Journal Pre-proof

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PII: S0929-1199(20)30086-9

DOI: https://doi.org/10.1016/j.jcorpfin.2020.101642

Reference: CORFIN 101642

To appear in: *Journal of Corporate Finance*

Received date: 4 December 2018

Revised date: 28 February 2020

Accepted date: 10 May 2020

Please cite this article as: H.J. Im, Y. Kang and J. Shon, How does uncertainty influence target capital structure?, *Journal of Corporate Finance* (2020), https://doi.org/10.1016/j.jcorpfin.2020.101642

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[a]We are grateful for the valuable comments from the editor Bart Lambrecht and two anonymous referees as well as Steve Bond, Soku Byoun, Hyunsoo Doh, Fangjian Fu, Rachita Gullapalli, Vidhan Goyal, Chang Yong Ha, Zhangkai Huang, Tim Jenkinson, Fuxiu Jiang, Jun-Koo Kang, Kenneth Kim, Sukjoong Kim, Jose Martinez, Colin Mayer, Alan Morrison, Thomas Noe, Stefano Rossi, Oren Sussman, Kelvin Tan, Yuhai Xuan and Alexander Vadilyev; to the conference participants at the 2018 China International Conference in Finance, the 2018 PKU-NUS Annual International Conference on Quantitative Finance and Economics, the 2017 AsFA Conference, the 2016 FMA Asia-Pacific Meeting and the 2016 FMA Annual Meeting; and to the seminar participants at Sungkyunkwan University and Yonsei University. Hyun Joong Im acknowledges Steve Bond's suggestions on this topic and insightful lectures on dynamic panel data analyses and GMM estimation methods provided during his doctoral studies at the University of Oxford.
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February 27, 2020

ABSTRACT

This study investigates how uncertainty affects firms' target capital structure using a panel data set of U.S. public manufacturers between 2003 and 2018 and finds that high-uncertainty firms have 10.1 (8.1) percentage points lower mean book (market) targets than low-uncertainty firms. This study also shows that the uncertainty effect on leverage targets is greater than the impact of firm size, market-to-book ratio, assets tangibility, R&D intensity, and industry median leverage, making uncertainty the most critical among all time-varying determinants of leverage targets. Further, this study finds that heightened uncertainty decreases debt tax shields, increases potential financial distress costs, and exacerbates debtholder–shareholder conflicts, thereby leading to a lower optimal or target leverage ratio.

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

Keywords: Uncertainty, Target Leverage, Capital Structure, Asset Volatility

1. Introduction

A growing body of literature has shown that uncertainty has material effects on decision-making—particularly investment and financing decisions. Emphasising the role of market frictions such as capital irreversibility and financial constraints and the importance of real option to wait and see, early studies have centred around the effect of uncertainty on corporate investments.[1] Given that uncertainty is unprecedentedly high around the globe, quite a few impressive studies regarding the implications of uncertainty on corporate financing decisions in different contexts exist Gungoraydinoglu et al., 2017; Çolak et al., 2018; Li and Qiu, 2018). For example, Gungoraydinoglu et al. (2017), using international data, show that the speed of leverage adjustment is lower when political or policy uncertainty is higher. In addition, Çolak et al. (2018) show that political uncertainty raises the securities' placement costs for financial intermediaries, who pass on these costs to the issuing firms in the form of higher underwriter spreads, thereby increasing the issuance costs for new equity and debt capital, and in turn leading to lower leverage ratios.

However, the impact of business uncertainty, i.e. asset volatility, on capital structure decisions has been little explored. Standard capital structure theories such as Leland (1994) and Lambrecht and Myers (2017) provide interesting testable predictions about the relationship between asset volatility and optimal capital structure, and Choi (2013) and Choi and Richardson (2016) provide a way to empirically estimate asset volatility. In addition, the dynamic panel regression estimators such as the difference generalised method of moments (GMM) (Arellano and Bond, 1991) or the system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998) allow us to estimate the optimal leverage using a partial adjustment framework, the relative scarcity of study on this subject is quite puzzling. Although actual leverage and optimal leverage tend to be highly positively correlated, target leverage estimated using a partial adjustment framework is closer to the optimal leverage in theoretical literature such as Leland (1994) and Lambrecht and Myers (2017).[2] In this study, we examine the impact of asset volatility on optimal capital structure

[1] For example, Bernanke (1983) and Bloom et al. (2007) show that uncertainty increases the value of real options to the firm, inducing it to wait for additional information before investing.

[2] Few prior studies have been conducted on the relationship between stock return or cash flow volatility and actual leverage; however, the empirical findings are mixed. For example, Kim and Sorensen (1986) report a positive relationship, whereas Bradley et al. (1984), Friend and Lang (1988) and Keefe and Yaghoubi (2016) report a negative relationship between stock return or cash flow volatility and actual leverage. Frank and Goyal (2009) also investigate which of the 25 explanatory variables used in prior studies (including stock return volatility) are reliably important to

and investigate the economic mechanisms through which asset volatility influences optimal capital structure.

To capture operating uncertainty or business uncertainty independent of capital structure, we use the asset return volatility measure proposed by Choi (2013) and Choi and Richardson (2016) as a main measure of uncertainty. Modigliani and Miller (1958) suggest that the value of real assets can be represented by the value of financial assets so that the nature of a firm's free cash flow stream is unaffected by the way in which it is carved up. Thus, the return on a firm's assets can be considered as a weighted average of the return on each of the firm's financial assets, where the weights are determined by the relative market value of each financial asset.[3] Choi and Richardson (2016) argue that the approach of viewing a firm's assets as a portfolio of the firm's individual securities provides a distinct advantage over other approaches in the literature in that it does not rely on a specific model of capital structure. This measure can attenuate endogeneity bias because asset returns, unlike stock returns, are highly likely to be determined by the fundamental characteristics of businesses rather than the leverage level.[4]

To estimate optimal capital structure, we employ the partial adjustment model of capital structure which is often used to study the speed of leverage adjustment. Dynamic trade-off models, such as that of Fischer et al. (1989), maintain that market imperfections such as taxes and

a firm's capital structure decision. They report that six factors, including firm size, market-to-book ratio, profitability and tangibility, reliably influence a firm's capital structure; however, they do not find a robust relationship between stock return variance and actual leverage.

[3] Modigliani and Miller's (1958) second proposition suggests that the corporate cost of capital is independent of the corporation's capital structure. In equilibrium, the return on assets should be equal to the corporate cost of capital so that according to Modigliani and Miller's proposition, the return on assets is independent of the firm's capital structure. Hence, as the leverage ratio changes, the returns on debt and equity must alter to ensure that the weighted average of the return on each of the firm's financial assets is equal to the return on assets.

[4] Many studies including Leahy and Whited (1996), Bloom et al. (2007), Bloom (2009), Kellogg (2014), Kim and Kung (2016), Bloom et al. (2018) and Alfaro et al. (2018) use the standard deviation of daily stock returns as an uncertainty measure. Although this measure has some attractive features, as discussed in Bloom et al. (2007), reverse causality remains a concern when studying the effect of stock return volatility on actual/optimal capital structure. Stock returns, unlike asset returns, are influenced by both the leverage level and fundamental characteristics of businesses. Thus, to mitigate the reverse causality concern, we use asset return volatility as our main uncertainty measure. Moreover, the measurement error concern arising from ignoring debt volatility is mitigated by including the debt-side information.

bankruptcy costs generate a link between capital structure and firm value; however, most of the time, firms allow their leverage to diverge from their optimal leverage and only take actions to offset deviations from their optimal leverage if it gets too far out of line. 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) propose a partial adjustment model in which firms partially or incompletely adjust towards their optimal/target leverage ratios, which depend on firm characteristics.

Uncertainty influences optimal leverage ratios through various channels: debt tax shields, potential financial distress costs, the agency costs of debt and the agency benefits of debt. Although the effects of uncertainty on target leverage ratios through potential financial distress costs and shareholder–debtholder agency conflicts are expected to be *negative*, the impacts through debt tax shields and agency benefits of debt can be either *positive* or *negative*. Furthermore, recent theory papers based on dynamic agency models such as Lambrecht and Myers (2017) show that the *negative* effect of uncertainty on optimal leverage can be more pronounced if managers are risk averse.[5] Thus, whether uncertainty will increase or decrease optimal leverage ratios is an empirical question. In this paper, we address this question by first identifying the directional effect of heightened uncertainty on leverage targets and then considering through which mechanisms uncertainty affects optimal/target leverage ratios. The results of this study provide evidence that uncertainty increases potential financial distress costs and exacerbates shareholder–debtholder conflicts (e.g. underinvestment and risk-shifting problems), thereby leading to a lower optimal leverage ratio.

Endogeneity is the obvious problem that we must address in identifying the causal effect of uncertainty on optimal/target leverage ratios. Although we use asset volatility as an uncertainty measure to address the reverse causality and measurement error concerns that arise when using equity volatility, further endogeneity concerns remain. First, target leverage ratios may be influenced by some important omitted factors (e.g. managerial risk aversion). Although we take

[5] Refer to Section 2 for a detailed discussion.

into account the firm fixed effects in target leverage to minimise the omitted variables bias and measurement errors arising from the omission of some important factors, there may be some omitted unobservable, time-varying variables correlated with the included target determinants. Second, both asset volatility and target/optimal capital structure are quite possibly driven by a third factor (e.g. the amount and nature of investment opportunities and industry life cycles). Finally, the reverse causality problem may not completely disappear even when we use asset volatility as an uncertainty measure. To address these endogeneity concerns, we use instrumental variables (IVs) suggested by Alfaro et al. (2018). Our identification strategy exploits firms' differential exposure to 10 aggregate sources of uncertainty shock, such as the annual changes in the expected return volatilities of energy, currencies and 10-year treasury bonds. Using this approach, we confirm our main findings.

This study makes a significant contribution to the dynamic capital structure literature. First, this paper proposes firm-level asset volatility as a new crucial determinant of optimal capital structure. The asset volatility measure is in line with a volatility term (σ) in most dynamic capital structure studies such as Leland (1994) and Lambrecht and Myers (2017). Most of the empirical dynamic capital structure studies do not find that asset volatility plays a crucial role in explaining capital structure (Frank and Goyal, 2009; Leary and Roberts, 2005; Antoniou et al., 2008). Thus, to the best of our knowledge, this study is the first in the literature to propose firm-level asset volatility as a vital determinant of target/optimal leverage. We also show that the uncertainty effect on leverage targets is greater than the impact of firm size, market-to-book, assets tangibility, R&D intensity and industry median leverage, making uncertainty the most crucial determinant among all time-varying determinants of leverage targets.

Second, we explore various economic mechanisms through which asset volatility influences optimal capital structure. We employ a partial adjustment model of capital structure to precisely estimate optimal capital structure. This allows us to evaluate the importance of uncertainty in accounting for the variation in optimal capital structure. Using theory-based proxies for uncertainty and optimal leverage ratios, we show that uncertainty significantly lowers optimal leverage ratios by decreasing debt tax shields, increasing potential financial distress costs and exacerbating shareholder–debtholder conflicts (e.g. underinvestment and risk-shifting problems). In addition, we show that firms with more risk averse managers have lower optimal leverage ratios, consistent with a dynamic agency model (e.g. Lambrecht and Myers, 2017) predicting that the *negative* effect of uncertainty on optimal leverage can be more pronounced if managers are risk averse.

The remainder of the paper is organised as follows. In Section 2, we present the theoretical predictions about the effects of uncertainty on optimal/target capital structure. Section 3 describes the sample selection procedures, measurement of variables, descriptive statistics and research design, and Section 4 presents empirical findings. Section 5 concludes the study.

2. Predictions from theory

Quite a few standard theories on optimal capital structure (e.g. Leland, 1994; Lambrecht and Myers, 2017) predict that optimal leverage is significantly negatively affected by asset volatility, i.e. the volatility of rate of return on assets.[6] In addition, recent theory papers based on dynamic agency models such as Lambrecht and Myers (2017) predict that the *negative* effect of uncertainty on optimal leverage can be more pronounced if managers are risk averse. Lambrecht and Myers (2017) show that the firm has an optimal target leverage ratio, similar to the leverage target predicted by the trade-off theory of capital structure. Their model predicts a significantly lower leverage level because of the manager's desire to smooth rents and that higher managerial risk aversion leads to a lower leverage ratio.[7] Keefe and Yaghoubi (2016) employ the Black–Scholes model (Black and Scholes, 1973) to illustrate the relationship between cash flow volatility and the cost of debt.[8]

In addition, the dynamic trade-off literature such as Fischer et al. (1989) and other related influential papers in capital structure Harris and Raviv, 1991; Fama and French, 2002; Frank and

[6] Figures 7 and 13 in Leland's (1994) paper show the significant negative effect of asset volatility of optimal leverage. In his paper, σ is the standard deviation of the instantaneous rate of return on V, where V is the value of the unlevered firm assumed to be unaffected by the capital structure of the firm. Thus, an appropriate proxy for σ is the asset volatility used as a main uncertainty measure in this study.

[7] Figure 2 in their paper clearly shows that higher asset volatility leads to a lower optimal leverage and that higher relative risk aversion lowers optimal leverage. In Section 4.4, we further discuss the moderating role of managerial risk aversion in the relationship between asset volatility and optimal leverage and provide some tests related to the predictions.

[8] In their model, σ is the standard deviation of the return on the asset. Thus, their model also provides support for using asset volatility as a main uncertainty measure.

Goyal, 2009) show that leverage targets are driven by several forces such as tax shields, financial distress costs and agency costs and benefits related to debt. We extend Fama and French's (2002) discussion of the static/dynamic trade-off theory to derive some predictions regarding the potential channels through which uncertainty influences target leverage ratios.[9]

First, the effects of uncertainty on optimal/target leverage ratios through debt tax shields can be *negative* or *positive* depending on the magnitude of two conflicting effects. The *negative* impact is related to the impact of uncertainty on the volatility of earnings. A high-uncertainty firm is more likely to have more volatile earnings than a low-uncertainty firm. As a result, a high-uncertainty firm is expected to have a higher chance of having no taxable income, and consequently, its expected future taxable income will be lower and its expected payoff from interest tax shields will be lower. Thus, the effects of uncertainty on optimal leverage ratios through debt tax shields can be negative. This reasoning is well in line with Blouin et al. (2010) who argue that the classic literature like Graham (1996), Graham (2000) and Graham and Kim (2009) underestimates the future income volatility and thus overestimates the future taxable income and the value of tax of debt.

The potential *positive* impact is derived from the impact of uncertainty on non-debt tax shields (DeAngelo and Masulis, 1980). A high-uncertainty firm is expected to benefit less from non-debt tax shields because higher uncertainty leads to lower R&D expenditures and lower future depreciation expenses, which are driven by the reduction in capital expenditures, as is evidenced by Bloom et al. (2007) and Gulen and Ion (2015). In this case, it is possible that the firm benefits more from debt tax shields if the amount of debt is given, in which case the effects of uncertainty on optimal leverage ratios through debt tax shields can be positive. However, the reduction in debt tax shields owing to increased earnings volatility is likely to be the first-order effect, whereas the increase in debt tax shields arising from the reduction in nondebt tax shields is most likely the second-order effect.

Second, the effects of uncertainty on optimal/target leverage ratios through potential

[9] Different predictions are derived from the pecking order theory (Myers, 1984; Myers and Majluf, 1984) and market timing theory (Baker and Wurgler, 2002). As Graham and Harvey (2001) report that 81% of firms consider a target debt ratio or range when making their capital structure decisions, some firms' capital structure policies may not be consistent with what the trade-off theory predicts. In Section 4.4, we discuss the predictions from the two different theories and try to address some related concerns.

financial distress costs are expected to be *negative*. A high-uncertainty firm tends to have higher expected bankruptcy costs because it is expected to have a higher probability of bankruptcy and meet higher direct and indirect bankruptcy costs given bankruptcy. A high-uncertainty firm is expected to have more volatile earnings. Consequently, the probability of bankruptcy increases. This is well supported by Merton's (1974) distance to default (DD) model.[10] When uncertainty is higher, indirect costs are expected to be higher, wherein suppliers may withdraw trade credits, customers may turn to competitors and some key employees may leave firms.[11] Thus, *ceteris paribus*, uncertainty is positively associated with bankruptcy costs. Consequently, it has a negative effect on optimal leverage ratios.

Third, the effects of uncertainty on optimal/target leverage through debtholder–shareholder agency problems are predicted to be *negative*. Agency problems such as assets substitution and under-investment arise when shareholders' interests are not aligned with debtholders' interests (Fama and Miller, 1972; Jensen and Meckling, 1976; Myers, 1977). A high-uncertainty firm, compared with a low-uncertainty firm, is expected to face more severe under-investment and asset substitution problems because high uncertainty will make both assets in place and investment projects riskier. As a result, its debt will become riskier. Therefore, a high-uncertainty firm has a stronger incentive to control shareholder–debtholder conflicts and will have a lower optimal leverage ratio.

Finally, the effects of uncertainty on optimal/target leverage through the agency benefits of debt can be either *negative* or *positive*. Jensen (1986) shows that agency costs increase with free cash flows.[12] However, debt may reduce the free cash flow agency problem by ensuring that managers are disciplined to make efficient investment decisions and do not pursue private benefits, as this increases bankruptcy risk (Jensen, 1986; Stulz, 1990). The direction of the effect of uncertainty on optimal leverage through agency benefits arising from the disciplining role of debt

[10] Although Bharath and Shumway (2008) find that Merton's DD model does not provide sufficient statistics for the probability of default, they conclude that its functional form is still useful for forecasting defaults.

[11] The indirect costs of financial distress—identified as the reduction in valuable capital expenditures, losses of critical customers, losses of important suppliers, etc.—are known to be much larger than the direct costs of financial distress (Andrade and Kaplan, 1998).

[12] In the agency models of Jensen and Meckling (1976), Easterbrook (1984), Jensen (1986) and Stulz (1990), the interests of managers are not aligned with those of shareholders, and managers tend to waste free cash flows on perquisites such as corporate jets, plush offices and building empires as well as on bad investments.

depends on the composition of a firm's free cash flow, i.e. its earnings from the assets in place *vs.* the size of its profitable investments, given that a firm's free cash flow is defined as its earnings from assets in place minus the size of its profitable investments (Jensen, 1986).[13]

In summary, although the effects of uncertainty on optimal/target leverage ratios through potential financial distress costs and shareholder–debtholder agency conflicts are expected to be *negative*, the effects through debt tax shields and agency benefits of debt can be either *negative* or *positive*. Therefore, whether uncertainty will increase or decrease optimal/target leverage ratios is an open question. Furthermore, the magnitude of the effect of uncertainty depends on managerial risk aversion. Thus, this study aims to understand the magnitude of uncertainty's effect on a firm's optimal/target capital structure and the underlying mechanisms through which uncertainty lowers optimal capital structure.

3. Empirical framework

3.1. Sample selection

Our empirical analysis uses the CRSP/Compustat Merged (CCM) database for annual financial statements data, the Center for Research in Security Prices (CRSP) database for monthly stock return data, the Trade Reporting and Compliance Engine (TRACE) database for monthly bond pricing data, the Loan Syndications and Trading Association (LSTA) Mark-to-Market Pricing database for monthly loan sale pricing data, the Compustat database for credit rating data and the Bureau of Economic Analysis (BEA) database for GDP deflator data from 2002 to 2018. Our sample period starts from 2003 because bond return data is available in the TRACE database only from 2002.[14]

[13] We extended Fama and French's (2002) framework to come up with the predictions. If a firm has many profitable assets in place, the profitability of its assets in place will be lower when it is faced with high uncertainty. For the firm, high uncertainty will lead to less free cash flows and therefore lower shareholder–manager agency costs. Thus, high uncertainty will lower the value of debt as a disciplining device to the firm, implying that the effect of uncertainty on the optimal leverage ratio will be *negative*. However, if a firm has many profitable investment opportunities, a high-uncertainty firm will have a higher value of the real option to wait (Bloom et al., 2007; Gulen and Ion, 2015), leading to more free cash flows and therefore higher shareholder–manager agency costs. Thus, it is possible that a high-uncertainty firm could receive more benefits from the disciplining role of debt.

[14] We use the TRACE database for monthly bond pricing data because the TRACE database incorporates all

To construct our final sample, we go through the following sample selection and data cleaning procedures. The dataset covers all manufacturing firms with the two-digit North American Industry Classification System (NAICS) sector codes of 31, 32 or 33.[15] We require that each firm has at least 10 years of uninterrupted observations. We exclude firms with missing or negative total assets or negative book equity and the firms whose stock is not traded on the three major stock exchanges in the U.S. (i.e. NYSE, NASDAQ, and AMEX). We retain the firm-year observation if variables other than total assets and book equity are missing. The final sample is an unbalanced panel dataset comprising 14,546 firm-year observations corresponding to 1,455 firms.

3.2. Measurement of variables

3.2.1. Measuring uncertainty

As the main uncertainty proxy, we use asset volatility (i.e. volatility of the return on assets) proposed by Choi (2013) and Choi and Richardson (2016). Specifically, asset volatility ($\sigma_{i,t}$) is defined as the sample standard deviation of monthly return on assets (R^A) in a given year, where the monthly return on assets is defined as follows.

$$R^A = \frac{E}{E+B+L} R^E + \frac{B}{E+B+L} R^B + \frac{L}{E+B+L} R^L, \tag{1}$$

where R^E, R^B and R^L denote the monthly returns on equity, bonds and bank loans, respectively, and E, B and L are market values of equity, bonds and loans, respectively.[16]

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over-the-counter transactions on corporate bonds and has been widely used in prior research (e.g. Edwards et al., 2007). In addition, the TRACE database has an advantage in that it provides transaction prices rather than dealer quotes as in other databases such as the Bridge EJV (now Thomson Reuters Pricing Service) database.

[15] By focusing on the manufacturing sector, one can rule out unobserved heterogeneity across sectors or industries that cannot be captured by industry fixed effects. In addition, as reported in Flannery and Rangan's (2006) study, it was not possible to find a dynamic panel regression model that satisfies the Sargan-Hansen test of over-identifying restrictions when we use the sample covering all the sectors. If the validity of the instruments is not satisfied, one cannot make a reliable inference based on the target leverage ratio estimated using the dynamic panel regression model.

[16] As the market value of loans is not readily available, we use the book value of debt minus the market value of bonds to approximate the loan value. Choi (2013) reports that loans and bonds constitute about 94% of the book value of debt, suggesting that it is reasonable to approximate the loan value by subtracting market value of bonds from book debt.

That is, asset returns are defined as weighted averages of returns on a firm's various sources of financing, including equity, loans and bonds (Choi, 2013; Choi and Richardson, 2016). The weights given to different claims are determined by their market values.

The monthly total returns, i.e. returns taking dividends into consideration, and market value of equity are from the CRSP database. The monthly bond returns are obtained from the TRACE database and are computed as the value-weighted averages of returns on individual bonds issued by a given firm. Individual bond returns are calculated by considering the transaction prices, coupon rates and accrued interests at the end of each month.[17] After the initiation of a syndicated loan in the primary market, a bank decides whether to keep it on its balance sheet or sell it off in the secondary market. LSTA collects more than 80% of all U.S. trading volume of the secondary loan market on a daily basis according to Drucker and Puri (2008), allowing us to calibrate the loan returns. However, the following two issues make the calibration complex: (1) of all syndicated loans, only around 20% are traded in the secondary market (Drucker and Puri, 2008); and (2) our loan sale data covers the period of 2003–2013 whereas our sample period is up to 2018. Treating both loans and bonds as contingent claims on the same underlying assets, in the spirit of Choi (2013), we estimate loan returns using bond returns at monthly frequency for firm-month observations without loan sale data. The idea is to approximate the hypothetical transaction prices assuming that those loans are traded. A detailed account of the estimation of loan returns can be found in the Appendix.

Asset volatility is an appealing uncertainty measure for the following reasons. First, it is a forward-looking uncertainty measure that implicitly incorporates future business prospects and changes in business environments. Insofar as asset returns reflect the prospect of firms' future performances and business environments reasonably well, we expect the impact of different sources of business uncertainty to be adequately incorporated into the asset returns. Therefore, asset return volatility correctly weighs the relative effect of different sources of business uncertainty on the firm value.[18] Earnings volatility and cash flows volatility are also reasonable

[17] Dick-Nielsen (2009, 2014) provides guidance on how to appropriately clean the TRACE bond pricing data. The method involves taking into account the change in data structure in 2012, removing all corrections and cancellations related to the data and deleting agency–customer transactions without commissions to avoid any duplication.

[18] Note that realised (or implied) stock return volatility shares this attribute (Bloom et al., 2007). However, the realised (or implied) stock return volatility is a noisier proxy for a firm's overall business uncertainty.

proxies for business uncertainty, but they are not as good as asset volatility because those measures are not forward-looking measures and the low frequency of earnings and cash flows, i.e. yearly or quarterly, makes exploiting within-firm temporal variations difficult.

Second, unlike equity return volatility that is directly affected by financing decisions, asset return volatility is not directly affected by leverage.[19] Because this study attempts to examine the causal effect of uncertainty on target/optimal capital structure, using an uncertainty measure that is not directly influenced by capital structure is important. If we use equity return volatility as the uncertainty measure, reverse causality prevents us from identifying the causal effect of uncertainty on target leverage. Although several ways to obtain asset returns (asset betas) from equity returns (equity betas) have been proposed (e.g. Hamada, 1972; Miles and Ezzell, 1985), Choi's (2013) and Choi and Richardson's (2016) approach is more straightforward given that the authors directly calculate asset returns instead of estimating asset returns using assumptions about the capital structure policy.[20]

Finally, asset volatility varies across firms and over time, allowing us to evaluate if the target leverage ratios of high-uncertainty firms are significantly different from those of low-uncertainty firms. Given the stylised facts that there is substantial unobserved heterogeneity across firms' leverage ratios (Lemmon et al., 2008) and that some determinants of firms' leverage ratios, such as financial distress costs, are influenced by macroeconomic conditions (Chen, 2010), an uncertainty measure with both cross-sectional and temporal variations is more suitable than an uncertainty measure with only cross-sectional variation (e.g. annual earnings volatility) or an uncertainty measure with only temporal variation (e.g. macroeconomic uncertainty measures).[21]

3.2.2. Measuring control variables

Following the dynamic capital structure literature, such as Fama and French (2002), Flannery and Rangan (2006), Faulkender et al. (2012) and Elsas et al. (2014), we control for a vector of firm and

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[19] A number of studies (e.g. Christie, 1982; Bhandari, 1988; George and Hwang, 2010) suggest that leverage ratios proxying distress risk affect stock returns and variances.

[20] Hamada (1972) calculates a delevering formula with the Modigliani–Miller assumptions, under which the level of corporate debt is exogenously fixed. In contrast, Miles and Ezzell (1985) derive a delevering formula with the assumption that leverage ratios remain constant.

[21] We further investigate the relationship between asset volatility and macroeconomic uncertainty in Section 4.4.

industry characteristics that may affect a firm's target/optimal capital structure. All variables are computed for firm i over its fiscal year t. In the dynamic panel data regressions used to estimate target leverage, the control variables include the firm size measured by the natural logarithm of book total assets denominated in year-2000 dollars; market-to-book ratio defined as a ratio of the sum of the book value of debt and the market value of equity to the book value of total assets; profitability measured by the ratio of earnings before interests and taxes (EBIT) to total assets; assets tangibility measured by the ratio of net property, plant and equipment (PP&E) to total assets; depreciation and amortisation measured by the ratio of depreciation and amortisation expenses to total assets; R&D intensity measured by research and development (R&D) expenses as a proportion of total assets; a zero R&D firm indicator defined as a dummy variable for zero R&D expenses; and industry median book (or market) leverage ratios based on Fama and French's (1997) 48 industries. Detailed definitions of the variables used in this study are provided in Panel A, Table 1.

[Insert Table 1 Here]

3.3. Descriptive statistics

To minimise the effect of outliers, we winsorize all ratio variables at the top and bottom 1% of each variable's distribution. Panel B in Table 1 provides the summary statistics for the main variables used in this study. On average, a firm in the final sample has a book (market) leverage ratio of 17.1% (15.2%) and a book (market) target leverage ratio of 18.5% (16.1%).[22] The

[22] Note that the mean market and book leverage ratios are lower than those reported in other papers (e.g. Flannery and Rangan (2006): 24.9% and 27.8% for book and market leverage ratios, respectively; Frank and Goyal (2009): 29% and 28% for book and market leverage ratios, respectively; and Faulkender et al. (2012): 25.3% and 27.6% for book and market leverage ratios, respectively). The main reason for the differences is that this study focuses on the manufacturing sector. We find that manufacturing firms have lower leverage ratios compared with most non-manufacturing firms in the same sample period. For example, mean book (market) leverage ratio of firms in mining, utilities and construction industries is 30.2% (35.4%), which is much higher than that of manufacturing firms. When we consider all firms from the CRSP/Compustat Merged (CCM) database for the same sample period, the mean book and market leverage ratios are 22.7% and 24.6%, respectively, which are very close to those reported in the previous literature. In addition, there is a weakly declining trend in leverage ratios in the recent period. Note that our sample period is from 2003 to 2018 owing to the availability of some data required to calculate our main uncertainty

uncertainty measure, asset volatility ($\sigma_{i,t}$), has a mean value of 0.099 and a median value of 0.088. Panel B in Table 2 also reports the summary statistics for the control variables. In the sample, an average firm has book total assets of US$517 million, a market-to-book ratio of 1.68, EBIT scaled by total assets of 2.0%, PP&E scaled by total assets of 20.0%, depreciation expenses scaled by total assets of 3.8% and R&D expenses scaled by total assets of 6.6%.

Before investigating the effect of uncertainty on target leverage ratios, we examine whether actual leverage ratios are associated with uncertainty. Assuming that uncertainty is an important factor in determining target leverage ratios and that firms actually manage their leverage towards target leverage, actual leverage ratios should be correlated with targets. Thus, as a preliminary analysis, we sort firms based on uncertainty and test whether uncertainty is correlated with actual leverage ratios.[23] Panel A of Table 2 reports the summary statistics for actual leverage ratios for high- and low-uncertainty firms. A firm-year observation is categorised into either high- or low-uncertainty group depending on whether its asset volatility is above the sample median or equal to or below the sample median. The table shows that high-uncertainty firms tend to have substantially lower book and market leverage ratios than low-uncertainty firms. Panel A shows that the mean (median) difference in actual book leverage ratios between high-uncertainty and low-uncertainty firms is −10.9% (−16.3%), whereas the mean (median) difference in actual market leverage ratios is −9.3% (−12.5%).[24] Using Student's t-test and Wilcoxon's rank-sum test, we show that the mean and median differences are statistically significant at the 1% level. The differences are also economically significant, especially given that we define high-uncertainty and low-uncertainty firms based on the median of our uncertainty measure.

In addition, we examine whether the target leverage ratios estimated following the procedure used in Faulkender et al. (2012) are associated with uncertainty. In particular, we follow the procedure described in Section 3.4; however, we do not include asset volatility as a regressor to estimate target leverage ratios. Panel B of Table 2 shows that the mean (median) difference in book target leverage ratios between high-uncertainty and low-uncertainty firms is −8.8% (−12.4%), whereas the mean (median) difference in market target leverage ratios between high-uncertainty

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measure, i.e. asset volatility.

[23] We sincerely appreciate an anonymous referee's suggestion on this analysis.

[24] The difference in means (medians) is calculated as the mean (median) of high-uncertainty firms minus the mean (median) of low-uncertainty firms.

and low-uncertainty firms is -5.9% (-7.1%). Using Student's t-test and Wilcoxon's rank-sum test, we show that the mean and median differences are statistically significant at the 1% level. The differences are also economically significant, given that the mean book and market target leverage ratios are 18.5% and 18.7%, respectively.

[Insert Table 2 Here]

3.4. Research design

To investigate the effect of uncertainty on long-run leverage targets, we extend Flannery and Rangan's (2006) partial adjustment framework as stated below:

$$L_{i,t} - L_{i,t-1} = \lambda(L^*_{i,t} - L_{i,t-1}) + \kappa_t + \upsilon_{i,t}, \tag{2}$$

where $L_{i,t}$ is firm i's current leverage, $L^*_{i,t}$ is firm i's target leverage ratio, κ_t is an error component reflecting year fixed effects and $\upsilon_{i,t}$ is a white-noise error term. $L_{i,t} - L_{i,t-1}$ measures the actual change in leverage, or leverage adjustment, and $L^*_{i,t} - L_{i,t-1}$ measures the deviation from the target leverage ratio. The speed of adjustment parameter, λ, measures how fast a typical firm's actual leverage adjusts to its target leverage. The parameter is expected to lie between 0 and 1 with a higher λ indicating a faster speed of adjustment. Each year, a typical firm closes a proportion λ of the gap between where it stands ($L_{i,t-1}$) and where it hopes to be ($L^*_{i,t}$). As leverage measures ($L_{i,t}$), we consider both the book leverage ratio ($BL_{i,t}$) and market leverage ratio ($ML_{i,t}$).

To estimate target leverage ratios, we assume that a firm's target leverage ($L^*_{i,t}$) is a linear function of various firm characteristics ($\mathbf{X}_{i,t-1}$) with firm fixed effects (η^*_i) included.

$$L^*_{i,t} = \alpha + \beta'\mathbf{X}_{i,t-1} + \eta^*_i \tag{3}$$

$\mathbf{X}_{i,t-1}$ includes a firm-level uncertainty measure ($\sigma_{i,t}$) described in Section 3 as well as a set of firm and industry characteristics used in recent dynamic capital structure studies including Fama and French (2002), Flannery and Rangan (2006), Antoniou et al. (2008), Faulkender et al. (2012) and Elsas et al. (2014). The variables include firm size, market-to-book ratio, profitability, assets tangibility, depreciation and amortisation, R&D intensity, a zero R&D firm indicator, and industry median leverage ratios. Unlike the existing literature, we explicitly assume that there is unobserved heterogeneity in target leverage.[25] This study proposes a method to estimate fixed effects in target leverage and evaluate the importance of the fixed effects in the variation of target leverage. Panel A in Table 1 presents the definitions and summary statistics for the variables used in this study.

Substituting the target leverage equation into Eq. (2), we obtain the following model:

$$L_{i,t} = \lambda\alpha + (1-\lambda)L_{i,t-1} + \lambda\beta'\mathbf{X}_{i,t-1} + \kappa_t + \lambda\eta_i^* + \upsilon_{i,t}, \tag{4}$$

where $\lambda\eta_i^*$ and κ_t represent firm fixed effects and year fixed effects in actual leverage, respectively. Eq. (2) can be rewritten as the following standard dynamic panel regression model, which will serve as our main econometric framework:

$$L_{i,t} = b_0 + b_1 L_{i,t-1} + b_2'\mathbf{X}_{i,t-1} + \kappa_t + \eta_i + \upsilon_{i,t}, \tag{5}$$

where $b_0 = \lambda\alpha$, $b_1 = (1-\lambda)$, $b_2 = \lambda\beta$, and $\eta_i = \lambda\eta_i^*$. We include year dummies to control for year fixed effects (κ_t).[26] The speed of adjustment can be estimated as $\lambda = 1 - \hat{b}_1$. After obtaining λ, it is straightforward to obtain α, β, η_i^* and target leverage estimates ($L_{i,t}^*$) using Eq. (3).[27]

We employ four econometric methodologies to ensure that the estimated effect of uncertainty on target leverage is not attributable to the choice of estimation methods or instrument sets, although more weight will be given to system GMM and least squares dummy variables with a bias correction (LSDVC) results. Considering the increasingly recognised important role in the estimation of dynamic panel data models in corporate finance research, there is a need to resolve

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[25] Most of the existing studies assume that there is unobserved heterogeneity in actual leverage and are silent about how they estimate the fixed effects in target leverage. Among others, Im (2019) uses an approach very similar to our approach.

[26] If one replaces year fixed effects with year dummies, caution is required. To restore $\lambda\alpha$, one needs to adjust $\hat{b}_0$ by adding a constant to ensure that the mean of year effects estimated using year dummies is zero. The adjusted $\hat{b}_0$, or $\hat{b}_0^*$, should be equal to $\lambda\alpha$.

[27] Given the residual of the regression (i.e. $\varepsilon_{it} = \eta_i + \upsilon_{i,t}$), the fixed effects in actual leverage (η_i) can be estimated by calculating within-firm average residuals. The fixed effects in target leverage (η_i^*) can be estimated by dividing the fixed effects in actual leverage (η_i) by the speed of adjustment estimate (λ).

several estimation issues arising from fixed effects and lagged dependent variables. For instance, the ordinary least squares (OLS) and within groups (WG) estimates of the coefficient of the lagged dependent variable tend to be biased upwards and downwards, respectively. This situation is particularly true when the data have short panel length (Nickell, 1981; Bond, 2002). Therefore, the OLS or WG estimates of the coefficients of $\mathbf{x}_{i,t-1}$ in Eq. (4) and Eq. (5) are also likely to be biased.

Using simulated panel data, Flannery and Hankins (2013) show that the estimation performance of various econometric methodologies substantially varies depending on data complications, such as fixed effects, the persistence of the dependent variable, endogenous independent variables and error term autocorrelations. Flannery and Hankins (2013) find that the LSDVC estimator proposed by Bruno (2005) performs the best in the absence of endogenous independent variables, whereas the system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) appears to be the best choice in the presence of endogenous independent variables and even second-order serial correlation if the dataset includes shorter panels. Thus, we employ both system GMM and LSDVC estimators as well as OLS and WG estimators.

4. Empirical results

4.1. The effect of uncertainty on long-run leverage targets

To examine whether uncertainty increases or decreases a typical firm's target leverage ratio, we first estimate the dynamic panel regression model specified in Eq. (4). Tables 3 and 4 present the estimation results for book and market leverage ratios as the dependent variable, respectively. The four columns in each panel report the estimation results based on OLS, WG, LSDVC and System GMM estimators. We include firm fixed effects to control for unobserved time-invariant firm-specific characteristics in all estimation methods save OLS whereas we incorporate year fixed effects to account for temporal variations in all four specifications. System GMM appears to perform slightly better than LSDVC because *i)* the goodness-of-fit scores of the system GMM models (0.761 and 0.729 in Tables 3 and 4, respectively) are higher than those of LSDVC models (0.759 and 0.700 in Tables 3 and 4, respectively) and *ii)* LSDVC estimates are reported to be the most accurate only in the absence of endogenous independent variables. Therefore, we use the system GMM estimators of Blundell and Bond (1998) for target leverage estimation and other analyses in the rest of the paper. The estimated target book leverage ratio and target market leverage ratio are denoted as BL^* and ML^*, respectively.

[Insert Table 3 Here]

As the results based on market and book leverage ratios are qualitatively similar to each other, the following discussion will be based on the results in Table 3. As predicted by Nickell (1981) and Bond (2002), the coefficients of the lagged dependent variable estimated by system GMM ($\hat{b}_1^{GMM} = 0.770$) and LSDVC ($\hat{b}_1^{LSDVC} = 0.742$) comfortably fall between the OLS ($\hat{b}_1^{OLS} = 0.847$) and WG ($\hat{b}_1^{WG} = 0.609$) estimates.[28] System GMM results in Column (4) of Table 3 indicate that the overall book adjustment speed is approximately 23.0% per annum. The sensitivity of book targets to uncertainty is estimated to be -0.441 with statistical significance at the 1% level. That is, a one-standard-deviation increase in uncertainty leads to a decrease in the book target leverage of 15.6% of its one standard deviation.

We have similar results in Table 4 for market leverage models.[29] The system GMM estimate of overall market adjustment speed is approximately 24.2%, which is comparable to the literature. The system GMM estimate of the target-uncertainty sensitivity remains significant at the 1% level, with the sensitivity being -0.485—suggesting that a one-standard-deviation

[28] The GMM-style instruments used in Column (4) include the fourth and all available further lags of a leverage measure (BL and ML in Tables 3 and 4, respectively), the second to tenth lags of uncertainty and the second to tenth lags of all control variables for first-difference equations. Moreover, the third lags of the change in leverage and the first lags of the changes in uncertainty and all control variables are used as instruments for level equations. The Sargan-Hansen test of over-identifying restrictions does not reject this specification (p-value = 0.229), which supports the validity of our choice of instruments. Arellano and Bond's (1991) serial correlation tests find no significant evidence of the second-order serial correlation in the first-differenced residuals (p-value = 0.860). Some additional lags are available as instruments for the model for book leverage, but we use the same lags as instruments as the model for market leverage. However, the models with additional lags produce almost identical results.

[29] The Sargan-Hansen test of over-identifying restrictions does not reject this specification (p-value = 0.118), which supports the validity of our choice of instruments. Arellano and Bond's (1991) serial correlation tests find significant evidence of the first- to third-order serial correlation but do not find any significant evidence of the fourth-order serial correlation in the first-differenced residuals (p-value = 0.542).

increase in uncertainty leads to a decrease in the market target leverage of 16.5% of its one standard deviation.

[Insert Table 4 Here]

As discussed in Section 2, the effects of uncertainty through debt tax shields and agency benefits of debt cannot be determined *a priori*, although the effects of uncertainty through potential financial distress costs and debtholder–shareholder agency conflicts are expected to be *negative*. The ultimate impact of uncertainty on target leverage, therefore, depends on which forces dominate. When the sensitivity of a firm's target leverage ratios to uncertainty is negative and both economically and statistically significant based on both system GMM and LSDVC estimates, this suggests that either the effects of uncertainty through potential financial distress costs and debtholder–shareholder agency conflicts offset the opposite effects through debt tax shields and disciplining role of debt, or the effects of uncertainty through debt tax shields and/or agency benefits of debt are also played in the direction of lowering target leverage ratios. We further analyse the mechanisms through which uncertainty decreases target leverage ratios in Section 4.3.

Having provided evidence about the marginal effects of uncertainty on target leverage ratios, we proceed to gain further insight by comparing the target leverage ratios between high-uncertainty firms and low-uncertainty firms. Consistent with the analyses of the marginal effects of uncertainty on target leverage ratios, high-uncertainty firms tend to have significantly lower target leverage ratios than low-uncertainty firms. Panel A in Table 5 shows that the mean (median) difference in book target leverage ratios between high-uncertainty and low-uncertainty firms is -10.1 (-13.7) percentage points, whereas Panel B in Table 5 shows that the mean (median) difference in market target leverage ratios is -8.1 (-9.4) percentage points. Using Student's t-test and Wilcoxon's rank-sum test, we show that the mean and median differences in both book targets and market targets are statistically significant at the 1% level. The differences are also economically significant, especially given that we define high-uncertainty and low-uncertainty firms based on the median of our uncertainty measure. The differences are even more significant if terciles are used to group firms as high-uncertainty and low-uncertainty firms. This observation confirms our main results regarding the negative sensitivity of leverage targets to uncertainty reported in Tables 3 and 4.

[Insert Table 5 Here]

Moreover, we examine the contribution made by firm fixed effects on the leverage targets. That is, to calculate the contribution made by firm fixed effects, we decompose target leverage estimates with firm fixed effects into *i)* firm fixed effects ($\hat{\eta}_i^*$) and *ii)* leverage targets net of the effects. Table 6 also reports the summary statistics for firm fixed effects in book and market targets and their proportions in book and market targets. It shows that the mean (median) proportion of firm fixed effects on the target leverage ratios is 36.1% (32.0%) for book targets and 40.6% (38.6%) for market targets. Thus, firm fixed effects constitute significant parts in both book and market target leverage ratios. Table 5 also shows that firm fixed effects, whether positive or negative, are consistently prominent across the distribution. The 5th and 95th percentiles of the firm fixed effects in book targets (market targets) are –16.9% (–16.2%) and 25.7% (29.1%), respectively.

Furthermore, we implement the analysis of covariance (ANCOVA) to further examine the relative importance of various determinants in capturing the variation in the 'target' leverage ratios estimated following the procedure detailed in Section 3.4, in contrast with Lemmon et al.'s (2008) study which performs the ANCOVA for 'actual' leverage ratios. Table 6 presents the results of the variance decompositions for several specifications. Each column in the table corresponds to a different model specification for target leverage ratios. The numbers in the body of the table, excluding the last two rows, correspond to the contribution of each variable in a particular model. That is, following Lemmon et al. (2008), we measure the contribution of each variable by dividing the partial sum of squares for each effect by the aggregate partial sum of squares across all effects in the model so that the columns sum to one.

[Insert Table 6 Here]

The results are summarised as follows. First, the ANCOVA results reported in the last columns of Panels A and B in Table 6 show that the total variation of both book and market targets explained by uncertainty is 0.8%. This result suggests that the uncertainty effects in both book and market targets are greater than the effects of firm size, market-to-book, profitability, assets tangibility, R&D intensity, a zero R&D firm indicator and industry median leverage. In particular, uncertainty is the most important determinant of market target leverage ratios among all time-varying determinants. Second, the ANCOVA results show that time-invariant firm-specific effects are the major source of the total variation of leverage targets. The total variation of market targets explained by all time-varying determinants is only 2.8%, whereas the total variation of book targets explained by all time-varying determinants is only 3.2%. In other words, 97.2% and 96.8% of the total variations in market and book targets are explained by time-invariant firm fixed effects, respectively. Intuitively, this finding suggests that much of the explanatory power of existing target leverage determinants comes from the cross-sectional, as opposed to time-series, variation.

4.2. Mitigating potential endogeneity concerns

As discussed in the introduction, endogeneity is the obvious problem that we must address in identifying the directional effect of uncertainty on target/optimal capital structure. Although we use asset volatility as an uncertainty measure to address the reverse causality and measurement error concerns that arise when using equity volatility (as discussed in Section 3.2), further endogeneity concerns remain. First, target leverage ratios may be influenced by some important omitted factors (e.g. managerial risk aversion). Although we take into account the firm fixed effects in target leverage to minimise the omitted variables bias and measurement errors arising from the omission of some important factors, there may be some omitted unobservable time-varying variables correlated with the included target determinants. Second, both asset volatility and target/optimal capital structure are quite possibly driven by a third factor (e.g. the amount and nature of investment opportunities and industry life cycles). Finally, the reverse causality problem may not completely disappear even when we use asset volatility as an uncertainty measure.

To address these endogeneity concerns, we use IVs suggested by Alfaro et al. (2018). Our identification strategy exploits firms' differential exposure to 10 aggregate sources of uncertainty shock, including the annual changes in the implied return volatilities of currencies, energy and 10-year treasury bonds and the annual change in the realised volatility of the economic policy uncertainty (EPU) index.[30]

We employ the first-differenced two-stage least squares (2SLS) estimator for the AR(1) panel data model proposed by Anderson and Hsiao (1981, 1982). The second-stage regression model is specified as follows:

$$\Delta L_{i,t} = constant + (1-\lambda)\Delta L_{i,t-1} + \lambda\beta\Delta\sigma_{i,t-1} + \lambda\gamma'\Delta\mathbf{C}_{i,t-1} + \Delta\upsilon_{i,t}, \tag{6}$$

where $\Delta\sigma_{i,t-1}$ is the instrumented uncertainty shock, $\Delta L_{i,t-1}$ is the instrumented lagged change in leverage and $\Delta\mathbf{C}_{i,t-1}$ is a vector containing the first-differences of all target determinants except asset volatility.

To address the endogeneity concerns related to the lagged leverage change ($\Delta L_{i,t-1}$), we instrument $\Delta L_{i,t-1}$ with the lagged leverage level $L_{i,t-2}$.[31] Suppose that we have the following AR(1) panel data model:

$$L_{i,t} = \lambda\alpha + (1-\lambda)L_{i,t-1} + \lambda\beta\sigma_{i,t-1} + \lambda\gamma'\mathbf{C}_{i,t-1} + \eta_i + \upsilon_{i,t}, \tag{7}$$

where $\sigma_{i,t-1}$ is asset volatility and $\mathbf{C}_{i,t-1}$ is a vector containing all the target determinants except asset volatility. The first-differencing transformation eliminates the individual effects from the following model:

$$\Delta L_{i,t} = (1-\lambda)\Delta L_{i,t-1} + \lambda\beta\Delta\sigma_{i,t-1} + \lambda\gamma'\Delta\mathbf{C}_{i,t-1} + \Delta\upsilon_{i,t}. \tag{8}$$

The dependence of $\Delta\upsilon_{i,t}$ on $\upsilon_{i,t-1}$ implies that the OLS estimates of $(1-\lambda)$ in the first-differenced model are not consistent. However, a consistent estimate of $(1-\lambda)$ can now be

[30] Alfaro et al. (2018) use the following factors to estimate the industry-level sensitivities to the 10 aggregate uncertainty shocks. As currency factors, they use the growth in the exchange rates of the Federal Reserve Board's seven major currencies: Australian Dollar (AUD), Japanese Yen (JPY), Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Swedish Krona (SEK) and Euro (EUR). As the energy factor, they use the growth in crude oil prices. As the treasury bond factor, they use the return on the US 10-year treasury bond. As the EPU factor, they use the growth in the EPU index proposed by Baker et al. (2016). Refer to Alfaro et al. (2018) for details on how to construct non-directional and directional exposure to the 10 aggregate uncertainty shocks. The data for the exposure to the 10 aggregate sources of uncertainty shock are available at the following website: https://www.policyuncertainty.com/firm_uncertainty.html.

[31] We are grateful to an anonymous referee for suggesting this. The second-stage control variables are also included in the first-stage regressions.

obtained using 2SLS with IVs that are both correlated with $\Delta L_{i,t-1}$ and orthogonal to $\Delta \upsilon_{i,t}$. Together with the assumption that the disturbances $\upsilon_{i,t}$ are serially uncorrelated, the predetermined initial conditions imply that the lagged level $L_{i,t-2}$ will be uncorrelated with $\upsilon_{i,t}$ and thus be available as an IV for the first-differenced equation (Bond, 2002). Thus, we instrument $\Delta L_{i,t-1}$ with the lagged leverage level $L_{i,t-2}$.[32]

To address the endogeneity concerns related to the uncertainty shock ($\Delta \sigma_{i,t-1}$), we instrument $\Delta \sigma_{i,t-1}$ with the lagged industry-level (i.e. SIC 3-digit) non-directional exposure to 10 aggregate sources of uncertainty shocks. Following Alfaro et al. (2018), we also control for the lagged directional exposure to the 10 aggregate uncertainty shocks.[33]

Table 7 reports the 2SLS regression results based on book and market leverage ratios in Columns (1) through (3) and in Columns (4) through (6), respectively. Columns (1) and (2) (Columns (4) and (5)) report the first-stage regression results for a model for the first-difference in book (market) leverage. We test for weak instruments in each specification. The reported Wald F-statistics based on Kleibergen and Paap (2006) are higher than the Stock-Yogo critical value (i.e. five percent maximal IV relative bias), indicating that the included instruments are not weak instruments at the 5% significance level.

The second-stage results in Columns (3) and (6) are consistent with the system GMM results reported in Tables 3 and 4, respectively. The results show that the instrumented uncertainty shock has negative effects on the first-difference in book leverage ($\Delta BL_{i,t-1}$) and the first-difference in market leverage ($\Delta ML_{i,t-1}$) with significance at the 1% level. The estimated sensitivity of target leverage to uncertainty (β) is -2.192 for book targets and -4.309 for market targets, and both sensitivities are statistically significant at the 1% level. The estimated sensitivities for book targets (market targets) are five times (nine times) larger than those obtained

[32] The difference GMM (Arellano and Bond, 1991) and system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998) estimators are more efficient estimators; however, the endogeneity concerns related to the uncertainty shock ($\Delta \sigma_{i,t-1}$) cannot be straightforwardly addressed using the GMM estimators.

[33] The first-differenced model in a 2SLS framework is estimated because the uncertainty shock ($\Delta \sigma_{i,t-1}$), rather than the uncertainty level ($\sigma_{i,t-1}$), is instrumented using the IVs suggested by Alfaro et al. (2018).

from the system GMM estimation of the dynamic panel regression model, as specified in Eq. (4).[34] Using IV regressions, we find that high-uncertainty firms have significantly lower leverage targets than their low-uncertainty counterparts. Therefore, the analysis in this section allays our major endogeneity concerns regarding the main results reported in Section 4.1.

4.3. Mechanisms through which uncertainty lowers long-run leverage targets

In Section 2, we have identified four potential mechanisms through which uncertainty affects optimal/target leverage ratios, i.e. debt tax shields, financial distress costs, agency costs of debt and agency benefits of debt. The effects of uncertainty on leverage targets through financial distress costs and debtholder–shareholder agency conflicts are expected to be negative, but the effects through debt tax shields and agency benefits of debt can be either negative or positive. Thus, we have investigated whether uncertainty increases or decreases leverage targets in Section 4.1, finding that uncertainty lowers optimal/target leverage ratios. In this subsection, we examine through which mechanisms uncertainty lowers leverage targets. The results are presented in Tables 8 and 9.

[Insert Table 8 Here]

4.3.1. Through debt tax shields

The effects of uncertainty on target leverage ratios through debt tax shields can be *negative* or *positive* depending on the magnitude of two conflicting effects. The negative effect is directly related to the impact of uncertainty on debt tax shields. A high-uncertainty firm that has lower and more volatile earnings is expected to have a higher chance of having no taxable income. Consequently, its expected tax rate and expected payoff from interest tax shields will be lower. Thus, uncertainty can lower target leverage ratios by lowering debt tax shields. The positive effect is derived from the impact of uncertainty on non-debt tax shields. A high-uncertainty firm that has lower R&D expenditures and depreciation expenses is expected to benefit more from debt tax shields if the amount of debt is given, in which case uncertainty can raise target leverage ratios by

[34] The estimates of the overall book and market adjustment speeds are similar to those obtained from the system GMM estimation of the dynamic panel regression model, as specified in Eq. (4).

increasing debt tax shields.

Given that we find evidence that uncertainty lowers target leverage ratios, we investigate whether some of the effects of uncertainty can be attributed to debt tax shields. A simple way to test this is to see if uncertainty reduces the present value of tax shields (Stage 1) and if the reduction in the present value of tax shields lowers target leverage (Stage 2), using a 2SLS procedure.[35] To measure the present value of debt tax shields, we first calculate tax rate, τ, as corporate tax payments divided by pre-tax income. Under the assumption of a perpetual debt, the present value of tax shields is computed as tax-deductible debt (the sum of long-term debt and short-term debt) multiplied by the tax rate (τ). We then scale the present value of tax shields by total assets to obtain a measure of debt tax shields, $TXSHLD_{i,t}$.

The first two columns in Tables 8 and 9 report the results of 2SLS analyses for book leverage targets and market leverage targets, respectively. The first-stage regression results show that heightened uncertainty ($\sigma_{i,t-1}$) reduces the present value of debt tax shields ($TXSHLD_{i,t}$) with significance at the 1% level. The second-stage regression results show that a higher present value of tax shields ($TXSHLD_{i,t}$) leads to a higher target leverage ratio ($BL^*_{i,t}$ and $ML^*_{i,t}$) with significance at the 1% level. The results provide evidence that high uncertainty leads to a lower optimal/target leverage ratio by decreasing the present value of debt tax shields.

4.3.2. Through financial distress costs

As a firm faced with higher uncertainty tends to have higher expected bankruptcy costs, the effects of uncertainty on target leverage ratios through potential financial distress costs are expected to be *negative*. Given that we find evidence that uncertainty lowers target leverage ratios, we further investigate whether some of the effects of uncertainty can be attributed to financial distress costs. Again, we employ a 2SLS procedure to examine if uncertainty increases bankruptcy costs (Stage 1) and if the increase in bankruptcy costs lowers target leverage (Stage 2). To implement this test, we employ the modified Altman's Z-score (MZ) proposed by Graham et al. (1998) and used by

[35] We employ the 2SLS procedure by assuming that the present value of tax shields is endogenous but asset volatility is exogenous. The first-stage regression can verify whether asset volatility increases or decreases the present value of tax shields, whereas the second-stage regression can verify whether the estimated present value of tax shields increases or decreases target leverage.

Chava et al. (2008) and Im (2012).[36]

Columns (3) and (4) in Tables 8 and 9 report the results of 2SLS analyses designed to test the financial distress costs channel for book leverage targets and market leverage targets, respectively. The first-stage regression results show that heightened uncertainty ($\sigma_{i,t-1}$) lowers the modified Altman's Z-score ($MZ_{i,t}$) (i.e. increases financial distress costs) with significance at the 1% level. The second-stage regression results show that a higher modified Altman's Z-score ($MZ_{i,t}$) leads to a higher target book leverage ratio ($BL^{*}_{i,t}$ and $ML^{*}_{i,t}$) with significance the 1% level.[37] The results provide evidence that heightened uncertainty leads to a lower optimal/target leverage ratio by increasing financial distress costs and exacerbating financial constraints.

[Insert Table 9 Here]

4.3.3. Through agency costs of debt

The effects of uncertainty on target leverage ratios through agency costs of debt are expected to be *negative*. A high-uncertainty firm faces more severe under-investment and asset substitution problems because uncertainty makes both assets in place and investment projects riskier. In response to the exacerbated agency conflicts, a high-uncertainty firm is expected to choose a *lower*

[36] The modified Altman's Z-score that is inversely related to bankruptcy costs is calculated as follows: $MZ = 1.2X_1 + 1.4X_2 + 3.3X_3 + X_4$, where X_1 is the ratio of working capital to total assets, X_2 is the ratio of retained earnings to total assets, X_3 is the ratio of earnings before interests and taxes to total assets and X_4 is the ratio of sales to total assets. The modified Altman's Z-score which does not include leverage is appropriate as we use it to predict target/optimal leverage.

[37] Following an anonymous referee's suggestion, we consider Hadlock and Pierce's (2010) financial constraints index (a.k.a. SA index) as another proxy of financial distress costs. Although financial constraints and financial distress are two different concepts, a more financially constrained firm is clearly more likely to have a higher probability of bankruptcy. We obtain similar results using the SA index, and they are reported in Columns (5) and (6) of Tables 8 and 9. The first-stage regression result shows that heightened uncertainty ($\sigma_{i,t-1}$) increases the SA index ($SA_{i,t}$) (i.e. exacerbates financial constraints) with significance at the 1% level. The second-stage regression result shows that a higher SA index ($SA_{i,t}$) leads to a lower target leverage ratio ($BL^{*}_{i,t}$ and $ML^{*}_{i,t}$) with significance at the 1% level.

optimal/target leverage ratio. Given that this study finds evidence that uncertainty lowers target leverage ratios, we further investigate whether some of the effects of uncertainty can be attributed to the exacerbated debtholder–shareholder conflicts. To investigate whether uncertainty increases agency costs of debt and whether the increase in agency costs lowers target leverage, we employ a 2SLS procedure. As a proxy for the debtholder–shareholder agency conflicts, we utilise the likelihood of covenant violation following Nini et al. (2009). To measure the likelihood of covenant violation $VIOLYR$, we use a dummy variable that equals one if a firm reports a loan covenant violation in an SEC 10-K or 10-Q filing for a given year and zero otherwise.[38]

Columns (7) and (8) in Tables 8 and 9 report the results of 2SLS analyses for book leverage targets and market leverage targets, respectively. The first-stage regression results show that heightened uncertainty ($\sigma_{i,t-1}$) increases the likelihood of covenant violation ($VIOLYR_{i,t}$) with significance at the 1% level. The second-stage regression results show that a higher likelihood of covenant violation ($VIOLYR_{i,t}$) leads to a lower target leverage ratio ($BL^*_{i,t}$ and $ML^*_{i,t}$) with significance at the 1% level. The results provide evidence that heightened uncertainty leads to a lower optimal/target leverage ratio by exacerbating debtholder–shareholder conflicts.

4.3.4. Through agency benefits of debt

Jensen (1986) shows that agency costs increase with free cash flows and that debt may reduce the free cash flow agency problem by ensuring that managers are disciplined. However, the effect of uncertainty on target leverage ratios through agency benefits of debt is not clear-cut. If a firm has many profitable assets in place, the profitability of its assets in place will be lower when it is faced with high uncertainty. For the firm, high uncertainty will lead to less free cash flows and therefore lower shareholder–manager agency costs. Thus, high uncertainty will lower the value of debt as a disciplining device to the firm, implying that the effect of uncertainty on the optimal leverage ratio will be *negative*. However, if a firm has many profitable investment opportunities, a high-uncertainty firm will have a higher value of the real option to wait (Bloom et al., 2007; Gulen

[38] Data regarding loan covenant violations are available at Amir Sufi's website: http://faculty.chicagobooth.edu/amir.sufi/data.html. We construct an annualised loan covenant violation measure by modifying an original quarterly measure. The firm-year specific loan covenant violation measure equals one if there is at least one violation across four quarters in that year and zero otherwise.

and Ion, 2015), leading to more free cash flows and therefore higher shareholder–manager agency costs. Thus, it is possible for a high-uncertainty firm to receive more benefits from the disciplining role of debt.

Given that we find evidence that uncertainty lowers target leverage ratios, we investigate whether some of the effects of uncertainty are attributed to the reduction in agency benefits of debt driven by increased uncertainty. A 2SLS procedure is employed to examine if uncertainty reduces shareholder–manager agency conflicts (Stage 1) and if the reduction in shareholder–manager conflicts lowers target leverage (Stage 2). To implement this test, we employ the percentage of shares held by blockholders, $SUMBLKS$, which is inversely related to the degree of the shareholder–manager agency conflicts.[39]

Columns (9) and (10) in Tables 8 and 9 report the results of 2SLS analyses for book leverage targets and market leverage targets, respectively. The first-stage regression results show that heightened uncertainty ($\sigma_{i,t-1}$) does not have a significant impact on the percentage of shares held by blockholders ($SUMBLKS_{i,t}$) (i.e. the agency conflicts between shareholders and managers). The second-stage regression results also show that a higher percentage of shares held by blockholders ($SUMBLKS_{i,t}$) does not have a significant influence on target leverage ($BL^{*}_{i,t}$ and $ML^{*}_{i,t}$). Thus, the results do *not* provide sufficient evidence that heightened uncertainty leads to a lower optimal/target leverage ratio by lowering agency benefits related to the disciplining role of debt.

The analyses reported above show evidence supporting the financial distress costs channel and the debtholder–shareholder conflicts channel as well as the debt tax shields channel. The results suggest that uncertainty decreases debt tax shields, increases potential financial distress costs and exacerbates debtholder–shareholder conflicts (e.g. under-investment and risk-shifting problems), thereby leading to a lower optimal/target leverage ratio.

4.4. Additional analyses

4.4.1. Moderating role of managerial risk aversion

[39] Data regarding blockholders' shareholdings used by Dlugosz et al. (2006) are available at Andrew Metrick's website: http://faculty.som.yale.edu/andrewmetrick/data.html.

In this subsection, we test whether the effect of uncertainty is greater for firms whose managers are more risk averse. Lambrecht and Myers (2017) suggest that the negative association between uncertainty and target leverage is moderated by managerial risk aversion. That is, when top managers are more risk averse, uncertainty may have a more pronounced negative effect on target leverage. To shed light on the moderating role of managerial risk aversion, we conduct a subsample analysis. Motivated by stock option research in which risk-averse and undiversified executives may choose to exercise options early (Hall and Murphy, 2002), we identify risk aversion based on their stock option holdings.[40] For the analysis, we focus on the risk aversion of CEOs. We classify a CEO as being risk averse if he/she holds options that are less than 67% in the money or if he/she chooses to exercise the stock options in a year. We further classify the CEOs without any option grant as being risk averse. Consistent with the notion that risk aversion is a persistent personal trait, the CEOs identified as being risk averse remain to be so for the entire sample period.[41] The threshold of 67% is chosen following Malmendier and Tate's (2005) study in which Hall and Murphy's (2002) model is calibrated. Option moneyness is estimated as the ratio of realisable value per option to exercise price (Campbell et al., 2011), where exercise price is estimated as the per-option realisable value net of stock price at the end of each fiscal year and the per-option realisable value is the total realisable value of exercisable options divided by the number of exercisable options.

The system GMM estimation results are presented in Table 10. In Column (1) and Column (2), the dependent variable is book leverage, whereas in Column (3) and Column (4), the dependent variable is market leverage. We partition the sample based on the option-based risk aversion measure into firms with more risk-averse CEOs and firms with less risk-averse CEOs. Columns (1) and (2) (Columns (3) and (4)) show that the negative effect of asset volatility on book (market) target leverage is more pronounced for firms with more risk-averse CEOs. In addition, the estimated sensitivities of both book and market target leverage to asset volatility are

[40] In an untabulated analysis, we define risk aversion based on a political-ideology-based measure following Hutton et al. (2014) andDeng et al. (2018). In particular, we consider a CEO as being risk averse if he/she exclusively makes political contributions to the Republican Party. We find that the results are robust to the use of the alternative measures.

[41] A similar method is found in the studies of Hirshleifer et al. (2012) and Hribar and Yang (2016), wherein overconfidence is considered as a persistent personal trait.

statistically significant for firms with more risk-averse CEOs but not for firms with less risk-averse CEOs. Thus, our results in Table 10 are consistent with Lambrecht and Myers' (2017) model predicting that managerial risk aversion moderates the negative association between firm uncertainty and target leverage.

4.4.2. Uncertainty and leverage under alternative capital structure theories

Some studies maintain that whether firms tend to adjust towards target leverage is inconclusive (Chang and Dasgupta, 2009; Welch, 2004). In addition, Graham and Harvey (2001) report that 81%, not 100%, of firms consider a target debt ratio or range when making their capital structure decisions. Therefore, some firms' capital structure policies may not be consistent with what the trade-off theory predicts. Thus, we first discuss the theoretical predictions of the effect of uncertainty on (optimal) leverage under two alternative capital structure theories (i.e. pecking order theory and market timing theory) and then empirically test whether the negative effect of uncertainty on (optimal) leverage is more pronounced for firms whose leverage adjustment patterns are more consistent with a dynamic trade-off theory.

Unlike the static/dynamic trade-off theory, the pecking order and market timing theories both suggest that uncertainty has a positive effect on (optimal) leverage. First, in the pecking-order world with asymmetric information between managers and outside investors (Myers, 1984; Myers and Majluf, 1984), higher-uncertainty firms are likely to face more severe information asymmetry and thus have higher information production costs. Thus, higher-uncertainty firms are expected to prefer debt over equity, implying a positive association between uncertainty and leverage. Second, in the market-timing world (Baker and Wurgler, 2002; Graham and Harvey, 2001), managers are more likely to issue (repurchase) equity when their market values are high (low) relative to book and past market values. Thus, higher-uncertainty firms are less likely to issue equity, implying a positive association between uncertainty and leverage.

To examine whether the negative effect of uncertainty on (optimal) leverage is more pronounced for firms whose leverage adjustment patterns are more consistent with a dynamic trade-off theory, we classify firms into two groups based on the first-order autoregressive regression coefficient (i.e. $1-\lambda$) of each firm's first-order autoregressive (i.e. AR(1)) model:

$$L_t = \lambda\alpha + (1-\lambda)L_{t-1} + \varepsilon_t, \tag{9}$$

for firm $i = 1, \cdots, N$.[42] In particular, we classify firms with λ in the range of (0,1) as 'trade-off firms' and firms with λ outside the range as 'non-trade-off firms'. We conduct a sub-sample analysis designed to examine whether the effect of uncertainty on target leverage is different between these two groups of firms.

Table 11 reports the system GMM estimation results for the models similar to those in Tables 3 and 4. Consistent with our predictions stated above, the effect of uncertainty on target leverage is negative and significant only for 'trade-off firms'. In the model for book (market) leverage, the coefficient of uncertainty for 'trade-off firms' is negative and statistically significant at the 5% (1%) level. However, the coefficients of uncertainty for 'non-trade-off firms' are not statistically significant at conventional levels in both models. We also report that the sensitivity of book (market) target leverage to uncertainty for 'trade-off firms' is negative and significant at the 5% (1%) level. The magnitudes of the target-uncertainty sensitivities are similar to those reported in Tables 3 and 4. However, target-uncertainty sensitivities are not significant for 'non-trade-off firms' in both book and market leverage models. Overall, the negative effect of uncertainty on target leverage is much more pronounced for firms whose capital structure decisions are consistent with the dynamic trade-off theory.

4.4.3. Robustness tests

As discussed in Section 3.2, asset volatility as an uncertainty measure has several advantages over alternative uncertainty measures, particularly when investigating the effect of uncertainty on actual/optimal leverage. However, many alternative uncertainty measures have been used in the literature. As alternative uncertainty measures, we consider the following four uncertainty proxies: volatility index (VIX) (Brenner and Galai, 1989), economic policy uncertainty (EPU) index (Baker et al., 2016), equity volatility (Bloom et al., 2007) and implied volatility (Alfaro et al., 2018). Among them, the first two are macro-level uncertainty measures whereas the remaining two are firm-level uncertainty measures. We perform several robustness tests using those proxies.

[42] A firm-by-firm AR(1) model is essentially the same as a partial adjustment model of leverage with a constant target leverage ratio. Thus, $(1 - \lambda)$ can be interpreted as each firm's speed of leverage adjustment. There are substantial sampling errors owing to limited sample size, but it makes sense to use the estimates to identify firms whose capital structure policies are more (or less) consistent with the dynamic trade-off theory. We are grateful to an anonymous referee for suggesting this analysis.

The robustness tests presented in the internet appendix (Section A) suggest that our main finding—asset volatility lowers target leverage—is not driven by the correlation between asset volatility and macroeconomic uncertainty and that asset volatility has a significant incremental impact on target leverage in excess of the impact of macroeconomic uncertainty. Furthermore, we show that a firm-level business uncertainty measure (independent of capital structure decisions)—asset volatility—has a significantly larger effect on target leverage than the two alternative firm-level uncertainty measures.[43]

Furthermore, we examine whether our results are driven by the use of manufacturing firms with detailed debt data. First, we estimate the dynamic panel regression models (in Section 4.1) using a less restricted sample. Following Fama and French (2002), Flannery and Rangan (2006) and Faulkender et al. (2012), we include all industries except financial services and regulated utilities in our sample. Next, we estimate the IV regression models (in Section 4.2) using the less restricted sample and using equity volatility as an uncertainty measure. By doing so, we include firms that do not have detailed debt data into the sample. The results are presented in the internet appendix (Section B). We find that the negative impact of uncertainty is still valid in a more generalized sample, suggesting that our main results are not driven by the selection of extreme firms or availability of detailed debt data.

5. Conclusion

This study investigates how uncertainty affects firms' optimal capital structures using a panel data set of U.S. public manufacturers between 2003 and 2018. In this paper, we address this question by first identifying the directional effect of increased uncertainty on leverage targets and then considering through which mechanisms uncertainty affects target leverage ratios. Using asset volatility as an uncertainty measure and target/optimal leverage ratios obtained by estimating a partial adjustment model, we find that uncertainty lowers firms' target leverage ratios. High-uncertainty firms have 10.1 (8.1) percentage points lower mean book (market) targets than low-uncertainty firms. This study also shows that the effect of uncertainty on leverage targets is

[43] As discussed earlier, the two alternative firm-level proxies based on stock returns may be influenced by capital structure decisions. Thus, the impact of uncertainty on target leverage cannot be estimated consistently when equity volatility or implied volatility is used as an uncertainty measure.

greater than the impact of firm size, market-to-book ratio, assets tangibility, R&D intensity and industry median leverage, making uncertainty the most crucial determinant among all time-varying determinants of leverage targets. This paper also explores several possible mechanisms through which uncertainty could influence target leverage ratios by empirically testing the effects of uncertainty on debt tax shields, financial distress costs and agency costs and benefits. The results suggest that heightened uncertainty leads to a lower optimal leverage ratio by decreasing debt tax shields, increasing potential financial distress costs and exacerbating debtholder–shareholder conflicts.

Appendix: Approximating loan returns

For firm-month observations without loan sale information, we approximate loan returns using bond returns following Choi (2013). First, we classify firms into three groups based on their S&P credit ratings. Second, we estimate the following regression model by the three groups:

$$R^L - R^F = \alpha + \beta_1(R^B - R^F) + \beta_2(R^T - R^F) + \varepsilon,$$

where R^T is the return on a one-year treasury bond, R^B is the return on bonds, R^L is the return on bank loans and R^F is one-month T-bill rate. The inclusion of $R^T - R^F$ allows us to consider the difference in interest sensitivities between bonds and loans. In addition, estimating separate regression models by credit rating groups allows us to take into account the differential correlation between bond returns and loan returns with respect to the varying credit risks of the underlying assets. Presumably, we expect to see a stronger predictive power of bond returns on loan returns for firms with a lower credit rating. Regression results are reported in Table A1.

Table A1: Regression results used to approximate loan returns

	Dependent variable: $R^L - R^F$		
	(1)	(2)	(3)
	BBB and above	Between BBB and B	Below B or unrated
$R^B - R^F$	0.232***	0.336***	0.381***
	(0.002)	(0.001)	(0.002)
$R^T - R^F$	-1.298***	-1.293***	-1.275***
	(0.009)	(0.009)	(0.015)

Adjusted R^2	0.325	0.592	0.432

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Table 1: Variable definitions and summary statistics

Panel A shows the definitions of the variables used in this study. The italicised codes in square brackets represent item codes in the CRSP/Compustat Merged database. Panel B shows the summary statistics for the variables used in this study. The variables are constructed using a sample of U.S. public firms in the manufacturing industry from 2003 to 2018. The sample comprises firms that have at least 10 years of uninterrupted observations. All ratio variables are winsorized at the 1st and 99th percentiles.

Panel A. Variable definitions

Definition	Calculation
Leverage-related variables	
Book leverage	Total debt ([*dltt*]+[*dlc*]) over book total assets [*at*]
Market leverage	Total debt ([*dltt*]+[*dlc*]) over market value of total assets ([*dltt*]+[*dlc*]+[*cshpri*]*[*prcc_f*])
Book target	Target book leverage ratio estimated using system GMM results in Table 3
Market target	Target market leverage ratio estimated using system GMM results in Table 4
Uncertainty-related variables	
Asset volatility	Standard deviation of a firm's monthly asset returns for each fiscal year, where asset returns are calculated following Choi and Richardson (2016)
Control variables	
Firm size	Natural logarithm of total assets denominated in year-2000 dollars
Market-to-book ratio	Market total assets ([*dlc*] + [*dltt*] + [*cshpri*] * [*prcc_f*]) to book total assets ([*at*])
Profitability	Earnings before interests and taxes ([*ib*]+[*xint*]+[*txt*]) over total assets ([*at*])
Tangibility	Total property, plant and equipment net of accumulated depreciation ([*ppent*]) over total assets ([*at*])
Depreciation	Depreciation and amortisation expenses ([*dp*]) over total assets ([*at*])
R&D intensity	R&D expenses ([*xrd*]) over total assets ([*at*]) (0 if missing)
Zero R&D firm indicator	Dummy variable, which equals one if a firm does not report R&D expenses in year t, and zero otherwise.
Industry median book leverage	Industry median book leverage, where the industry is defined following Fama and French (1997)
Industry median market leverage	Industry median market leverage, where the industry is defined following Fama and French (1997)

Panel B. Summary statistics

Variables	Obs.	Mean	S.D.	P05	P25	Median	P75	P95
Leverage-related variables								
Book leverage	14,546	0.171	0.157	0.000	0.009	0.152	0.278	0.465
Market leverage	14,546	0.153	0.168	0.000	0.005	0.106	0.232	0.506
Book target	14,546	0.185	0.150	0.000	0.054	0.169	0.278	0.462
Market target	14,546	0.161	0.156	0.000	0.041	0.123	0.233	0.485

Uncertainty-related variables								
Asset volatility	14,546	0.099	0.053	0.033	0.059	0.088	0.129	0.205
Control variables								
Firm size	14,546	6.249	2.045	3.028	4.741	6.184	7.662	9.789
Market-to-book ratio	14,546	1.684	1.287	0.540	0.897	1.307	1.991	4.133
Profitability	14,546	0.020	0.201	-0.395	-0.005	0.069	0.121	0.221
Tangibility	14,546	0.200	0.150	0.022	0.088	0.163	0.277	0.511
Depreciation	14,546	0.038	0.021	0.010	0.024	0.034	0.047	0.077
R&D intensity	14,546	0.066	0.103	0.000	0.004	0.027	0.084	0.272
Zero R&D firm indicator	14,546	0.206	0.405	0.000	0.000	0.000	0.000	1.000
Industry median book leverage	14,546	0.146	0.083	0.031	0.080	0.146	0.205	0.283
Industry median market leverage	14,546	0.117	0.087	0.013	0.045	0.099	0.174	0.295

Table 2: Comparison of actual and target leverage ratios by the level of uncertainty

This table reports the summary statistics for actual and target leverage ratios for high- and low-uncertainty firms in Panels A and B, respectively. Each panel reports the summary statistics for actual or target leverage ratios in the full sample and those for high- and low-uncertainty firms. In Panel B, target leverage ratios are estimated following the procedure used in Faulkender et al. (2012). In particular, we follow the procedure described in Section 3.4; however, we do not include asset volatility as a regressor to estimate target leverage ratios. A firm-year observation is classified into a subsample of high-uncertainty firms (low-uncertainty firms) if asset volatility is above median (is equal to or below median). The differences in mean and median leverage ratios between the two groups are reported with the t-statistic of Student's t test or z-statistic of Wilcoxon's rank-sum test. Superscript *** indicates statistical significance at the 1% level.

Panel A. Comparison of actual leverage ratios by the level of uncertainty

Variables	Obs.	Mean	S.D.	P05	P25	Median	P75	P95
Actual book leverage of all firms	14,546	0.171	0.157	0.000	0.009	0.152	0.278	0.465

High-uncertainty firms	7,273	0.117	0.142	0.000	0.000	0.061	0.197	0.405
Low-uncertainty firms	7,273	0.226	0.153	0.000	0.111	0.224	0.326	0.497
Difference (High – Low)		*-0.109****				*-0.163****		
t -stat/ z -stat		*44.57*				*44.67*		
Actual market leverage of all firms	14,546	0.153	0.168	0.000	0.005	0.106	0.232	0.506
High-uncertainty firms	7,273	0.107	0.149	0.000	0.000	0.039	0.165	0.429
Low-uncertainty firms	7,273	0.199	0.174	0.000	0.067	0.164	0.284	0.566
Difference (High – Low)		*-0.093****				*-0.125****		
t -stat/ z -stat		*34.58*				*40.21*		

Panel B. Comparison of target leverage ratios estimated without uncertainty by the level of uncertainty

Variables	Obs.	Mean	S.D.	P05	P25	Median	P75	P95
Book targets estimated without asset volatility	14,546	0.185	0.151	0.000	0.052	0.168	0.278	0.463
High-uncertainty firms	7,273	0.141	0.144	0.000	0.023	0.104	0.215	0.422
Low-uncertainty firms	7,273	0.229	0.145	0.005	0.118	0.227	0.319	0.483
Difference (High – Low)		*-0.088****				*-0.124****		
t -stat/ z -stat		*36.83*				*39.56*		
Market targets estimated without asset volatility	14,546	0.157	0.154	0.000	0.040	0.120	0.227	0.480
High-uncertainty	7,273	0.128	0.146	0.000	0.019	0.083	0.185	0.420

firms								
Low-uncertainty firms	7,273	0.187	0.156	0.000	0.073	0.154	0.258	0.505
Difference (High – Low)		*-0.059****				*-0.071****		
t *-stat/* z *-stat*		*23.55*				*28.66*		

Table 3: Estimation of the sensitivity of book leverage targets to uncertainty

This table reports the results of the book target leverage estimation regressions using the OLS, WG, LSDVC and system GMM estimators. The empirical model used is as follows: $BL_{i,t} = Constant + (1-\lambda)BL_{i,t-1} + \lambda\beta'\mathbf{X}_{i,t-1} + Year\ fixed\ effects + \eta_i + \upsilon_{i,t}$. The dependent variable is book leverage. A detailed description of the variables included in the models is provided in Panel A of Table 1. In the OLS and WG estimators, standard errors are clustered by firm and displayed in parentheses below. In the LSDVC models, the Blundell-Bond estimator is chosen as an initial estimator, and bootstrapped standard errors are reported. In the system GMM, we report two-step GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The IVs used in system GMM reported in Column (4) are the second to tenth lags of standardised uncertainty, the fourth to all available lags of leverage and the second to tenth lags of firm-specific control variables for the equations in first-differences, as well as the change in standardised uncertainty, the third lag of change in leverage and the 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 the Arellano-Bond tests for first-order and second-order serial correlations in first-differenced residuals, respectively. Sargan-Hansen represents the test statistic of the Sargan-Hansen test of over-identifying restrictions. Overall goodness-of-fit scores, measured as the square of the coefficient of correlation between the dependent variable and its predicted value, are reported for OLS, WG, LSDVC and system GMM. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Dependent variable: Book leverage			
	(1)	(2)	(3)	(4)

Estimation method	OLS	WG	LSDVC	System GMM
Lagged book leverage	0.847***	0.609***	0.742***	0.770***
	(0.007)	(0.011)	(0.008)	(0.019)
Asset volatility	-0.082***	-0.080***	-0.061***	-0.101***
	(0.017)	(0.021)	(0.019)	(0.030)
Firm size	0.003***	0.010***	0.007***	0.006***
	(0.000)	(0.002)	(0.002)	(0.002)
Market-to-book ratio	0.001*	0.001	0.001	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Profitability	-0.019***	-0.024***	-0.020***	-0.021*
	(0.006)	(0.009)	(0.006)	(0.011)
Tangibility	0.009	0.019	0.013	0.026
	(0.006)	(0.018)	(0.014)	(0.022)
Depreciation	-0.037	-0.239***	-0.260***	-0.394***
	(0.042)	(0.081)	(0.065)	(0.112)
R&D intensity	-0.009	0.013	-0.008	-0.006
	(0.013)	(0.026)	(0.018)	(0.030)
Zero R&D firm indicator	0.005**	0.014**	0.013**	0.009
	(0.002)	(0.006)	(0.005)	(0.008)
Industry median book leverage	0.028***	0.043**	0.032	0.042
	(0.010)	(0.022)	(0.023)	(0.027)
Firm fixed effects	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	14,546	14,546	14,547	14,546
Number of firms	1,455	1,455	1,455	1,455
Goodness of fit score	0.765	0.747	0.759	0.761
m1				-16.93
(p -value)				(0.000)
m2				-0.177
(p -value)				(0.860)
Sargan-Hansen				1049

(p -value)				(0.229)
Speed of adjustment (λ)	0.153***	0.391***	0.258***	0.230***
	(0.007)	(0.011)	(0.008)	(0.019)
Target-uncertainty sensitivity (β)	-0.537***	-0.203***	-0.235***	-0.441***
	(0.105)	(0.054)	(0.071)	(0.131)

Table 4: Estimation of the sensitivity of market leverage targets to uncertainty

This table reports the results of the market target leverage estimation regressions using the OLS, WG, LSDVC and system GMM estimators. The empirical model used is as follows: $ML_{i,t} = Constant + (1-\lambda)ML_{i,t-1} + \lambda\beta'\mathbf{X}_{i,t-1} + Year\ fixed\ effects + \eta_i + \upsilon_{i,t}$. The dependent variable is market leverage (ML). A detailed description of the variables included in the models is provided in Panel A of Table 1. In the OLS and WG estimators, standard errors are clustered by firm and displayed in parentheses below. In the LSDVC models, the Blundell-Bond estimator is chosen as an initial estimator, and bootstrapped standard errors are reported. In the system GMM, we report two-step GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The IVs used in system GMM reported in Column (4) are the second to tenth lags of standardised uncertainty, the fourth to all available lags of leverage and the second to tenth lags of firm-specific control variables for the equations in first-differences, as well as the change in standardised uncertainty, the third lag of change in leverage and the 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, m2, m3 and m4 represent the test statistics of the Arellano-Bond tests for first-order to fourth-order serial correlations in first-differenced residuals, respectively. Sargan-Hansen represents the test statistic of the Sargan-Hansen test of over-identifying restrictions. Overall goodness-of-fit scores, measured as the square of the coefficient of correlation between the dependent variable and its predicted value, are reported for OLS, WG, LSDVC and system GMM. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Dependent variable: Market leverage

	(1)	(2)	(3)	(4)
Estimation method	OLS	WG	LSDVC	System GMM
Lagged market leverage	0.815***	0.542***	0.664***	0.758***
	(0.008)	(0.013)	(0.009)	(0.019)
Asset volatility	-0.062***	-0.093***	-0.077***	-0.118***
	(0.020)	(0.025)	(0.021)	(0.036)
Firm size	0.002***	0.017***	0.015***	0.001
	(0.000)	(0.003)	(0.002)	(0.002)
Market-to-book ratio	-0.002***	-0.002*	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Profitability	-0.011*	-0.017*	-0.011*	0.002
	(0.006)	(0.009)	(0.007)	(0.013)
Tangibility	0.022***	0.048**	0.042***	0.059**
	(0.008)	(0.019)	(0.016)	(0.024)
Depreciation	-0.060	-0.132*	-0.215***	-0.349***
	(0.048)	(0.098)	(0.073)	(0.124)
R&D intensity	-0.022*	0.014	0.021	-0.047*
	(0.012)	(0.028)	(0.020)	(0.027)
Zero R&D firm indicator	0.011***	0.013	0.010*	0.013
	(0.005)	(0.008)	(0.006)	(0.009)
Industry median market leverage	0.009	0.053**	0.033	-0.047*
	(0.012)	(0.023)	(0.022)	(0.024)
Firm fixed effects	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	14,546	14,546	14,547	14,546
Number of firms	1,455	1,455	1,455	1,455
Goodness of fit score	0.732	0.673	0.700	0.729
m1				-17.19
(p -value)				(0.000)
m2				-4.939
(p -value)				(0.000)
m3				6.120

(p -value)				(0.000)
m4				-0.609
(p -value)				(0.542)
Sargan-Hansen				1070
(p -value)				(0.118)
Speed of adjustment (λ)	0.185***	0.458***	0.336***	0.242***
	(0.008)	(0.013)	(0.009)	(0.019)
Target-uncertainty sensitivity (β)	-0.336***	-0.203***	-0.228***	-0.485***
	(0.107)	(0.054)	(0.062)	(0.152)

Table 5: Comparison of target leverage ratios by the level of uncertainty

This table reports the summary statistics for book and market target leverage ratios in Panel A and Panel B, respectively. To estimate target leverage ratios, we first obtain the system GMM estimates for the following dynamic panel regression model:

$$L_{i,t} = \lambda\alpha + (1-\lambda)L_{i,t-1} + \lambda\beta'\mathbf{X}_{i,t-1} + Year\ Dummies + \lambda\eta_i^* + \upsilon_{i,t},$$

where $\lambda\eta_i^*$ represents firm fixed effects in actual leverage ($L_{i,t}$). Estimation results are reported in Tables 3 and 4. We then obtain λ , α , β and η_i^* following the procedure detailed in Section 3.4. Finally, we obtain book and market target leverage estimates using the following equation:

$$L_{i,t}^* = \alpha + \beta'\mathbf{X}_{i,t-1} + \eta_i^*.$$

Each panel reports the summary statistics for target leverage ratios including firm fixed effects ($L_{i,t}^*$) in the full sample and those for high- and low-uncertainty firms. A firm-year observation is classified into a sub-sample of high-uncertainty firms (low-uncertainty firms) if asset volatility is above median (is equal to or below median). The differences in mean and median target leverage ratios between the two groups are reported with the t -statistic of Student's t test or z -statistic of Wilcoxon's rank-sum test. Superscript *** indicates statistical significance at the 1% level. Each panel also reports the summary statistics for firm fixed effects in target leverage ratios (η_i^*) and the proportion of firm fixed effects in target leverage ratios ($\eta_i^* / L_{i,t}^*$).

Panel A. Book target leverage

Variables	Obs.	Mean	S.D.	P05	P25	Median	P75	P95
Book targets with firm fixed effects	14,546	0.185	0.150	0.000	0.054	0.169	0.278	0.462
High-uncertainty firms	7,273	0.134	0.141	0.000	0.019	0.096	0.205	0.411
Low-uncertainty firms	7,273	0.235	0.142	0.016	0.130	0.233	0.323	0.484
Difference (High – Low)		*-0.101****				*-0.137****		
t -stat/ z -stat		*43.11*				*45.66*		
Firm fixed effects in book targets	14,546	0.007	0.137	-0.169	-0.090	-0.017	0.075	0.257
Proportion of fixed effects in targets	10,039	0.361	0.245	0.028	0.160	0.320	0.530	0.826

Panel B. Market target leverage

Variables	Obs.	Mean	S.D.	P05	P25	Median	P75	P95
Market targets with firm fixed effects	14,546	0.161	0.156	0.000	0.041	0.123	0.233	0.485
High-uncertainty firms	7,273	0.120	0.144	0.000	0.010	0.073	0.176	0.408
Low-uncertainty firms	7,273	0.202	0.157	0.009	0.090	0.167	0.269	0.522
Difference (High – Low)		*-0.081****				*-0.094****		
t -stat/ z -stat		*32.69*				*39.99*		
Firm fixed effects in market targets	14,546	0.007	0.144	-0.162	-0.087	-0.025	0.065	0.291
Proportion of fixed effects in targets	9,339	0.406	0.248	0.049	0.203	0.386	0.582	0.862

Table 6: Variance decomposition of target leverage

This table presents the variance decomposition results for the two leverage targets based on several different ANCOVA model specifications. The ANCOVA results for book and market leverage targets are summarised in Panels A and B, respectively. To estimate target leverage ratios, we first obtain system GMM estimates for the following dynamic panel regression model:

$$L_{i,t} = \lambda\alpha + (1-\lambda)L_{i,t-1} + \lambda\beta'\mathbf{X}_{i,t-1} + Year\ Dummies + \lambda\eta_i^* + \upsilon_{i,t},$$

where $\lambda\eta_i^*$ represents firm fixed effects in actual leverage ($L_{i,t}$). Estimation results are reported in Tables 3 and 4. We then obtain λ, α, β and η_i^* following the procedure detailed in Section 3.4. Finally, we obtain book and market target leverage estimates using the following equation:

$$L_{i,t}^* = \alpha + \beta'\mathbf{X}_{i,t-1} + \eta_i^*.$$

A detailed description of the variables is provided in Panel A of Table 1. The estimated target book and market leverage ratios are denoted as $BL_{i,t}^*$ and $ML_{i,t}^*$, respectively. The numbers in the body of the table, excluding the last two rows, correspond to the contribution of each variable in a particular model. That is, we measure the contribution of each variable by dividing the partial sum of squares for each effect by the aggregate partial sum of squares across all effects in the model so that the columns sum to one.

Panel A. Book target leverage

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$BL_{i,t}^*$	$BL_{i,t}^*$	$BL_{i,t}^*$	$BL_{i,t}^*$	$BL_{i,t}^*$	$BL_{i,t}^*$
Firm fixed effects	0.987		0.989	0.965		0.968
Year fixed effects		0.022	0.003		0.025	0.000
Asset volatility	0.013	0.978	0.008	0.009	0.265	0.008
Firm size				0.004	0.374	0.003
Market-to-book ratio				0.003	0.014	0.003
Profitability				0.003	0.184	0.003
Tangibility				0.001	0.010	0.001
Depreciation				0.011	0.002	0.011
R&D intensity				0.000	0.011	0.000
Zero R&D firm indicator				0.001	0.015	0.001
Industry median book leverage				0.002	0.100	0.001

Number of observations	14,546	14,546	14,546	14,546	14,546	14,546
Adjusted R-squared	0.974	0.134	0.977	0.996	0.233	0.996

Panel B. Market target leverage

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$ML^*_{i,t}$	$ML^*_{i,t}$	$ML^*_{i,t}$	$ML^*_{i,t}$	$ML^*_{i,t}$	$ML^*_{i,t}$
Firm fixed effects	0.989		0.990	0.970		0.972
Year fixed effects		0.079	0.000		0.057	0.000
Asset volatility	0.011	0.921	0.009	0.009	0.196	0.008
Firm size				0.000	0.060	0.000
Market-to-book ratio				0.003	0.257	0.003
Profitability				0.000	0.193	0.000
Tangibility				0.005	0.048	0.004
Depreciation				0.007	0.006	0.007
R&D intensity				0.001	0.065	0.001
Zero R&D firm indicator				0.002	0.108	0.002
Industry median market leverage				0.002	0.009	0.002
Number of observations	14,546	14,546	14,546	14,546	14,546	14,546
Adjusted R-squared	0.978	0.089	0.979	0.996	0.228	0.996

Table 7: The effect of uncertainty on target leverage ratios—IV regressions

This table reports the results of the 2SLS regression analyses designed to examine the effect of uncertainty on target leverage ratios. The second-stage model is specified as follows: $\Delta L_{i,t} = \text{constant} + (1-\lambda)\Delta L_{i,t-1} + \lambda\beta\Delta\sigma_{i,t-1} + \lambda\gamma'\Delta\mathbf{C}_{i,t-1} + \Delta\upsilon_{i,t}$, where $\Delta\sigma_{i,t-1}$ is the instrumented uncertainty shock, $\Delta L_{i,t-1}$ is the instrumented lagged change in leverage and $\Delta\mathbf{C}_{i,t-1}$ is a vector containing the first-differences of all target determinants except asset volatility. To address the endogeneity concerns related to the lagged leverage change ($\Delta L_{i,t-1}$), we instrument $\Delta L_{i,t-1}$ with the lagged leverage level $L_{i,t-2}$. To address the endogeneity concerns related to the uncertainty shock ($\Delta\sigma_{i,t-1}$), we use IVs suggested by Alfaro et al. (2018). In particular, we instrument the uncertainty shock ($\Delta\sigma_{i,t-1}$) with the lagged industry-level (i.e. SIC 3-digit) non-directional exposure to 10 aggregate sources of uncertainty shocks, i.e. the annual changes in the implied return volatilities of currencies, energy and 10-year treasury bonds and the annual change in the realised volatility of the EPU index. When we estimate the industry-level sensitivities to the 10 shocks, we use the following factors. As currency factors, we use the growth in the exchange rates of the Federal Reserve Board's seven major currencies: Australian Dollar (AUD), Japanese Yen (JPY), Canadian Dollar (CAD), Swiss Franc (CHF), British Pound (GBP), Swedish Krona (SEK) and Euro (EUR). As the energy factor, we use the growth in crude-oil prices. As the treasury bond factor, we use the return on the U.S. 10-year treasury bond. As the EPU factor, we use the growth in the EPU index proposed by Baker et al. (2016). Following Alfaro et al. (2018), we also control for the lagged directional exposure to the 10 aggregate uncertainty shocks. Refer to Alfaro et al. (2018) for details on how to construct non-directional and directional exposure to the 10 aggregate uncertainty shocks. The table also reports the Kleibergen-Paap Wald F -statistic for a weak identification test. The Stock-Yogo critical value for the F -test (i.e. five percent maximal IV relative bias) is also reported. A detailed description of other control variables included in the models is provided in Panel A of Table 1. Standard errors are clustered at industry level. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Change in book leverage			Change in market leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$\Delta\sigma_{i,t-1}$	$\Delta L_{i,t-1}$	$\Delta L_{i,t}$	$\Delta\sigma_{i,t-1}$	$\Delta L_{i,t-1}$	$\Delta L_{i,t}$
$\Delta\sigma_{i,t-1}$			-0.542***			-1.632***
			(0.101)			(0.207)
$\Delta L_{i,t-1}$			0.753***			0.621***
			(0.038)			(0.051)
Exposure to $\Delta\sigma^{AUD}$	0.204**	0.100		0.155*	0.229	
	(0.087)	(0.111)		(0.086)	(0.155)	
Exposure to $\Delta\sigma^{JPY}$	0.504***	0.110		0.455***	0.300	
	(0.161)	(0.157)		(0.159)	(0.243)	
Exposure to $\Delta\sigma^{CAD}$	0.656***	0.083		0.623***	0.224	

	(0.087)	(0.195)		(0.086)	(0.280)	
Exposure to $\Delta\sigma^{CHF}$	0.141***	0.061		0.128**	0.204*	
	(0.051)	(0.074)		(0.051)	(0.119)	
Exposure to $\Delta\sigma^{GBP}$	0.116	0.244		0.114	0.078	
	(0.093)	(0.238)		(0.095)	(0.288)	
Exposure to $\Delta\sigma^{SEK}$	0.591***	-0.085		0.570***	0.288**	
	(0.066)	(0.079)		(0.067)	(0.127)	
Exposure to $\Delta\sigma^{EUR}$	0.108***	0.000		0.103***	0.156**	
	(0.038)	(0.034)		(0.038)	(0.074)	
Exposure to $\Delta\sigma^{EPU}$	26.667	75.777		-15.610	192.272*	
	(23.377)	(50.282)		(29.004)	(116.804)	
Exposure to $\Delta\sigma^{Oil}$	0.386***	0.141*		0.306***	0.702***	
	(0.101)	(0.082)		(0.102)	(0.228)	
Exposure to $\Delta\sigma^{Treasury}$	0.000***	0.000		0.000***	0.000**	
	(0.000)	(0.000)		(0.000)	(0.000)	
$L_{i,t-2}$	0.011***	-0.101***		0.016***	-0.114***	
	(0.001)	(0.009)		(0.002)	(0.006)	
Δ Firm size	-0.006***	0.087***	-0.066***	-0.004**	0.093***	-0.056***
	(0.002)	(0.014)	(0.014)	(0.002)	(0.014)	(0.013)
Δ Market-to-book ratio	0.003***	-0.003**	0.004***	0.004***	-0.015***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
Δ Profitability	0.005	-0.124***	0.102***	0.005	-0.175***	0.147***
	(0.004)	(0.019)	(0.019)	(0.003)	(0.029)	(0.033)
Δ Tangibility	-0.015	0.083***	0.003	-0.017	0.126***	-0.055
	(0.016)	(0.027)	(0.035)	(0.015)	(0.023)	(0.042)
Δ Depreciation	0.043	0.074	-0.314	0.037	0.203*	-0.218
	(0.057)	(0.129)	(0.238)	(0.057)	(0.106)	(0.155)
Δ R&D intensity	-0.031***	0.052**	-0.011	-0.029***	-0.073***	0.060*
	(0.007)	(0.021)	(0.035)	(0.007)	(0.022)	(0.034)
Δ Zero R&D firm indicator	-0.008**	0.021**	-0.011	-0.007**	0.013	-0.025*

	(0.004)	(0.010)	(0.011)	(0.004)	(0.012)	(0.013)
Δ Industry median leverage	0.049***	0.323***	-0.196***	0.090***	0.530***	-0.249***
	(0.019)	(0.028)	(0.043)	(0.017)	(0.037)	(0.057)
Kleibergen-Paap Wald F -statistic			23.07			54.07
(critical value at 5%)			(20.54)			(20.54)
Number of observations	11,057	11,057	11,057	11,057	11,057	11,057
Speed of adjustment (λ)			0.247***			0.379***
			(0.038)			(0.051)
Target-uncertainty sensitivity (β)			-2.192***			-4.309***
			(0.549)			(0.631)

Table 8: Mechanisms through which uncertainty affects book leverage targets

This table reports the results of the 2SLS analyses used to examine the mechanisms through which uncertainty affects book leverage targets. To estimate book target leverage ratios, we first obtain system GMM estimates for the following dynamic panel regression model:

$$BL_{i,t} = \lambda\alpha + (1-\lambda)BL_{i,t-1} + \lambda\beta'\mathbf{X}_{i,t-1} + Year\ Dummies + \lambda\eta_i^* + \upsilon_{i,t},$$

where $\lambda\eta_i^*$ represents firm fixed effects in actual book leverage. The estimation result is reported in Column (4) of Table 3. We then obtain λ , α , β and η_i^* following the procedure detailed in Section 3.4. Finally, we obtain book target leverage estimates using the following equation:

$$BL_{i,t}^* = \alpha + \beta'\mathbf{X}_{i,t-1} + \eta_i^*.$$

$TXSHLD$ is the value of tax shields scaled by total assets, where the value of the tax shield is estimated as the tax-deductible debt (i.e. the sum of long-term debt and short-term debt) multiplied by the corporate tax rate. MZ is the modified Z-score proposed by Graham et al. (1998) and used by Chava et al. (2008) and Im (2012), which is calculated as follows: $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + X_4$, where X_1 is the ratio of working capital to total assets, X_2 is the ratio of retained earnings to total assets, X_3 is the ratio of earnings before interests and taxes to total assets and X_4 is the ratio of sales to total assets. SA is a financial constraints index proposed by Hadlock and Pierce (2010). $VIOLYR$ is a proxy for the likelihood of covenant violation proposed by Nini et al. (2009), which equals one if a firm reports a loan covenant violation in an SEC 10-K or 10-Q filing for a given year and zero otherwise. $SUMBLKS$ is the percentage of shares held by all blockholders. Firm-clustered standard errors are reported in parentheses. Superscripts *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Tax Shields		Bankruptcy Costs		Financial Constraints		Agency Costs		Agency Benefits	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	$TXSHLD_{i,t}$	$BL^*_{i,t}$	$MZ_{i,t}$	$BL^*_{i,t}$	$SA_{i,t}$	$BL^*_{i,t}$	$VIOLYR_{i,t}$	$BL^*_{i,t}$	$SUMBLKS_{i,t}$	$BL^*_{i,t}$
$\sigma_{i,t-1}$	-0.300***		-23.867***		3.014***		0.428***		-0.071	
	(0.020)		(1.917)		(0.178)		(0.123)		(0.059)	
$TXSHLD_{i,t}$		3.660***								
		(0.250)								
$MZ_{i,t}$				0.044***						
				(0.004)						
$SA_{i,t}$						-0.352***				
						(0.028)				
$VIOLYR_{i,t}$								-2.067***		
								(0.631		

								)		
$SUMBLKS_{i,t}$										16.744
										(14.071)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	11,738	11,738	12,766	12,766	12,851	12,851	4,053	4,053	5,421	5,421

Table 9: Mechanisms through which uncertainty affects market leverage targets

This table reports the results of the 2SLS analyses used to examine the mechanisms through which uncertainty affects market leverage targets. To estimate market target leverage ratios, we first obtain system GMM estimates for the following dynamic panel regression model:

$$ML_{i,t} = \lambda\alpha + (1-\lambda)ML_{i,t-1} + \lambda\beta'\mathbf{X}_{i,t-1} + Year\ Dummies + \lambda\eta_i^* + \upsilon_{i,t},$$

where $\lambda\eta_i^*$ represents firm fixed effects in actual market leverage. The estimation result is reported in Column (4) of Table 4. We then obtain λ, α, β and η_i^* following the procedure detailed in Section 3.4. Finally, we obtain market target leverage estimates using the following equation:

$$ML_{i,t}^* = \alpha + \beta'\mathbf{X}_{i,t-1} + \eta_i^*.$$

$TXSHLD$ is the value of tax shields scaled by total assets, where the value of the tax shield is estimated as the tax-deductible debt (i.e. the sum of long-term debt and short-term debt) multiplied by the corporate tax rate. MZ is the modified Z-score proposed by Graham et al. (1998) and used by Chava et al. (2008) and Im (2012), which is calculated as follows:

$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + X_4$, where X_1 is the ratio of working capital to total assets, X_2 is the ratio of retained earnings to total assets, X_3 is the ratio of earnings before interests and taxes to total assets and X_4 is the ratio of sales to total assets. SA is a financial constraints index proposed by Hadlock and Pierce (2010). $VIOLYR$ is a proxy for the likelihood of covenant violation proposed by Nini et al. (2009), which equals one if a firm reports a loan covenant violation in an SEC 10-K or 10-Q filing for a given year and zero otherwise. $SUMBLKS$ is the percentage of shares held by all blockholders. Firm-clustered standard errors are reported in parentheses. Superscripts *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Tax shields		Bankruptcy costs		Financial constraints		Agency costs		Agency benefits	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	$TXSHLD_{i,t}$	$ML^*_{i,t}$	$MZ_{i,t}$	$ML^*_{i,t}$	$SA_{i,t}$	$ML^*_{i,t}$	$VIOLYR_{i,t}$	$ML^*_{i,t}$	$SUMBLKS_{i,t}$	$ML^*_{i,t}$
$\sigma_{i,t-1}$	-0.300***		-23.867***		3.044***		0.428***		-0.071	
	(0.020)		(1.917)		(0.178)		(0.123)		(0.059)	
$TXSHLD_{i,t}$		2.657***								
		(0.223)								
$MZ_{i,t}$				0.033***						
				(0.004)						
$SA_{i,t}$						-0.263***				
						(0.026)				
$VIOLYR_{i,t}$								-1.692		

								***		
								(0.550)		
$SUMBLKS_{i,t}$										13.038
										(10.899)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	11,738	11,738	12,766	12,766	12,851	12,851	4,053	4,053	5,421	5,421

Table 10: **Moderating effect of managerial risk aversion on target leverage ratios**

This table reports the sub-sample analyses designed to examine whether the effect of uncertainty on target leverage is greater for firms whose managers are more risk averse. In Column (1) and Column (2), the dependent variable is book leverage, whereas in Column (3) and Column (4), the dependent variable is market leverage. We adopt the system GMM estimation method. The empirical models used are similar to those used in Table 3 and Table 4. We use an option-based measure to identify CEO's risk aversion. In particular, a CEO is classified as being more risk averse if he/she holds stock options that are less than 67% in the money at least twice over the sample period. Otherwise, the CEO is classified as being less risk averse. Option moneyness is estimated as the ratio of realisable value per option to estimated exercise price (Campbell et al., 2011). Exercise price is estimated as the per-option realisable value net of stock price at the end of each fiscal year, where the per-option realisable value is the total realisable value of exercisable options divided by the number of exercisable options. A detailed description of all variables included in the models is provided in Panel A of Table 1. We report two-step GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The IVs are selected considering the Arellano-Bond tests and Sargan-Hansen tests. Note that year dummies are treated as instruments for the equations in levels only. m1, m2, m3 and m4 represent the test statistics of the Arellano-Bond tests for first-order to fourth-order serial correlations in first-differenced residuals, respectively. Sargan-Hansen represents the test statistic of the Sargan-Hansen test of over-identifying restrictions. The overall goodness-of-fit score, measured as the square of the coefficient of correlation between the dependent variable and its predicted value, is reported in each column. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Book leverage		Market leverage	
	(1)	(2)	(3)	(4)
Sample	More risk averse	Less risk averse	More risk averse	Less risk averse
Lagged leverage	0.770***	0.851***	0.691***	0.708***
	(0.021)	(0.025)	(0.024)	(0.030)
Asset volatility	-0.146***	-0.082	-0.235***	-0.110
	(0.054)	(0.068)	(0.067)	(0.081)
Other target determinants	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,810	2,824	4,810	2,824
Number of firms	743	520	743	520
Goodness of fit score	0.782	0.803	0.741	0.725
m1	-11.24	-9.542	-10.67	-8.001
(p -value)	(0.000)	(0.000)	(0.000)	(0.000)
m2	-0.802	-1.106	-1.502	-3.145
(p -value)	(0.422)	(0.269)	(0.133)	(0.002)
m3			3.141	2.511
(p -value)			(0.002)	(0.012)
m4			-1.493	1.568
(p -value)			(0.136)	(0.117)

Sargan-Hansen	554.3	413.9	570.5	423.3
(p -value)	(0.982)	(0.076)	(0.945)	(0.040)
Speed of adjustment (λ)	0.230***	0.149***	0.309***	0.292***
	(0.021)	(0.025)	(0.024)	(0.030)
Target-uncertainty sensitivity (β)	-0.632***	-0.553	-0.759***	-0.378
	(0.230)	(0.440)	(0.215)	(0.281)

Table 11: Estimation of the sensitivity of leverage targets to uncertainty: 'trade-off firms' versus 'non-trade-off firms'

This table reports a sub-sample analyse designed to examine whether the effect of uncertainty on target leverage varies between two groups of firms: 'trade-off firms' versus 'non-trade-off firms'. To examine whether the negative effect of uncertainty on optimal leverage is more pronounced for firms whose leverage adjustment patterns are more consistent with a dynamic trade-off theory, we classify firms into two groups based on the first-order autoregressive regression coefficient (i.e. $1-\lambda$) of each firm's first-order autoregressive (i.e. AR(1)) model: $L_t = \lambda\alpha + (1-\lambda)L_{t-1} + \varepsilon_t$ for firm $i = 1, \cdots, N$. In particular, we classify firms with λ in the range of (0,1) as 'trade-off firms' and firms with λ outside the range as 'non-trade-off firms'. In Column (1) and Column (2), the dependent variable is book leverage, whereas in Column (3) and Column (4), the dependent variable is market leverage. We adopt the system GMM estimation method. The empirical models used are similar to those used in Table 3 and Table 4. A detailed description of all variables included in the models is provided in Panel A of Table 1. We report two-step GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation and that use the finite-sample correction proposed by Windmeijer (2005). The IVs are selected considering the Arellano-Bond tests and Sargan-Hansen tests. Note that year dummies are treated as instruments for the equations in levels only. m1, m2, m3 and m4 represent the test statistics of Arellano-Bond tests for first-order to fourth-order serial correlations in first-differenced residuals, respectively. Sargan-Hansen represents the test statistic of the Sargan-Hansen test of over-identifying restrictions. The overall goodness-of-fit score, measured as the square of the coefficient of correlation between the dependent variable and its predicted value, is reported in each column. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Book leverage		Market leverage	
	(1)	(2)	(3)	(4)
Sample	Trade-off firms	Non-trade-off firms	Trade-off firms	Non-trade-off firms
Lagged leverage	0.801***	0.793***	0.686***	0.758***
	(0.013)	(0.088)	(0.023)	(0.066)
Asset volatility	-0.081**	0.023	0.166***	0.144
	(0.033)	(0.082)	(0.035)	(0.094)
Other target determinants	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	9,048	1,498	9,048	1,498
Number of firms	689	123	689	123
Goodness of fit score	0.773	0.759	0.693	0.726
m1	-15.49	-3.826	-14.30	-4.151
(p -value)	(0.000)	(0.000)	(0.000)	(0.000)
m2	-0.220	0.951	-5.011	-2.125
(p -value)	(0.826)	(0.341)	(0.000)	(0.034)
m3			5.651	1.906
(p -value)			(0.000)	(0.057)
m4			-0.920	0.836
(p -value)			(0.358)	(0.403)
Sargan-Hansen	644.8	111.1	682.4	110.0
(p -value)	(0.323)	(0.660)	(0.996)	(0.428)
Speed of adjustment (λ)	0.199***	0.207**	0.314***	0.242***
	(0.013)	(0.088)	(0.023)	(0.066)
Target-uncertainty	-0.405**	0.111	-0.530***	0.596

sensitivity (β)				
	(0.164)	(0.386)	(0.117)	(0.409)

Highlights

- This study examines how uncertainty measured by asset volatility affects a firm's target capital structure.
- High-uncertainty firms have 10.1 (8.1) percentage points lower mean book (market) targets than low uncertainty firms.
- Uncertainty is the most critical time-varying determinant of target leverage.
- High uncertainty lowers the present value of debt tax shields, while increasing financial distress costs and exacerbating debtholder–shareholder conflicts.