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Uncertainty, Major Investments, and Capital Structure Dynamics

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Abstract

This study examines the effects of uncertainty on firms' capital structure dynamics. We find that high-uncertainty firms have some 19% lower leverage targets and 17% higher adjustment speeds toward targets than low-uncertainty firms, and that over-levered firms faced with high uncertainty have 44% higher adjustment speeds than those with low uncertainty, while under-levered firms' adjustment speeds are not influenced by uncertainty. Comparing over-levered and under-levered firms' adjustment speeds during major and routine investment periods reveals that over-levered firms with high uncertainty converge to their targets substantially faster to avoid bankruptcy threat, while those with low uncertainty tend to deviate from their targets due to transitory-debt-financed major investments, thereby reconciling two opposing leverage dynamics documented in the literature. On the other hand, under-levered firms with high uncertainty converge to their targets more slowly than those with low uncertainty due to the increased value of the option to wait and see. We provide some evidence that both bankruptcy threat and real option channels could account for the findings.

JEL classification: G31, G32, G33, D22, D81, D92

Keywords: Uncertainty, Leverage, Capital Structure Dynamics, Major Investments

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1 Introduction

Uncertainty affects various aspects of firms' business activities. A rich body of literature has shown that uncertainty has material effects on firms' decision-making—particularly on their investment decisions. Emphasizing the existence of market frictions such as capital irreversibility, financial constraints, fixed costs, and employment costs, early studies in this line centered around the question, "how does uncertainty affect corporate investment?". For example, Bernanke (1983), using a Bayesian learning framework, shows that uncertainty related to investment increases the value of real options to the firm, rendering it to wait for additional information to invest. This real option insight for explaining the relation between a firm's investment decision and uncertainty has been further explored and ramified to produce a multitude of subsequent studies which propose other probable causes of the effect of uncertainty on corporate investment[1]. Asset pricing literature also has a long tradition to ask how stock-return volatility, a commonly used uncertainty measure, is related to stock returns at both aggregate and individual firm levels[2].

On the financing side, however, the effects of uncertainty on a firm's capital structure decision have been little explored although a large number of studies following the seminal work by Modigliani and Miller (1958) have endeavored to grasp firms' financing behaviors in different contexts and frameworks. Given that uncertainty affects firms' business activities including major investments and financing decisions both directly and indirectly, the relative scarcity of research on this subject is quite puzzling. In so far as the value of debt and capital structure are interrelated and to the extent that uncertainty affects firms' investment and financing decisions, a careful examination of the effect of uncertainty on capital structure will contribute to a better understanding of a firm's financing behavior in a dynamic context and its implications on the firm value.

This paper addresses how a firm responds to the uncertainty levels that it is faced with, so as to

[1] See, for example, Fisher *et al.* (1989), Kale *et al.* (1991), Abel and Eberly (1994, 1996). Bertola and Caballero (1994), Leland (1994), Leahy and Whited (1996), Bloom (2000), Graham and Harvey (2001), Veracierto (2002), Korajczyk *et al.* (2003), Welch (2004), Leary and Roberts (2005), Hackbarth *et al.* (2006), Flannery and Rangan (2006), Bloom *et al.* (2007), Strebulaev (2007), Titman and Tsyplakov (2007), Bloom (2008), Byoun (2008), Lemmon *et al.* (2008), Tserlukevich (2008), Frank and Goyal (2009), Harford *et al.* (2009), Huang and Ritter (2009), Cook and Tang (2010), DeAngelo *et al.* (2011), Faulkender *et al.* (2012), Öztekin and Flannery (2012), Flannery and Hankins (2013), Lin and Flannery (2013), and Elsas *et al.* (2014) for the subsequent studies in this vein.

[2] See, among numerous others, Black (1978), Christie (1982), McDonald and Siegel (1985), French *et al.* (1987), Campbell and Hantschel (1992), Duffee (1996), Campbell *et al.* (2001), Ang *et al.* (2006, 2009), Grullon *et al.* (2012) for example studies in this area.

optimize its financing decisions. Specifically, we examine the following issues:

(i) how uncertainty affects a firm's target capital structure and dynamic rebalancing behaviors;

(ii) how a firm's current leverage in relation to its target leverage interacts with uncertainty in influencing its capital structure dynamics;

(iii) whether uncertainty affects a firm's major investments, and if so, how a firm's major investments affect its financing behaviors in the presence of varying degrees of uncertainty.

The main contribution of our study is threefold. First, we show that uncertainty affects a typical firm's target leverage. Specifically, the target leverage decreases with uncertainty in a statistically significant and economically meaningful way. Second, we provide evidence that uncertainty has asymmetric effects on capital structure adjustment. Specifically, we find that the speed of capital structure adjustment is affected by uncertainty facing the firm, and further, this uncertainty-driven rebalancing behavior is differentiated across the firms conditional on their current leverage ratios. Third, we analyze how firms fund *major* investments in the presence of varying degrees of uncertainty[3]. By incorporating uncertainty into the firm's dynamic capital structure decision, our analysis nests and reconciles conflicting results documented in the past studies of firms' financing behavior around major investments. That is, our findings illustrate that both temporary deviations from the target leverage in DeAngelo *et al.* (2011) and the opposite tendency in Elsas *et al.* (2014) can be comfortably accommodated in our empirical specification, thereby offering deeper insight into the factors underlying a firm's dynamic capital structure decision.

In order to investigate our hypotheses, we adopt the partial adjustment model of dynamic capital structure proposed by Flannery and Rangan (2006). The underlying rationale for the existence of *target* debt level is provided by the trade-off theory of capital structure. As long as the markets are frictionless, firms would have no reason to deviate from their target leverage. The theory postulates, however, that firms attain their target debt levels as firms trade off tax benefits of debt financing against financial distress costs, which often include default-related agency costs in a broadly interpreted framework[4]. While numerous studies have been conducted and found to be supportive of the trade-off theory, many other studies seem to give credence to alternative views

[3]We will precisely define a major investment in Section 4.

[4]The theoretical underpinning of the trade-off theory dates back to Modigliani and Miller (1963).

such as pecking order and market timing hypotheses. Frank and Goyal (2009) attribute these apparent inconsistencies to the fact that many empirical studies are designed to give support for a particular theory and thus produce *different* sets of significant variables.

This study is partly motivated by these opposite findings in the past literature concerning factors that affect firms' capital structure decisions in a dynamic context. Notably, Titman and Wessels (1988), and Harris and Raviv (1991), two classic survey papers, each identify their own sets of significant variables that are vastly different from each other. In particular, volatility is shown to be insignificant in the former but quite the opposite in the latter. We postulate that their measures of volatility may be related, more or less, to *uncertainty*, the variable of our interest[5].

Uncertainty comes as different beings in different contexts, and firms are constantly faced with it in reality. While uncertainty is often elusive, yet comprehensive and collective in nature, researchers in economics and finance have used the term to represent particular sources of uncertainty pertinent to individual firms or the aggregate market such as changes in consumer tastes and production technologies, regulatory and institutional changes, interest rates and foreign exchange rates, political disruptions and so on.

We consider two aspects in determining the uncertainty measure for this study. First, ample past literature has confirmed that a firm's business environment is affected by a wide range of sources of uncertainty including demand, interest rates, exchange rates, and changes in technology and regulations. Second, since uncertainty is likely to affect the underlying valuation process of debt and equity, the firm needs to take into account the collective value implications of uncertainty on its capital structure decision[6]. As such, we want our measure of uncertainty to be inclusive of a broad range of relevant sources of uncertainty facing a firm.

In an effort to capture all relevant uncertainty factors using a single measure, we follow the approach proposed by Leahy and Whited (1996) to use the standard deviation of daily stock returns for individual firms to examine the effects of uncertainty on firms' leverage decision[7]. Past litera-

[5]Titman and Wessels (1988) use earnings volatility whereas Harris and Raviv (1991) consider volatility of cash flows.

[6]See Leland (1994) for this point. Also Grullon, Lyanders, and Zhdanov (2012) made a similar argument to establish positive relations between firm-level stock returns and firm-level volatility utilizing real options owned by firms.

[7]Another attractive feature of using a stock-returns-based measure of uncertainty is that the data are reported at a sufficiently high frequency.

ture has well documented benefits of using stock return volatility as a proxy to capture uncertainty facing a firm. In sofar as asset returns, particularly stock returns, reflect prospect of firms' future business environment reasonably well, we expect the impact of different sources of uncertainty to be adequately incorporated into the returns. We can, therefore, consider stock return volatility a forward-looking measure of uncertainty that correctly weighs the relative impact of different sources of uncertainty on the firm value. In addition, a stock-return-based measure has an additional advantage due to data availability at sufficiently high frequency. Also it has been shown that firm-level stock return volatility is significantly correlated with a variety of alternative uncertainty proxies, thereby lending credence to its use as a comprehensive uncertainty measure (e.g., Bloom, Bond, and Van Reenen, 2007)[8]. Based on their simulation-based (SMM) model, DeAngelo, DeAngelo, and Whited (2011) propose a set of testable predictions, some of which share the similar spirit to the main subject of this study[9].

By incorporating uncertainty into leverage dynamics, this study offers substantially different and richer interpretations of firms' dynamic capital structure decisions than what has been documented in the existing literature. We find that uncertainty has a strong negative effect on firms' target leverage levels. The coefficient estimates of uncertainty on target leverage are all significantly negative in various model specifications tested. These results support our prediction that firms with higher level of uncertainty are willing to lower their target leverage. Thus our results complement what has been documented in the trade-off theory literature. We posit these results arise from firms' decision to reduce debt in response to increased chance of bankruptcy induced by higher uncertainty[10]. The coefficients of other control variables are similar in magnitude to those in previous studies (Flannery and Rangan (2006), Lemmon *et al.* (2008), Elsas *et al.* (2014)). While parameter estimates based on pooled OLS and fixed effects (henceforth referred to as FE) estimators are highly likely to be biased (Nickell, 1981), the gaps between those parameter estimates for lagged leverage are 0.184 and 0.198 based on book leverage and market leverage, respectively. The same coefficients estimated by LSDVC and System GMM, on the other hand, sit closer to each

[8] The proxies in their study include sale growth volatility and within-year variability of analysts' earnings forecasts. Bond, Moessner, Mumtaz, and Syed (2005) also report similar results.

[9] They suggest the need for future studies that link capital structure to second moments of investment and capital adjustment costs.

[10] We will further explore, later in the paper, two possible channels through which uncertainty affects firms' dynamic capital structure decisions.

other, both falling between pooled OLS estimate and FE estimate. Our results closely correspond to the findings of Flannery and Hankins (2013), who suggest that the LSDVC and system GMM estimators work well in the dynamic capital structure estimation.

In order to gain further insight, we divide the full sample into two groups; over-levered firms vs. under-levered firms. Approximately 44.8% (39.2%) of firms are categorized as over-levered based on their book leverage (market leverage). Because the characteristics and behavior of the two sub-samples are likely to differ substantially (Faulkender *et al.*, 2012), separate investigation of the two groups, along with the full sample study, provides deeper insight into their financing behaviors. High-uncertainty firms tend to have substantially lower target leverage ratios than low-uncertainty firms in full sample and over-levered firm sample. The average difference in book target leverage between low- and high-uncertainty firms hovers around 3.7% for the full sample (3.6% for market leverage). This uncertainty-induced target leverage difference becomes larger (smaller) for over-levered (under-levered) firms, which further confirms the results described above. This also suggests that uncertainty facing over-levered firms tend to bring in greater deviations from the target. It is also noteworthy that firm fixed effects have significant impact on the target leverage ratios with the median proportion equal to 11.3% (14.0%) for book leverage (market leverage).

We turn next to examine how uncertainty affects leverage adjustment speeds. Average firms facing high uncertainty tend to adjust their leverage toward the target faster. However, further investigation reveals that uncertainty only affects adjustment speed of over-levered firms with insignificant effect on under-levered firms. Specifically, high-uncertainty firms in the over-levered group have higher adjustment speeds than low-uncertainty counterpart by an average of 11.2% (5.0%) on the book (market) value scale. These results corroborate the traditional arguments of the trade-off theory in a couple of respects. First, under-levered firms have little motivation to adjust their leverage ratios to further reduce the default risk because they probably don't have to worry about potential default risk. Second, over-levered firms, once faced with high uncertainty, are exposed to heightened levels of default risk and bankruptcy costs compared to low-uncertainty firms in over-levered territory.

In order to address the potential endogeneity problem arising from reverse causality, we employ a difference-in-differences (DiD) approach using a large exogenous uncertainty shock during our sample period, namely the 2007-2008 Global Financial Crisis. The Crisis did increase the market-wide uncertainty substantially as demonstrated in figure 1. Due to the global nature of the shock it is difficult to classify the sample into the treatment and control groups, which entails the propensity score matching procedure before conducting the test of the effect of the exogenous uncertainty shock on the capital structure dynamics. The panels A to C of Table 5 show that the firms in treatment group are well matched with those in control group. The difference-in-differences analysis in Panels D and E of Table 5 verify our main results of capital structure effects of uncertainty. That is, the Global Financial Crisis lowered the target leverage ratios of treatment firms—more so than control group. In addition, the exogenous shock accelerated speed of leverage adjustment.

When there arises a major investment opportunity, an over-levered firm will grab the opportunity mainly by issuing debts as long as benefits of doing so are expected to outweigh the costs, which may well be the case when the firm is faced with relatively low level of uncertainty. Consequently then, they may want to voluntarily deviate from the leverage targets at the time of investment spikes. This closely corresponds to the findings in DeAngelo *et al.* (2011). If uncertainty is high, on the other hand, over-levered firms would choose to delay taking the investment and/or repay debt to ensure future borrowing capacity, especially if such delay creates high enough value of *wait and see*. Alternatively, they would probably issue equity rather than debt to finance potential investment projects because high uncertainty and excessive leverage together may expose the firms to high default risk. As a result, their leverage will be adjusted towards the target rendering the adjustment speed faster when there are investment spikes. This is consistent with the findings in Elsas *et al.* (2014). Under-levered firms, on the other hand, will likely take the major investment opportunity mainly with debt financing[11], for those firms are relatively better shielded from default risk. Hence they will increase leverage toward the target making the adjustment speed faster when there are investment spikes.

We provide empirical evidence that over-levered and under-levered firms have opposite reactions to investment spikes. Over-levered firms tend to temporarily deviate from their target leverage ratios at investment spikes with slower or even negative speed of adjustment depending on the severity of uncertainty facing the firm. On the other hand, under-levered firms tend to fully adjust

[11] See the findings in Mayer and Sussman (2005), Bond *et al.* 2006), and Im *et al.* (2016) for firms' financing patterns at major investments.

or even over-adjust their leverage toward their targets. Notably, uncertainty plays an important role in both groups of firms with its impact on over-levered sample being greater in magnitude. Our results show that over-levered firms with low uncertainty tend to temporarily deviate from the targets at investment spikes with negative speed of adjustment (-4.8% for book leverage and -46.1% for market leverage) while over-levered firms with high uncertainty tend to adjust towards the target leverage ratios with positive speed of adjustment (45.6% for book leverage and 5.2% for market leverage). For under-levered firms, difference between low uncertainty and high uncertainty groups is smaller yet still significant. In under-levered firm sample, speed of adjustment at investment spikes for low uncertainty group is 114.6% for book leverage (overshooting) and 77.9% for market leverage whereas adjustment speed at spikes for high uncertainty firms are 100.1% for book leverage (overshooting) and 72.1% for market leverage.

Large investments are mostly financed externally as evidenced in prior research. Thus the heavy reliance of major investments on external financing is likely to reveal the managers' attitude toward leverage and firms' capital structure adjustment dynamics more prominently (DeAngelo *et al.*, 2011; Elsas *et al.*, 2014). Interestingly, these two studies offer somewhat contrary results regarding firms' leverage decisions around major investments, particularly for over-levered firms. Elsas *et al.* (2014) find that firms tend to move toward the estimated leverage target faster when they have major investments whereas in DeAngelo *et al.* (2011) firms purposefully but temporarily move away from permanent leverage targets by issuing transitory debt to fund large investments. If an investment relies mostly on debt financing, over-levered firms will deviate from targets over the investment period. To the contrary, under-levered firms will converge to the targets with varying speed depending on the severity of uncertainty they are faced with. So the total effects will ultimately be determined by which side dominates in the sample. Our paper shows that the two opposing results could be reconciled and comfortably nested in our empirical specifications by incorporating the effects of uncertainty on the capital structure dynamics.

We also consider the channels or mechanisms through which uncertainty affects firms' financing behavior at the time of investment shocks. We propose two possible channels. First, uncertainty might hinder firms' investment decisions, pushing them to downsize the investments at the shock, or even delay the investment altogether as Bloom *et al.* (2007) suggest. Given the large investments are financed by debt in general, firms with high uncertainty would use less amount of debt, thereby incurring smaller increase in leverage at the time of investment shock. The other channel is that firms with higher uncertainty may have different financing patterns at the investment shocks. In other words, it may be the case that firms with different levels of uncertainty still make similar investment decisions, but their modes of financing are different. In this case, firms with high uncertainty do not delay the investment while using different proportion of debt for financing. We expect the results in Table 7 to be obtained through either or both channels.

To further explore the two possible channels just described, namely *investment* channel and *financing* channel, we study how a typical firm's uncertainty influences its investment propensity by utilizing each individual firm's sales growth as a proxy for demand shock designed to capture its future investment opportunity. Since the demand shock as measured in this study can well capture future investment opportunity *ex ante*, our empirical specifications allow to detect the investment downsizing or delay. The estimation results in Table 8 demonstrate that firms' with high level of uncertainty tend to respond more cautiously to given investment opportunities. We interpret this as evidentce that the investment channel is at work.

We also examine whether firms' financing patterns at investment spikes differ by uncertainty level. After classifying each firm's financing methods into debt financing, equity financing, cash flow financing, and other financing, we estimate a system of four seemingly unrelated regression equations (*SURE*) to see how a typical firm finances its major investments. The results show that debt is the major financing source for firms at investment spikes with the overall proportion of debt financing hovering around 80.3% in the full sample. This result corresponds to existing literature including Mayer and Sussman (2005) and Bond *et al.* (2006). To further investigate if uncertainty plays an important role in firms' financing patterns at major investments, we split the sample into high- and low-uncertainty groups to show that debt is still the major financing source for high uncertainty firms at investment spikes (74.0) whereas their debt reliance is lower than that of lower uncertainty firms (86.0%). These findings are in support of what we term the *financing* channel, demonstrating that firms with higher uncertainty tend to fund their investments with lower proportion of debt. Our results are robust to using book leverage ratios for industry median leverages and to estimating the system of equations without control variables. Overall, the results presented in Table 8 and Table 9 indicate that the two channels considered so far work together to affect firms' capital structure dynamics at major investments. More specifically, firms with higher uncertainty tend to respond more cautiously to the investment opportunity leading to investing in smaller amount. At the same time, they also tend to fund their investment with relatively lower proportion of debt. These two mechanisms together tend to increase the gap between high- and low- uncertainty firms' leverage adjustments at the time of investment shock[12].

The remainder of the paper is organized as follows. We describe our empirical model and data in Section 2. In Section 3, we reports the main results on firms' target leverage decisions and rebalancing behaviors. We also analyze in Section 3 the robustness of our results, employing the 2007-2008 Global Financial Crisis as an exogenous shock in Diff-in-Diff framework. Focusing on the investment spike sample, we analyze and discuss how the capital structure dynamics around major investments is influenced by uncertainty, and elaborate on its possible transmission channels in Section 4. Section 5 summarizes our findings and concludes the discussion.

2 Data and empirical model

2.1 Data

We obtain annual accounting data from the CRSP/Compustat Merged Database (CCM), daily stock return data from the CRSP, credit rating data from Compustat Monthly Updates, and GDP deflator data from the UN database for the period 1988 to 2014[13]. The data start from 1988 because investigating financing patterns around major investments requires firm-level flow-of-funds data available from cash flow statements, which replaced the "cash statements by sources and uses of fund" in that year by the Financial Accounting Standards Boards #5. Our dataset consists of all manufacturing firms with the two-digit North American Industry Classification System (NAICS) sector code of 31, 32, or 33.

We require that each firm have at least 10-year long uninterrupted observations. We exclude firms with missing or negative total assets, negative book equity, or whose stock are not traded

[12]The finding we address earlier in this section that uncertainty adversely affects a firm's investment propensity at spikes (i.e., the investment channel) is in line with the smaller number of spike observations assigned to high uncertainty group documented in Table 9.

[13]The US GDP deflator data are used to construct $LnTA_{i,t}$, which is the natural logarithm of total assets denominated in year-2000 dollars.

on the three major stock exchanges in the U.S. (i.e., NYSE, NASDAQ, and AMEX). We keep the firm-year observation if variables other than total assets and book equity are missing in that year. We winsorize all the continuous variables at the 1st and 99st percentiles to mitigate the effects of outliers and eradicate the errors in the data. The final sample is an unbalanced panel of 23,283 firm-year observations corresponding to 1,389 firms.

2.2 Construction of the uncertainty measure

Firms are uncertain about a broad range of factors such as demand, productivity, technological change, inflation, interest rates, regulation, and policy changes. In an attempt to capture all relevant uncertainty sources, we use the standard deviation of a firm's daily stock returns for each fiscal year suggested by Leahy and Whited (1996) and Bloom *et al.* (2007). The stock-returns-based measure of uncertainty is defined as:

$$UNC\_LEVEL_{i,t} = \sqrt{\frac{1}{D_t - 1}\sum_{d=1}^{D_t}(r_{i,t,d} - \bar{r}_{i,t})^2}, \tag{1}$$

where D_t is the number of trading days in year t, $r_{i,t,d}$ is firm i's stock return on day d in year t, and $\bar{r}_{i,t}$ is the annual average of firm i's daily stock returns in year t. Our variable of interest, $UNC_{i,t}$, is constructed by standardizing the firm-year-specific uncertainty measure specified in Equation (1). We also calculate a dummy variable for high uncertainty level, $D\_HighUNC_{i,t}$, which equals one if the uncertainty measure is higher than its sample median and zero otherwise.

The stock-returns-based measure of uncertainty is very attractive for the following reasons. First, this measure is a forward-looking indicator that implicitly weighs the relative impact of different sources of uncertainty on the firm value (Bloom *et al.*, 2007). Second, this measure utilizes stock returns measured at a sufficiently high frequency. Our sampling frequency for daily stock returns is on average 245 observations per year, producing low sample variance. Consequently, movements in the uncertainty measure are likely to reflect the change in the underlying process or fundamentals rather than pure noise (see Bloom *et al.*, 2007). Third, as Bond *et al.* (2005) and Bloom *et al.* (2007) indicate, this stock returns-based measure is highly correlated with other possible proxies for uncertainty such as the within-year variability of analysts' earnings forecasts and the cross-sectional dispersion across forecasts made by different analysts for the same firm. Finally, this measure varies across firms and over time, allowing us to evaluate if high-uncertainty firms have leverage dynamics significantly different from that of low-uncertainty firms in general, and more specifically during major investments.

2.3 Empirical model and descriptive statistics

The dynamic trade-off theory of capital structure is arguably one of the most significant innovations in empirical capital structure research. The dynamic trade-off theory maintains that market imperfections generate a link between capital structure and firm value, and firms take actions to offset deviations from their optimal debt ratios (Flannery and Rangan, 2006). According to the survey by Graham and Harvey (2001), 81% of firms consider a target debt ratio or range when making their capital structure decisions. The speed at which firms adjust toward target leverage ratios depends on the costs and benefits of adjusting leverage. With zero adjustment costs, the dynamic trade-off theory implies that firms should stick to their optimal leverage at all times. However, if adjustment costs are very high, firms are more likely to be reluctant to adjust toward their optimal leverage. Flannery and Rangan (2006) proposed a partial adjustment model in which firms partially or incompletely adjust toward a target leverage ratio that depends on firm characteristics.

To investigate the impact of uncertainty on capital structure dynamics (i.e., target leverage and adjustment speeds), we extend Flannery and Rangan's (2006) framework as stated below:

$$L_{i,t} - L_{i,t-1} = \gamma(L^{\star}_{i,t} - L_{i,t-1}) + \kappa_t + \varepsilon_{i,t}, \tag{2}$$

where $L_{i,t}$ is firm i's contemporaneous leverage, and $L^{\star}_{i,t}$ is firm i's target leverage ratio, κ_t is an error component reflecting year fixed effects and $\varepsilon_{i,t}$ is a white-noise error term. $L_{i,t} - L_{i,t-1}$ measures actual change in leverage, or leverage adjustment, and $L^{\star}_{i,t} - L_{i,t-1}$ measures deviation from the target leverage ratio. Each year, a typical firm closes a proportion γ of the gap between where it stands ($L_{i,t-1}$) and where it wishes to be ($L^{\star}_{i,t}$). As a leverage measure ($L_{i,t}$), we consider both book leverage ratio ($BDR_{i,t}$) and market leverage ratio ($MDR_{i,t}$). Book leverage ratio is defined as total debt divided by book total assets, while market leverage ratio is defined as total debt divided by the sum of total debt and market value of equity.

First, to investigate if firms take uncertainty into account when they set their leverage targets, we model target leverage $L^{\star}_{i,t}$ as a linear function of uncertainty as well as lagged firm characteristics and firm fixed effects:

$$L^{\star}_{i,t} = \beta_0 + \beta_1 X_{i,t-1} + \beta_2 UNC_{i,t-1} + \eta^{\star}_i, \tag{3}$$

where $\eta^{\star}_i$ is an error component reflecting firm fixed effects in target leverage, and $X_{i,t-1}$ is a vector containing a set of firm characteristics often used in recent dynamic capital structure studies such as Fama and French (2002), Flannery and Rangan (2006), Faulkender *et al.* (2012), and Elsas *et al.* (2014). It includes natural logarithm of book total assets denominated in year-2000 dollars ($LnTA_{i,t-1}$), market to book ratio of total assets ($MV\_BV_{i,t-1}$), earnings before interests and taxes (EBIT) to book total assets ratio ($EBIT\_TA_{i,t-1}$), ratio of net property, plant, and equipment (PP&E) to book total assets ($FA\_TA_{i,t-1}$), ratio of depreciation and amortization to book total assets ($DEP\_TA_{i,t-1}$), research and development (R&D) expenses as a proportion of total assets ($RD\_TA_{i,t-1}$), a dummy variable for R&D expenses reporting ($D\_RD_{i,t-1}$), a dummy variable for long-term debt rating availability in Compustat ($D\_Rated_{i,t-1}$), and industry median leverage ratio based on Fama and French's (1997) 48 industries.

Substituting $L^{\star}_{i,t}$ in Equation (3) into Equation (2), we obtain the following estimable equation:

$$L_{i,t} = \gamma\beta_0 + \gamma\beta_1 X_{i,t-1} + \gamma\beta_2 UNC_{i,t-1} + (1-\gamma)L_{i,t-1} + \kappa_t + \gamma\eta^{\star}_i + \varepsilon_{i,t}, \tag{4}$$

where the coefficient γ denotes the speed of adjustment, which measures how fast a typical firm's actual leverage adjusts to its target leverage. It is expected to lie between 0 and 1, with a higher γ meaning a faster speed of adjustment. Equation (4) can be re-written as the following standard dynamic panel regression model:

$$L_{i,t} = b_0 + b_1 X_{i,t-1} + b_2 UNC_{i,t-1} + b_3 L_{i,t-1} + Year\ Dummies + \eta_i + \varepsilon_{i,t}, \tag{5}$$

where $b^{\star}_0 = \gamma\beta_0$, $b_1 = \gamma\beta_1$, $b_2 = \gamma\beta_2$, $b_3 = (1-\gamma)$, and $\eta_i = \gamma\eta^{\star}_i$. We include year dummies to control for year fixed effects (κ_t)[14]. The speed of adjustment can be estimated as $\widehat{\gamma} = 1 - \widehat{b}_3$. Once we have obtained $\widehat{\beta}_0$, $\widehat{\beta}_1$, $\widehat{\beta}_2$, and $\widehat{\eta}_i^\star$, it is straightforward to estimate target leverage ratios[15]. The target book leverage ratio and target market leverage ratio are denoted $BDR^\star$ and $BDR^\star$, respectively. If uncertainty has a substantial impact on a typical firm's target leverage ratio, the coefficient of the uncertainty measure $UNC_{i,t-1}$ in Equation (3), β_2, is expected to be significantly different from zero for both leverage measures.

Once deviated from their leverage targets, firms tend to adjust their leverage back to their leverage targets gradually. Note that γ in Equation (2) represents the proportion of gross leverage gap that is closed per period. Considering that a firm's leverage is mechanically adjusted due to net income at each fiscal year's end, the leverage gap in Equation (2) can be decomposed into *i*) the gap to be closed by net income-induced involuntary adjustment, and *ii*) the remainder gap to be filled by the firm's voluntary, or active, leverage adjustment (Faulkender *et al.*, 2012).

To estimate the speed at which active adjustment is made and the uncertainty effect therein, we first calculate firm *i*'s hypothetical book leverage $BDR^p_{i,t-1}$ as the proportion between $D_{i,t-1}$ and the sum of $A_{i,t-1}$ and $NI_{i,t}$[16]. Thus, $BDR^p_{i,t-1}$ is what a firm's leverage is expected to be at the end of time t if the firm engages in no net capital market activities. We decompose the change in book leverage $BDR_{i,t} - BDR_{i,t-1}$ (denoted $\Delta BDR_{i,t}$) into two parts: passive adjustment due to net income accounting ($BDR^p_{i,t-1} - BDR_{i,t-1}$) and active adjustment arising from active financial decisions ($BDR_{i,t} - BDR^p_{i,t-1}$ or $\Delta BDR^p_{i,t}$). We then estimate a typical firm's active adjustment speed using the following models:

$$\Delta BDR^p_{i,t} = Constant + \lambda BDEV^p_{i,t} + \varepsilon_{i,t}, \tag{6}$$

and

$$\Delta MDR_{i,t} = Constant + \lambda MDEV_{i,t} + \varepsilon_{i,t}, \tag{7}$$

where $BDEV^p_{i,t} = BDR^\star_{i,t} - BDR^p_{i,t-1}$, $MDEV_{i,t} = MDR^\star_{i,t} - MDR_{i,t-1}$, and λ captures the active

[14]Note that $\widehat{b}_0$ has been adjusted to $\widehat{b}_0^\star$ to ensure that the mean of year effects estimated using year dummies is zero.

[15]Given the residual of the regression (i.e., $\widehat{e}_{it} = \widehat{\eta}_i + \widehat{\varepsilon}_{i,t}$), the fixed effects in leverage ($\widehat{\eta}_i$) can be estimated to be within-firm average residuals. The fixed effects in target leverage ($\widehat{\eta}_i^\star$) can be estimated by dividing the fixed effects in leverage ($\widehat{\eta}_i$) by the speed of adjustment estimate ($\widehat{\gamma}$).

[16]$D_{i,t-1}$ and $A_{i,t-1}$ denote firm *i*'s total debt and book total assets in year $t-1$. Similarly, $NI_{i,t}$ denotes its net income during year t.

adjustment speed[17].

To examine if the heterogeneity in the active adjustment speed is driven by firm-year-specific uncertainty, we specify λ in Equations (6) and (7) as a function of an uncertainty measure as follows:

$$\lambda = \lambda_0 + \lambda_1 UNC_{i,t-1}, \tag{8}$$

or

$$\lambda = \lambda_0 + \lambda_1 D\_HighUNC_{i,t-1}. \tag{9}$$

By substituting Equation (8) or (9) into Equations (6) and (7), we obtain empirical specifications that allow us to test whether uncertainty determines a typical firm's leverage adjustment speed. How an uncertainty measure ($UNC_{i,t-1}$ or $D\_HighUNC_{i,t-1}$) affects the leverage adjustment speed is of our primary interest here. To examine if the adjustment speed is influenced by uncertainty, we investigate if the coefficient of the interaction term between current leverage deviation ($BDEV^p_{i,t}$ or $MDEV_{i,t}$) and an uncertainty measure ($UNC_{i,t-1}$ or $D\_HighUNC_{i,t-1}$), λ_1, is significantly different from zero. Table 1 shows definitions and summary statistics of the variables used in this study. Panel A provides detailed descriptions of major variables, and Panel B presents summary statistics for the variables.

[Insert Table 1 Here]

3 Uncertainty and capital structure dynamics

3.1 Does uncertainty lower target leverage ratios?

In this section we first examine the impact of uncertainty on a typical firm's target leverage ratio. The basic insight behind the modeling tradition in which target leverage is specified as a function of underlying variables such as firm characteristics is that those selected variables are likely to affect, or interact with, the firm's leverage in the way to affect the firm value. Whatever variables/firm

[17] We do not make any net-income-related adjustment in the case of market leverage because we assume that the market value of a firm's equity (and possibly debt) will properly reflect the firm's net income.

characteristics are chosen as potent target leverage determinants are meant to capture the target's essential nature of being "desired" or "optimum". Likewise, uncertainty, our main variable of interest, will have a significant explanatory ability for a firm's leverage target determination if our uncertainty measure affects, or closely relates to, sources of variability of the firm's business environment. This is because these sources of variability will likely to put forward what level of leverage the firm wants to achieve toward the maximum value of the firm. Based on the arguments we addressed in the previous section, we expect that uncertainty proxied for by daily stock return volatility will be a significant determinant for a typical firm's leverage target.

As the process in which firms' leverage targets are determined is an important issue in capital structure dynamics (Faulkender *et al.*, 2012), we employ several econometric methodologies to estimate the model specified in Equation (5). Panel A and Panel B of Table 2 present the estimation results for book and market leverage targets, respectively. Specifically, the four columns in each panel are target estimation results using pooled OLS, within groups fixed effect regressions (FE), corrected LSDV (LSDVC), and system GMM. The GMM-style instruments used in the fourth column include first to fourth lags of standardized uncertainty, second to fifth lags of leverage (*BDR* and *MDR* in Panel A and B), and second to fifth lags of firm-specific control variables for first-difference equations. Similarly, change in standardized uncertainty, first lag of change in leverage, and first lag of change in all firm-specific control variables are used for level equations. The Sargan-Hansen test of overidentifying restrictions does not reject this specification, and there is no significant evidence of second-order serial correlation in the first-differenced residuals, which supports the validity of our choice of instruments. In all but OLS estimation we include firm fixed effects to control for unobserved time-invariant firm specific characteristics while incorporating year fixed effects to account for temporal variation in all four specifications. Implied coefficients of uncertainty on firms' target leverage ratios, whether calculated in book value or market value, are negative and both economically and statistically significant with all four estimation methods. These results corroborate our prediction that firms with high uncertainty may want to lower their leverage targets to stay away from potential bankruptcy.

Because we use dynamic panel data with lagged dependent variable, however, the pooled OLS estimate, $(1-\gamma)$, on lagged dependant variable is likely to be biased upwards while the Within-Groups FE estimate is likely to be biased downwards when data duration is not long enough

(Nickell, 1981, and Bond *et al.*, 2002). As a result, coefficient estimates for other explanatory variables are also likely to be biased. LSDVC and GMM can well address this issue as demonstrated by Flannery and Hankins' (2013) simulation results[18]. Consistent with the arguments in Nickell (1981), Bond (2002) and Flannery and Hankins (2013), the coefficient estimates by system GMM ($(1-\gamma)^{GMM} = 0.762$) and LSDVC ($(1-\gamma)^{LSDVC} = 0.748$) comfortably fall between pooled OLS estimate ($(1-\gamma)^{OLS} = 0.828$) and FE estimate ($(1-\gamma)^{FE} = 0.644$). See Panel A of Table 2. Similar results also hold for market leverage model in Panel B of Table 2. system GMM appears to perform slightly better than LSDVC in that (i) the goodness-of-fit scores with System GMM model (0.744 and 0.737) are higher than LSDVC model (0.742 and 0.703), and (ii) LSDVC estimates are most accurate only in the absence of endogenous independent variables. So we use the Blundell and Bond (1998) system GMM for target leverage estimation and other analyses that follow in the rest of the paper. System GMM results in Column (4) of Panel A indicate that overall book adjustment speed is around 23.8% per annum. Implied marginal effect of uncertainty on book leverage target can then be derived to be 1.97%. That is, one standard deviation increase in uncertainty leads to 1.97% decrease in target leverage. The coefficients of other control variables are comparable to previous findings (Flannery and Rangan, 2006; Elsas *et al.*, 2014); target leverage increases with tangibility, decrease with profitability and has no direct relationship with firm size. We have similar results in Panel B for market leverage estimation, where the coefficient estimates of uncertainty remain significant, both economically and statistically, with its marginal effect being as high as 6.84%. The negative relationship between uncertainty and target leverage points to our insight addressed earlier in this section. High uncertainty in our measure is likely to foretell that the future business will be volatile, which, in turn, will increase the chance of default, *ceteris paribus*. When the probability of default is expected to rise due to heightened uncertainty, firms will reduce their leverage to counteract its adverse effect on external finance premium and the firm value. Furthermore, the relationship between leverage and bankruptcy costs is convex because, with high bankruptcy costs, firms tend to rely more on internal financing or switch to more equity financing to reduce their chance of default significantly (Aysun and Honig, 2011). We discuss this

[18]Using simulated dynamic panel data, Flannery and Hankins' (2013) examine relative performances of various econometric methodologies. They show the estimation performances vary substantially depending on data complications such as fixed effects, persistence of dependent variable, endogenous independent variables, and error term autocorrelations. On average, they conclude, Blundell Bond system GMM appears to be the best choice in the presence of endogeneity and even second order serial correlation if the dataset includes shorter panels.

issue in more detail and provide empirical evidence in Section 4.2.

[Insert Table 2 Here]

Having provided evidence about the relation between uncertainty and target leverage, we proceed to gain further insight by examining the contribution made by firm fixed effects on the target. Table 3 presents the summary statistics for target leverage ratios of the full sample with and without firm fixed effects. That is, we decompose target leverage estimates with firm fixed effects into i) firm fixed effects and ii) leverage target net of the effects. It can be shown that median proportions of firm fixed effects on the target leverage ratios is 11.3% for book leverage, and 14.0% for market leverage[19]. Thus firm fixed effects, on average, have significant impacts on the target leverage ratios. Table 3 also shows that firm fixed effects, whether positive or negative, are consistently prominent across the distribution and that the difference in firm fixed effects between the 1-st and 99-th percentiles is quite large. We also decompose target leverage with firm fixed effects into high- and low- uncertainty firms. As expected, high uncertainty firms tend to have lower target leverage ratios than low uncertainty firms. We use t-test and Wilcoxon rank-sum test to show that the difference is generally significant, which confirms our main results of target leverage reported in Table 2.

[Insert Table 3 Here]

3.2 Does uncertainty increase leverage adjustment speeds?

Dynamic tradeoff theory posits that firms will adjust their leverages back to the targets gradually if they deviate from their optimal leverage ratios. The theory maintains that the adjustment speed depends on the cost of adjusting leverage, and analyzes observed capital structure policies based on the trade-off between costs and benefits of leverage. Naturally, therefore, this stance of dynamic tradeoff theory has conduced researchers to a search for plausible sources of adjustment costs. The novel insight taken by Faulkender *et al.* (2012), among others, is of particular interest to our paper for the issue of leverage adjustment speed. By relating *relative* cash flow of a firm to the firm's

[19] Although it is straightforward to calculate, estimates of the median proportion are not reported for brevity. They are available upon request.

need to access capital markets, they propose a *marginal* notion of adjustment costs to show that firms' leverage dynamics could be better understood by considering the joint effect of cash flows and adjustment costs.

This paper instead modifies the standard partial adjustment model by incorporating *uncertainty* as an important leverage determinant. Our insight underlying the modification is that uncertainty could affect firms' capital structure dynamics through several channels including investment-related real option channel. In other words, to the extent that asset returns capture a firm's business environment comprehensively (Leahy and Whited, 1996), it is likely that the firm would have uncertainty as measured by return volatilities factored in for its decision on the amount and timing of investment and subsequent financing. The speed of adjustment towards target will then be affected by the decision as well.

Before investigating the role of uncertainty on determining speed of adjustment, we provide, in Panel A of Table 4, the summary statistics for leverage deviation from the target and subsequent adjustment toward the target[20]. To gain further insight into potentially asymmetric effect of uncertainty on capital structure dynamics, we split the full sample into over-levered and under-levered firm samples based on the signs of their leverage deviations from the targets. Characteristics and behaviors of over-levered firms and those of under-levered firms could differ substantially (Faulkender *et al.*, 2012).

Overall, 44.8% of firms in our sample are over-levered in terms of book leverage, and 39.2% in terms of market leverage. Note that there is little difference in leverage deviation between over- and under-levered firm samples in absolute term. Panel B and Panel C of Table 4 present our main results for the relationship between uncertainty and active adjustment speeds. For the base model without uncertainty factor (Columns (1), (4), and (7)), coefficients of book active deviation ($BDEV_{i,t}^{p}$) and market deviation ($MDEV_{i,t}$) are both close to 30%. Thus, for the overall sample, approximately 30% of leverage deviation from target is closed per period, which is in line with the existing literature (see, for instance, Fama and French, 2002; Flannery and Rangan, 2006; Lemmon *et al.* 2008, DeAngelo *et al.*, 2011).

When we split the sample based on the current leverage level relative to the target, both over-

[20]Adjustment speed is defined as the ratio of leverage adjustment made during the year to beginning-of-the-year deviation from the target.

levered and under-levered firms tend to actively adjust leverage towards the targets. For instance, a typical over-levered firm will actively decrease leverage towards target by 33.6% of the gap on average (Column 6, $0.254+0.112$). In addition, no significant difference in active adjustment speed is observed between the two sub-samples. This result is in contrast to Hovakimian (2004) and Faulkender *et al.* (2012), who find adjustment speeds toward target leverage ratios are faster for over-levered firms[21].

Regarding the role of uncertainty in active adjustment speed, the significantly positive sign of interaction term $BDEV_{i,t}^{p} \times UNC_{i,t-1}$ suggests that uncertainty accelerates adjustment speed towards the target. Results remain unchanged when we replace the standardized uncertainty measure with uncertainty dummy. However, sub-sample analysis suggest that the results are mostly driven by over-levered firms, as the coefficient of the interaction term remains significantly positive in over-levered firm sample whereas it is insignificant for under-levered firms. Similar findings are obtained if market leverage is used as shown in Panel C of Table 4. Overall, higher uncertainty group tends to have higher speed of adjustment with 11.2% faster for book active adjustment and 5.0% faster for market adjustment.

These results substantiate our bankruptcy explanation that heightened uncertainty of over-levered firms would make them more vulnerable to bankruptcy risk. Consequently, they tend to speed up adjusting leverage back to target by repaying debts. Under-levered firms, to the contrary, are more likely to be located in a "default-safe" zone and thus are not as much motivated to adjust leverage ratios.

[Insert Table 4 Here]

3.3 Alternative identification strategy using the Diff-in-Diff analysis using the 2007-2008 Global Financial Crisis as a shock

In the previous section, we show that uncertainty affects not only target leverage, but also the speed of adjustment towards the target. However, one major concern in using stock-return-based measure of uncertainty is the potential endogeneity problem due to reversed causality running from capital

[21] We conjecture this difference is mainly due to the different samples used in those studies.

structure to stock prices. This problem may not entirely be solved by using GMM estimator while GMM estimator could preclude unobserved fixed effects that affect both stock prices and firm leverage. To address this concern and further investigate the causal effect of uncertainty on capital structure dynamics, we utilize a difference-in-differences (DiD) approach. We identify a large exogenous shock to uncertainty during our sample period, i.e., the 2007-2008 Financial Crisis. The sub-prime mortgage issuance was peaked in 2005-2006, which was followed by a sudden surge of the default rates on those mortgages leading up to 2007. On July 17, 2007, Bear Stearns, the then-fifth largest investment bank in the U.S., announced huge losses in its two struggling hedge funds that were heavily exposed to sub-prime mortgages. This was one of the first notable signs of the imminent crisis. Soon afterwards fear set in. Investors started to lose confidence in the market and uncertainty dramatically increased in every venue of the market[22]. Figure 1 depicts the average level of uncertainty and its change year by year. As Figure 1 shows, uncertainty increased dramatically between 2007 and 2008—by almost one standard deviation of the full-sample uncertainty distribution. The figure confirms that the Global Financial Crisis substantially increased firms' uncertainty, and as it turns out, changes in uncertainty around the crisis exhibit a noticeable cross-sectional variation. Because this dramatic change in uncertainty brought about by the crisis is unlikely to be affected by firms' capital structure changes, examination of leverage change following the change in uncertainty during the crisis will provide a quasi-natural experiment.

[Insert Figure 1 Here]

To conduct a difference-in-differences analysis, we first construct a treatment group and a control group using propensity score matching. This sample matching procedure is indispensable in that one key assumption of DiD technique is parallel trends of the control group and the treatment group in the absence of the treatment. To identify a treatment group and a control group, we first calculate average annual firm-level uncertainty for the three pre-crisis years and for the three post-crisis years and take the difference as the average uncertainty change for each firm due to the crisis. We then define the top tercile of firms whose uncertainty increased the most at the time of crisis (i.e., year 2007) as the treatment group and bottom tercile as the control group. Our sample

[22] See the following Federal Reserve Bank of St. Louis website for more detailed description of 2007-2008 global financial crisis timeline: https://www.stlouisfed.org/financial-crisis/full-timeline.

consists of 679 firms at the time of shock, so 224 firms each are assigned to treatment group and control group. To apply the propensity score matching, we estimate a probit model. The dependent variable is a dummy variable, which equals one if a firm belongs to the treatment group and zero otherwise. We use the same set of explanatory variables as the one used in the target leverage estimation. Because the 2008 Global Financial Crisis had a substantial impact on a firm's market value of equity, we use market leverage ratio as our main measurement in the difference-in-differences analysis. Column (1) in Panel A of Table 5 shows the pre-match regression results. A pseudo-R^2 of 15.1% and a chi-square statistic of 93.90 suggest that the specification is well defined. We then perform one-to-one propensity score matching using the propensity scores, i.e., the predicted probabilities of being assigned to treatment group. We keep all pairs of firms with the smallest distance in propensity scores, thus obtaining 106 pairs in the final sample. In Column (2) of Panel A, we use the matched sample to run the probit model again. If the 106 pair of firms are well matched, then we expect the coefficients of independent variables to be statistically insignificant. As displayed in the Table 5, this is actually the case. A chi-square statistic with the corresponding p-value equal to 0.505 indicates that the null hypothesis regarding the overall model fit can not be rejected. These well justify the parallel trend assumption of DiD approach and increase the likelihood that the changes in leverage are caused by the exogenous change in uncertainty as a result of the crisis.

We conduct a series of additional tests, in the spirit of Fang *et al.* (2014), to further confirm that this parallel trend assumption is satisfied in our setting: First, Panel B of Table 5 presents the estimated propensity score distribution for the treatment and control groups. It shows that differences in propensity scores between the two groups across distance percentiles are all trivial and statistically insignificant; Second, we compare the differences in pre-crisis characteristics of the two groups using univariate test. Results are reported in Panel C of Table 5. The t-statistic shows that differences in average values of independent variables between the two groups, including uncertainty measure, are all insignificant. Note that we could infer that both groups of firms have almost the same uncertainty level right before the crisis although they are affected by the financial crisis in different manners.

We use the following empirical specifications incorporating DiD technique to identify the effects of uncertainty on leverage targets and adjustment speeds:

$$\begin{aligned} MDR_{i,t} &= Constant + (1-\gamma)MDR_{i,t-1} + \gamma\beta_1 X_{i,t-1} + \gamma\beta_2 D\_Treatment_{i,t-1} + \gamma\beta_3 D\_Post_{i,t-1} \\ &\quad + \gamma\beta_4 D\_Treatment_{i,t-1} \times D\_Post_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{10}$$

and

$$\begin{aligned} \Delta MDR_{i,t} &= Constant + \beta_0 MDEV_{i,t} + \beta_1 MDEV_{i,t} \times D\_Treatment_{i,t} + \beta_2 MDEV_{i,t} \times D\_Post_{i,t} \\ &\quad + \beta_3 MDEV_{i,t} \times D\_Treatment_{i,t} \times D\_Post_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{11}$$

where *D_Treatment* is a dummy variable, which is equal to one if observations belong to treatment group and zero otherwise. *D_Post* is a time dummy variable for the post-shock period (i.e., $D\_Post = 1$ if year $\geq$ 2008). Note that the regressions are based on the matched pairs using 7 years (2004-2010) around the shock[23].

[Insert Table 5 Here]

Panel D and Panel E of Table 5 present the results from estimating the impact of the exogenous shock on target leverage ratio and speed of adjustment, respectively. We estimate target leverage ratios using two different models, namely, OLS and system GMM[24]. Instrumental variables used in the system GMM are third to fourth lags of market leverage ratios, and second to third lags of all firm-specific control variables for the first-differenced equations. Similarly, the second lag of change in market leverage, and the first lag of change in all firm-specific control variables are used for the level equations. The estimated negative coefficients (-0.012) of $D\_Post_{i,t-1}$ for both OLS and system GMM in Panel D suggest that the Global Financial Crisis indeed has a negative impact on a typical firm's target leverage ratio. One step further, this impact of the exogenous shock is greater for firms whose uncertainty increases at the time of the crisis are substantially higher. Note that the coefficient on $D\_Treatment_{i,t-1} \times D\_Post_{i,t-1}$ remains significant at 1% level for both OLS (-0.041) and system GMM (-0.024).

[23] We use 3 years each for pre- and post-shock.

[24] The other two empirical specifications used in previous section, i.e., FE and LSDVC, are not feasible for DiD analysis for target leverage and adjustment speed due to identification issue.

Panel E of Table 5 reports a strong positive impact of the exogenous shock on speed of adjustment[25]. Similar to its effect on the firm's target leverage, the Financial Crisis has a significant positive impact on firms' speed of adjustment as well. Coefficients of $MDEV_{i,t} \times D\_Treatment_{i,t} \times D\_Post_{i,t}$ are all large in magnitude and remain significant at 5% level or better for both over-levered and under-levered samples. Still, the impact of the uncertainty shock is greater for over-levered firm sample[26]. Firms with larger uncertainty changes tend to adjust their leverages toward targets more quickly than firms with smaller uncertainty changes, which confirms our main results obtained in the previous section for leverage adjustment. Our results also suggest that the overall speed of adjustment decreased following the shock possibly due to the increased post-shock cost of accessing capital markets. We further illustrate the impact of uncertainty shock on leverage adjustment in the DiD context in Figure 2 describing market adjustment ratios around the exogenous shock.

[Insert Figure 2 Here]

3.4 Does uncertainty increase bankruptcy risk?

In this subsection, we empirically test whether uncertainty is related to the risk of default. Recall that our measure of uncertainty is judiciously chosen to include a wide range of relevant sources of uncertainty. So we expect, broadly speaking, our uncertainty measure to capture the risk arising from both uncertain future cash flows and uncertain future interest rates.

High uncertainty about future cash flows will exacerbate the bankruptcy probability, particularly for a firm having a high level of debt already. This is because a firm relying heavily on debt could be faced with much higher chance of bankruptcy if the prospect for future cash flows becomes more uncertain. The knock-in nature of bankruptcy gives rise to asymmetric effects of uncertainty on both target leverage and adjustment speed. That is, uncertainty will affect more significantly the over-levered firms than the under-levered firms. In the previous sections, our explanation for the negative relationship between uncertainty and target leverage or adjustment speed

[25]Deviation from the target is estimated with the initial results of Table 2, not with the results of Table 5.

[26]Note that the coefficient of $MDEV_{i,t} \times D\_Treatment_{i,t} \times D\_Post_{i,t}$ in under-levered sample is positive. It indicates that there might exist some unknown benefits from increasing the leverage toward the target. We leave this finding to future research which, we hope, could shed more light on it.

relies on the assumption that uncertainty leads to higher default risk. In this subsection, we examine whether this postulated relation between uncertainty and bankruptcy risk can be corroborated.

In order to to assess firms' default risk, we utilize the Standard & Poor's domestic long-term issuer credit ratings to assess firms' default risk. Although credit rating agencies are often blamed for their failure to predict high-profile corporate debacles, Standard & Poor's credit ratings are still among the most widely used measures for assessing firms' likelihood of default. According to the statistics provided by S&P (2015), credit ratings show a strong negative correlation with the default events. These ratings are determined by the agent's (S&P's) team based on information from published reports, as well as from interviews and discussions with the issuer's management. One might be concerned that the rating criteria used by S&P could be incomplete only capturing some specific components of the default risk. To mitigate this concern we also use rating changes (i.e., downgrade events) in addition to absolute ratings. Using the credit rating data from Compustat, we test 1) whether firms with high uncertainty tend to experience more rating downgrades during our sample period, and 2) whether firms with high uncertainty tend to be graded lower, specifically, graded as speculative.

Table 6 shows the credit rating/rating change results for over-levered and under-levered firm samples. The results are striking. First, for over-levered and under-levered samples alike, the proportion of firms assigned to each credit rating in investment grade category (i.e., from AAA down to BBB) is higher with low-uncertainty group. And the exact opposite is true for non-investment category. In other words, each rating in the speculative territory is taken up by a higher proportion of firms, and increasingly so going south[27]. Uncertainty also shows a clear link to credit rating change. High uncertainty firms tend to suffer more credit rating downgrades by 5.67% (3.98%) in over-levered firm sample (under-levered firm sample). Note that the difference between high-uncertainty and low-uncertainty firms in over-levered sample is greater than in under-levered sample. Of particular interest is the relative proportion of firms falling from investment grade to speculative grade. For over-levered sample, 2.8% of high-uncertainty firms take the fall whereas less than 1% of low-uncertainty firms do. We document similar findings for under-levered sam-

[27] An immediate corollary of this finding is that firms with higher uncertainty are more likely to be graded as speculative. The results show that the high-uncertainty group consist of a significantly lower proportion of investment grade firms and a higher proportion of speculative grade firms.

ple[28]. These results provide a solid empirical ground for us to relate uncertainty to the risk of default.

[Insert Table 6 Here]

4 Uncertainty and capital structure dynamics during investment shocks

We address the following question in this section: "How does uncertainty affect firms' dynamic capital structure decision at major investments?" Specifically, we explore the effect of uncertainty on the leverage adjustment speed.

4.1 How does uncertainty affect adjustment speeds during major investments?

Corporate financing behavior for large investment opportunities has recently attracted researchers' attention for two reasons. First, episodes of major investments could provide valuable opportunities to gain insight into the firms' capital structure decision because major investments entail external financing most of the time as opposed to retained-earnings-dependant financing patterns for routine, replacement investments[29]. For instance, for all Compustat firms, more than two thirds of capital expenditures and more than four fifths of acquisitions are financed with externally-raised funds, whereas less than one third of smaller investments are financed by external funding (Elsas *et al.*, 2014). Second, and related to the first, financing pattern around major investments may prove to favor particular capital structure theories for good reasons.

Mayer and Sussman (2005) is one of the earliest studies documenting that financing patterns during investment *spikes* tend to be distinct from those of *normal* times, with their heavier reliance on debt financing[30]. Substantial amount of research has been followed in this vein, and broadly

[28] see Panel B of Table 6 for comparison.
[29] See Mayer (1988), and Rajan and Zingales (1995) for this point.
[30] We use the term *normal* to refer to non-spike.

speaking, the main interest centers around the issue, “how do firms adjust their capital structure in response to major investment opportunities, and why?” One of the contributions of our study is to propose uncertainty as a significant leverage determinant, which interacts with the current leverage so as to affect the firm’s dynamic leverage decision during investment spikes as well as normal times. By taking into consideration the level of uncertainty facing the firm together with the current leverage standing, our study offers additional insight into the existing literature on how firms seek to close the leverage gap between where they are and where they want to be in the presence of uncertainty effect. As an added benefit, we show that our empirical specifications can reconcile some important, yet seemingly opposing, results documented in the prior studies[31].

In our paper, an investment spike is defined similar to Elsas *et. al.* (2014). However, while they study built investment and acquisition investment separately, we identify investment spikes based on the sum of those two types of expenditure. Specifically, a firm is considered to have an investment spike if its investment ratio in a given fiscal year exceeds both 200% of the previous 3-year average and 30% of the previous year’s total assets[32]. We identify 575 investment spikes in our sample, or equivalently, 2.8% of firm-year observations, comparable to 3.39% of Elsas *et al.* (2014).

We noted earlier in Section 1 that major investment might be one important channel through which uncertainty affects speed of leverage adjustment. That is, uncertainty could play a differential role on firms’ leverage rebalancing behavior conditional on whether they are faced with major investment opportunities or not. Or alternatively, major investment opportunities would affect a firm’s mode of financing and subsequent leverage adjustment conditional on the severity of uncertainty facing the firm. To investigate the joint effect of uncertainty and major investments, we build the following model for speed of leverage adjustment:

$$\lambda = \beta_0 + \beta_1 D\_HighUNC_{i,t-1} + \beta_2 D\_Spike_{i,t} + \beta_3 D\_HighUNC_{i,t-1} \times D\_Spike_{i,t}, \tag{12}$$

where $D\_Spike_{i,t}$ is a dummy for investment spikes which equals one if firm i experiences an investment spike at time t and zero otherwise. To investigate how uncertainty and investment

[31] We provide a detailed exposition on this point in connection with our empirical findings later in the section.

[32] Investment ratio in this paper is calculated as the ratio of the sum of capital expenditures and total cash paid-in acquisition to total assets at the prior fiscal year’s end.

shock interact so as to affect firms' leverage adjustment, we establish the following models of book and market leverage dynamics by substituting Equation (12) into Equations (6) and (7):

$$\begin{aligned} \Delta MDR_{i,t} &= Constant + \beta_0 MDEV_{i,t} + \beta_1 MDEV_{i,t} \times D\_HighUNC_{i,t-1} + \beta_2 MDEV_{i,t} \times D\_Spike_{i,t} \\ &\quad + \beta_3 MDEV_{i,t} \times D\_HighUNC_{i,t-1} \times D\_Spike_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{13}$$

and

$$\begin{aligned} \Delta BDR^p_{i,t} &= Constant + \beta_0 BDEV^p_{i,t} + \beta_1 BDEV^p_{i,t} \times D\_HighUNC_{i,t-1} + \beta_2 BDEV^p_{i,t} \times D\_Spike_{i,t} \\ &\quad + \beta_3 BDEV^p_{i,t} \times D\_HighUNC_{i,t-1} \times D\_Spike_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{14}$$

where detailed variable definitions are presented in Table 1. Based on the analysis provided above, we expect a non-trivial coefficient (β_3) for the interaction term, $BDEV^p_{i,t}$ ($MDEV_{i,t}$) $\times$ $D\_HighUNC_{i,t-1} \times D\_Spike_{i,t}$. When a major investment opportunity becomes available in a *low* uncertainty environment, firms might issue *transitory* debt to fund the investment with relatively low marginal cost of additional debt, aided by low uncertainty, which will appear to be purposeful deviations from the targets when their current leverages are above the targets (DeAngelo *et al.*, 2011). We, therefore, expect that $\beta_0 + \beta_2$ is negative for over-levered firms. However, when a large investment opportunity becomes available for a firm faced with high uncertainty, the firm's leverage will instead converge to the target at a faster speed than with low uncertainty. Consequently, $\beta_0 + \beta_1 + \beta_2 + \beta_3$ will likely be positive. For under-levered firms, on the other hand, both $\beta_0 + \beta_2$ and $\beta_0 + \beta_1 + \beta_2 + \beta_3$ are expected to be positive.

Table 7 presents the results for the effects of uncertainty and investment shock on a typical firm's speed of adjustment with respect to book leverage (Panel A) and market leverage (Panel B). In each panel, we report results for full sample, over-levered firm sample and under-levered firm sample. Consistent with our predictions, over-levered and under-levered firms have the opposite reactions to investment spikes. Over-levered firms tend to temporarily deviate from their target leverage ratios at investment spikes with slower or even negative speeds of adjustment depending on the severity of uncertainty facing them. On the other hand, under-levered firms tend to fully adjust or even over-adjust their leverages toward the targets. Notably, uncertainty plays an important role in both groups of firms with its impact on over-levered sample being greater in magnitude. Our results show that over-levered firms with low uncertainty tend to temporarily deviate from the targets at spikes with negative speed of adjustment (-4.8% for book leverage and -46.1% for market leverage), while over-levered firms with high uncertainty tend to adjust towards the target leverage ratios with positive speed of adjustment (45.6% for book leverage and 5.2% for market leverage). For under-levered firms, the difference between low uncertainty and high uncertainty groups is smaller but still significant. In under-levered firm sample, speed of adjustment at spikes for low uncertainty group is 114.6% for book leverage (i.e., overshooting) and 77.9% for market leverage whereas the speed of adjustment at spikes for high uncertainty firms are 100.1% for book leverage (overshooting) and 72.1% for market leverage.

It is noteworthy, however, that existing studies fail to reach a consensus regarding firms' leverage adjustment behavior around major investments. Introducing the notion of *intentional temporary* deviation from target leverage, DeAngelo *et al.* (2011) argue that the apparent slow leverage adjustment can be accounted for by this intentional deviation arising from the role of *transitory* debt for major investments. While their simulation-based study offers rich insight into the firms' spike financing behavior, somewhat different stories have been told by other researchers as well. In particular, Elsas *et al.* (2014) find that firms tend to move faster toward estimated targets on average when they have major investment opportunities.

In this paper, we show that these two seemingly contrary arguments, particularly for over-levered firms, can be reconciled by taking uncertainty into account in explaining leverage adjustment process. While debt is usually the main source of financing for large investments (Mayer and Sussman (2005), Bond *et al.* (2006), and Im *et al.* (2016)), debt financing comes with a potential hazard for the firm, i.e., high default risk particularly for the firms already having more debt than desired as we evidence in Section 3.4 and Table 6 therein. Moreover, default risk gets even worse if uncertainty facing the firm grows higher. Considering both uncertainty and current leverage level together, we expect that i) firms' leverage adjustment patterns are varied depending on the level of uncertainty involved and that ii) these uncertainty-driven variations are likely to be stronger among over-levered firms compared to under-levered firms.

When an over-levered firm is given a major investment opportunity, it will grab the opportunity, primarily issuing debts, as long as benefits of doing so are expected to outweigh the costs, which may well be the case when the firm is faced with relatively low level of uncertainty. Consequently, the firm may want to voluntarily deviate from the leverage targets at the time of investment spikes. This is consistent with the findings in DeAngelo *et al.* (2011). If uncertainty is high, on the other hand, over-levered firms would want to delay taking the investment and/or repay debt to ensure future borrowing capacity, if, in particular, such delay creates high enough value of *wait and see*. Alternatively, they would probably issue equity rather than debt to finance potential investment projects because high uncertainty and excessive leverage together may quickly expose the firms to high default risk. As a result, they will adjust their leverages toward the targets faster when there are investment spikes. This is consistent with the findings in Elsas *et al.* (2014). Under-levered firms, on the other hand, will likely take the major investment opportunity mainly with debt financing, as those firms are relatively better shielded from default risk[33]. Hence they will increase leverage toward the target making the adjustment speed faster when there are investment spikes.

[Insert Table 7 Here]

4.2 Mechanisms through which uncertainty influences adjustment speeds during major investments

In this section, we investigate two possible channels through which uncertainty affects firms' financing behavior at the time of investment shocks. While the findings in Table 7 are significant in that they clearly evidence the impact of uncertainty on financing behavior at the time of investment shock, they do not provide information about potential channels or mechanisms through which uncertainty eventually bears upon firms' capital structure decisions.

Two channels might explain. One possible channel is that uncertainty might hinder firms' investment decisions. Uncertainty can push the firms to invest less at major investment opportunities, or even delay the investments altogether as Bloom *et al.* (2007) suggest. Given those large investments are financed by debt in general, firms with high uncertainty would use less amount

[33]See Mayer and Sussman (2005), Bond *et al.* 2006), and Im *et al.* (2016).

of debt, thereby incurring smaller increase in leverage at the time of investment shock. The other channel is that firms with higher uncertainty may have different financing patterns at the time of investment shocks. In other words, it may be the case that firms with different levels of uncertainty still make similar investment decisions, but their modes of financing are different. In this case, firms with high uncertainty do not delay the investments while using different proportions of debt for financing. We expect that the results in Table 7 are to be obtained through either or both of the two channels just described. In this subsection, we examine the two channels separately.

First, we provide an empirical test on the first channel using the model employed in Bloom *et al.* (2007). Specifically, we use sales growth of each individual firm as a proxy for demand shock to capture the investment opportunity in the investment-ratio regression specified below. We interpret the coefficient for the interaction between uncertainty and demand shock as the marginal effect of uncertainty on a firm's investment responsiveness to the demand shock. If uncertainty has a substantial adverse effect on the firm's propensity to invest at major investments, then the interaction coefficient should be negative. Note that our original investment spike is an *ex post* measure and thus cannot capture those delays of investment, which is not unrealized as investment shock. Demand shock used in the model can capture *ex ante* investment opportunity and thus can capture the delay of the investment opportunity. Table 8 shows the results of the model. The following model is used:

$$\begin{aligned} I_{it}/K_{i,t-1} &= Constant + \beta_1 \Delta y_{it} + \beta_2 C_{it}/K_{i,t-1} + \beta_3 (y-k)_{i,t-1} \\ &\quad + \beta_4 (\Delta y_{i,t})^2 + \beta_5 SD_{i,t-1} + \beta_6 \Delta SD_{i,t} \\ &\quad + \beta_7 SD_{it} * \Delta y_{it} + Year\ Dummies + \varepsilon_{i,t}, \end{aligned} \tag{15}$$

where $I_{it}/K_{i,t-1}$ is the ratio of investment(INV_{it}) to capital stock at the prior year's end ($K_{i,t-1}$), and $C_{it}/K_{i,t-1}$ is the ratio of cash flow(CF_{it}) to capital stock at the prior year's end ($K_{i,t-1}$), y (Sales) is measured as the natural log of a firm's annual sales, k is the natural log of capital stock (K), $SD_{i,t}$ is the standardized uncertainty (UNC) used in the paper[34].

Table 8 reports the estimation results. We estimate the model using system GMM with one-step

[34] Investment (INV) is the sum of capital and acquisition expenditures, cash flow (CF) is the sum of income before extraordinary item and depreciation and amortization, and capital stock (K) is estimated using perpetual inventory method.

estimators with calculated robust covariance estimators. Instrument variables used are $\Delta I_{it-1}/K_{i,t-2}$, $\Delta\Delta y_{it-1}$, $\Delta(y-k)_{i,t-2}$, $\Delta\Delta(y-k)_{i,t-2}$, $\Delta C_{i,t-1}/K_{i,t-2}$, $\Delta\Delta C_{i,t-1}/K_{i,t-2}$, and ΔSD_{t-1} for level equations, and second to ninth lags of $I_{it}/K_{i,t-1}$, Δy_{it}, $(y-k)_{it}$, $\Delta(y-k)_{it}$, $C_{it}/K_{i,t-1}$, $\Delta C_{it}/K_{i,t-1}$, and SD_{it} for first difference equations, and year dummies as strict instrumental variables. Note that uncertainty measures are not included in IV in column (1) and (2). Note that the estimation results in Table 8 closely resemble the findings in Bloom *et al.* (2007). That is, firms with higher levels of uncertainty tend to respond more cautiously to given investment opportunities, which suggests that the *investment* channel is at work.

[Insert Table 8 Here]

Second, we also examine whether firms' financing patterns at investment spikes differ by their uncertainty levels. To classify different financing methods of each firm, we first construct financing variables by calculating debt financing, equity financing, cash flow financing, and other financing as proportions of lagged total assets[35]. Then we estimate a system of equations as follows.:

$$DEBT\_TA_{i,t} = Constant + \beta_D INT\_TA_{i,t} + Controls + Year\ Dummies + \varepsilon^D_{i,t} \quad (16)$$

$$EQUITY\_TA_{i,t} = Constant + \beta_E INT\_TA_{i,t} + Controls + Year\ Dummies + \varepsilon^E_{i,t} \quad (17)$$

$$CF\_TA_{i,t} = Constant + \beta_C INT\_TA_{i,t} + Controls + Year\ Dummies + \varepsilon^C_{i,t} \quad (18)$$

$$OTHER\_TA_{i,t} = Constant + \beta_O INT\_TA_{i,t} + Controls + Year\ Dummies + \varepsilon^O_{i,t} \quad (19)$$

where $INT\_TA_{i,t}$ is a ratio of a firm's investment to its lagged total assets, and controls include $LnTA_{i,t-1}$, $MV\_BV_{i,t-1}$, $EBIT\_TA_{i,t-1}$, $FA\_TA_{i,t-1}$, $DEP\_TA_{i,t-1}$, $RD\_TA_{i,t-1}$, $D\_RD_{i,t-1}$, $\overline{MDR}_{j,t-1}$, and $D\_Rated_{i,t-1}$[36]. Note that β_D is the proportion of debt used to finance the investment at the time of investment shock. (β_E, β_C, and β_O are defined likewise). Naturally, four proportions should sum to 1. So we estimate the system of the four seemingly unrelated regressions equations (*SURE*) with the constraint:

$$\beta_D + \beta_E + \beta_C + \beta_O = 1. \quad (20)$$

[35] We calculate other financing source as the residual investment amount after deducting debt, equity, and cash flow financing sources from the total investment.

[36] Detailed descriptions of the control variables are presented in Table 1.

The estimation results explain how a typical firm finances its investment spike. To further test if uncertainty plays an important role in firms' financing patterns at the time of investment shock, we split our sample into high- and low-uncertainty groups. A firm year observation at its investment spike is included in high (low) uncertainty group if its uncertainty level at the previous year's end is higher (lower) than the median uncertainty of the full sample. Note that the sample is not split based on the median uncertainty of spike sample. As we show earlier in this section that uncertainty affects firms' investment decisions, the findings in Table 8 are confirmed by the smaller number of spike observations assigned to high uncertainty group based on the full sample confirms .

[Insert Table 9 Here]

The results in Table 9 show that debt is the major financing source for firms at investment spikes. The overall proportion of debt financing is 80.3% in full sample. These results correspond to Im *et al*'s (2016) finding, which shows that firms tend to use debt as their major financing source at the time of large investments. Although debt is still the major financing source for high uncertainty firms at investment spikes (74.0%), their debt reliance is lower than those of lower uncertainty firms (86.0%). These findings are in support of what we term the *financing* channel, illustrating that firms with higher uncertainty tend to fund their investment with lower proportion of debt. Our results are robust to using book leverage ratios for industry median leverages and to estimating the system of equations without control variables.

Overall, results of Table 8 and Table 9 suggest that the two channels considered so far—investment decision and financing decision—work together to affect firms' capital structure dynamics at major investments. More specifically, firms with higher uncertainty tend to respond more cautiously to the investment opportunity leading to investing in smaller amount. At the same time, they also tend to fund their investment with relatively lower proportion of debt. These two mechanisms together tend to increase the gap between high- and low- uncertainty firms' leverage adjustments at the time of investment shock.

5 Conclusions

The effects of uncertainty on firms' capital structure dynamics have little been explored. Furthermore, existing literature also lacks consensus on the relation between capital structure and uncertainty measured in various forms. Our study proposes an econometric model of dynamic partial adjustment to show how uncertainty is related to various aspects of firms' capital structure. Using individual stock return volatility as collective measure of uncertainty, we found that uncertainty does affect firms' target leverage, speeds of leverage adjustment, as well as financing behaviors around major investments. We demonstrate that uncertainty, on average, affects target leverage across all firms considered. This uncertainty effect extends to the speeds at which firms adjust existing leverage ratios toward the targets—yet asymmetrically depending on the current debt proportion. That is, uncertainty has asymmetric effects on the speed of leverage adjustment, interacting with the current leverage standing. Further, we confirm that the seemingly conflicting results related to leverage decisions around investment spikes documented in the past research can be reconciled by introducing the interplay between uncertainty and firms' current leverage ratios.

Specifically, we demonstrate first that uncertainty is a significant determinant for a typical firm's leverage target. Implied coefficient estimates for uncertainty on firms' target leverage ratios are negative, and both economically and statistically significant with all estimation methods including LSDVC and Blundell-Bond system GMM. Systerm GMM results indicate that overall adjustment speed is around 24% per annum, and one standard deviation increase in uncertainty leads to 1.97% decrease in target leverage. This negative relationship between uncertainty and target leverage conforms to our insight that uncertainty in our measure is likely to be informative about future business prospect of a firm, particularly how volatile it will be. If a firm evaluates that the default probability will likely rise due to increased uncertainty, the firm will reduce its leverage to counteract the adverse effect on external finance premium and the firm value.

Our results also confirm that average firms facing higher uncertainty tend to adjust their leverage toward the target faster. Further investigation reveals that uncertainty affects adjustment speeds of only over-levered firms with insignificant effect on the under-levered firms. Specifically, high-uncertainty firms in the over-levered group have higher adjustment speeds than low-uncertainty counterpart by an average of 11.2% (5.0%) on the book (market) value scale. These results corroborate the traditional arguments of the trade-off theory in a couple of respects. First, under-levered firms have little motivation to adjust their leverage ratios to further reduce the default risk because they probably do not need to be concerned about potential default risks. Second, over-levered firms, once faced with high uncertainty, are exposed to heightened level of default risks and bankruptcy costs, and more so, compared to low-uncertainty firms in over-levered territory.

As further supporting evidence, we examine the credit rating implications of uncertainty. Using the Standard & and Poor's domestic long-term issuer credit ratings, we find that uncertainty is significantly correlated both with firms' current credit ratings and with the likelihood of downgrade as well. That is, firms facing high uncertainty are more likely to be those with lower credit ratings and higher downgrade probabilities. We interpret these findings as evidence of close link between uncertainty and bankruptcy risk. High level of uncertainty about a firm's business prospect such as uncertain future cash flows will deteriorate its bankruptcy probability, particularly for a firm with a high level of debt. This is because a firm relying heavily on debt could be faced with much higher chance of bankruptcy if the prospect for future cash flows becomes more uncertain. The knock-in nature of bankruptcy gives rise to asymmetric effects of uncertainty on both target leverage and adjustment speed. Therefore, uncertainty will affect more significantly the over-levered firms than the under-levered firms.

We also analyze the robustness of our results using the 2007-2008 Global Financial Crisis as a large exogenous uncertainty shock. We show that the Global Financial Crisis did, in fact, increase the market-wide uncertainty substantially, and bear significant impacts on the capital structure dynamics. The Diff-in-Diff analysis confirms that our results are robust to the alternative measure of uncertainty and consistent with our prior results. Specifically, the Global Financial Crisis lowered the target leverage ratios of treatment firms, and more so than control group. In addition, the exogenous shock of the Crisis is shown to have accelerated the speed of leverage adjustment. Thus our robustness analysis, overall, confirms and supports the findings of our study.

Large investments, or investment spikes, are mostly financed externally, and hence the heavy reliance of major investments on external financing is likely to reveal the managers' attitude toward leverage, and firms' capital structure adjustment dynamics more prominently. We find that over-levered and under-levered firms have the opposite reactions to investment spikes in terms of their financing behavior. Over-levered firms tend to temporarily deviate from their target leverage ratios at investment spikes with slower or even negative speeds of adjustment depending on the severity of uncertainty facing them. On the other hand, under-levered firms tend to fully adjust or even over-adjust their leverage ratios toward the targets. Overall, uncertainty plays significant, yet opposite, roles in both groups of firms with its impact on over-levered sample being greater in magnitude. Therefore, our study demonstrates that the seemingly conflicting results documented in DeAngelo *et al.* (2011) and Elsas *et al.* (2014), particularly for over-levered firms, can be reconciled and comfortably nested in our empirical specifications by incorporating the effects of uncertainty on capital structure dynamics.

Lastly, we identify two possible channels through which uncertainty affects firms' financing behavior around major investments: Uncertainty affects firms' capital structure decisions around major investments either by altering the responsiveness to demand shocks (investment channel) or by disproportionate rebalancing between debt and equity (direct financing channel) to fund the investments.

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Table 1: Variable definitions and summary statistics

This table shows definitions and summary statistics of the variables used in this study. Panel A provides definitions and formulae of the main variables used in this study. The italicized codes in brackets ([]) represent item codes in CRSP/Compustat Merged Database. Panel B reports the summary statistics for the variables.

Panel A. Variable definitions

Abbreviation	Definition	Calculation
Leverage-related variables		
$BDR_{i,t}$	Book leverage	Total debt ([*dltt*]+[*dlc*]) over book total assets [*at*]
$BDR^{p}_{i,t-1}$	Book leverage before active adjustment	Total debt ([*dltt*]+[*dlc*]) at the beginning of year t over the sum of book total assets [*at*] at the beginning of year t and net income [*ni*] during year t
$MDR_{i,t}$	Market leverage	Total debt ([*dltt*]+[*dlc*]) over market value of total assets ([*dltt*]+[*dlc*]+[*cshpri*]*[*prcc_f*])
$BDR^{\star}_{i,t}$	Book target	Target book leverage ratio estimated using System GMM in Table 2, Panel A
$MDR^{\star}_{i,t}$	Market target	Target market leverage ratio estimated using System GMM in Table 2, Panel B
$\Delta BDR^{p}_{i,t}$	Active book adjustment	Change in book leverage from the book leverage before active adjustment ($BDR_{i,t}-BDR^{p}_{i,t-1}$)
$\Delta MDR_{i,t}$	Market adjustment	Change in market leverage during year t ($MDR_{i,t}-MDR_{i,t-1}$)
$BDEV^{p}_{i,t}$	Active book deviation	Deviation of book leverage before active adjustment from book target at the beginning of year t ($BDR^{\star}_{i,t}-BDR^{p}_{i,t-1}$)
$MDEV_{i,t}$	Market deviation	Deviation of market leverage from market target at the beginning of year t ($MDR^{\star}_{i,t}-MDR_{i,t-1}$)
Uncertainty-related variables		
$UNC\_LEVEL_{i,t}$	Raw uncertainty measure	Standard deviation of firm i's daily stock returns available for fiscal year t
$UNC_{i,t}$	Standardized uncertainty measure	$\frac{UNC\_LEVEL_{i,t}-\overline{UNC\_LEVEL_{i,t}}}{\sigma(UNC\_LEVEL_{i,t})}$, where $\overline{UNC\_LEVEL_{i,t}}$ and $\sigma(UNC\_LEVEL_{i,t})$ are the mean and standard deviation of $UNC\_LEVEL_{i,t}$
$D\_HighUNC_{i,t}$	High-uncertainty dummy	Dummy variable which has 1 if a firm's uncertainty ($UNC\_LEVEL_{i,t}$) is higher than its sample median, and 0 otherwise.
Control variables		
$LnTA_{i,t}$	Firm size	Natural logarithm of total assets denominated in year-2000 dollars
$MV\_BV_{i,t}$	Market-to-book ratio	Market total assets ([*dlc*] + [*dltt*] + [*cshrpi*] * [*prcc_f*]) to book total assets [*at*]
$EBIT\_TA_{i,t}$	Profitability	Earnings before interests and taxes ([*ib*]+[*xint*]+[*txt*]) over total assets [*at*]
$FA\_TA_{i,t}$	Tangibility	Total property, plant and equipment net of accumulated depreciation [*ppent*] over total assets [*at*]
$DEP\_TA_{i,t}$	Depreciation	Depreciation and amortization [*dp*] over total assets [*at*]
$RD\_TA_{i,t}$	R&D intensity	R&D expenses [*xrd*] over total assets [*at*] (0 if missing)
$D\_RD_{i,t}$	R&D dummy	Dummy variable which has 1 if a firm has reported R&D expenses in year t, and 0 otherwise.
$\overline{BDR}_{j,t}$	Industry median book leverage	Industry median book leverage, where industry is defined following Fama and French (1997)
$\overline{MDR}_{j,t}$	Industry median market leverage	Industry median market leverage, where industry defined following Fama and French (1997)
$D\_Rated_{i,t}$	Debt-rating dummy	Dummy variable which has 1 if a firm has a S&P long-term debt rating, and 0 otherwise.
Investment-related variables		
$INV\_TA_{i,t}$	Investment rate	Sum of capital and acquisition expenditures ([*capx*]+[*aqc*]) over total assets [*at*]
$D\_Spike_{i,t}$	Investment-spike dummy	Dummy variable which has 1 if a firm has experienced an investment spike in year t, and 0 otherwise.

Table 1 (Continued): Variable definitions and summary statistics

Panel B. Summary statistics

Variables	Obs.	Mean	S.D.	P01	P25	Median	P75	P99
Leverage-related variables								
$BDR_{i,t}$	23,283	0.180	0.158	0.000	0.026	0.158	0.287	0.612
$MDR_{i,t}$	23,283	0.183	0.195	0.000	0.015	0.124	0.287	0.789
$BDR^{\star}_{i,t}$	21,636	0.181	0.134	0.000	0.073	0.166	0.267	0.548
$MDR^{\star}_{i,t}$	21,636	0.194	0.172	0.000	0.057	0.156	0.289	0.715
$\Delta BDR^{p}_{i,t}$	21,636	0.001	0.077	-0.260	-0.025	0.000	0.022	0.290
$\Delta MDR_{i,t}$	21,636	0.000	0.100	-0.309	-0.037	0.000	0.032	0.333
$BDEV^{p}_{i,t}$	21,636	0.002	0.128	-0.398	-0.063	0.009	0.079	0.318
$MDEV_{i,t}$	21,636	0.009	0.173	-0.511	-0.076	0.012	0.109	0.462
Uncertainty-related variables								
$UNC\_LEVEL_{i,t}$	23,283	0.036	0.020	0.010	0.022	0.031	0.045	0.111
$UNC_{i,t}$	23,283	0.000	1.000	-1.319	-0.727	-0.234	0.459	3.824
$D\_HighUNC_{i,t}$	23,282	0.500	0.500	0.000	0.000	0.500	1.000	1.000
Control variables								
$LnTA_{i,t}$	23,283	5.298	1.981	1.261	3.852	5.184	6.615	10.250
$MV\_BV_{i,t}$	23,283	1.563	1.265	0.347	0.810	1.162	1.818	8.085
$EBIT\_TA_{i,t}$	23,283	0.053	0.160	-0.697	0.017	0.082	0.137	0.346
$FA\_TA_{i,t}$	23,283	0.222	0.143	0.013	0.111	0.195	0.307	0.646
$DEP\_TA_{i,t}$	23,283	0.042	0.023	0.005	0.026	0.038	0.052	0.127
$RD\_TA_{i,t}$	23,283	0.052	0.067	0.000	0.000	0.026	0.077	0.347
$D\_RD_{i,t}$	23,283	0.254	0.435	0.000	0.000	0.000	1.000	1.000
$\overline{BDR}_{j,t}$	23,283	0.157	0.080	0.019	0.088	0.155	0.217	0.355
$\overline{MDR}_{j,t}$	23,283	0.135	0.093	0.007	0.056	0.117	0.199	0.404
$D\_Rated_{i,t}$	23,283	0.212	0.408	0.000	0.000	0.000	0.000	1.000
Investment-related variables								
$INV\_TA_{i,t}$	20,769	0.088	0.141	0.001	0.024	0.050	0.098	0.648
$D\_Spike_{i,t}$	20,769	0.028	0.164	0.000	0.000	0.000	0.000	1.000

Table 2: Estimation of target leverage ratios

This table reports the results of the target leverage estimation regressions using pooled OLS, FE, LSDVC, and System GMM. The empirical model used is $L_{i,t} = Constant + \gamma\beta_1 X_{i,t-1} + \gamma\beta_2 UNC_{i,t-1} + (1-\gamma)L_{i,t-1} + Year\ Dummies + \eta_i + \varepsilon_{i,t}$. The dependent variables are book leverage (*BDR*) and market leverage (*MDR*) in Panels A and B, respectively. Details for variables included in the models are provided in Table 1. In LSDVC models, Blundell-Bond estimators are chosen as an initial estimator. We calculated a bootstrap variance-covariance matrix for corrected LSDV using 10 repetitions. In System GMM, we report two-step GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation, and which use the finite-sample correction proposed by Windmeijer (2005). Instrument variables used in System GMM are first to fourth lags of standardized uncertainty, second to fifth lags of leverage (*BDR* and *MDR* in Panel A and B), and second to fifth lags of firm-specific control variables for the equations in first-differences, and change of standardized uncertainty, first lag of change in leverage, and first lag of change in all firm-specific control variables for level equations. Note that year dummies are treated as instruments for the equations in levels only. m1 and m2 represent the test statistics of Arellano-Bond tests for first-order and second-order serial correlations in first-differenced residuals, respectively. Sargan/Hansen represents the J stats for overidentifying restrictions. Overall Goodness of fit are reported for OLS, FE, LSDVC, and System GMM. Robust standard errors are reported in parentheses, where *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Book leverage ratios

Variables	OLS $BDR_{i,t}$	FE $BDR_{i,t}$	LSDVC $BDR_{i,t}$	System GMM $BDR_{i,t}$
$BDR_{i,t-1}$	0.828***	0.644***	0.748***	0.762***
	(0.005)	(0.009)	(0.004)	(0.011)
$UNC_{i,t-1}$	-0.001	-0.003***	-0.004***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
$LnTA_{i,t-1}$	0.001***	0.009***	0.007***	-0.000
	(0.000)	(0.002)	(0.001)	(0.001)
$MV\_BV_{i,t-1}$	-0.001*	-0.001	-0.001***	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)
$EBIT\_TA_{i,t-1}$	-0.015***	-0.028***	-0.028***	-0.018**
	(0.005)	(0.007)	(0.005)	(0.008)
$FA\_TA_{i,t-1}$	0.028***	0.061***	0.053***	0.085***
	(0.006)	(0.012)	(0.009)	(0.016)
$DEP\_TA_{i,t-1}$	-0.134***	-0.199***	-0.209***	-0.371***
	(0.037)	(0.060)	(0.058)	(0.078)
$RD\_TA_{i,t-1}$	-0.034**	-0.031	-0.027	-0.066**
	(0.014)	(0.026)	(0.018)	(0.032)
$D\_RD_{i,t-1}$	0.005***	0.002	0.001	0.008
	(0.001)	(0.004)	(0.004)	(0.006)
$\overline{BDR}_{j,t-1}$	0.037***	0.053***	0.032	0.045**
	(0.009)	(0.018)	(0.019)	(0.022)
$D\_Rated_{i,t-1}$	0.010***	0.004	0.002	0.011**
	(0.002)	(0.004)	(0.002)	(0.005)
Constant	0.036***	0.032***		0.049***
	(0.005)	(0.010)		(0.010)
Firm Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	21,636	21,636	21,636	21,636
Number of firms	1,386	1,386	1,386	1,386
Goodness of fit—$Corr(BDR_{i,t}, \widehat{BDR}_{i,t})^2$	0.748	0.734	0.742	0.744
m1				-20.40
(p-value)				0.000
m2				0.617
(p-value)				0.537
Sargan/Hansen				1,326
(p-value)				0.312

Table 2 (Continued): Estimation of target leverage ratios

Panel B. Market leverage ratios

Variables	OLS $MDR_{i,t}$	FE $MDR_{i,t}$	LSDVC $MDR_{i,t}$	System GMM $MDR_{i,t}$
$MDR_{i,t-1}$	0.829***	0.631***	0.741***	0.767***
	(0.005)	(0.009)	(0.002)	(0.011)
$UNC_{i,t-1}$	-0.005***	-0.009***	-0.010***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.002)
$LnTA_{i,t-1}$	-0.001	0.019***	0.017***	-0.004**
	(0.001)	(0.002)	(0.001)	(0.002)
$MV\_BV_{i,t-1}$	-0.002***	-0.001**	-0.001*	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
$EBIT\_TA_{i,t-1}$	-0.014**	-0.030***	-0.028***	-0.014
	(0.006)	(0.008)	(0.006)	(0.009)
$FA\_TA_{i,t-1}$	0.036***	0.086***	0.075***	0.088***
	(0.007)	(0.015)	(0.011)	(0.019)
$DEP\_TA_{i,t-1}$	-0.228***	-0.256***	-0.262***	-0.479***
	(0.042)	(0.066)	(0.072)	(0.090)
$RD\_TA_{i,t-1}$	-0.044***	-0.030	-0.025	-0.079***
	(0.014)	(0.024)	(0.022)	(0.031)
$D\_RD_{i,t-1}$	0.009***	0.005	0.003	0.015**
	(0.002)	(0.006)	(0.004)	(0.007)
$\overline{MDR}_{j,t-1}$	0.043***	0.104***	0.084***	0.025
	(0.010)	(0.020)	(0.021)	(0.020)
$D\_Rated_{i,t-1}$	0.009***	0.010**	0.008***	0.007
	(0.002)	(0.005)	(0.003)	(0.006)
Constant	0.054***	-0.023**		0.079***
	(0.005)	(0.012)		(0.011)
Firm Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	21,636	21,636	21,636	21,636
Number of firms	1,386	1,386	1,386	1,386
Goodness of fit—$Corr(MDR_{i,t}, \widehat{MDR}_{i,t})^2$	0.743	0.679	0.703	0.737
m1				-20.99
(p-value)				0.000
m2				-0.807
(p-value)				0.419
Sargan/Hansen				1,340
(p-value)				0.227

Table 3: Effects of uncertainty on target leverage ratios

The table shows summary statistics for target leverage ratios, both with and without firm fixed effects. The data are further split into into high and low uncertainty groups. Difference in target leverage between those high and low uncertainty groups are also presented. t-stat/z-stat reports t-stat and z-stat (Wilcoxon rank-sum test).

Variables	Obs.	Mean	S.D.	P01	P25	Median	P75	P99
Book target without firm fixed effects	21,636	0.176	0.080	0.000	0.120	0.176	0.230	0.368
Firm fixed effects in book target ($\widehat{\eta}_i^{\star}$)	1,386	0.008	0.129	-0.233	-0.084	-0.008	0.079	0.384
Book target with firm fixed effects	21,636	0.180	0.133	0.000	0.071	0.165	0.266	0.546
High uncertainty	10,818	0.161	0.138	0.000	0.050	0.132	0.244	0.559
Low uncertainty	10,818	0.198	0.126	0.000	0.101	0.195	0.281	0.533
Difference		*-0.037*				*-0.064*		
t-stat/z-stat		*-20.85*				*-25.32*		
Market target without firm fixed effects	21,636	0.185	0.102	0.000	0.115	0.188	0.256	0.405
Firm fixed effects in market target ($\widehat{\eta}_i^{\star}$)	1,386	0.015	0.166	-0.298	-0.088	-0.007	0.092	0.510
Market target with firm fixed effects	21,636	0.188	0.166	0.000	0.059	0.150	0.275	0.699
High uncertainty	10,818	0.170	0.174	0.000	0.027	0.120	0.259	0.711
Low uncertainty	10,818	0.206	0.154	0.000	0.093	0.175	0.288	0.688
Difference		*-0.036*				*-0.054*		
t-stat/z-stat		*-16.26*				*-25.16*		

Table 4: Effects of uncertainty on leverage adjustment speeds

This table reports the impact of uncertainty on the speed of adjustment. Panel A presents summary statistics for deviations from target leverage and amount of leverage adjustment of full sample, over-levered firm sample and under-levered firm sample. Note that speed of adjustment toward book (market) leverage target is defined as the ratio of book (market) adjustment to book (market) deviation . Panel B and Panel C give the regression results of the impact of uncertainty on the speed of adjustment with respect to book leverage and market leverage respectively. Column (1) of Panel B presents results from the regression model $\Delta BDR^{p}_{i,t} = Constant + \lambda BDEV^{p}_{i,t} + \varepsilon_{i,t}$, where λ captures leverage adjustment speed. In Column (2) and Column (3), to investigate the impact of uncertainty on the speed of adjustment, we replace λ with $\lambda = \lambda_0 + \lambda_1 UNC_{i,t-1}$ or $\lambda = \lambda_0 + \lambda_1 D\_HighUNC_{i,t-1}$, with $UNC_{i,t-1}$ denoting standardized uncertainty level for firm i at time $t-1$ and $D\_HighUNC_{i,t-1}$ the dummy variable for uncertainty which equals one if firm i belongs to high uncertainty group relative to the median uncertainty level at time $t-1$ and zero otherwise. In Panel B, we also split the sample into over-levered firm sample and under-levered firm sample and repeat the analyses. In Panel C, we conduct similar empirical analyses with respect to market leverage, instead of book leverage. Detailed description of the variables included in the models is provided in Table 1. Bootstrapped standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary statistics for deviations and adjustments

Sample	Variables	Obs.	Mean	S.D.	P01	P25	Median	P75	P99
Full sample	Active book deviation	21,636	0.000	0.116	-0.377	-0.056	0.007	0.069	0.294
	Active book adjustment	21,636	0.001	0.077	-0.260	-0.025	0.000	0.022	0.290
	Market deviation	21,636	0.004	0.150	-0.465	-0.063	0.009	0.086	0.396
	Market adjustment	21,636	0.000	0.100	-0.309	-0.037	0.000	0.032	0.333
Over-levered firms	Active book deviation	9,721	-0.091	0.092	-0.377	-0.133	-0.066	-0.023	0.022
	Active book adjustment	9,721	-0.025	0.074	-0.260	-0.054	-0.016	0.010	0.157
	Market deviation	9,216	-0.123	0.118	-0.466	-0.178	-0.084	-0.031	-0.001
	Market adjustment	9,216	-0.035	0.108	-0.310	-0.087	-0.024	0.016	0.254
Under-levered firms	Active book deviation	11,159	0.080	0.072	-0.047	0.031	0.066	0.117	0.294
	Active book adjustment	11,159	0.024	0.074	-0.142	-0.005	0.000	0.041	0.290
	Market deviation	11,562	0.105	0.091	0.002	0.037	0.079	0.146	0.396
	Market adjustment	11,562	0.028	0.088	-0.161	-0.008	0.000	0.051	0.333

Table 4 (Continued): Effects of uncertainty on adjustment speeds

Panel B. Book leverage ratios

	Full sample			Over-levered firms			Under-levered firms		
Variables	(1) $\Delta BDR^p_{i,t}$	(2) $\Delta BDR^p_{i,t}$	(3) $\Delta BDR^p_{i,t}$	(4) $\Delta BDR^p_{i,t}$	(5) $\Delta BDR^p_{i,t}$	(6) $\Delta BDR^p_{i,t}$	(7) $\Delta BDR^p_{i,t}$	(8) $\Delta BDR^p_{i,t}$	(9) $\Delta BDR^p_{i,t}$
$BDEV^p_{i,t}$	0.313***	0.302***	0.282***	0.344***	0.304***	0.254***	0.347***	0.348***	0.364***
	(0.004)	(0.005)	(0.008)	(0.009)	(0.013)	(0.013)	(0.015)	(0.011)	(0.015)
$BDEV^p_{i,t} \times UNC_{i,t-1}$		0.033***			0.046***			-0.002	
		(0.004)			(0.006)			(0.010)	
$BDEV^p_{i,t} \times D\_HighUNC_{i,t-1}$			0.049***			0.112***			-0.028
			(0.010)			(0.013)			(0.018)
Constant	0.001**	0.002***	0.002***	0.006***	0.005***	0.005***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	21,636	21,636	21,635	9,721	9,721	9,721	11,159	11,159	11,159
R-squared	0.225	0.229	0.227	0.183	0.192	0.190	0.114	0.114	0.115

Panel C. Market leverage ratios

	Full sample			Over-levered firms			Under-levered firms		
Variables	(1) $\Delta MDR_{i,t}$	(2) $\Delta MDR_{i,t}$	(3) $\Delta MDR_{i,t}$	(4) $\Delta MDR_{i,t}$	(5) $\Delta MDR_{i,t}$	(6) $\Delta MDR_{i,t}$	(7) $\Delta MDR_{i,t}$	(8) $\Delta MDR_{i,t}$	(9) $\Delta MDR_{i,t}$
$MDEV_{i,t}$	0.289***	0.275***	0.258***	0.349***	0.316***	0.307***	0.247***	0.248***	0.241***
	(0.005)	(0.006)	(0.009)	(0.011)	(0.011)	(0.018)	(0.009)	(0.009)	(0.011)
$MDEV_{i,t} \times UNC_{i,t-1}$		0.036***			0.031***			0.016	
		(0.005)			(0.006)			(0.012)	
$MDEV_{i,t} \times D\_HighUNC_{i,t-1}$			0.049***			0.050**			0.012
			(0.013)			(0.020)			(0.012)
Constant	-0.001	0.001	-0.000	0.008***	0.006***	0.007***	0.002*	0.002**	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	21,636	21,636	21,635	9,216	9,216	9,216	11,562	11,562	11,562
R-squared	0.189	0.192	0.190	0.146	0.150	0.147	0.065	0.066	0.065

Table 5: Difference-in-differences analysis

This table presents DiD analysis on how uncertainty changes due to exogenous shock of 2007-2008 Global Financial Crisis affect firms' capital structure dynamics, i.e., target leverage and speed of adjustment towards the target. We identify treatment group and control group by calculating average annual uncertainty for the three pre-crisis years and the three post-crisis years and take the difference as the average change in uncertainty for each firm due to the crisis. We then define the top tercile of firms whose uncertainty increased the most at the time of crisis (2007) as the treatment group and bottom tercile as the control group. Panel A provides prematch propensity score regression and postmatch diagnostic regression. Both regressions are based on a probit model and the dependent variable is a dummy variable, which equals one if a firm belongs to the treatment group and zero otherwise. We use the same set of explanatory variables as the one in the target leverage estimation. Note that we perform one-to-one propensity score matching, where we retain the pair of firms with the smallest distance in propensity scores. Panel B gives the estimated propensity score distributions, specifically differences in propensity scores between the two groups across percentiles of the distance. Panel C presents the differences in characteristics of the two groups using univariate test. Panel D provides the estimation results for the impact of the exogenous shock on the target leverage ratios. The regression in Panel D is based on two different models, OLS and system GMM for the same reasons as that in Table 2. Panel E provides the estimation results for the impact of exogenous shock on the speed of adjustments. In all panels, bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Prematch propensity score regression and postmatch diagnostic regression

	Dummy=1 if in treatment group; 0 if control group	
	(1)	(2)
Variables	Prematch	Postmatch
$UNC_{i,t-1}$	-32.294***	2.854
	(8.419)	(12.272)
$MDR_{i,t-1}$	2.171***	-0.341
	(0.596)	(0.818)
$LnTA_{i,t-1}$	-0.203***	0.151*
	(0.055)	(0.080)
$MV\_BV_{i,t-1}$	-0.073***	-0.026
	(0.025)	(0.034)
$EBIT\_TA_{i,t-1}$	-2.361***	-1.134
	(0.599)	(0.849)
$FA\_TA_{i,t-1}$	1.119*	1.167
	(0.672)	(0.894)
$DEP\_TA_{i,t-1}$	2.151	-7.551
	(4.058)	(6.062)
$RD\_TA_{i,t-1}$	-2.680**	2.771
	(1.356)	(1.923)
$D\_Rated_{i,t-1}$	0.274	-0.297
	(0.219)	(0.299)
Constant	1.923***	-0.792
	(0.452)	(0.641)
Observations	448	212
χ^2	93.90	8.295
p-value of χ^2	0.000	0.505
Pseudo R^2	0.151	0.028

Table 5 (Continued): Difference-in-differences analysis

Panel B. Estimated propensity score distributions

Propensity Scores	Obs.	Mean	Min	P5	P25	P50	P75	P95	Max
Control	106	0.507	0.031	0.219	0.370	0.493	0.635	0.797	0.967
Treatment	106	0.507	0.030	0.218	0.371	0.494	0.635	0.799	0.965
Difference	-	0.001	0.000	0.000	0.000	0.001	0.001	0.003	0.009

Panel C. Differences in pre-shock characteristics

	Treatment	Control	Difference	t-statistic
$UNC_{i,t-1}$	0.026	0.025	0.000	0.081
$MDR_{i,t-1}$	0.110	0.110	0.000	0.027
$LnTA_{i,t-1}$	5.858	5.665	0.193	0.783
$MV\_BV_{i,t-1}$	2.657	2.910	-0.253	-0.720
$EBIT\_TA_{i,t-1}$	0.051	0.075	-0.024	-1.369
$FA\_TA_{i,t-1}$	0.186	0.187	-0.001	-0.063
$DEP\_TA_{i,t-1}$	0.034	0.035	-0.001	-0.359
$RD\_TA_{i,t-1}$	0.056	0.045	0.010	1.229
$D\_Rated_{i,t-1}$	0.217	0.226	-0.009	-0.165

Table 5 (Continued): Difference-in-differences analysis

Panel D. Target leverage ratios

Variables	OLS $MDR_{i,t}$	System GMM $MDR_{i,t}$
$MDR_{i,t-1}$	0.787***	0.661***
	(0.019)	(0.047)
$D\_Treatment_{i,t-1}$	0.025***	0.021**
	(0.007)	(0.010)
$D\_Post_{i,t-1}$	-0.012*	-0.012*
	(0.007)	(0.006)
$D\_Treatment_{i,t-1} \times D\_Post_{i,t-1}$	-0.041***	-0.024**
	(0.010)	(0.012)
$LnTA_{i,t-1}$	0.006***	0.021***
	(0.002)	(0.006)
$MV\_BV_{i,t-1}$	0.001	0.001
	(0.001)	(0.001)
$EBIT\_TA_{i,t-1}$	-0.012	-0.034
	(0.022)	(0.033)
$FA\_TA_{i,t-1}$	0.056**	0.026
	(0.023)	(0.054)
$DEP\_TA_{i,t-1}$	-0.483***	-1.035***
	(0.144)	(0.240)
$RD\_TA_{i,t-1}$	-0.004	0.088
	(0.049)	(0.074)
$D\_Rated_{i,t-1}$	0.014	0.027
	(0.009)	(0.026)
Constant	0.001	-0.049
	(0.013)	(0.033)
Observations	1,468	1,468
Number of firms	212	212
Goodness of fit—$Corr(MDR_{i,t}, \widehat{MDR}_{i,t})^2$	0.653	0.618
m1 (p-value)		0.000
m2 (p-value)		0.666
Sargan/Hansen (p-value)		0.140

Panel E. Speed of Adjustment

Variables	Full sample $\Delta MDR_{i,t}$	Over-levered $\Delta MDR_{i,t}$	Under-levered $\Delta MDR_{i,t}$
$MDEV_{i,t}$	0.370***	0.370**	0.430***
	-0.054	-0.173	-0.045
$MDEV_{i,t} \times D\_Post_{i,t}$	-0.179***	-0.210	-0.208***
	-0.058	-0.180	-0.055
$MDEV_{i,t} \times D\_Treatment_{i,t}$	-0.110	-0.211	-0.125*
	-0.076	-0.197	-0.071
$MDEV_{i,t} \times D\_Treatment_{i,t} \times D\_Post_{i,t}$	0.313***	0.420**	0.278***
	-0.090	-0.190	-0.079
Constant	0.003	0.014*	-0.004
	-0.002	-0.008	-0.003
Observations	1,484	154	756
R-squared	0.346	0.236	0.360

Table 6: Uncertainty and credit ratings transition frequency matrix

This table reports the relationship between uncertainty and credit ratings. Panel A shows the results of over-levered firm sample and Panel B shows the results of under-levered firm sample. S&P domestic long term issuer credit rating is used for categorizing credit rating, we have merged minor categories into broader ones, e.g., credit ratings such as AA+, AA, and AA- are all categorized into AA. Proportion of each credit ratings and proportion of downgrades of each credit ratings are calculated, and difference of those are reported and tested. Z-stat of tests on the equality of proportions are shown in z-stat.

Panel A. Over-levered firms

		Rating at year end (frequency)												
Sample	Initial rating	AAA	AA	A	BBB	BB	B	CCC/CC	D	Total	Down	Prop.(%)	*Diff.(%)*	*z-stat*
High uncertainty	AAA	0	0	0	0	0	0	0	0	0	n.a.	n.a.	n.a.	n.a.
	AA	0	12	2	0	0	0	0	0	14	2	14.29	*-1.84*	*-0.16*
	A	0	0	92	15	0	0	0	0	107	15	14.02	*9.20*	*3.18*
	BBB	0	0	3	213	23	2	0	0	241	25	10.37	*8.09*	*4.01*
	BB	0	0	0	9	274	34	1	0	318	35	11.01	*10.35*	*3.95*
	B	0	0	0	0	13	200	4	1	218	5	2.29	*2.29*	*0.67*
	CCC/CC	0	0	0	0	0	3	2	0	5	0	0.00	n.a.	n.a.
	D	0	0	0	0	0	0	0	0	0	0	n.a.	n.a.	n.a.
	Total	0	12	97	237	310	239	7	1	903	82	9.08	*5.67*	*4.8*
	Prop. (%)	0.00	1.33	10.74	26.25	34.33	26.47	0.78	0.11	100.00				
Low uncertainty	AAA	0	0	0	0	0	0	0	0	0	n.a.	n.a.		
	AA	0	26	5	0	0	0	0	0	31	5	16.13		
	A	0	0	296	15	0	0	0	0	311	15	4.82		
	BBB	0	0	8	292	7	0	0	0	307	7	2.28		
	BB	0	0	0	13	138	1	0	0	152	1	0.66		
	B	0	0	0	0	4	15	0	0	19	0	0.00		
	CCC/CC	0	0	0	0	0	0	0	0	0	0	n.a.		
	D	0	0	0	0	0	0	0	0	0	0	n.a.		
	Total	0	26	309	320	149	16	0	0	820	28	3.41		
	Prop. (%)	0.00	3.17	37.68	39.02	18.17	1.95	0.00	0.00	100.00				
Diff. in proportions	*Diff. (%)*	n.a.	*-1.84*	*-26.94*	*-12.78*	*16.16*	*24.52*	*0.78*	*0.11*					
	z-stat	n.a.	*-2.60*	*-13.16*	*-5.66*	*7.58*	*14.31*	*2.53*	*0.95*					

Table 6 (Continued): Uncertainty and credit ratings transition frequency matrix

Panel B. Under-levered firms

Sample	Initial rating	Rating at year end (frequency) AAA	AA	A	BBB	BB	B	CCC/CC	D	Total	Down	Prop.(%)	*Diff.(%)*	*z-stat*
High uncertainty	AAA	0	0	0	0	0	0	0	0	0	0	n.a.	n.a.	n.a.
	AA	0	18	3	1	0	0	0	0	22	4	18.18	*10.84*	*1.60*
	A	0	0	132	10	3	0	0	0	145	13	8.97	*4.61*	*2.03*
	BBB	0	0	8	206	15	1	0	0	230	16	6.96	*4.85*	*2.85*
	BB	0	0	0	12	248	21	1	0	282	22	7.80	*6.90*	*2.62*
	B	0	0	0	0	16	74	3	0	93	3	3.23	*3.23*	*0.55*
	CCC/CC	0	0	0	0	0	1	1	1	3	1	33.33	n.a.	n.a.
	D	0	0	0	0	0	0	0	0	0	n.a.	n.a.	n.a.	n.a.
	Total	0	18	143	229	282	97	5	1	775	59	7.61	*3.98*	*3.62*
	Prop. (%)	0	2.32	18.45	29.55	36.39	12.52	0.65	0.13	100.00				
Low uncertainty	AAA	6	2	0	0	0	0	0	0	8	2	25		
	AA	0	101	8	0	0	0	0	0	109	8	7.34		
	A	0	2	349	15	1	0	0	0	367	16	4.36		
	BBB	0	0	20	305	7	0	0	0	332	7	2.11		
	BB	0	0	0	12	98	1	0	0	111	1	0.90		
	B	0	0	0	0	6	3	0	0	9	0	0.00		
	CCC/CC	0	0	0	0	0	0	0	0	0	n.a.	n.a.		
	D	0	0	0	0	0	0	0	0	0	n.a.	n.a.		
	Total	6	105	377	332	112	4	0	0	936	34	3.63		
	Prop. (%)	0.64	11.22	40.28	35.47	11.97	0.43	0.00	0.00	100.00				
Diff. in proportions	*Diff. (%)*	*-0.64*	*-8.90*	*-21.83*	*-5.92*	*24.42*	*12.09*	*0.65*	*0.13*					
	z-stat	*-2.23*	*-7.09*	*-9.77*	*-2.60*	*11.94*	*10.56*	*2.46*	*1.10*					

Table 7: Uncertainty, major investments, and adjustment speeds

This table reports the results of impact of uncertainty on the speed of adjustment when investment spikes occur. Panel A presents the results from a regression analysis where the dependent variable is adjusted adjustment which is the change in book leverage restricted to active adjustment, and Panel B presents the results from a regression analysis where the dependent variable is change in market leverage. Details for variable included in the models are provided in Table 1. Investment spike is defined following Elsas *et. al.* (2014), more specifically, a firm experienced an investment spike when its investment exceeds previous 3-year benchmark and greater than 30% of previous year's total assets. Standard errors reported in parentheses are bootstrapped to account for generated regressors. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

Panel A. Book leverage ratios

	Full sample		Over-levered firms		Under-levered firms	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$\Delta BDR^p_{i,t}$	$\Delta BDR^p_{i,t}$	$\Delta BDR^p_{i,t}$	$\Delta BDR^p_{i,t}$	$\Delta BDR^p_{i,t}$	$\Delta BDR^p_{i,t}$
$BDEV^p_{i,t}$	0.249***	0.242***	0.252***	0.256***	0.279***	0.274***
	(0.008)	(0.006)	(0.013)	(0.013)	(0.014)	(0.012)
$BDEV^p_{i,t} \times D\_HighUNC_{i,t-1}$	0.060***	0.070***	0.111***	0.105***	-0.009	0.002
	(0.011)	(0.008)	(0.015)	(0.015)	(0.015)	(0.014)
$BDEV^p_{i,t} \times D\_Spike_{i,t}$	0.633***	0.750***	-0.018	-0.304**	0.805***	0.872***
	(0.037)	(0.052)	(0.086)	(0.154)	(0.041)	(0.046)
$BDEV^p_{i,t} \times D\_HighUNC_{i,t-1} \times D\_Spike_{i,t}$		-0.230***		0.399**		-0.147**
		(0.071)		(0.186)		(0.067)
Constant	0.000	0.000	0.004***	0.004***	-0.002**	-0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	20,768	20,768	9,353	9,353	10,688	10,688
R-squared	0.263	0.265	0.189	0.190	0.207	0.208

Panel B. Market leverage ratios

	Full sample		Over-levered firms		Under-levered firms	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$\Delta MDR_{i,t}$	$\Delta MDR_{i,t}$	$\Delta MDR_{i,t}$	$\Delta MDR_{i,t}$	$\Delta MDR_{i,t}$	$\Delta MDR_{i,t}$
$MDEV_{i,t}$	0.236***	0.231***	0.310***	0.311***	0.184***	0.180***
	(0.008)	(0.009)	(0.017)	(0.016)	(0.015)	(0.012)
$MDEV_{i,t} \times D\_HighUNC_{i,t-1}$	0.060***	0.067***	0.047***	0.045***	0.029*	0.036***
	(0.009)	(0.012)	(0.018)	(0.014)	(0.016)	(0.013)
$MDEV_{i,t} \times D\_Spike_{i,t}$	0.449***	0.529***	-0.418***	-0.772***	0.558***	0.599***
	(0.034)	(0.041)	(0.152)	(0.235)	(0.035)	(0.042)
$MDEV_{i,t} \times D\_HighUNC_{i,t-1} \times D\_Spike_{i,t}$		-0.172**		0.468*		-0.094*
		(0.079)		(0.250)		(0.055)
Constant	-0.002**	-0.002**	0.006***	0.006***	0.003**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	20,768	20,768	8,831	8,831	11,111	11,111
R-squared	0.208	0.208	0.149	0.149	0.120	0.120

Table 8: Effects of uncertainty on investments' responsiveness to a demand shock

This table reports the results of the impact of uncertainty on responsiveness of demand shock using system GMM. The variables used are defined following Bloom *et al.* (2007). Specifically, investment ratio ($I_{it}/K_{i,t-1}$) is the ratio of investment(INV_{it}) to its lagged capital stock ($K_{i,t-1}$), and cash flow ($C_{it}/K_{i,t-1}$) is the ratio of cash flow (C) to its lagged capital stock. Investment (INV) is the sum of capital and acquisition expenditures (*capx* and *aqc*), and capital stock (K) is estimated using perpetual inventory method, sales growth (Δy_{it}) is measured as natural logarithm of a firm's annual sales (*sale*), cash flow (C) is the sum of income before extraordinary item (*ib*) and depreciation and amortization (*dp*). Small k stands for natural logarithm of capital stock (K) and uncertainty(SD) is measured as the same as our main model (UNS). We estimated the model using one-step estimators with calculated robust estimator of the covariance matrix of the parameter. Instrument variables used in the system GMM are $\Delta I_{it-1}/K_{i,t-2}$, $\Delta\Delta y_{i,t-1}$, $\Delta((y-k)_{i,t-1})$, $\Delta\Delta((y-k)_{i,t-1})$, $\Delta C_{i,t-1}/K_{i,t-2}$, $\Delta\Delta C_{i,t-1}/K_{i,t-2}$, and ΔSD_{t-1}, for level equations, and second to ninth lags of $I_{it}/K_{i,t-1}$, Δy_{it}, $(y-k)_{it}$, $\Delta(y-k)_{i,t}$, $C_{it}/K_{i,t-1}$, $\Delta C_{it}/K_{i,t-1}$, and SD_{it} for first difference equations, and year dummies as strict iv. Note that uncertainty measures are not included in IV in column (1) and (2). Note that year dummies are treated as instruments for the equations in levels only. m1 and m2 represent the test statistics of Arellano-Bond test for AR(1) and AR(2) in first differences, respectively. Sargan/Hansen represents the J stats for overidentifying restrictions. The goodness-of-fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

Variables	(1) $I_{it}/K_{i,t-1}$	(2) $I_{it}/K_{i,t-1}$	(3) $I_{it}/K_{i,t-1}$	(4) $I_{it}/K_{i,t-1}$	(5) $I_{it}/K_{i,t-1}$
Sales growth (Δy_{it})	0.548***	0.420***	0.532***	0.503***	0.511***
	(0.044)	(0.044)	(0.047)	(0.048)	(0.048)
Cash flow ($C_{it}/K_{i,t-1}$)	0.026***	0.033***	0.036***	0.035***	0.038***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Error correction term $(y-k)_{i,t-1}$	0.220***	0.234***	0.227***	0.227***	0.227***
	(0.020)	(0.020)	(0.018)	(0.018)	(0.019)
Sales growth squared $(\Delta y_{i,t})^2$		0.456***	0.423***	0.464***	0.448***
		(0.076)	(0.071)	(0.075)	(0.075)
Lagged uncertainty ($SD_{i,t-1}$)				-0.770**	0.003
				(0.313)	(0.477)
Change in uncertainty ($\Delta SD_{i,t}$)					0.041**
					(0.018)
Uncertainty × sales growth ($SD_{it} * \Delta y_{it}$)			-0.143***	-0.125***	-0.130***
			(0.045)	(0.046)	(0.046)
Constant	0.013	-0.008	-0.013	0.004	-0.088**
	(0.023)	(0.023)	(0.022)	(0.023)	(0.035)
Observations	19,161	19,161	19,161	19,161	19,161
Number of firms	1,371	1,371	1,371	1,371	1,371
Goodness of fit—$Corr(I/K,\widehat{I/K})^2$	0.152	0.168	0.180	0.180	0.177
m1	-16.46	-16.52	-16.67	-16.67	-16.69
(p-value)	0.000	0.000	0.000	0.000	0.000
m2	0.661	1.176	1.406	1.396	1.318
(p-value)	0.508	0.240	0.160	0.163	0.187
Sargan/Hansen	1,169	1,164	1,333	1,332	1,332
(p-value)	0.159	0.181	0.369	0.364	0.360

Table 9: Effects of uncertainty on financing sources during investment shocks

This table reports the impact of uncertainty on the financing patterns at time of investment shocks. Dependent variables are ratios of debt financing, equity financing, cashflow financing, and other financing source to its lagged total assets. $INV\_TA_{i,t}$ is a ratio of investment to its lagged total assets. Details for other independent variables used in the models are provided in Table 1. A firm-year observation at spike is categorized into either high uncertainty or low uncertainty group depending on whether its uncertainty level at the previous year ending is higher or lower than the sample median of uncertainty level. Within each sample set, the system of equations is estimated using the constraint that four coefficients of $INV\_TA_{i,t}$ on each financing sources sum to 1. Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Full sample				High uncertainty sample				Low uncertainty sample			
Variables	Debt	Equity	Cashflow	Other	Debt	Equity	Cashflow	Other	Debt	Equity	Cashflow	Other
$INV\_TA_{i,t}$	0.803***	0.190***	-0.020	0.027	0.740***	0.208***	0.046	0.007	0.860***	0.153***	-0.066***	0.053***
	(0.022)	(0.029)	(0.024)	(0.019)	(0.047)	(0.072)	(0.056)	(0.044)	(0.021)	(0.018)	(0.016)	(0.018)
$LnTA_{i,t-1}$	0.005	-0.021**	0.006	0.011**	0.024*	-0.048**	0.025	0.002	-0.002	-0.006	-0.012**	0.017***
	(0.006)	(0.008)	(0.007)	(0.005)	(0.014)	(0.021)	(0.016)	(0.012)	(0.008)	(0.006)	(0.005)	(0.006)
$MV\_BV_{i,t-1}$	-0.037***	0.077***	-0.014**	-0.027***	-0.031***	0.080***	-0.015	-0.032***	-0.041***	0.034***	0.026***	-0.018**
	(0.007)	(0.009)	(0.007)	(0.006)	(0.011)	(0.017)	(0.013)	(0.010)	(0.011)	(0.008)	(0.008)	(0.009)
$EBIT\_TA_{i,t-1}$	0.088	-1.089***	1.072***	0.048	-0.037	-0.975***	1.154***	0.063	0.078	-0.614***	0.442***	0.017
	(0.072)	(0.096)	(0.075)	(0.062)	(0.112)	(0.172)	(0.128)	(0.101)	(0.146)	(0.115)	(0.106)	(0.116)
$FA\_TA_{i,t-1}$	0.162*	-0.154	-0.075	0.065	0.187	-0.459**	0.092	0.199	0.071	0.023	-0.039	-0.044
	(0.086)	(0.115)	(0.090)	(0.075)	(0.153)	(0.234)	(0.175)	(0.138)	(0.106)	(0.084)	(0.077)	(0.085)
$DEP\_TA_{i,t-1}$	-0.674	0.986	0.707	-0.753	-1.646*	2.960**	0.486	-1.242	0.485	-0.253	-0.102	-0.124
	(0.564)	(0.749)	(0.586)	(0.487)	(0.916)	(1.399)	(1.044)	(0.825)	(0.729)	(0.576)	(0.528)	(0.580)
$RD\_TA_{i,t-1}$	-0.156	-0.155	-0.283	0.797***	-0.285	0.035	-0.154	0.820***	-0.102	-0.638***	-0.287	0.924***
	(0.192)	(0.255)	(0.200)	(0.166)	(0.318)	(0.486)	(0.363)	(0.287)	(0.253)	(0.200)	(0.184)	(0.202)
$D\_RD_{i,t-1}$	0.005	0.001	0.003	-0.005	0.023	-0.018	0.055	-0.056	0.003	-0.028	-0.003	0.025
	(0.021)	(0.029)	(0.022)	(0.019)	(0.048)	(0.073)	(0.055)	(0.043)	(0.022)	(0.018)	(0.016)	(0.018)
$\overline{MDR}_{j,t-1}$	0.252**	-0.098	-0.013	-0.075	0.423*	-0.354	0.073	0.066	0.142	-0.094	-0.017	-0.057
	(0.118)	(0.157)	(0.122)	(0.102)	(0.238)	(0.363)	(0.271)	(0.214)	(0.133)	(0.105)	(0.096)	(0.106)
$D\_Rated_{i,t-1}$	-0.011	0.048	-0.025	-0.007	-0.048	-0.013	-0.011	0.079	0.004	0.006	0.022	-0.019
	(0.028)	(0.037)	(0.029)	(0.024)	(0.093)	(0.141)	(0.105)	(0.083)	(0.026)	(0.021)	(0.019)	(0.021)
Constant	-0.263**	0.675***	-0.359***	-0.021	-0.146	1.317***	-1.031***	-0.112	-0.363***	0.037	0.322***	0.031
	(0.108)	(0.143)	(0.112)	(0.093)	(0.186)	(0.284)	(0.212)	(0.168)	(0.123)	(0.097)	(0.089)	(0.098)
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	616	616	616	616	239	239	239	239	377	377	377	377
R-squared	0.676	0.423	0.403	0.132	0.572	0.494	0.510	0.161	0.774	0.237	0.263	0.222

Figure 1: Level of uncertainty and change in uncertainty during the sample period

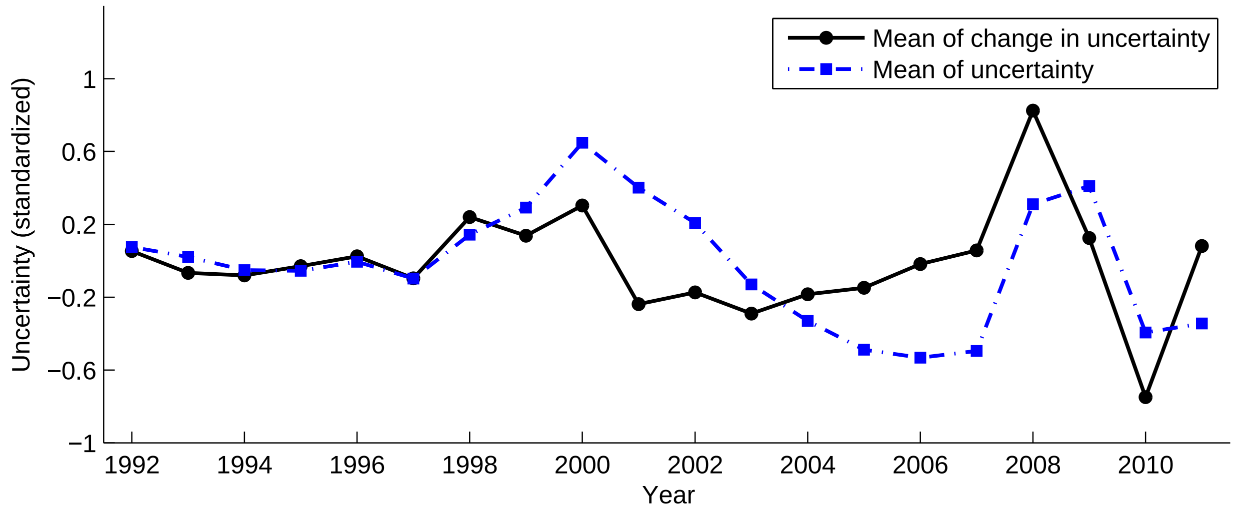

Figure 2: Adjustment rates around the recent global financial crisis