.00261)	(0.00402)	(0.00237)	(0.00312)	(0.00276)
ΔVIX*QuickRatio*CF Insolvent	-0.00714		0.00166	-0.0153	-0.00569
	(0.0139)		(0.0133)	(0.0115)	(0.0120)
ΔVIX*QuickRatio*BS Insolvent		-0.0380*	-0.0663		-0.160
		(0.0223)	(0.122)		(0.135)
ΔVIX*QuickRatio*Both Insolvent			0.0368		0.131
			(0.125)		(0.142)
Observations	53,801	53,801	53,801	53,801	53,801
Firm FEs	Yes	Yes	Yes	Yes	Yes
Industry-date FEs	Yes	Yes	Yes	Yes	Yes

This table presents the full version of Table 7. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Full Version of Table 8

	(1) Daily Ret	(2) Daily Ret	(3) Daily Ret	(4) Daily Ret	(5) Daily Ret	(6) Daily Ret Orth Target+Path	(7) Daily Ret Orth Full	(8) Daily FF3 Orth Full	(9) Intraday Ret Orth Full
ΔVIX	-0.546***	-0.559***	-0.536***	-0.264***					
	(0.0681)	(0.0675)	(0.0638)	(0.0530)					
ΔVIX*CF Insolvent				0.526***	0.541***	0.575***	0.579***	0.268	0.293*
				(0.133)	(0.127)	(0.147)	(0.163)	(0.170)	(0.159)
ΔVIX*BankLeverage		0.122***	0.0985**	0.0287	0.0128	-0.00279	-0.00123	0.0808	-0.0874**
		(0.0381)	(0.0404)	(0.0526)	(0.0471)	(0.0537)	(0.0577)	(0.0528)	(0.0344)
ΔVIX*BankLeverage*CF Insolvent				0.205**	0.235***	0.210**	0.256***	0.191***	0.253**
				(0.0855)	(0.0731)	(0.0963)	(0.0865)	(0.0578)	(0.111)
ΔVIX*NonBankLeverage			-0.136**	0.00300	0.0123	0.0158	0.0306	0.0906	-0.0553**
			(0.0595)	(0.0577)	(0.0603)	(0.0678)	(0.0676)	(0.0734)	(0.0241)
ΔVIX*NonBankLeverage*CF Insol.				0.0872	0.0624	0.00865	-0.108	-0.250*	0.0773
				(0.0953)	(0.121)	(0.112)	(0.108)	(0.135)	(0.0810)
ΔVIX*TobinQ				-0.00944	-0.0193**	-0.0187*	-0.0137	-0.0131	-0.00179
				(0.0172)	(0.00899)	(0.00973)	(0.0114)	(0.0104)	(0.00701)
ΔVIX*TobinQ*CF Insolvent				-0.0357**	-0.0308**	-0.0279**	-0.0333**	-0.00689	-0.0152**
				(0.0158)	(0.0129)	(0.0133)	(0.0140)	(0.0126)	(0.00734)
ΔVIX*LogAssets				-0.0410***	-0.0389***	-0.0390***	-0.0361***	0.00130	-0.0248***
				(0.00829)	(0.00824)	(0.00844)	(0.00801)	(0.00559)	(0.00801)
ΔVIX*LogAssets*CF Insolvent				-0.112***	-0.115***	-0.123***	-0.118***	-0.0500	-0.0497**
				(0.0239)	(0.0241)	(0.0279)	(0.0299)	(0.0316)	(0.0234)
ΔVIX*QuickRatio				0.00736	0.00584	0.00369	0.000254	0.00453	-0.00214
				(0.00530)	(0.00425)	(0.00414)	(0.00541)	(0.00638)	(0.00575)
ΔVIX*QuickRatio*CF Insolvent				-0.00367	-0.00237	-0.00199	0.00311	-0.00156	-0.00551
				(0.0103)	(0.00997)	(0.00997)	(0.0103)	(0.0116)	(0.00858)
CF Insolvent				0.111	0.104	0.140	0.164	0.0832	-0.0372
				(0.264)	(0.237)	(0.234)	(0.238)	(0.246)	(0.0979)
BankLeverage		0.256	0.248	0.273	0.167	0.161	0.163	0.179	-0.0296
		(0.190)	(0.209)	(0.238)	(0.130)	(0.132)	(0.134)	(0.111)	(0.0255)
BankLeverage*CF Insolvent				0.124	0.305	0.293	0.339	0.306	0.193**
				(0.352)	(0.302)	(0.300)	(0.303)	(0.282)	(0.0900)
NonBankLeverage			-0.0494	0.104	0.261**	0.263**	0.264**	0.314***	-0.0515**
			(0.146)	(0.161)	(0.122)	(0.124)	(0.128)	(0.109)	(0.0201)
NonBankLeverage*CF Insol.				-0.0341	-0.240	-0.284	-0.346	-0.364	0.0113
				(0.274)	(0.238)	(0.236)	(0.235)	(0.257)	(0.0649)
TobinQ				-0.0412	-0.0385*	-0.0392*	-0.0375*	-0.0624***	-0.00160
				(0.0429)	(0.0203)	(0.0210)	(0.0222)	(0.0166)	(0.00388)
TobinQ*CF Insolvent				0.00328	0.00249	0.00629	0.00110	0.0291	-0.00302
				(0.0404)	(0.0242)	(0.0247)	(0.0260)	(0.0235)	(0.00450)
LogAssets				-0.192***	-0.160***	-0.163***	-0.165***	-0.168***	-0.0255***
				(0.0712)	(0.0317)	(0.0320)	(0.0320)	(0.0298)	(0.00689)
LogAssets*CF Insolvent				-0.0215	-0.00403	-0.0126	-0.0137	0.000682	0.00210
				(0.0497)	(0.0437)	(0.0424)	(0.0433)	(0.0468)	(0.0155)
QuickRatio				-0.0216	-0.00590	-0.00685	-0.00891	-0.00628	-0.00484
				(0.0148)	(0.0111)	(0.0114)	(0.0121)	(0.0123)	(0.00375)
QuickRatio*CF Insolvent				0.0219	0.00483	0.00421	0.00726	0.00512	0.00485
				(0.0214)	(0.0173)	(0.0173)	(0.0169)	(0.0196)	(0.00500)
Observations	174,784	174,784	174,784	174,784	174,784	174,784	174,784	174,666	127,851
Stock FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Date FEs	No	No	No	No	Yes	Yes	Yes	Yes	Yes

This table presents the full version of Table 8. The industry-date fixed effects are based on the two-digit SIC codes. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Full Version of Table 9

	(1) ΔLn(STDebt)	(2) ΔLn(STDebt)	(3) ΔLn(STDebt)	(4) ΔLn(STDebt)	(5) ΔLn(DebtPayment)	(6) ΔLn(DebtPayment)	(7) ΔLn(DebtPayment)	(8) ΔLn(DebtPayment)
ΔLn(EPU)	0.0417*	0.0297	0.0425		0.0237	0.0258	-0.0226	
	(0.0241)	(0.0267)	(0.0766)		(0.0195)	(0.0241)	(0.0592)	
ΔLn(EPU)*CF Insolvent		-0.0251	0.172	0.155		-0.0373	0.115	0.0959
		(0.0697)	(0.181)	(0.185)		(0.0527)	(0.160)	(0.159)
ΔLn(EPU)*BankLeverage		0.0848	0.0959	0.0831		0.0116	0.0349	0.0242
		(0.101)	(0.107)	(0.100)		(0.0608)	(0.0648)	(0.0647)
ΔLn(EPU)*BankLeverage*CF Insolvent		-0.560**	-0.540**	-0.535**		-0.336***	-0.261**	-0.256*
		(0.246)	(0.237)	(0.230)		(0.123)	(0.129)	(0.132)
ΔLn(EPU)*NonBankLeverage		0.0490	0.0656	0.0588		0.00810	-0.0121	-0.00890
		(0.112)	(0.0996)	(0.0977)		(0.0663)	(0.0756)	(0.0750)
ΔLn(EPU)*NonBankLeverage*CF Insolvent		0.0947	0.121	0.111		0.0497	0.112	0.101
		(0.159)	(0.176)	(0.175)		(0.126)	(0.141)	(0.136)
ΔLn(EPU)*TobinQ			-0.0159	-0.0224			-0.00715	-0.0162
			(0.0137)	(0.0137)			(0.0134)	(0.0131)
ΔLn(EPU)*TobinQ*CF Insolvent			-0.00157	0.00581			-0.0213	-0.0121
			(0.0223)	(0.0226)			(0.0204)	(0.0209)
ΔLn(EPU)*LogAssets			-0.000290	-0.00173			0.00791	0.00571
			(0.0107)	(0.00920)			(0.00838)	(0.00795)
ΔLn(EPU)*LogAssets*CF Insolvent			-0.0328	-0.0308			-0.0187	-0.0175
			(0.0341)	(0.0341)			(0.0356)	(0.0349)
ΔLn(EPU)*QuickRatio			0.0126	0.0137			0.00561	0.00621
			(0.0132)	(0.0145)			(0.0119)	(0.0125)
ΔLn(EPU)*QuickRatio*CF Insolvent			-0.0248	-0.0272			-0.00497	-0.00594
			(0.0193)	(0.0205)			(0.0142)	(0.0148)
CF Insolvent		0.0509**	0.0661	0.0422		0.0273	0.0462	0.0328
		(0.0194)	(0.0627)	(0.0590)		(0.0167)	(0.0517)	(0.0508)
BankLeverage		0.124***	0.127***	0.119***		0.0682**	0.0891***	0.0829***
		(0.0346)	(0.0320)	(0.0338)		(0.0269)	(0.0251)	(0.0268)
BankLeverage*CF Insolvent		-0.198***	-0.168***	-0.162***		-0.101**	-0.0855**	-0.0836*
		(0.0580)	(0.0536)	(0.0545)		(0.0473)	(0.0421)	(0.0435)
NonBankLeverage		0.210***	0.208***	0.196***		0.107***	0.110***	0.102***
		(0.0393)	(0.0344)	(0.0290)		(0.0261)	(0.0247)	(0.0246)
NonBankLeverage*CF Insol.		-0.135*	-0.123*	-0.119*		-0.0362	-0.0215	-0.0223
		(0.0706)	(0.0683)	(0.0674)		(0.0438)	(0.0431)	(0.0442)
TobinQ			-0.00788*	-0.00961**			-0.00695	-0.00848*
			(0.00429)	(0.00429)			(0.00468)	(0.00479)
TobinQ*CF Insolvent			0.00284	0.00489			0.00333	0.00486
			(0.00552)	(0.00547)			(0.00573)	(0.00574)
LogAssets			0.0265*	0.0169*			0.0155	0.00911
			(0.0136)	(0.00979)			(0.00953)	(0.00696)
LogAssets*CF Insolvent			-0.000574	0.00289			-0.000310	0.00161
			(0.0132)	(0.0128)			(0.0107)	(0.0105)
QuickRatio			0.0166**	0.0168**			0.0239***	0.0242***
			(0.00715)	(0.00752)			(0.00817)	(0.00850)
QuickRatio*CF Insolvent			-0.0105	-0.0108			-0.0163**	-0.0165*
			(0.00765)	(0.00806)			(0.00801)	(0.00835)
Observations	69,619	69,619	69,619	69,619	75,476	75,476	75,476	75,476
R-squared	0.018	0.018	0.019	0.022	0.016	0.016	0.017	0.020
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	No	No	No	Yes	No	No	No	Yes

This table presents the full version of Table 9. Standard errors in parentheses are double-clustered by firm and by date. *** p<0.01, ** p<0.05, * p<0.1.