Business shocks and corporate leverage

Tan, Kelvin Jui Keng; Zhou, Qing; Pan, Zheyao; Faff, Robert

Published in:
Journal of Banking and Finance

DOI:
10.1016/j.jbankfin.2021.106208

Business Shocks and Corporate Leverage ⋆

Kelvin Jui Keng Tan[a,*], Qing Zhou[b], Zheyao Pan[b], Robert Faff[c,a]

[a]*The University of Queensland*
[b]*Macquarie University*
[c]*Bond University*

Abstract

We examine whether and to what extent business shocks explain the puzzling instabilities of corporate leverage. We find that business shocks explain a large portion of the unexplained leverage deviation, cross-sectional leverage position migration, and evaporating leverage similarities in the cross-section of firms. The cross-sectional distribution of corporate leverage is relatively persistent when there are fewer and smaller business shocks but becomes unstable for firms with larger business shocks. Our findings suggest that business shocks lead to discontinuities in the corporate value creation process and investment, thereby affecting corporate financing decisions. Put simply, the lumpiness of investment creates a "lumpy" need for external financing. Our analysis implies that the empirical modeling of capital structure adjustment and, indeed, the modeling of other corporate policies, should be conditioned on business shocks.

JEL classification: *G32*

Keywords: Capital structure, instability, business shock, leverage deviation

⋆We thank Vidhan Goyal, Hyun Joong Im, and seminar and conference participants at the Asian Financial Association Meeting and the University of Queensland for their helpful comments and suggestions. Tan and Zhou acknowledge financial support from the Accounting and Finance Association of Australia and New Zealand (AFAANZ) and the University of Queensland.

*Corresponding author.
Email addresses: Tan k.tan@business.uq.edu.au, Zhou clara.zhou@mq.edu.au, Pan terry.pan@mq.edu.au, Faff rfaff@bond.edu.au

Version: June 2021; Forthcoming in *Journal of Banking and Finance*

1. Introduction

Technological breakthroughs, globalization, privatization, deregulation, the availability of venture capital, and political instability are profoundly changing the business environment (Gassmann et al., 2014). The business environment has become more dynamic and disruptive, making firms' competitive advantages less sustainable and generating shocks to firms' economic fundamentals. In this paper, a business shock is viewed as a nontrivial shock to corporate strategy, inducing a major discontinuity in the value creation process. The discontinuities in the value creation process violate the stationarity assumptions that underlie many empirical corporate finance tests, thus resulting in puzzling findings. One such area is empirical corporate capital structure, wherein recent studies document the lack of persistence in capital structure patterns (DeAngelo and Roll, 2015; Graham et al., 2015). In this paper, we examine the relation between the discontinuities in firms' value creation process and the instabilities in their financial leverage.

Evolutionary economic theories (Schumpeter, 1934) suggest that a firm's competitive success depends on its ability to adapt the business strategy to changes in its external business environment. When taking an evolutionary perspective on corporate strategy (Barnett and Burgelman, 1996; Braguinsky and Hounshell, 2016), rent-seeking firms change their business strategies and transition from one competitive advantage to another, inducing disruptive changes in their value generation process. For example, the wave of online businesses and digitalization is reshaping traditional ways of doing business.[1] The new wave of technological shocks brings growth opportunities for some businesses while disrupting others. For example, the advent of smartphones presented challenges to traditional mobile phone companies such as Nokia, while Airbnb challenged traditional hotels, and Uber did the same with regard to taxi services.

These disruptive business shifts do not happen instantaneously; firms (especially those that are highly successful) plan these strategic moves ahead of business changes in a forward-looking fashion. As financial market frictions and adjustment costs prevent firms from instantly adjusting their capital stock, in response to anticipated future investment and divestment, such firms adjust their capital stock pre-emptively. Given the unevenness of investment (Whited, 2006), there is a "lumpy" financing demand, which leads to instabilities in firms' target capital

[1] Netflix shifted from a low tech (mail order DVDs) to a high tech (streaming) platform; Amazon started with selling books and shifted to 24/7 logistic services. Adobe transformed its creative software from transactional (single licenses) to recurring revenue (subscription service).

structure.

To illustrate our ideas more tangibly, we use an anecdotal example of Holiday RV Superstores, Inc. (Ticker: RVEE). The company owns and operates a chain of stores that engage in the sale, finance, and servicing of recreational vehicles (RVs) and recreational boats. In Figure 1, we plot the magnitude of the business shock and leverage deviation for Holiday RV between 1989 and 2002. The plot shows that the business shock is positively correlated with leverage deviation. In the early 1990s, the business shock increased, reflecting that the holiday recreation industry in the United States faced lower consumer spending due to the Persian Gulf War (1990-1991). In 1992, Holiday RV obtained the industry's largest single contract ($4.3 million, or equivalently 16.7% of its total assets) from the Federal Emergency Management Agency (FEMA) to provide trailers for emergency shelter in the aftermath of Hurricane Andrew.

Figure 1 also shows that business shocks began increasing since 1997, likely in response to a flood of baby boomers purchasing RVs. To meet this demand, Holiday RV responded in two key ways: (1) they launched their first business-to-customer (e-commerce) website (www.RecUSA.com) in May 1999; and (2) they acquired seven new dealerships, which doubled their number of dealerships between 1996 and 1999.[2] This indicates that the business shock also predicts a spike in investment. To finance their investment spikes, Holiday RV increased their long-term debt from $156,000 in 1999 to $11.7 million in 2000. As a result, their leverage deviation increased approximately 1.07 times between 1999 and 2000.

[Insert Figure 1]

In many empirical corporate finance models (e.g., the widely used partial adjustment model), based on the underlying assumption that firm-based fundamentals are persistent, target financial leverage is estimated using lagged firm fundamental leverage determinants (e.g., Flannery and Rangan, 2006). Accordingly, in these models, a one-period lag of fundamentals is used to predict future fundamentals. The assumption is reasonable provided that all underlying economic fundamentals are persistent and absent any disruptive shock events. However, business shocks will lead to discontinuities in many related fundamental variables. For example, suppose there is a first-moment shock to a firm, then the expectation of future levels of economic fundamentals, such as profitability and growth, will experience a regime shift, such as a shift from a low

[2] Detailed information can be found in Holiday RV's 10K filings via the EDGAR portal (URL: https://www.sec.gov/Archives/edgar/data/1000753/000095012310011398/c96049e10vk.htm).

regime to a high regime or vice versa. Moreover, the mean shift in these fundamentals will lead to a mean shift in the underlying target leverage because it is determined by these firm-level fundamental variables.[3] However, empirical research based on a simple "smooth" evolution of fundamentals is logically inadequate as this smooth modeling cannot appropriately capture the regime shift in the target leverage, leaving a large unexplained deviation in leverage.

Following the above reasoning, we expect that large, unexplained leverage deviations are associated with large business shocks. To test this hypothesis, we examine non-financial corporate data for the U.S. from 1968 to 2015. We find that when there is a large business shock, it is 4.1% more likely that there will be a large unexplained leverage deviation from the target leverage. The 4.1% amount represents an 8.7% increase from the conditional mean (47%) of the large leverage deviation. We also find that the size of the leverage deviation is positively related to the size of the business shock. Economically, a one standard deviation (1.11) increase in the business shock measure is associated with an increase of 66.6% relative to the mean (0.17) of the size of the leverage deviation.

Apart from the large unexplained leverage deviation, business shocks contribute to the instability of cross-sectional leverage distribution. Although at the aggregate level the shocks and firm responses can conform to long-run stationarity conditions, the equilibrium level of these variables is affected by the parameters of firm-specific shocks. Camouflaged by aggregate stability, there is likely a great deal of randomness and fluctuation: firms enter, invest, and exit in response to idiosyncratic shocks. Thus, there might well be stationarity at the aggregate level but not at the firm level. Exogenous shocks simultaneously affect production, investment, and financing decisions (Dixit and Pindyck, 1994). The interaction between financing decisions and production decisions influences the stationary distribution of firms and their survival probabilities (Miao, 2005). Firm-specific business shocks may change productivity and profitability, as well as investment and financing decisions, which may result in shifts in the relative ranking of the firm's leverage within the cross-section of firms.

In our empirical tests, we find that the probability of a firm migrating from one leverage quartile to another is much higher for firms that experience larger cumulative business shocks. Such evidence indicates that the cross-sectional distribution of corporate leverage is more persistent when there are fewer business shocks, and can become quite unstable when there is a

[3] In this paper, we assume that the determinants of target leverage used in the literature are true determinants of target leverage. The issue that we are concern with is the prediction of these determinants.

high incidence of these shocks. We also find that cumulative business shocks are significantly positively associated with the cross-sectional leverage dispersion within an industry, and this pattern is more pronounced in industries with less persistent economic rents. Although the inter-industry variation in financial leverage is well understood (e.g., accounted for by including industry-median leverage in the target leverage regressions), there is a lack of understanding on the drivers (or consequences) of intra-industry variation in financial leverage. Our results suggest that business shocks intensify intra-industry leverage variation.

Collectively, our empirical results highlight the role of business shocks in explaining the three major forms of leverage instability in DeAngelo and Roll (2015); namely, the large unexplained leverage deviations from target leverage derived from finance theory, the unstable cross-sectional distribution of the leverage ratio, and evaporating leverage similarities among the cross-section of firms. One concern regarding our empirical design is the potential endogeneity problems that may bias our inference. For example, our business shock measure may not be exogenous but reversely determined by firms' capital structure decisions. To address this concern, we employ an instrumental variable (IV) estimation approach. Specifically, we use the advent of e-commerce in the late 1990s, which created an exogenous shock to adopting firms (Agrawal et al., 2004; Pástor and Veronesi, 2009), as the IV of our business shock measure. The results of our IV analysis confirm the causal effect of business shocks on leverage deviation.

More generally, endogeneity problems can also arise from measurement error, sample selection bias, and omitted variables. We use the following strategies to address such endogeneity issues: two-stage least squares-instrumental variables (2SLS-IV); propensity score matching (PSM); additional control variables; multiple alternative proxies; and subsample analyses. Furthermore, in addition to tests that focus on the leverage ratio, we examine how business shocks affect real external financing activities (e.g., debt and equity issuance). As pointed out by Mitton (2021), freedom in empirical corporate finance research can potentially overstate the statistical significance of variables of interest. We provide the results of various empirical specifications and discuss their economic significance, which provides support for the reliability of our results.

We further examine the channel through which business shocks might lead to capital structure discontinuities. We argue that business shocks affect corporate financing decisions through investments. The lumpiness of capital expenditures (Whited, 2006) creates a "lumpy" need for external financing. Our results show that business shocks significantly increase the probability of investment spikes across all time horizons. We find that the association between business shocks and leverage deviation is stronger among firms experiencing investment spikes.

Therefore, what are the main empirical implications of our study? It is important to appreciate that we are not simply arguing that a business shock variable should be added to the conventional target leverage model as another target leverage determinant. While our evidence shows that leverage deviation is positively associated with business shocks, this does not necessarily occur in a linear form. The target leverage is time-varying. Unconditional historical mean target leverage is not a good proxy for target leverage in the presence of a business shock that can, for example, shift the mean level of the target leverage. The biased target leverage estimates can skew the estimated leverage adjustment speed towards zero, resulting in false inferences regarding dynamic leverage adjustment behavior. Indeed, when conditioning on business shocks, we find that firms with an above-median business shock adjust 37% more slowly towards the target leverage than firms with a below-median business shock.

Our primary contribution to the literature is centered on advancing knowledge in the area of empirical capital structure. We draw on the theoretically backed empirical implications of dynamic capital structure models and test their implications in reduced-form regressions. Second, we offer a strong lead that business shocks can help resolve the puzzle relating to leverage persistence (Lemmon et al., 2008; DeAngelo and Roll, 2015). While Lemmon et al. (2008) claim capital structure in the cross-section is remarkably stable, DeAngelo and Roll (2015) disagree. We show that leverage is more persistent among firms that have less dominant (in relative terms) business shocks. That is, according to our analysis, the (lack of) persistence of leverage observed in Lemmon et al. (2008) (DeAngelo and Roll, 2015) is likely driven by the small (large) business shock subset. Hence, our results reconcile the findings of Lemmon et al. (2008) and DeAngelo and Roll (2015).

Furthermore, our arguments are broadly transferable beyond the capital structure setting. Our key generic message is that discontinuities in the corporate value creation process offer the real prospect of much deeper knowledge creation. Given that these discontinuities often violate the stationarity assumptions underlying many empirical settings, our basic approach of allowing business shocks to enter the analysis can be further investigated as a possible explanation of other puzzling findings across the broad spectrum of the empirical corporate finance literature.

The remainder of our study is organized as follows. In Section 2, we discuss related theories and the literature. In Section 3, we describe our sample and define the key variables. In Section 4, we present our empirical findings on business shocks and leverage instabilities. In Section 5, we discuss the channel through which business shocks affect corporate leverage dynamics. In Section 6, we provide empirical implications of our work for capital structure studies, and we conclude in Section 7.

2. Theory and related literature

Our study is motivated by the strategic management and corporate capital structure literature, as well as recent dynamic corporate finance models. We take an evolutionary perspective on corporate strategy. Drawing on evolutionary economics, evolutionary strategic theory attends to the dynamics of strategic change. Researchers create models based on this theory to examine the pace and paths of how organizations will grow, change their performance, or experience strategic events, such as restructuring, product innovations, mergers, technological changes, and/or failure due to internal or external forces (Braguinsky and Hounshell, 2016). It has become customary to define strategy as dynamic moves and counter moves rather than as the static positioning of resources, routines, capabilities, generic strategies, industry structures, and strategic groups (Grimm et al., 2005). The creation and management of temporary competitive advantages has emerged as an alternative to sustainable models of competitive advantage in the strategy literature (D'Aveni et al., 2010). There is also a growing theme in strategy research of the importance of the temporary (volatile) component of competitive advantage compared to the long-run component of sustainable competitive advantage (Thomas and D'Aveni, 2009).

Considerable thought has also been given to the idea that continuous strategic innovation is necessary in a disruptive environment. In fact, the vigorous pursuit of a series of temporary rents has become an enticing strategy, an approach where firms do not stick with just one advantage over time (e.g., Destri and Dagnino, 2005). Such strategic behavior focuses on continuously matching the firm's evolution with the rapidly evolving environment (Kavadias et al., 2016). The disruptive changes in firms' value creation processes due to business shocks challenge both corporate practice and research. The basic principle of corporate finance is to efficiently use capital to maximize shareholder value. Following the ground-breaking work of Modigliani and Miller (1958), a large amount of effort has been devoted to studying the value relevance of various corporate financing decisions, given the presence of market imperfections. In contrast, little attention has been paid to examining how a firm's value creation process (i.e., its business model) affects its financing decisions. To a large extent, this limited attention can be attributed to the (arguably outdated) belief that sustainable competitive advantage exists, thus the value creation process is stable.

Concurrently, recent corporate finance studies challenge the conventional view of a stable corporate leverage ratio by documenting its instability over time at both the aggregate and individual firm levels (DeAngelo and Roll, 2015; Graham et al., 2015). Why firms' relative positions in the leverage cross-section are sticky in the short run but far from stable over horizons of more than a few years is a significant intellectual puzzle, with similarities between cross-sections evaporating as the time between them lengthens. Moreover, the leverage changes around departures from stable regimes are typically far larger than contemporaneous changes in target ratio estimates based on the industry-median leverage and other previously identified determinants (DeAngelo and Roll, 2015). These findings suggest that there are underlying break points in a firm's leverage that change dramatically and can exceed the time boundaries set by corporate leverage models.

Furthermore, dynamic corporate finance models (e.g., Strebulaev and Whited, 2011) suggest that the time-varying target leverage model fits empirical data the best according to goodness-of-fit measures. Large variations in leverage can arise due to sizable changes in the target ratios (e.g., Frank and Shen, 2013). While research findings suggest that changing macroeconomic factors (e.g., Graham et al., 2015) and industry conditions (Miao, 2005; Hoberg and Phillips, 2010) can account for the time series instability of aggregate leverage, these factors alone cannot explain the relative positional changes in firm leverage within an industry over time. In contrast to the literature on the time-varying nature of corporate leverage (e.g., Halling et al., 2016), which primarily draws on cycles and shocks in the macro economy, our novel insight is to focus on idiosyncratic business shocks to individual firms and on the heterogeneity of their sensitivity to industry shocks.

We contend that business shocks affect a firm's financing decisions through changes in investment opportunities, echoing the sentiment of dynamic corporate finance models, suggesting that financing decisions depend primarily on the dynamics of investment opportunities (e.g., Hennessy and Whited, 2005; Tserlukevich, 2008). Some studies explore the implications of dynamic corporate finance models by analyzing the correlation between leverage and investment spikes (e.g., Harford et al., 2009; DeAngelo et al., 2011; Dudley, 2012; Denis and McKeon, 2012; Elsas et al., 2014; Im et al., 2020b). However, these studies do not directly examine shocks to corporate investment opportunity sets (Bargeron et al., 2018). In contrast to these studies, we analyze business shocks to firms' investment opportunities.

Our paper also relates to the literature on the alignment between corporate strategies and capital structure decisions. When there are idiosyncratic shocks to a firm's value creation process, management reacts by strategically reshaping the firm's business model. A critical assumption underlying many strategic management theories is that in any given industry, consumers are heterogeneous with respect to their tastes and preferences. These different segments of consumers are best served by firms with different strategic approaches, as a firm that attempts to serve all segments will serve all of them poorly (Porter, 1980). Therefore, within a given industry, we are likely to observe different competitive strategies. If a competitive strategy guides a firm's investment decisions (Chandler Jr, 1962), and the choice of investment can influence the choice of financing (Williamson, 1988), we should expect that different capital structures best serve the needs and requirements of different strategies. Furthermore, we should then expect to observe non-trivial variation in capital structures across firms within the same industry. Herein lies the potential for a strategy to help resolve the capital structure puzzle. The most promising application of strategy to the topic of capital structure is to explain why we should expect to see as much variation within an industry as between industries (Harris and Raviv, 1991). We, therefore, examine how business shocks intensify intra- and inter-industry leverage variation and lead to the dynamic patterns that we observe over time.

During periods when firms experience large economic shocks that reshape their business, we may observe large discontinuities in their financing decisions, which are difficult to reconcile with capital structure theories. However, this difficulty is not an indication of the failure of theories. Ex ante, a firm determines its optimal leverage by following certain models; ex post, because of unexpected shocks to its fundamentals, the firm reacts to the changes and decides on a new optimal leverage that is known to managers but, contemporaneously, unobservable to empirical researchers.[4]

Synthesizing all of the arguments and ideas above, our core hypothesis is:

Hypothesis*: Larger corporate business shocks induce greater instability in financial leverage.*

[4]Eventually, all the changed fundamentals are reflected in the firm's financial reports but lag behind the actual changes. It should be noted that our point here is different from the concern about omitted variable bias when estimating the target leverage regression, which mainly involves the missing leverage determinants. Even if the theory is correct in capturing all the fundamental variables, unexpected shocks can cause the model to appear unsuccessful in explaining the observed leverage ratio.

3. Sample construction and variables

3.1. Sample construction

Our sample covers all public firms in the U.S. that are in the Compustat database from 1968 to 2015. Our key variable of interest (business shock) requires 24 monthly observations of the four-factor data from Hou et al. (2015) to construct. Since the first available monthly observation in Hou et al. (2015) is in January 1967, we start our cross-sectional sample in 1968. We obtain financial statement information from Compustat and monthly stock return data from CRSP. Following the common practice in the finance literature, we exclude firms in the utility and financial industries (Standard Industrial Classification (SIC) codes from 4900 to 4999 and 6000–6999, respectively) as these firms are highly regulated and their capital structure decisions are different from those of firms in other industries. We also omit firm-years that are missing necessary data for the variables we use. Finally, we winsorize all the continuous variables at their 1st and 99th percentiles to ameliorate the effect of outliers. After these filtering procedures, we are left with a sample of 78,927 firm-years[5], drawn from 8,927 unique firms.

3.2. Measurement

3.2.1. Leverage deviation

We measure leverage deviation as the absolute value of the difference between the actual financial leverage (L) and the estimated target leverage (TL). Following the recommendation in Welch (2011), we use the ratio of total debt (*dlc* + *dltt*, Compustat acronyms) to the sum of total debt and the book value of equity (*ceq*+*mib*, Compustat acronyms) as our main measure [6] for firms' financial leverage.

To estimate TL, we follow the literature (e.g., Byoun, 2008; Uysal, 2011; Zhou et al., 2016) and estimate cross-sectional regressions of financial leverage on leverage determinants (X_i), as shown below:

$$TL_{i,t} = \alpha + X'_{i,t-1}\beta + \varepsilon_{i,t}, \tag{1}$$

We then use fitted values from equation (1) to estimate the target leverage for each firm-year observation. Studies (e.g., Titman and Wessels, 1988; Rajan and Zingales, 1995; Hovakimian

[5] Our initial sample from Compustat from 1967 to 2015 contains 268,626 firm-year observations. We drop 189,699 observations due to the following three filters to reach our final sample of 78,927 observations: (1) financial firms (60,754 observations), (2) utilities (8,340), and (3) missing values (120,605).

[6] We also conduct robustness checks using alternative leverage measures. See detailed discussion and results in Section 4.

et al., 2001; Fama and French, 2002; Flannery and Rangan, 2006; Kayhan and Titman, 2007) use different sets of leverage determinants (X_i). We follow Flannery and Rangan (2006), Frank and Goyal (2009), Marchica and Mura (2010), and Woods et al. (2019), among many others, and use eight core factors to model target leverage: (1) median industry leverage ($IndustLev$); (2) market-to-book ratio ($Mktbk$); (3) tangibility ($Tangibility$); (4) profitability (ROA); (5) log of assets ($LnAssets$); (6) R&D to total assets ratio (RD_AT); (7) missing R&D dummy (RD_DUM); and (8) depreciation to total assets ratio (DP_AT). We provide detailed definitions and calculations of these factors in the Appendix.

3.2.2. Business shock

In our setting, business shock is an event that alters a firm's strategy, resulting in discontinuities in its value creation process. For example, regulatory changes, technological innovations, and market entry by new (or existing) firms cause firms to alter their business strategies. We construct a business shock proxy by "cleaning" firms' idiosyncratic volatility to extract the "shock" component of firms' equity value. In Elton (1999), the equity value of a firm has three components – systematic, shock, and a random noise component – implying that idiosyncratic equity volatility contains the shock component. We first run the following monthly regression of firm i's returns on the monthly industry returns (excluding its own firm) and the Q factor model of Hou et al. (2015) for years t to t-1 using a rolling window of 24 months:

$$r_{i,T} = \alpha_{i,T} + \beta_1 r_{j,T} + \beta_2 r_{MKT,T} + \beta_3 r_{ME,T} + \beta_4 r_{I/A,T} + \beta_5 r_{ROE,T} + \varepsilon_{i,T}, \qquad (2)$$

where $r_{i,T}$ is firm i's monthly stock returns, $r_{j,T}$ is firm i's monthly value-weighted two-digit SIC industry returns (excluding firm i's returns in industry j), $r_{MKT,T}$ is the value-weighted market returns, and $r_{ME,T}$, $r_{I/A,T}$, and $r_{ROE,T}$ are the size, investment, and profitability factors in Hou et al. (2015) respectively,[7] where T refers to 24 months (years t and t-1). $BusinessShock$ is computed as the natural logarithm of the mean of the squared residuals from equation (2).

In an informationally efficient market, the stock price impounds all public and private information. Major fundamental information (e.g., about future earnings) is embedded in stock prices (e.g., Durnev et al., 2003; Chen et al., 2006). Accordingly, a stock's idiosyncratic volatility should capture firm-specific cash flow shocks arising from business shocks (e.g., Gaspar and

[7]We source the factors data from `http://global-q.org/factors.html`.

Massa, 2006; Irvine and Pontiff, 2008; Owens et al., 2017). One major concern of using the idiosyncratic volatility measure as a proxy for business shock is that the idiosyncratic volatility measure might capture not only the business shock, but also other shocks (i.e., tax and legal shocks, among others), which are also potential drivers of leverage deviations.[8] To address this concern, in our robustness tests, we additionally control for alternative firm risk measures from Campbell et al. (2014), such as financial risk, tax risk, and litigation risk when testing the effect of business shocks on leverage deviation.

Ideally, in equation (2), we should also control for all the economic drivers of a firm's business prospects that are related to stock prices. These economic drivers include investment, profitability, firm size, and so on. However, it is empirically problematic because the firm-level variables remain unchanged on an annual or quarterly basis, while the stock return data are sampled monthly. We address this issue in two ways. On the one hand, in addition to the market return and industry return as used in Owens et al. (2017), we incorporate the investment-based asset pricing factors of Hou et al. (2015) in equation (2). On the other hand, we control for these firm-level economic drivers when estimating the effect of the idiosyncratic volatility measure on leverage deviation. As such, we reduce the likelihood that the impact of business shock is driven by its connection to the omitted factors.

Further, to validate the business shock measure ($BusinessShock$), we follow Owens et al. (2017) and test whether $BusinessShock$ can capture four real operational changes within a firm.[9] These operational changes include: (1) a large merger or acquisition ($LargeMergAcq$); (2) industry change (based on the four-digit SIC code) ($IndChange$); (3) large special items ($LargeSpecItem$); and (4) one of the three above mentioned operational changes ($OpShock$). To account for other firm-level drivers of these operational changes, following Lee et al. (2018) and Von Beschwitz (2018), we also control for the market-to-book ratio ($Mktbk$), profitability (ROA), log of total assets ($LnAssets$), R&D intensity (RD_AT), free cash flows ($FreeCashFlows$), cash holdings ($CashHoldings$), and sales growth rate ($SalesGrowth$). The validation test results are in Table 1. The table shows that firms with higher magnitudes of $BusinessShock$ are more likely to engage in all four operational changes, suggesting that $BusinessShock$ is an

[8] We thank an anonymous reviewer for raising these concerns.

[9] In addition to this test, Owens et al. (2017) randomly examine 100 firm-year observations in the highest business shock decile. They identify the month within that year with the largest magnitude abnormal stock return, and they read all the news stories on Factiva for that firm-month. They find that firms experience significant business events during months with large abnormal returns, which further confirms that our business shock measure contains a significant amount of information relating to the business model and strategic changes.

appropriate measure of business shocks.

[Insert Table 1 here.]

Instead of using real operational shock measures, we use *BusinessShock* as our main business shock measure for three reasons. First, each of the real operational events can capture only one type of shock at a time. A cross-event comparison is not viable. Our business shock measure is a composite measure that can be used to measure, compare, and aggregate business shocks in both cross-sectional and time series dimensions. Second, these real events can only be observed ex post, and the effects of these real events may already be incorporated into firm fundamentals that determine target leverage. Our return-based measure contains firms' future prospect information. Third, our focus is on the broad impacts of general business shocks on leverage instabilities. Focusing on one or a subset of specific business shocks provides cleaner inference, nonetheless limiting our scope for broader implications. To show that our main hypothesis also applies to real shock events, we also provide additional tests on the relation between each of the real shocks and the leverage instability in Section 4.

3.3. Other variables

Our main control variables in the leverage deviation regressions include the indicator of dividend non-payer (*NonDivPayer_Dum*), the size–age (*SA*) used in Hadlock and Pierce (2010), industry-adjusted market-to-book ratio (*AdjMktbk*), the absolute value of realized operating cash flows ($|OperatingCF|$), and earnings volatility (*Earns_Vol*).[10] These variables are documented in the literature (e.g., Byoun, 2008; Dang et al., 2012; Faulkender et al., 2012) as significant determinants of firms' leverage deviation or speed of leverage adjustment. In addition, we control for other economic drivers of firms' business prospects, including size (*LnAsset*), asset growth rate (ΔAT_AT), and profitability (*ROA*). All control variables are measured in year $t-1$, while the dependent variable (*LevDev*) is measured in year t. We provide detailed definitions and data sources for the variables used in this study in the Appendix.

3.4. Variable description

We present descriptive statistics in Table 2. Panel A of the table provides the distributional statistics of the variables. The average firm size (*LnAssets*) in our sample is 4.75, which

[10]Macroeconomic conditions (Cook and Tang, 2010), business cycle (Halling et al., 2016), and credit market condition (Faulkender et al., 2012) are also important determinants for leverage deviation. We therefore include the year fixed effect to control for these factors.

translates into approximately \$887 million of raw value of total assets. The average firm size (4.75) in our sample is comparable to the average firm size reported (4.58) in Frank and Goyal (2009). The mean and median values of book financial leverage (LEV_{FDBCP}) are 29% and 25%, respectively. These values are largely comparable to the other capital structure studies (e.g., Devos et al., 2017; Nguyen et al., 2020). On average, a sample firm has an *ROA* of 8%, a leverage deviation of 0.17, and business shock of -4.96. Panel B shows the correlation matrix between our main dependent variable (*LevDev*), key variable of interest (*BusinessShock*), and the determinants of leverage deviation. Our univariate analysis shows that *BusinessShock* is positively correlated with leverage deviation, providing some preliminary evidence supporting our main hypothesis. The leverage deviation determinants are generally not highly correlated, except *ROA* and $|OperatingCF|$. This largely mitigates the concern of a potential collinearity problem. In unreported results, we show that our main results are qualitatively similar or even stronger if we exclude *ROA* and/or $|OperatingCF|$ from the leverage deviation regression.

[Insert Table 2 here.]

4. Business shocks and leverage instabilities

In this section, we examine how business shocks can address instabilities in corporate financial leverage. In subsections 4.1 to 4.3, we analyze the three major forms of leverage instability that DeAngelo and Roll (2015) document: large unexplained leverage deviations from target leverage derived from finance theory, the unstable cross-sectional distribution of the leverage ratio, and evaporating leverage similarities among the cross-section of firms. In subsection 4.4, we address potential empirical specification concerns.

4.1. Large unexplained leverage deviation

The first form of leverage instability is the large unexplained leverage deviation from the target leverage, which cannot be readily explained by finance theories. To examine whether large business shocks increase the likelihood of large unexplained leverage deviation, we use the following logit model:

$$Prob(LargeLevDev_{i,t} = 1) = \frac{e^{\alpha+\beta(LargeBusShock_{i,t})+\omega Controls_{i,t-1}+\epsilon_{i,t}}}{(1 + e^{\alpha+\beta(LargeBusShock_{i,t})+\omega Controls_{i,t-1}+\epsilon_{i,t}})}, \tag{3}$$

where $Prob(LargeLevDev_{i,t})$ is the probability of firm i experiencing a large leverage deviation in year t. *LargeLevDev* is a binary variable taking a value of 1 if the leverage deviation of a firm-year is greater than the firm's sample median leverage deviation and 0 otherwise. We capture a large business shock, *LargeBusShock*, via a dummy variable taking a value of 1 if the shock of a firm-year is greater than the firm's sample median shock and 0 otherwise. We discuss the control variables in subsection 3.3. We use bootstrapped standard errors (Pagan, 1984) in our estimation.

We present the logit regression results in columns (1) to (3) in Panel A of Table 3. We do not include fixed effects in the regression for column (1) because of the incidental parameters problem of nonlinear models (Greene, 2004). Column (1) shows that holding all variables at their means, a firm that experiences a large business shock is 4.1% more likely to experience a large leverage deviation than a firm that does not experience a large business shock, and this result is statistically significant at the 1% level. Our results are also economically significant. For example, the 4.1% represents an 8.7% increase from the conditional mean (47%) of the large leverage deviation.

Even when we control for year fixed effects, the results in column (2) show that the marginal value of 4.3% (p-value < 0.01) on *LargeBusShock* is almost identical to the one reported in column (1). To avoid the incidental parameters problem while including many dummy variables, such as firm fixed effects, we run a conditional logit regression. When we control for firm fixed effects, the marginal value on *LargeBusShock* drops to 1.4% in column (3), but it is still positive and statistically related to a large leverage deviation at the 1% level of significance.

[Insert Table 3 here.]

We also examine whether the size of a business shock is positively associated with the size of leverage deviation. We use a linear regression of leverage deviation ($LevDev_{i,t}$) against the business shock ($BusinessShock_{i,t}$). We also control for the set of leverage deviation determinants we define in subsection 3.3. In the estimation, we use bootstrapped standard errors. We can see from column (4) in Panel A of Table 3 that the magnitude of *BusinessShock* is significantly positively related to the magnitude of leverage deviation at the 1% level of significance when we control for year fixed effects. When we control for firm fixed effects in the regression for column (5) or firm and year fixed effects in the regression for column (6), the coefficient of *BusinessShock* in both columns (5) and (6) drops by approximately one-quarter; however, our results remain statistically significant at the 1% level. Most importantly, our results are also economically significant. For example, column (6) shows that a one standard deviation increase in $BusinessShock$ (1.11) is associated with an increase of 66.6% (=0.102*1.11/0.17) in the mean (0.17) leverage deviation. To ensure that our results are not affected by zero leverage firms, we remove zero leverage firms from the sample. The results in column (7) show that the coefficient on $BusinessShock$ is approximately 36% larger in magnitude than that in column (6).

To ensure that our baseline results are robust to various alternative measures of leverage, we repeat our baseline regression analysis (shown in column (6)) using three alternative leverage measures, including: (1) long-term book leverage (Lev_{LFDBCP}), which is the ratio of long-term financial debt to book capital; (2) market leverage (Lev_{FDMCP}), which is the ratio of financial debt to market capital; and (3) long-term market leverage (Lev_{LFDMCP}), which is the ratio of long-term financial debt to market capital. The results in columns (8) to (10) show that the magnitudes of the coefficients (t-stats) on $BusinessShock$ range from 0.105 to 0.107 (6.22 to 8.68), which are qualitatively similar to the coefficient of 0.102 (t-stat=6.45) reported in column (6). Therefore, our results are insensitive to alternative measures of leverage.

One may be concerned that our business shock measure is not a sufficiently tight measure of business shock. Therefore, we examine whether there may be other potential drivers of our business shock measure. Guided by Campbell et al. (2014), we augment our model with three proxies of firm risk; financial risk, tax risk, and litigation risk. These measures are constructed using textual analysis on firms' 10-K filings. We report the results in column (11) in Panel A of Table 3. Limited by the data availability of these additional text-based controls, in column (11), the sample period is confined to 1994 to 2015. Column (11) shows that $BusinessShock$ remains positively correlated with leverage deviation at the 1% level of significance.

We next examine whether our results are driven by macroeconomic uncertainties rather than firm-level shocks. Recent studies investigate the impact of uncertainty on external finance, security issuance, and leverage adjustment behavior (e.g., Cao et al., 2013; Francis et al., 2014; Gungoraydinoglu et al., 2017; Çolak et al., 2018; Im et al., 2020a). Uncertainty has been shown to significantly and negatively affect both the target leverage and its target adjustment speed. However, to mitigate endogeneity, simultaneity, and reverse causality issues, the uncertainty measures in these papers are at the macro level. Some of the uncertainty measures capture the election-driven uncertainty prevalent before national elections and other key elections that change the veto players in the country. The non-election-based uncertainty measures capture how concentrated the prevailing government's power is and whether the media coverage of economic policy uncertainty is fervent, such as Baker et al.'s (2016) Economic Policy Uncertainty Index (*EPU*). Pástor and Veronesi (2013) show that macro-level uncertainty measures such as political uncertainty are also associated with higher stock volatility. Thus, macro-level and firm-level uncertainty measures are likely highly positively correlated, which poses a threat to the reliability of our inferences. To address this concern, we add two time-varying macro variables, *EPU* and the annual realized return volatility of the S&P 500 index ($SP_{V}ol$), as additional controls and remove year fixed effects. We report the results in column (12) in Panel A of Table 3. Column (12) shows that our main findings remain unchanged.

As a further confirmation that our results in Panel A truly capture the impact of business shocks, we also use real operational shocks (see Section 3.2.2) as alternative business shock measures to examine how each of the shocks affects leverage deviation. We can see from Panel B of Table 3 that firms experiencing some large economic shock events, such as industry change (*IndChange*), large special items (*LargeSpecItem*), or operational shock (*OpShock*), are more likely to exhibit a large leverage deviation across columns (1) to (5) using the same conditional logit model as in column (3) of Panel A. For example, column (2) shows that if a firm changes its industry classification, the probability of experiencing a large leverage deviation shock increases by 4.9%, which translates into a 10.4% increase from the mean (0.47) of a large leverage deviation. To further examine the impact of the real shocks on the size of the leverage deviation, in the regressions for columns (6) to (10) of Panel B, we replace the binary dependent variable (*LargeBusShock*) in columns (1) to (5) with a continuous variable (*LevDev*) as our dependent variable. Given the nature of the dependent variable (*LevDev*), in columns (6) to (10), we use the panel regression method. Columns (6) to (10) show that firms experiencing some large economic shock events, such as industry change (*IndChange*), large special items (*LargeSpecItem*), or operational shock (*OpShock*), are more likely to exhibit an approximately 20% larger leverage deviation.

In addition, to understand how important business shocks are in explaining the leverage deviation, we use the Shapley-Owen value method (see Shorrocks, 1999) to decompose the regression R^2 for each determinant of leverage deviation in our baseline regression model. We report the R^2 decomposition results in Table 4. Differing from the regression coefficients that measure the sensitivity of the dependent variable to the changes in the independent variables, the decomposed R^2 of an independent variable measures the relative importance of the independent variable in explaining the variance of the dependent variable. The results reveal that our business shock measure, *BusinessShock*, is the most important driver of leverage deviation, which accounts for approximately 27% of the sample variance of leverage deviation. Notably, the contribution of *BusinessShock* to the regression's R^2 is greater than any other determinants used in prior studies (e.g., Byoun, 2008; Dang et al., 2012; Faulkender et al., 2012). Taken together, our results suggest that a significant proportion of the unexplained leverage deviation in most empirical studies may be associated with business shocks.[11]

[Insert Table 4 here.]

4.2. Cross-sectional leverage position migration

The second form of leverage instability is the unstable cross-sectional distribution of the corporate leverage ratio. The relative leverage positions in the cross-section are sticky in the short run but far from stable over horizons of more than a few years. To examine the association between business shocks and the cross-sectional instabilities of financial leverage, we first sort sample firms into small-, moderate- and large-shock groups based on the terciles of the average business shocks that a firm experiences in a rolling 20-year window; second, we calculate the frequency at which a firm switches its relative leverage positions (Koller et al., 2010; DeAngelo and Roll, 2015) by counting the average frequency of the leverage's quartile changes in the cross-section each year in the rolling 20-year window. We require at least 12 years of non-missing observations for this analysis, and then we compare the average frequency of firms' leverage position change among the small-, moderate- and large-shock groups of firms.

We present the sorting results in Panel A of Table 5. As we can see from row (1) of Panel A, the probability that a firm transitions from one leverage quartile to another each year on average is 22.5% in the small business shock group, increases to 24.2% in the moderate business shock group, and then further increases to 30.1% in the large business shock group. We further require that all included firms have 20 years of non-missing data on leverage, and we find a similar pattern. Considering that some firms may jump more than one quartile in one year, in rows (3) and (4), we report the results of calculating the average frequency of absolute changes in leverage quartiles (which is equivalent to counting the number of quartile changes),

[11] We thank the anonymous reviewer for providing this new insight.

requiring 12 years and 20 years of non-missing data, respectively. In both rows (3) and (4), we find consistent results that the cross-sectional instability of leverage positions monotonically increases as business shock increases.

[Insert Table 5 here.]

In addition, to control for other firm characteristics that may contribute to the cross-sectional migration of leverage positions, we perform a multivariate panel regression analysis. We regress the average frequency of leverage quartile changes (using the rolling 20-year window) on the business shock measure. In the regression, we control for the historical average of the leverage deviation determinants. Moreover, we control for the time interval (i.e., each 20-year rolling window) and industry fixed effects. As shown in Panel B of Table 5, the estimated coefficient on the average business shock is positive and significant at the 1% level regardless of what approach we use to calculate the average frequency of leverage migration. Collectively, our results in Table 5 suggest that the cross-sectional migration of leverage positions is tightly associated with business shocks; and, the cross-sectional leverage distribution is more persistent among firms that experience persistently lower business shocks.

4.3. Evaporating similarities in leverage

The third form of leverage instability is that the similarities in leverage among the cross-section of firms evaporate over time; in particular, the intra-industry leverage similarities. To examine to what extent the business shock contributes to evaporating leverage similarities (or increased leverage dispersion), we regress the within-industry leverage dispersion ($Dispersion\_Lev_{j,t}$) on the proportion of firms ($PropFirmShock_{j,t}$) that have experienced large business shocks in each 2-digit SIC industry. We measure $Dispersion\_Lev_{j,t}$ as the standard deviation of the financial leverage in industry (two-digit SIC code) j in year t. We include the industry-level dispersion of other leverage determinants as control variables. These controls are measured with a one-year lag relative to the measure of the dependent variable ($Dispersion\_Lev_{j,t}$). We also control for year fixed effects in the regression.

We present the regression results in Table 6. As shown in column (1), $PropFirmShock$ is positively related to the leverage dispersion in the full sample, and the relationship is statistically significant at the 1% level. Our results indicate that over time, the cumulative effect of firm-specific business shocks in an industry can increase the observed intra-industry leverage dispersion.

[Insert Table 6 here.]

We also examine the heterogeneity across different industries. Industries have different economic structures, and thus the persistence of intra-industry rents varies across industries. For example, in some industries, there are more persistent economic rents where some firms consistently earn significantly higher returns than their competitors. In contrast, in other industries, firm-specific rents (or comparative advantages) quickly diminish over time when firms encounter business shocks. Hence, we should expect that the amplifying effect of business shocks on intra-industry leverage dispersion is more pronounced in industries with less persistent rents (Waring, 1996). To test this prediction, we compare the effect of the proportion of firm-specific business shocks in each industry on the cross-sectional leverage dispersion in the bottom (other four) quintile of the least (more) rent-persistent industry by including an interaction term between $PropFirmShock_{j,t}$ and $DummyLowPersist_t$. $DummyLowPersist_t$ takes the value of one (zero) if the industry is in the bottom (other) industry-rent persistence quintile in year t.

Following Waring (1996), we measure rent persistence as the coefficient estimates obtained by regressing the current firm-specific ROA on the lagged firm-specific ROA for each two-digit SIC industry as follows:

$$ROA_{i,j,t} = \beta_j(ROA_{i,j,t-1}) + \epsilon_{i,t}, \tag{4}$$

where ROA is return on assets, i represents firm, j represents the two-digit SIC industry, t represents year, and β_j represents the rent persistence in the jth industry.

We show in column (2) of Table 6 that the estimated coefficient on the interaction term ($PropFirmShock_{j,t} \times DummyLowPersist_t$) is significantly positive at the 10% level, which is consistent with our conjecture that the amplifying effect of business shocks on intra-industry leverage dispersion is more pronounced in industries with less persistent rents. The results suggest that business shocks have a greater impact on leverage dispersion in low-rent-persistent industries because the comparative advantage of firms in the industry dissipates more quickly when business shocks occur. Our industry rent-persistence results are also economically significant. For example, column (2) shows that for firms in the bottom quintile of industry-rent persistence, the cumulative effect of business shocks on the dispersion of financial leverage is 67% ($= \frac{0.057-0.009}{0.071}$) more than for firms in the other quintile of industry-rent persistence.

Taken together, our results show that business shocks increase firms' leverage instabilities. These shocks are not only associated with large leverage deviations but are also related to leverage position migration across the cross-section of firms and enlarge leverage variations over time. This evidence supports our key hypothesis.

4.4. Addressing empirical issues

4.4.1. Endogeneity

One potential endogeneity concern of using $BusinessShock$ as a proxy for business shock is that $BusinessShock$ may not be exogenous to corporate leverage. For example, $BusinessShock$ might be reversely determined by a firm's capital structure decisions (e.g., Dennis and Strickland, 2004). In this case, the effect of idiosyncratic volatility on leverage deviation would be overestimated. Another potential source of endogeneity is the measurement error embedded using idiosyncratic volatility as a proxy for business shocks. This type of endogeneity, however, could underestimate our coefficients on idiosyncratic volatility. Endogeneity problems can also arise from sample selection bias and omitted variables.

To address endogeneity issues, we adopt a two-stage least squares instrumental variables (2SLS-IV) method with PSM. We exploit the setting of e-commerce adoption. Since the late 1990s, traditional retailers in the U.S. market have increasingly adopted e-commerce as an alternative approach (Agrawal et al., 2004). This business shock provides an IV to mitigate endogeneity concerns. First, firms that adopt e-commerce experience higher firm-specific stock volatility than those that do not (e.g., Agrawal et al., 2004; Pástor and Veronesi, 2009). Thus, e-commerce adoption satisfies the relevance condition of a valid IV. Second, although a firm's decision to adopt e-commerce is not random, it is unlikely driven by its unsigned deviation from the target capital structure. More importantly, as shown by Agrawal et al. (2004), the impact of e-commerce adoption on idiosyncratic volatility is due to increased demand volatility, not firm-specific characteristics. Hence, the exclusion condition is also satisfied.

Following Agrawal et al. (2004), we define e-commerce adoption as the action of a brick-and-mortar firm launching a website for online retail transactions. We disregard firms that launch an information-only website or one for business-to-business e-commerce. To identify the information on e-commerce adoption, we first extract all the 10-K, 10-Q, 8-K, and press release documents containing related keywords on e-commerce from 1997 to 2000.[12] We then

[12] We acknowledge the assistance of SeekiNF in extracting the documents.

manually read the text containing these keywords, and we evaluate the information for relevance.[13] Since there are some firms with missing information regarding the launch of an e-commerce website, we use Factiva to search further for these firms. We identify 125 firms that initiated websites for e-commerce from 1997 to 2000. This sample size is similar to the sample size of Agrawal et al. (2004). After dropping ADRs, closed-end funds, REITs, financial firms, and utility firms, and merging with our initial sample, we are left with 56 firms.

We use PSM based on industry (four-digit SIC code), size, and market-to-book ratio to produce a more comparable control sample. We define the IV *Ecommerce_Dum* as an indicator variable that takes a value of 1 for the year (and subsequent years) in which a firm initiates e-commerce and 0 otherwise. The sample period is from 1995 to 2000. In the first stage, we regress *BusinessShock* on *Ecommerce_Dum* and the various sets of control variables. As shown in column (1) of Table 7, *Ecommerce_Dum* is positively associated with *BusinessShock*. After confirming the relevance of the instrument, in the second stage, we regress our measure of leverage deviation (*LevDev*) on the fitted values of *BusinessShock*, which is denoted by $\widehat{BusinessShock}$. Column (2) shows that the coefficient on $\widehat{BusinessShock}$ is positive and significant at the 10% level, confirming our finding that business shocks increase the magnitude of leverage deviation. The robustness of our earlier results in Table 3 to the two-stage IV regression approach suggests that our main results are unlikely driven by potential endogeneity. Our test is limited to a specific subsample, and thus, the estimated magnitude is not directly applicable to the full sample results in Table 3.

[Insert Table 7 here].

4.4.2. External financing activities

Logically, if we observe that business shocks result in changes in firms' leverage ratio, we should also observe real external financing activities around business shocks. To verify this conjecture, we test whether our *BusinessShock* measure can predict a higher probability of engaging in external financing in debt or equity. Specifically, we use a logit model to estimate the probability of engaging in external financing (debt and/or equity) by firms facing different

[13] Specifically, the keywords we use include "ecommerce," "online retailing," "online shopping," "internet transaction," and "online transaction."

levels of business shocks as follows:[14]

$$Prob(ActiveIssuer_{i,t} = 1) = \frac{e^{\alpha+\beta(BusinessShock_{i,t})+\omega Controls_{i,t-1}+\epsilon_{i,t}}}{(1 + e^{\alpha+\beta(BusinessShock_{i,t})+\omega Controls_{i,t-1}+\epsilon_{i,t}})}, \tag{5}$$

where $Prob(ActiveIssuer_{i,t} = 1)$ is the probability of firm i having an active net issuance in year t. $ActiveIssuer$ is a dummy variable that takes a value of 1 if a firm issues net (issuance - repurchase) debt and/or net equity that exceeds a threshold c% of total assets and 0 otherwise (e.g., Hovakimian et al., 2004; Brav, 2009; Autore et al., 2014). In our analysis, we use three commonly used threshold values for c% in the literature, including 3%, 5%, and 10%. We follow Hovakimian et al. (2004) and include the same list of the 12 determinants for firms' external financing decisions. We provide detailed definitions for these 12 variables in the Appendix. We report the marginal effects of the external financing results in Table 8.

[Insert Table 8 here.]

In column (1), we define active (passive) issuers as issuing a security (debt or equity) when the net amount issued (debt or equity) exceeds (does not exceed) 3% of one-year lagged total assets. We can see from column (1) that firms experiencing larger business shocks are more likely to engage in external financing by issuing debt and/or equity, and this relation is statistically significant at the 1% level. Our results are also economically significant. For example, a one standard deviation increase in $BusinessShock$ (1.10) increases the probability of engaging in external financing by approximately 5% (=1.10*0.028/0.617) relative to the conditional mean of external financing of 62%. We also redefine active (passive) issuers using larger financing thresholds, namely, the 5% and 10% thresholds, and report the results in columns (2) and (3). As shown in the two columns, the marginal effects and the t-stats on $BusinessShock$ are stronger than those in column (1). Most importantly, there is a monotonic increase relative to the financing threshold we use: if we increase $BusinessShock$ by one standard deviation (1.10), firms are 7.55% (15.4%) more likely to engage in external financing that exceeds more than 5% (10%) of total assets relative to their respective conditional mean of external financing of 48.1% (28.6%). One possible explanation is that such a large level of external financing is only needed when firms encounter large business shocks.

[14]In unreported results, we show that the marginal effects of $BusinessShock$ from an alternative estimation method (the probit model) are qualitatively similar (ranging from 0.029 to 0.041, with t-stats range from 12.4 to 19.41) to those reported using a logit model.

4.4.3. Other empirical specification issues

In empirical capital structure studies, there are variations in empirical model specifications, and often empirical results can be sensitive to the choice of models (Mitton, 2021). To address this concern, we conduct additional robustness tests. The results are in Table 9.

[Insert Table 9 here.]

First, we check the sensitivity of our baseline regression results in Panel A of Table 3 to different methods for estimating the target leverage. In the regression for column (1) of Table 9, instead of estimating the target leverage with a yearly cross-sectional regression, we estimate target leverage using the full sample data with a panel regression approach to obtain the coefficients for all leverage determinants in equation (1) for the whole sample. In the regression for column (2), we further control for the GDP growth rate (*GDP*) in our target leverage model (equation (1)) using a full sample panel regression approach. In the regression for column (3), we further add term spread ($TermSpread$) and default spread ($DefaultSpread$) to our target leverage estimation. In the regression for column (4), we keep the same panel regression approach but replace the time-varying macroeconomic variables (*GDP*, $TermSpread$, and $DefaultSpread$) with the year fixed effects in the target leverage estimation. The results across columns (1) to (4) show that our conclusions are robust to alternative target leverage estimation approaches.

Second, we check the robustness of the results when controlling for leverage dynamism in capital structure decisions. We control the dynamism in two ways. First, in the regression for column (5), we control for the lagged one-year leverage ratio when estimating the target leverage ratio and then re-estimate our leverage deviation regression on business shock. Second, in the regression for column (6), we include the lagged one-year leverage deviation in the regression of leverage deviation on business shock. Our main findings are insensitive to these variations.

Third, to show that our results are not affected by CEO characteristics, we control CEO fixed effects and report the results in column (7) of Table 9. Given that CEO information is only available from 1992 for S&P 1500 firms from the Execucomp data, our sample size drops by approximately 74% when we include the CEO fixed effect. The results in column (7) show that our findings on the relation between business shock and leverage deviation are robust to the inclusion of CEO fixed effects.

Finally, we check whether our results are robust to using a signed leverage deviation measure. The results in column (8) show that *BusinessShock* is positively related to the signed leverage deviation measure. We also analyze subsamples of positive and negative leverage deviation observations. We find that the estimated coefficients on *BusinessShock* for both cases are positive and statistically significant at the 1% level (columns (9) and (10)). These results suggest that the estimated target leverage tends to underestimate the true target leverage more when a firm is facing a larger business shock, especially for firms with positive leverage deviations. Indeed, the estimated coefficient on *BusinessShock* for the positive leverage deviation cases is ten times the magnitude of the corresponding coefficient for negative leverage deviations.

5. Economic channel: Lumpy investment

In the framework of dynamic capital structure models (e.g., Hennessy and Whited, 2005; Tserlukevich, 2008; DeAngelo et al., 2011; Dudley, 2012), the dynamics of corporate leverage are tied to the dynamics of a firm's investment opportunities. Drawing on the implications from these models, we posit that a business shock affects a firm's financing decisions through investments. When there is a business shock to a firm's economic fundamentals, it adjusts its strategic positions, and these adjustments typically involve large investments. The lumpiness of the investment (Whited, 2006) creates a "lumpy" need for external financing, resulting in sudden and discontinuous adjustments in capital structure. In this section, we first examine the link between business shocks and investment, and then we test whether the interplay of investment and business shocks amplifies the gap between a firm's leverage and its target leverage.

5.1. Business shocks and investment spikes

We use a hazard model[15] to examine the influence of business shocks on investment "spikes" (large investments). We focus on both the frequency of "spikes" and the "spells" between

[15]The hazard model is preferable to a linear regression here for two primary reasons. First, the measurement error in firm-specific investment opportunities can bias the coefficients and inferences in linear regressions. Second, our findings suggest that there are discontinuities in the time series of investment and lumpy (rather than smooth) capital expenditures (e.g., Whited, 2006; Billett et al., 2011). The intertemporal pattern of investment violates a necessary assumption built into linear regressions of investment on q: convex adjustment costs that are both differentiable and quadratic (e.g., Whited, 2006; Billett et al., 2011).

spikes. Following Whited (2006) and Billett et al. (2011), we use the hazard model[16] established in Meyer (1990). The model takes the following form:

$$\lambda_i(t) = \omega_i \lambda_0(t) exp(x_i(t)'\beta), \tag{6}$$

where t represents the length of a spell, $\lambda_i(t)$ represents the hazard function, $x_i(t)$ represents a column vector of covariates, β represents the corresponding vector of unknown coefficients, and $\lambda_0(t)$ represents the baseline hazard. ω is a random variable that represents unobserved heterogeneity, and it is assumed to be independent of $x_i(t)$ and to have a zero-mean gamma distribution. The values of the covariates and the β on the covariates, $x_i(t)$, allow the hazard to shift up and down.

We divide the full sample into two subsamples based on the annual median threshold of $BusinessShock$: one with large business shocks ($BusinessShock$ above the annual median $BusinessShock$) and the other with small business shocks ($BusinessShock$ below the annual median). We report the semiparametric hazard estimates and baseline rates based on these samples in Table 10. Our results show that the hazard rate is higher in the large business shock sample than in the small business shock sample. For example, our log-rank test rejects the null hypothesis that the hazards are equal when collectively allowing for all time horizons at the 1% level of significance. Individually, our log-rank test shows that two hazard coefficients (i.e., 1- and 5-year cases) differ significantly between the large and small business shock samples. Overall, our results suggest that a large business shock is more likely to increase the probability of an investment spike across all time horizons, especially in the first and fifth years. Collectively, our results suggest that business shocks significantly affect the occurrence of investment spikes.

[Insert Table 10 here.]

[16] To avoid aggregation bias, we follow Whited (2006) and Billett et al. (2011) to include only small firms, deemed to be firms with real assets below the 33rd percentile of the real assets of firms in the first year that the testing firm appears in the sample. An investment is deemed to be a spike when the firm's investment rate (capex/total assets) is higher than twice the firms' own median investment rate over the entire sample period. We define the "spell" as the length of time that has elapsed since the firm's prior investment spike. Similar to other studies such as Billett et al. (2011), our hazard model suffers from a right censoring problem due to the use of a finite sample. To address this issue, we follow Meyer (1990) and Billett et al. (2011) to exclude the "right" censored data, defined as those firms with a prior year of the censored spell that is shorter than the uncensored spell.

5.2. Investment spikes: The amplifier

We further verify the investment channel by testing whether investment spikes amplify the impact of business shocks on leverage deviation. Intuitively, if business shocks affect the firms' leverage via large investments, we should observe that the impact of the business shock on large leverage deviation is more evident in the sample of firms that experience investment spikes. To test this, we add an interaction term between a large business shock ($LargeBusShock$) and an investment spike dummy ($Investmentspike_{t(t+1)}$) in the baseline logit regression (equation (3)). $Investmentspike_{t(t+1)}$ is a dummy variable that equals 1 if a firm's investment in year t ($t + 1$) exceeds 100% of the firm's past three years' average "benchmark" investment and is at least 20% of the firm's prior year-end total assets and is otherwise a value of 0.

We present the results in Table 11. Column (1) of the table shows that the estimated coefficient on $LargeBusShock$ is positively and statistically related to the large leverage deviation. Most importantly, column (1) also shows that when firms experience concurrent investment spikes ($Investmentspike_t$), the impact of large business shocks ($LargeBusShock_t$) on the large leverage deviation is amplified 1.56 times (=0.039/0.025), which is consistent with our expectation that leverage deviation is larger when firms respond to large business shocks by investing a large amount of capital. If we consider when firms experience investment spikes ($Investmentspike_{t+1}$) one year after large business shocks ($LargeBusShock_t$) in column (2), the impact of large business shocks on large leverage deviations through investment spikes becomes marginally insignificant (z-stat=1.34). Taken together, the results in Table 11 suggest that the impact of the large business shock on large leverage deviation is most pronounced when firms experience concurrent investment spikes.

[Insert Table 11 here.]

6. Empirical implications

Our results suggest that there are discontinuities in corporate financial leverage. The popular target leverage model using past financial variables to estimate target leverage cannot adequately capture disruptive shifts in the leverage regime, leaving a large gap between the estimated target leverage and the unobservable actual target leverage ratio. Our results suggest that business shocks play a significant role in driving this gap. The estimated target leverage TL is thus a biased estimator of the true target leverage TL^*, and the bias is a function of the business shock. Intuitively, as the business shock enlarges the estimated leverage deviation, the speed of leverage adjustment (SOA) appears slower than what it should be, placing capital structure adjustment theory in a more negative light than is warranted.

Empirically, the above line of reasoning implies that the SOA in the subsample absent large business shocks is a far more reliable estimate and should be significantly different from and speedier than the SOA in the subsample with large business shocks. We test this conjecture using a two-step procedure (e.g., Byoun, 2008). In the first step, we estimate target leverage $\hat{TL}_{it+1}$ using yearly regression; then, in the second step, we estimate the following partial adjustment model:

$$Lev_{i,t} - Lev_{i,t-1} = \lambda(\hat{TL}_{i,t} - Lev_{i,t-1}) + \epsilon_{i,t}, \tag{7}$$

where $Lev_{i,t}$ is the financial leverage ratio of firm i at year t. In this estimation, we use Lev_{FDBCP} to be consistent with our other main tests. Next, we examine the impact of business shocks on the estimation of SOA by augmenting equation (7) with an interaction term between the deviation from the target leverage ($\hat{TL}_{i,t} - Lev_{i,t-1}$) and a dummy variable ($LargeBusShock$) indicating whether there is a large business shock. That is,

$$Lev_{i,t} - Lev_{i,t-1} = \lambda(\hat{TL}_{i,t} - Lev_{i,t-1}) + \gamma_1(\hat{TL}_{i,t} - Lev_{i,t-1}) \times LargeBusShock + \epsilon_{i,t} \tag{8}$$

To control for other determinants of SOA (i.e., the control variables used in our main leverage deviation regressions), we then interact these variables with the leverage deviation variable and thus we have:

$$\begin{aligned} Lev_{i,t} - Lev_{i,t-1} = \lambda(\hat{TL}_{i,t} - Lev_{i,t-1}) + \gamma_1(\hat{TL}_{i,t} - Lev_{i,t-1}) \times LargeBusShock \\ + \gamma_2(\hat{TL}_{i,t} - Lev_{i,t-1}) \times Controls + \epsilon_{i,t}, \end{aligned} \tag{9}$$

We estimate the leverage adjustment model using both the ordinary least square (OLS) and fixed effect (FE) methods to give lower- and upper-bound (e.g., Flannery and Hankins, 2013) estimates for SOA. We present the results in Table 12. Columns (1) to (3) present the results using the OLS method, while columns (4) to (6) present the results using the FE method. Consistent with the literature (e.g., Flannery and Hankins, 2013), the estimated coefficients on $LevDev_{i,t}$ ($=\hat{TL}_{i,t} - Lev_{i,t-1}$), i.e., SOA, using the FE method are much higher than those using the

OLS method. The SOA estimates in columns (1) and (4) are comparable to the SOA estimates in previous studies (e.g., Fama and French, 2002; Flannery and Rangan, 2006). As we can see from the table, the estimated coefficients of the interaction term between leverage deviation and large business shocks are significantly negative across different model specifications, indicating that the subsample with large business shocks demonstrates a significantly lower SOA than the subsample with small business shocks. As shown in column (3), the subsample with small business shocks has an SOA of 17.9%, corresponding to a half-life adjustment of 3.5 ($\frac{ln(0.5)}{ln(1-0.179)}$) years, and the subsample with large business shocks has an SOA of 13.4% (0.179 − 0.045), corresponding to a half-life adjustment of 4.8 ($\frac{ln(0.5)}{ln(1-0.134)}$) years. The firms that experienced large business model shocks on average adjust 37% ((4.8 − 3.5)/3.5) slower to close half of their leverage deviation from the target leverage, which is economically significant.

[Insert Table 12 here.]

7. Conclusion

In recent decades, the business environment has become increasingly disruptive. Evolutionary strategic theory suggests that firms adapt to such changes by reshaping their business models, resulting in discontinuities in the value creation process. These "jumps" violate the stationarity assumptions underlying many corporate finance models. In this paper, we examine whether and to what extent the discontinuities in firms' value creation process emanating from business shocks can reconcile the puzzling findings regarding the instability of corporate financial leverage (DeAngelo and Roll, 2015).

We extract a measure of business shock from corporate expected return (Elton, 1999; Owens et al., 2017). We test whether business shocks are associated with large unexplained deviations in leverage from the target leverage. We find that large business shocks significantly increase the probability of large unexplained leverage deviations, and the magnitude of these shocks has a substantial economic impact on leverage deviation. Moreover, we find that business shocks are associated with the unstable cross-sectional distribution of financial leverage. The persistence of the cross-sectional distribution of the firm's leverage is thus conditional on business shocks. This finding provides a helpful way to reconcile the conflicting views of Lemmon et al. (2008) and DeAngelo and Roll (2015) on the persistence of leverage. In addition, our results show that business shocks are associated with intra-industry leverage variation, which is important for explaining the overall large cross-sectional variation in corporate capital structure (Graham and Leary, 2011).

In channel tests, we show that business shocks affect corporate financing decisions through "lumpy" investment. Using a hazard model, we find large business shocks significantly increase the probability of investment spikes. We also find that the association between business shocks and leverage deviation is stronger in the subsample of firms that experience an investment spike. Our results imply that modeling corporate financial leverage adjustment should condition on business shocks. Indeed, we find that corporate leverage adjusts much faster (slower) for firms that experience small (large) business shocks.

Our key message is that discontinuities in the value creation process offer the prospect of much deeper knowledge creation. Given that these discontinuities often violate the stationarity assumptions underlying many empirical settings, our basic approach of allowing business shocks to enter the analysis can be further investigated as a possible explanation for other puzzling findings across the broad spectrum of the empirical corporate finance literature.

Appendix: Variable definitions

Variable	Measurement (Compustat acronym)	References	Sources
Panel A: Leverage measures			
Lev_{FDBCP}	Total debt to the sum of total debt and book value of equity = (dlc+dltt)/(dlc+dltt+ceq+mib).	Welch (2011)	Compustat
Lev_{LFDBCP}	Long-term debt to the sum of total debt and book value of equity = dltt/(dlc+dltt+ceq+mib).	Welch (2011)	Compustat
Lev_{FDMCP}	Total debt to the sum of total debt and market value of equity = (dlc+dltt)/(dlc+dltt+prcc_f*csho).	Welch (2011)	Compustat
Lev_{LFDMCP}	Long-term debt to the sum of total debt and market value of equity = dltt/(dlc+dltt+prcc_f*csho).	Welch (2011)	Compustat
LevDev	Absolute value of the difference between the actual financial leverage level and the estimated target leverage. *LevDev* is in a natural log form. Financial leverage is based on the definition of Lev_{FDBCP} in the main manuscript. We report *Lev_Dev* based on various definitions of financial leverage in Table 3.		
LargeLevDev	A dummy variable that is equal to one if the leverage deviation (*Lev_Dev*) of a firm is greater than its median leverage deviation throughout its own sample period and zero otherwise.		
Panel B: Key variables of interest - Idiosyncratic shocks			
BusinessShock	Firm-specific stock return heterogeneity is defined as the mean squared residuals from a regression of monthly firm *i*'s returns on monthly industry (excluding its own firm), market returns, and on the size, investment, and profitability factors of Hou et al. (2015) for years *t* to *t*-1 (i.e., 24 monthly return observations). We then take the natural logarithm of this variable.	Owens et al. (2017)	CRSP
LargeBusShock	A dummy variable that takes a value of one if a firm's business shock is greater than its median business shock through its own sample period and zero otherwise.		
PropFirmShock	*PropFirmShock* measures the proportion of firm *i*'s business shocks within each two-digit SIC industry in each year that is greater than the top 20% of firm shocks in the whole sample.		

table continued onto next page

Variable	Measurement (Compustat acronym)	References	Sources
Panel C: Key variables of interest - Operational shocks			
LargeMergAcq	A dummy variable that takes a value of one if firm *i* has a large merger or acquisition, indicated by Compustat sales footnote code (*sale_fn=AB*) in year *t* or zero otherwise.	Owens et al. (2017)	Compustat
IndChange	A dummy variable that takes a value of one if firm *i* changed its industry based on the four-digit SIC code from year *t*-1 to year *t* or zero otherwise.	Owens et al. (2017)	Compustat
LargeSpecItem	A dummy variable that takes a value of one if firm *i* has special items greater than 5% of sales (*spi>5%*) in year *t* and zero otherwise.	Owens et al. (2017)	Compustat
OpShock	Operational shock is a dummy variable that takes a value of one if firm *i* experiences at least one of the following operational shock items in year *t*: (1) *LargeMergAcq*; (2) *IndChange*, (3) *LargeSpecItem*; and zero otherwise.	Owens et al. (2017)	Compustat
Panel D: Leverage determinants			
ROA	Profitability (*ROA*) is the ratio of operating income before depreciation to the book value of total assets *(oibdp/at)*.	Frank and Goyal (2009)	Compustat
LnAssets	Natural logarithm of total assets.	Frank and Goyal (2009)	Compustat
IndustLev	Median industry book leverage is calculated each year based on the four-digit SIC code. We require at least ten observations in each four-digit SIC code. If there are less than ten observations in a four-digit SIC code, we use the median of book leverage in the three-digit SIC code. Similarly, if the three-digit SIC code has less than ten observations, we use the median of the two-digit SIC code.	Frank and Goyal (2009)	Compustat
Mktbk	Market-to-book is the ratio of the market value of assets to the book value of total assets.	Frank and Goyal (2009)	Compustat
Tangibility	Asset tangibility is the ratio of total net property, plants and equipment to the book value of total assets *(ppent/at)*.	Frank and Goyal (2009)	Compustat
RD_AT	The ratio of R&D expenses to total assets.	Flannery and Rangan (2006)	Compustat
RD_DUM	A dummy variable that equals one if a firm did not report R&D expenses and zero otherwise.	Flannery and Rangan (2006)	Compustat
DP_AT	The ratio of depreciation to total assets.	Marchica and Mura (2010)	Compustat

table continued onto next page

Variable	Measurement (Compustat acronym)	References	Sources
Panel E: Control variables			
$FreeCashFlow$	Free cash flow is defined as the ratio of operating income before depreciation (OIBDP) minus interest expense (XINT) minus income taxes (TXT) minus capital expenditures (CAPX) to total book assets (AT).	Lee et al. (2018)	Compustat
$CashHoldings$	Cash holdings are defined as the ratio of cash equivalents (CHE) to total book assets (AT).	Lee et al. (2018)	Compustat
$SalesGrowth$	Sales growth is defined as the difference of net sales ($SALE$) divided by net sales in the previous year.	Lee et al. (2018)	Compustat
ΔAT_AT	Asset growth ratio is defined as the difference of total assets (AT) divided by total assets in previous year.	Hou et al. (2015)	Compustat
SA	Financial constraint index, measured as $-0.737*LnAssets+0.043*LnAssets^2+0.040*Firmage$, where $Firmage$ is the number of years the firm has been on Compustat with a nonmissing stock price.	Hadlock and Pierce (2010)	Compustat
$\lvert OperatingCF \rvert$	Absolute value of a firm's operating cash flow, which is measured as $\frac{(OIBD_{i,t}-T_{i,t}-Int_{i,t})}{A_{i,t-1}} - IndustryCapEx_t$, where $OIBD$ is the operating income before depreciation, T is the total taxes allocated on the income statement, Int is the interest paid, and $IndustryCapEx$ is the mean value of capital expenditures scaled by lagged book assets.	Faulkender et al. (2012)	Compustat
$AdjMktbk$	Firm market-to-book ratio ($Mktbk$) minus the industry mean market-to-book ratio.	Faulkender et al. (2012)	Compustat
$NonDivPayer\_Dum$	A dummy variable that equals 1 if the firm did not pay dividends in year t and zero otherwise.	Faulkender et al. (2012)	Compustat
$Earns\_Vol$	Earnings volatility measured as the standard deviation of asset-scaled earnings over the last eight quarters	Dang et al. (2012)	Compustat
$FinancialRisk$	Financial risk constructed based on textual analysis on 10-K files.	Campbell et al. (2014)	SeekEdgar
$TaxRisk$	Tax risk constructed based on textual analysis on 10-K files.	Campbell et al. (2014)	SeekEdgar
$LitigationRisk$	Litigation risk constructed based on textual analysis on 10-K files.	Campbell et al. (2014)	SeekEdgar
EPU	The average of monthly Economic Policy Uncertainty index in each year.	Baker et al. (2016)	www.policyuncertainty.com
$SPVol$	Realized volatility of S&P 500 index returns for each year.		CRSP
GDP	The real GDP growth rate.		FRED
Term Spread	The difference in yield between long-term government bonds and Treasury bills.		FRED
Default Spread	The difference between Moody's Baa and Aaa rated corporate bond yields.		FRED
$StockReturn$	The split- and dividend-adjusted return over the last pre-issue year	Hovakimian et al. (2004)	CRSP
$NOLC$	The net operating loss carry forwards scaled by total assets	Hovakimian et al. (2004)	Compustat
$SellingExpense$	The selling and administrative expenses scaled by sales	Hovakimian et al. (2004)	Compustat
$R\&DExpense$	The research and development expenses scaled by sales	Hovakimian et al. (2004)	Compustat
$EPS\ dilutiondummy$	A dummy variable that equals one if issuing equity dilutes the firm's earnings per share (EPS) more than issuing debt does and zero otherwise	Hovakimian et al. (2004)	Compustat
$Mktbk > 1\ dummy$	A dummy variable that equals one if the market-to-book ratio is larger than one and zero otherwise	Hovakimian et al. (2004)	Compustat

References

Agrawal, D., Bharath, S.T., Viswanathan, S., 2004. Technological change and stock return volatility: Evidence from ecommerce adoptions. Available at SSRN 387543 .

Autore, D.M., Hutton, I., Peterson, D.R., Smith, A.H., 2014. The effect of securities litigation on external financing. Journal of Corporate Finance 27, 231–250.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Quarterly Journal of Economics 131, 1593–1636.

Bargeron, L., Denis, D., Lehn, K., 2018. Financing investment spikes in the years surrounding World War I. Journal of Financial Economics 130, 215–236.

Barnett, W.P., Burgelman, R.A., 1996. Evolutionary perspectives on strategy. Strategic Management Journal 17, 5–19.

Billett, M.T., Garfinkel, J.A., Jiang, Y., 2011. The influence of governance on investment: Evidence from a hazard model. Journal of Financial Economics 102, 643–670.

Braguinsky, S., Hounshell, D.A., 2016. History and nanoeconomics in strategy and industry evolution research: Lessons from the Meiji-Era Japanese cotton spinning industry. Strategic Management Journal 37, 45–65.

Brav, O., 2009. Access to capital, capital structure, and the funding of the firm. Journal of Finance 64, 263–308.

Byoun, S., 2008. How and when do firms adjust their capital structures toward targets? Journal of Finance 63, 3069–3096.

Campbell, J.L., Chen, H., Dhaliwal, D.S., Lu, H.M., Steele, L.B., 2014. The information content of mandatory risk factor disclosures in corporate filings. Review of Accounting Studies 19, 396–455.

Cao, W., Duan, X., Uysal, V.B., 2013. Does political uncertainty affect capital structure choices? Working paper, University of Oklahoma .

Chandler Jr, A.D., 1962. Strategy and structure: Chapters in the history of the industrial enterprise. MIT press, Cambridge, MA.

Chen, Q., Goldstein, I., Jiang, W., 2006. Price informativeness and investment sensitivity to stock price. Review of Financial Studies 20, 619–650.

Çolak, G., Gungoraydinoglu, A., Öztekin, Ö., 2018. Global leverage adjustments, uncertainty, and country institutional strength. Journal of Financial Intermediation 35, 41–56.

Cook, D.O., Tang, T., 2010. Macroeconomic conditions and capital structure adjustment speed. Journal of Corporate Finance 16, 73–87.

Dang, V.A., Kim, M., Shin, Y., 2012. Asymmetric capital structure adjustments: New evidence from dynamic panel threshold models. Journal of Empirical Finance 19, 465–482.

D'Aveni, R.A., Dagnino, G.B., Smith, K.G., 2010. The age of temporary advantage. Strategic Management Journal 31, 1371–1385.

DeAngelo, H., DeAngelo, L., Whited, T.M., 2011. Capital structure dynamics and transitory debt. Journal of Financial Economics 99, 235–261.

DeAngelo, H., Roll, R., 2015. How stable are corporate capital structures? Journal of Finance 70, 373–418.

Denis, D.J., McKeon, S.B., 2012. Debt financing and financial flexibility evidence from proactive leverage increases. Review of Financial Studies 25, 1897–1929.

Dennis, P., Strickland, D., 2004. The determinants of idiosyncratic volatility. Unpublished working paper, University of Virginia .

Destri, A.M.L., Dagnino, G.B., 2005. The development of the resource-based firm between value appropriation and value creation. Advances in Strategic Management 22, 213–248.

Devos, E., Rahman, S., Tsang, D., 2017. Debt covenants and the speed of capital structure adjustment. Journal of Corporate Finance 45, 1–18.

Dixit, A.K., Pindyck, R.S., 1994. Investment under uncertainty. Princeton University Press, Princeton, NJ.

Dudley, E., 2012. Capital structure and large investment projects. Journal of Corporate Finance 18, 1168–1192.

Durnev, A., Morck, R., Yeung, B., Zarowin, P., 2003. Does greater firm-specific return variation mean more or less informed stock pricing? Journal of Accounting Research 41, 797–836.

Elsas, R., Flannery, M.J., Garfinkel, J.A., 2014. Financing major investments: Information about capital structure decisions. Review of Finance 18, 1341–1386.

Elton, E.J., 1999. Presidential address: Expected return, realized return, and asset pricing tests. Journal of Finance 54, 1199–1220.

Fama, E.F., French, K.R., 2002. Testing trade-off and pecking order predictions about dividends and debt. Review of Financial Studies 15, 1–33.

Faulkender, M., Flannery, M.J., Hankins, K.W., Smith, J.M., 2012. Cash flows and leverage adjustments. Journal of Financial Economics 103, 632–646.

Flannery, M.J., Hankins, K.W., 2013. Estimating dynamic panel models in corporate finance. Journal of Corporate Finance 19, 1–19.

Flannery, M.J., Rangan, K.P., 2006. Partial adjustment toward target capital structures. Journal of Financial Economics 79, 469–506.

Francis, B.B., Hasan, I., Zhu, Y., 2014. Political uncertainty and bank loan contracting. Journal of Empirical Finance 29, 281–286.

Frank, M.Z., Goyal, V.K., 2009. Capital structure decisions: Which factors are reliably important? Financial Management 38, 1–37.

Frank, M.Z., Shen, T., 2013. Common factors in corporate capital structure. Available at SSRN 2288767 .

Gaspar, J.M., Massa, M., 2006. Idiosyncratic volatility and product market competition. Journal of Business 79, 3125–3152.

Gassmann, O., Frankenberger, K., Csik, M., 2014. The business model navigator: 55 models that will revolutionise your business. Pearson UK.

Graham, J.R., Leary, M.T., 2011. A review of empirical capital structure research and directions for the future. Annual Review of Financial Economics 3, 309–345.

Graham, J.R., Leary, M.T., Roberts, M.R., 2015. A century of capital structure: The leveraging of corporate America. Journal of Financial Economics 118, 658–683.

Greene, W., 2004. The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. The Econometrics Journal 7, 98–119.

Grimm, C.M., Lee, H., Smith, K.G., 2005. Strategy as action: Competitive dynamics and competitive advantage. Oxford University Press, UK.

Gungoraydinoglu, A., Çolak, G., Öztekin, Ö., 2017. Political environment, financial intermediation costs, and financing patterns. Journal of Corporate Finance 44, 167–192.

Hadlock, C.J., Pierce, J.R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. Review of Financial Studies 23, 1909–1940.

Halling, M., Yu, J., Zechner, J., 2016. Leverage dynamics over the business cycle. Journal of Financial Economics 122, 21 – 41.

Harford, J., Klasa, S., Walcott, N., 2009. Do firms have leverage targets? Evidence from acquisitions. Journal of Financial Economics 93, 1–14.

Harris, M., Raviv, A., 1991. The theory of capital structure. Journal of Finance 46, 297–355.

Hennessy, C.A., Whited, T.M., 2005. Debt dynamics. Journal of Finance 60, 1129–1165.

Hoberg, G., Phillips, G., 2010. Real and financial industry booms and busts. Journal of Finance 65, 45–86.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Review of Financial Studies 28, 650–705.

Hovakimian, A., Hovakimian, G., Tehranian, H., 2004. Determinants of target capital structure: The case of dual debt and equity issues. Journal of Financial Economics 71, 517–540.

Hovakimian, A., Opler, T., Titman, S., 2001. The debt-equity choice. Journal of Financial and Quantitative Analysis 36, 1–24.

Im, H.J., Kang, Y., Shon, J., 2020a. How does uncertainty influence target capital structure? Journal of Corporate Finance 64, 101642.

Im, H.J., Mayer, C., Sussman, O., 2020b. Heterogeneity in investment spike financing. Available at SSRN 2468424 .

Irvine, P.J., Pontiff, J., 2008. Idiosyncratic return volatility, cash flows, and product market competition. Review of Financial Studies 22, 1149–1177.

Kavadias, S., Ladas, K., Loch, C., 2016. The transformative business model. Harvard Business Review 94, 91–98.

Kayhan, A., Titman, S., 2007. Firms' histories and their capital structures. Journal of Financial Economics 83, 1–32.

Koller, T., Goedhart, M., Wessels, D., et al., 2010. Valuation: Measuring and managing the value of companies. John Wiley and Sons, Hoboken, NJ.

Lee, K.H., Mauer, D.C., Xu, E.Q., 2018. Human capital relatedness and mergers and acquisitions. Journal of Financial Economics 129, 111–135.

Lemmon, M.L., Roberts, M.R., Zender, J.F., 2008. Back to the beginning: Persistence and the cross-section of corporate capital structure. Journal of Finance 63, 1575–1608.

Marchica, M.T., Mura, R., 2010. Financial flexibility, investment ability, and firm value: Evidence from firms with spare debt capacity. Financial Management 39, 1339–1365.

Meyer, B.D., 1990. Unemployment insurance and unemployment spells. Econometrica 58, 757–782.

Miao, J., 2005. Optimal capital structure and industry dynamics. Journal of Finance 60, 2621–2659.

Mitton, T., 2021. Methodological variation in empirical corporate finance. Review of Financial Studies Forthcoming.

Modigliani, F., Miller, M.H., 1958. The cost of capital, corporation finance and the theory of investment. American Economic Review 48, 261–297.

Nguyen, N.H., Phan, H.V., Lee, E., 2020. Shareholder litigation rights and capital structure decisions. Journal of Corporate Finance 62, 101601.

Owens, E., Wu, J.S., Zimmerman, J., 2017. Idiosyncratic shocks to firm underlying economic and abnormal accruals. The Accounting Review 92, 183–219.

Pagan, A., 1984. Econometric issues in the analysis of regressions with generated regressors. International Economic Review 25, 221–247.

Pástor, L., Veronesi, P., 2009. Technological revolutions and stock prices. American Economic Review 99, 1451–83.

Pástor, L., Veronesi, P., 2013. Political uncertainty and risk premia. Journal of Financial Economics 110, 520–545.

Porter, M.E., 1980. Competitive strategy: Techniques for analyzing industries and companies. The Free Press, New York, NY.

Rajan, R.G., Zingales, L., 1995. What do we know about capital structure? Some evidence from international data. Journal of Finance 50, 1421–1460.

Schumpeter, J., 1934. The theory of economic development. Harvard University Press, Cambridge, MA.

Shorrocks, A.F., 1999. Decomposition procedures for distributional analysis: A unified framework based on the Shapley value. Technical Report. University of Essex.

Strebulaev, I.A., Whited, T.M., 2011. Dynamic models and structural estimation in corporate finance. Foundations and Trends ® in Finance 6, 1–163.

Thomas, L., D'Aveni, R., 2009. The changing nature of competition in the U.S. manufacturing sector, 1950-2002. Strategic Organization 7, 387–431.

Titman, S., Wessels, R., 1988. The determinants of capital structure choice. Journal of Finance 43, 1–19.

Tserlukevich, Y., 2008. Can real options explain financing behavior? Journal of Financial Economics 89, 232–252.

Uysal, V.B., 2011. Deviation from the target capital structure and acquisition choices. Journal of Financial Economics 102, 602–620.

Von Beschwitz, B., 2018. Cash windfalls and acquisitions. Journal of Financial Economics 128, 287–319.

Waring, G.F., 1996. Industry differences in the persistence of firm-specific returns. American Economic Review 86, 1253–1265.

Welch, I., 2011. Two common problems in capital structure research: The financial-debt-to-asset ratio and issuing activity versus leverage changes. International Review of Finance 11, 1–17.

Whited, T.M., 2006. External finance constraints and the intertemporal pattern of intermittent investment. Journal of Financial Economics 81, 467–502.

Williamson, O.E., 1988. Corporate finance and corporate governance. Journal of Finance 43, 567–591.

Woods, K., Tan, K.J.K., Faff, R., 2019. Labor unions and corporate financial leverage: The bargaining device versus crowding-out hypotheses. Journal of Financial Intermediation 37, 28–44.

Zhou, Q., Tan, K.J.K., Faff, R., Zhu, Y., 2016. Deviation from target capital structure, cost of equity and speed of adjustment. Journal of Corporate Finance 39, 99–120.

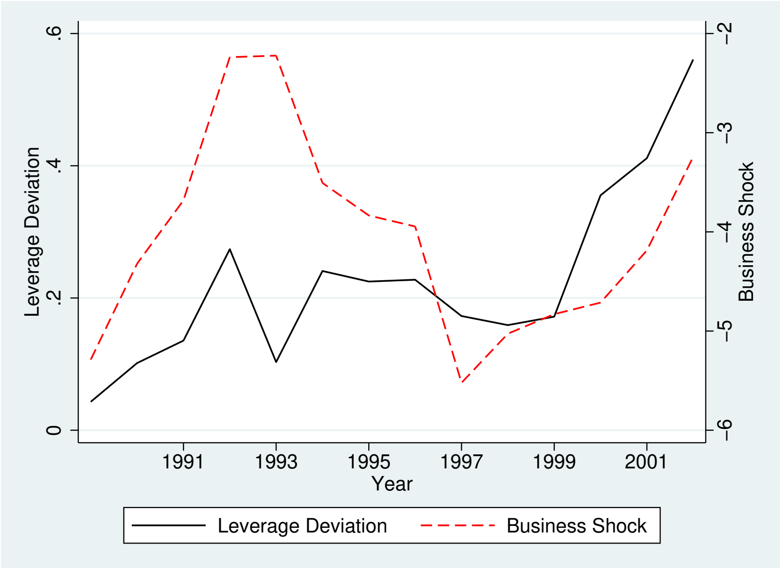

Figure 1: Anecdotal example: Time series plot of business shock and leverage deviation for Holiday RV Superstores, Inc.

This figure plots the business shock and leverage deviation for Holiday RV Superstores, Inc. between 1989 and 2002. Business shock ($BusinessShock$) is the natural logarithm of the mean squared residuals from a regression of monthly firm i's returns on monthly industry and market returns (excluding its own firm) for years t to $t-1$ (i.e., 24 monthly return observations). Leverage deviation ($LevDev$) is the absolute value of residuals from the regression of a target leverage equation (equation (1)).

Table 1: Validation tests: The predictability of the business shock on operational shocks

This table presents the logistic regression results of the four real operational shock measures on the business shock measure (*BusinessShock*). The four operational shock measures include: (1) a large merger or acquisition (*LargeMergAcq*); (2) industry change (based on four-digit SIC code) (*IndChange*); (3) large special items (*LargeSpecItem*); and (4) at least one of the three operational changes (*OpShock*). Each of the four dependent variables is a dummy variable that takes a value of one if firm *i* has an observed operational shock in year *t* and a value of zero the otherwise. The Appendix provides detailed definitions and data sources of the variables. Robust *t*-statistics corrected for firm clustering are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	*LargeMergAcq*		*IndChange*		*LargeSpecItem*		*OpShock*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BusinessShock	0.000**	0.001***	0.013***	0.011***	0.062***	0.049***	0.067***	0.055***
	(2.21)	(2.64)	(18.70)	(12.33)	(39.71)	(28.18)	(41.29)	(29.13)
Mktbk		0.000**		-0.002***		-0.005***		-0.007***
		(2.42)		(-2.64)		(-5.05)		(-6.04)
ROA		-0.006*		-0.097***		-0.197***		-0.264***
		(-1.88)		(-8.96)		(-10.47)		(-13.07)
LnAssets		0.000		0.002***		0.024***		0.025***
		(1.24)		(3.96)		(20.11)		(19.06)
RD_AT		0.001		-0.049***		0.042**		0.009
		(0.20)		(-5.67)		(2.39)		(0.44)
FreeCashFlow		0.006*		0.036***		0.003		0.031
		(1.86)		(3.37)		(0.17)		(1.59)
CashHoldings		-0.001		-0.003		0.073***		0.062***
		(-0.43)		(-0.72)		(9.28)		(7.17)
SalesGrowth		-0.000		-0.008***		-0.004		-0.006**
		(-1.16)		(-4.82)		(-1.63)		(-2.41)
Observations	78,469	29,296	78,469	73,059	78,469	73,059	78,927	73,483
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo-R^2	0.0088	0.0579	0.0287	0.0833	0.0509	0.1180	0.0494	0.1060

Table 2: Summary statistics and correlation matrix

This table provides detailed descriptive statistics and correlation coefficients of our key variables. Panel A provides summary statistics. Panel B presents Pearson correlation coefficients. The Appendix provides detailed definitions and data sources for these variables. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Descriptive Statistics

Variable	Mean	SD	P1	P25	Median	P75	P99
Lev_{FDBCP}	0.29	0.26	0.00	0.05	0.25	0.45	1
$AT(\$mil)$	887	2,735	2	31	109	447	20,785
$LevDev$	0.17	0.14	0.00	0.07	0.14	0.24	0.69
$BusinessShock$	-4.96	1.11	-7.40	-5.75	-5.00	-4.22	-2.18
$LnAsset$	4.75	1.94	0.78	3.36	4.61	6.00	9.86
ΔAT_AT	0.14	0.37	-0.49	-0.03	0.07	0.20	2.16
SA	-4.15	1.35	-7.46	-5.05	-4.13	-3.24	-0.94
$NonDivPayer\_Dum$	0.62	0.49	0	0	1	1	1
$AdjMktbk$	-1.22	2.23	-8.76	-2.20	-0.74	-0.12	5.89
$\lvert OperatingCF \rvert$	0.12	0.17	0.00	0.03	0.06	0.13	1.02
$Earns\_Vol$	0.29	1.09	0.00	0.02	0.04	0.12	8.89
ROA	0.08	0.20	-0.92	0.05	0.12	0.18	0.40

Panel B: Pearson correlation coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) $LevDev$	1									
(2) $BusinessShock$	0.14***	1								
(3) $LnAssets$	-0.06***	-0.51***	1							
(4) ΔAT_AT	-0.03***	0.01***	0.05***	1						
(5) SA	0.07***	0.54***	-0.96***	-0.02***	1					
(6) $NonDivPayer\_Dum$	0.14***	0.55***	-0.35***	0.06***	0.41***	1				
(7) $AdjMktbk$	-0.05***	-0.02***	-0.22***	0.09***	0.23***	-0.11***	1			
(8) $\lvert OperatingCF \rvert$	0.09***	0.36***	-0.28***	0.18***	0.31***	0.26***	0.12***	1		
(9) $Earns\_Vol$	0.06***	0.25***	-0.16***	0.01**	0.18***	0.18***	-0.01***	0.55***	1	
(10) ROA	-0.13***	-0.45***	0.33***	0.15***	-0.35***	-0.33***	0.05***	-0.70***	-0.54***	1

Table 3: Type one leverage instability: The effect of business shocks on unexplained leverage deviation

This table reports the results of the relation between business shocks and leverage deviation. Columns (1) to (3) of Panel A present logistic regression results for large leverage deviation on large business shock. The dependent variable is large leverage deviation, *LargeLevDev*, which is a dummy variable equal to one if the leverage deviation of a firm is greater than its median leverage deviation (*LevDev*) throughout its own sample period, and zero otherwise. Leverage deviation (*LevDev*) is the absolute value of residuals from the regression of a target leverage equation (equation (1)). The variable of interest is large business shock, *LargeBusShock*, which is a dummy variable that takes a value of one if a firm's business shock (*BusinessShock*) is greater than its median business shock through its own sample period, and zero otherwise. *BusinessShock* is the firm-specific stock return variation for firm i in years $t-1$ and t, and is in a natural log form. Column (1) reports the logistic regressions outputs in terms of marginal values. Column (2) provides the results when we control for year fixed effects, and column (3) presents the estimation results of a conditional logit regression. Columns (4) to (12) of Panel A present the regression results of the leverage deviation (*LevDev*) on business shock (*BusinessShock*) using the panel regression methods. Column (4) reports the year fixed effects (FEs) results, column (5) reports the firm fixed effects results, and column (6) reports firm fixed effects and year fixed effects. In the regression for column (7), we remove zero leverage firms from the sample in column (6), which is our baseline regression. We repeat the baseline analysis in column (6) with three alternative leverage measures in columns (8) to (10). In the regressions for columns (8) to (10), we use long-term book leverage (Lev_{LFDBCP}), market leverage (Lev_{FDMCP}), and long-term market leverage (Lev_{LFDMCP}) as alternative proxies for leverage. In the regression for column (11), we add financial risk, tax risk, and litigation risk constructed by textual analysis on 10-K files as additional control variables, and the sample period is confined to 1994 to 2015 due to data availability. In the regression for column (12), we repeat our baseline regression by adding the EPU index, and annualized S&P 500 index return volatility as additional controls and remove the year fixed effect. In Panel B columns (1) to (5) [columns (6) to (10)], we re-estimate all the conditional logit [panel regression] analyses by replacing $BusinessShock_t$ with four operational shock measures in the same setting as column (3) and [(6)] of Panel A. The Appendix provides detailed definitions and data sources for these variables. Bootstrapped t-statistics are reported in parentheses. Constants are included in the logit and conditional logit models. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Business shock and leverage deviation												
Regression Method	Logit	Logit	Conditional Logit	Panel Regression								
Dependent variables:	*LargeLevDev* (1)	*LargeLevDev* (2)	*LargeLevDev* (3)	*LevDev* (4)	*LevDev* (5)	*LevDev* (6)	*LevDev* (7)	*LevDev_LFDBCP* (8)	*LevDev_FDMCP* (9)	*LevDev_LFDMCP* (10)	*LevDev* (11)	*LevDev* (12)
LargeBusShock	0.041***	0.043***	0.014***									
	(13.73)	(11.61)	(4.99)									
BusinessShock				0.140***	0.105***	0.102***	0.139***	0.105***	0.107***	0.107***	0.091***	0.097***
				(15.19)	(7.58)	(6.45)	(7.55)	(6.22)	(6.41)	(8.68)	(3.92)	(5.67)
LnAsset	-0.028***	-0.028***	0.023*	0.058***	0.007	0.032	-0.062	0.146*	0.042	0.198***	-0.295***	0.211***
	(-8.36)	(-9.69)	(1.91)	(4.29)	(0.12)	(0.48)	(-0.79)	(1.70)	(0.65)	(2.91)	(-2.84)	(3.26)
ΔAT_AT	-0.040***	-0.047***	-0.025***	-0.207***	-0.110***	-0.127***	-0.099***	-0.174***	-0.140***	-0.169***	-0.151***	-0.118***
	(-8.23)	(-7.60)	(-4.62)	(-8.51)	(-3.97)	(-4.93)	(-2.63)	(-6.13)	(-5.19)	(-5.81)	(-4.54)	(-4.15)
SA	-0.063***	-0.069***	-0.004	0.038*	-0.153**	-0.080	-0.139	-0.058	-0.175*	-0.042	-0.832***	0.213***
	(-12.86)	(-15.21)	(-0.25)	(1.91)	(-2.20)	(-0.76)	(-1.11)	(-0.43)	(-1.75)	(-0.38)	(-4.48)	(2.62)
NonDivPayer_Dum	0.001	-0.002	0.040***	0.228***	0.204***	0.145***	0.139***	0.166***	0.095*	0.102**	0.091	0.091
	(0.17)	(-0.27)	(3.95)	(11.30)	(3.77)	(2.63)	(3.00)	(3.39)	(1.87)	(2.05)	(1.49)	(1.57)
AdjMktbk	-0.006***	-0.011***	-0.012***	-0.030***	-0.042***	-0.069***	-0.026***	-0.068***	-0.063***	-0.065***	-0.078***	-0.064***
	(-6.68)	(-11.95)	(-7.24)	(-6.15)	(-6.07)	(-7.52)	(-2.60)	(-9.28)	(-8.63)	(-8.72)	(-8.47)	(-7.60)
$\lvert OperatingCF \rvert$	-0.047***	-0.021	0.028	0.328***	0.322***	0.372***	0.525***	0.426***	-0.500***	-0.501***	0.485***	0.372***
	(-2.72)	(-1.43)	(1.05)	(4.76)	(2.77)	(2.76)	(3.02)	(3.50)	(-4.05)	(-4.21)	(3.62)	(3.08)
Earns_Vol	-0.010***	-0.008***	0.001	-0.010	0.013	0.015	0.012	-0.006	0.008	0.002	-0.006	0.012
	(-5.08)	(-4.12)	(0.30)	(-1.31)	(0.89)	(1.08)	(0.61)	(-0.46)	(0.59)	(0.19)	(-0.33)	(0.76)
ROA	-0.208***	-0.201***	-0.416***	-0.544***	-1.461***	-1.355***	-0.835***	-1.700***	-1.532***	-1.732***	-1.616***	-1.274***
	(-14.76)	(-14.19)	(-16.86)	(-8.76)	(-12.24)	(-12.50)	(-7.66)	(-17.65)	(-13.50)	(-15.36)	(-11.76)	(-13.26)
FinancialRisk											-0.030	
											(-0.51)	
TaxRisk											-0.114	
											(-1.07)	
LitigationRisk											0.072	
											(0.51)	
EPU												-0.001*
												(-1.83)
SP_Vol												0.795**
												(2.52)
Constant				-4.549***	-4.592***	-5.150***	-4.942***	-5.280***	-5.935***	-6.426***	-5.894***	-3.913***
				(-22.13)	(-40.38)	(-20.52)	(-16.46)	(-26.90)	(-34.02)	(-34.08)	(-18.26)	(-26.15)
Remove zero-leverage firms							Yes					
Observations	78,927	78,927	77,817	78,927	78,927	78,927	67,379	78,927	78,927	78,927	36,676	61,024
Firm FE	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No
Within (Pseudo) R^2	(0.0091)	(0.0140)	(0.0173)	0.0421	0.0192	0.0266	0.0189	0.0339	0.0354	0.0444	0.0251	0.0176
Proprtion of Dependent Variable =1	0.47	0.47	0.47									

(continued to next page)

Table 3
(continued)

Panel B: Real operational shock events and leverage deviation										
Regression Method	Conditional Logit Model					Panel Regression				
Dependent variables	*LargeLevDev*					*LevDev*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LargeMergAcq	-0.069				-0.077	-0.219				-0.257
	(-1.43)				(-1.11)	(-0.51)				(-0.67)
IndChange		0.049***			0.046***		0.201***			0.181***
		(6.04)			(5.37)		(3.51)			(3.38)
LargeSpecItem			0.038***		0.036***			0.208***		0.204***
			(6.81)		(6.79)			(9.58)		(8.27)
OpShock				0.042***					0.216***	
				(7.60)					(8.68)	
LnAsset	0.018	0.018	0.017	0.015	0.017	0.029	0.030	0.023	0.015	0.023
	(1.08)	(1.34)	(1.05)	(0.99)	(1.22)	(0.36)	(0.42)	(0.30)	(0.23)	(0.32)
ΔAT_AT	-0.026***	-0.025***	-0.026***	-0.026***	-0.025***	-0.119***	-0.117***	-0.118***	-0.120***	-0.116***
	(-4.27)	(-4.75)	(-4.96)	(-5.24)	(-4.65)	(-4.18)	(-3.72)	(-4.11)	(-3.62)	(-3.83)
SA	-0.002	-0.002	-0.002	-0.003	-0.001	-0.045	-0.042	-0.041	-0.052	-0.039
	(-0.10)	(-0.09)	(-0.07)	(-0.13)	(-0.06)	(-0.32)	(-0.38)	(-0.39)	(-0.45)	(-0.33)
NonDivPayer_Dummy	0.027***	0.026***	0.026***	0.025***	0.026***	0.180***	0.179***	0.177***	0.173***	0.176***
	(2.99)	(2.83)	(3.07)	(2.90)	(2.85)	(4.18)	(3.70)	(3.35)	(3.11)	(4.10)
AdjMktbk	-0.017***	-0.016***	-0.016***	-0.016***	-0.016***	-0.070***	-0.069***	-0.068***	-0.067***	-0.068***
	(-9.54)	(-7.92)	(-7.49)	(-7.63)	(-7.19)	(-7.82)	(-7.74)	(-7.73)	(-8.98)	(-7.55)
$\lvert OperatingCF \rvert$	0.038*	0.037	0.037*	0.036	0.037*	0.379***	0.380***	0.374**	0.378***	0.375***
	(1.67)	(1.55)	(1.76)	(1.50)	(1.74)	(3.26)	(2.83)	(2.56)	(3.80)	(3.08)
Earns_Vol	0.001	0.001	0.001	0.001	0.001	0.016	0.015	0.014	0.015	0.013
	(0.47)	(0.53)	(0.42)	(0.41)	(0.31)	(1.04)	(0.99)	(1.04)	(1.03)	(0.93)
ROA	-0.349***	-0.339***	-0.345***	-0.334***	-0.337***	-1.420***	-1.407***	-1.384***	-1.365***	-1.373***
	(-11.81)	(-9.79)	(-10.34)	(-8.66)	(-10.44)	(-13.89)	(-12.59)	(-12.78)	(-14.25)	(-11.33)
Constant						-5.586***	-5.620***	-5.570***	-5.601***	-5.598***
						(-24.49)	(-24.27)	(-21.49)	(-21.97)	(-20.00)
Observations	77,363	77,363	77,363	77,817	77,363	78,469	78,469	78,469	78,927	78,469
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within (Psuedo) R^2	(0.0250)	(0.0253)	(0.0258)	(0.0259)	(0.0261)	0.0258	0.0261	0.0270	0.0269	0.0272
Proportion of Dependent Variable=1	0.47	0.47	0.47	0.47	0.47					

Table 4: R^2 Decomposition analysis

This table presents the Shapley-Owen R^2 decomposition of the baseline model shown in column (4) of Panel A in Table 3. Columns (1) and (2) report the Shapley value and the percentage of R^2 explained for each explanatory variable, respectively. Column (3) reports the rankings of explanatory variables based on the percentage of R^2 explained. The Appendix provides detailed definitions and data sources for these variables.

Variables	Shapley value	Percentage of R^2 explained	Ranking
$BusinessShock$	0.00473	27.21	1
ROA	0.00393	22.57	2
$NonDivPayer\_Dum$	0.00317	18.2	3
$\|OperatingCF\|$	0.00147	8.46	4
ΔAT_AT	0.00115	6.59	5
SA	0.00099	5.67	6
$LnAssets$	0.00077	4.4	7
$AdjMktbk$	0.00063	3.62	8
$Earns\_Vol$	0.00057	3.28	9

Table 5: Type two leverage instability: Cumulative business shocks and cross-sectional leverage position migration probability

This table presents the results of the relation between leverage migration probability and business shocks. In Panel A, we compare the migration probability among three groups of firms with different levels of business shocks. Rows (1) and (2) present the average frequency of changing leverage quartiles per year in a 20-year rolling window, requiring at least 12 and 20 years of non-missing data, respectively. The average frequencies are compared in three groups that are sorted based on the average business shock experienced in the rolling 20-year window. Rows (3) and (4) provide the average frequency of absolute changes in leverage quartile changes. The *t*-statistics for our comparison of the average frequencies in the Small (Moderate) shock group and in the Moderate (Large) shock group are presented in parentheses in the column indicating Moderate (Large) shock. Panel B presents the estimation results for a panel regression where the dependent variable is the average frequency of leverage quartile changes in the 20-year rolling window, and the independent variable is the average business shock measure. Controls indicate the average firm-level control variables in Table 3 over a rolling 20-year window. Internal FE denotes the time interval (20-year rolling windows) and Industry FE stands for the industry fixed effect. The dependent variables in the regression for Panel B correspond to the measures referred to rows (1) to (4) in Panel A, respectively. Robust *t*-statistics are reported in parentheses. *** denotes significance at the 1% level.

Panel A: Leverage migration probability across three business shock groups

		Small Shock	Moderate Shock	Large Shock
(1)	Average frequency of changing quartiles in the 20 years window (requiring at least 12 years of observations)	0.225	0.242***	0.301***
			(24.520)	(14.073)
(2)	Average frequency of changing quartiles in the 20 years window (requiring 20 years of observations)	0.210	0.241***	0.287***
			(9.021)	(10.057)
(3)	Average frequency of absolute changes quartiles in the 20 years window (requiring at least 12 years of observations)	0.241	0.301***	0.362***
			(34.028)	(22.022)
(4)	Average frequency of absolute changes quartiles in the 20 years window (requiring 20 years of observations)	0.219	0.263***	0.326***
			(9.699)	(10.720)

Panel B: Regression analysis of leverage migration probability

	(1)	(2)	(3)	(4)
$AverageShock$	0.038***	0.067***	0.057***	0.081***
	(16.427)	(12.522)	(20.572)	(13.515)
Controls	Yes	Yes	Yes	Yes
Internal FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.101	0.185	0.150	0.218

Table 6: Type three leverage instability: Cumulative business shocks and leverage dispersion

This table presents the OLS regression results of industry-level leverage dispersion on the proportion of firms experiencing significant business shocks. The dependent variable is the standard deviation of financial leverage within each SIC two-digit industry by year, $Dispersion\_Lev_{j,t}$. $PropFirmShock_{j,t}$ measures the proportion of firms experiencing large business shocks in industry j in year t. $Dummy_{LowPersist_t}$ takes the value of 1 if the rent persistence coefficient estimates are equal to or below the bottom quintile of rent persistence in year t and zero the otherwise. The persistence coefficient estimates are obtained by regressing the current firm-specific ROA on the lagged firm-specific ROA for each two-digit SIC industry. All control variables are measured with a one year lag relative to the dependent variable. The Appendix provides detailed definitions and data sources for these variables. Column (1) reports the industry-level leverage dispersion for the full sample. We rerun our leverage dispersion analysis by including the interaction term between $PropFirmShock_{j,t}$ and $Dummy_{LowPersist_t}$ to compare the bottom quintile of the least rent-persistent industry with the other four quintiles of the more rent-persistent industries, and present the results in column (2). Bootstrapped t-statistics are reported enclosed in parentheses. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Variables	Dependent variable=$Dispersion\_Lev$	
	(1)	(2)
$PropFirmShock$	0.085***	0.071**
	(3.47)	(2.56)
$DummyLowPersist$		-0.009**
		(-2.09)
$PropFirmShock \times DummyLowPersist$		0.057*
		(1.86)
$Dispersion\_LnAssets$	0.001	0.001
	(0.14)	(0.14)
$Dispersion\_IndustLev$	0.163**	0.163**
	(2.39)	(2.42)
$Dispersion\_Mktbk$	-0.002	-0.002
	(-0.27)	(-0.26)
$Dispersion\_Tangibility$	0.093	0.090
	(1.23)	(1.17)
$Dispersion\_ROA$	-0.037	-0.039
	(-0.66)	(-0.70)
$Dispersion\_RD\_AT$	-0.010	0.002
	(-0.11)	(0.02)
$Dispersion\_RD\_DUM$	0.020	0.019
	(0.90)	(0.89)
$Dispersion\_DP\_AT$	0.629**	0.646**
	(2.11)	(2.18)
Constant	0.102***	0.104***
	(3.59)	(3.61)
Observations	1,424	1,424
Adjusted R^2	0.330	0.332
Year FE	Yes	Yes

Table 7: Addressing endogeneity: Instrumental variable analysis using e-commerce adoption

This table reports two-stage-lease squares (2SLS) regression results. Column (1) reports the first-stage regression results of *BusinessShock* on *Ecommerce_Dum*. $BusinessShock_t$ is the firm-specific stock return variation for firm i in years $t-1$ and t, and is in a natural log form. *Ecommerce_Dum* is an indicator variable that equals 1 for the year (and subsequent years) in which a firm initiates e-commerce, and 0 otherwise. Column (2) reports the second-stage regression results of *LevDev* on predicted $\widehat{BusinessShock}$ estimated from the first-stage regression results in column (1). Leverage deviation (*LevDev*) is the absolute value of residuals from the regression of a target leverage equation (equation (1)), and it is in a natural log form. We match our firms that launched e-commerce websites with a control firm between 1995 and 2001 based on the market-to-book ratio, firm size and industry (two-digit SIC code). The robust t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	First-stage *BusinessShock* (1)	Second-stage *LevDev* (2)
Ecommerce_Dum	0.535**	
	(2.00)	
$\widehat{BusinessShock}$		3.586*
		(1.74)
LnAssets	-0.230*	0.496
	(-1.83)	(0.73)
ΔAT_AT	0.079	0.080
	(0.69)	(0.14)
SA	-0.188	0.001
	(-0.80)	(0.00)
NonDivPayer_Dum	1.142***	-2.659
	(4.57)	(-0.97)
AdjMktbk	-0.067	0.184
	(-1.57)	(0.85)
$\lvert OperatingCF \rvert$	0.046	0.169
	(0.12)	(0.10)
Earns_Vol	0.102**	-0.409
	(2.51)	(-1.52)
ROA	-1.029**	4.715
	(-2.61)	(1.60)
Constant	-5.317***	12.214
	(-8.90)	(1.07)
Observations	166	166
Adjusted R^2	0.4415	0.5119
Year FE	Yes	Yes

Table 8: Business shocks and capital issuance decisions

This table presents logit regression results of the external financing decision on business shocks. We report the marginal effects in this table. The dependent variable, *ActiveIssuer*, takes a value of 1 if a firm issues debt and/or equity that exceeds c% of total assets at the beginning of the year, and 0 otherwise. In the regression for column (1), we define active (passive) issuers as issuing security (debt or equity) when the net amount issued (debt or equity) exceeds (does not exceed) 3% of total assets. In the regressions for columns (2) and (3), we redefine active (passive) issuers using 5% and 10% thresholds, respectively. $BusinessShock_t$ is the firm-specific stock return variation for firm *i* in years *t*-1 and *t* and is in natural log form. Following Hovakimian et al. (2004), we control for 12 external financing determinants, including the market-to-book ratio (*Mktbk*), a dummy variable indicating whether is greater than 1 or not ($Mktbk > 1dummy$), prior issuance stock return (*StockReturn*), profitability (*ROA*), net operating loss carry forwards (*NOLC*), firm size (*LnAssets*), *Tangibility*, Selling expenses (*SellingExpense*), R&D expenses (*R&DExpense*), leverage (Lev_{FDBCP}), industry leverage (*IndustLev*), and the EPS dilution dummy variable (*EPSdilutiondummy*). Robust *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable=Likilihood of issuance		
Threshhold values	3%	5%	10%
	(1)	(2)	(3)
BusinessShock	0.028***	0.033***	0.040***
	(12.43)	(13.94)	(17.34)
Mktbk	0.026***	0.028***	0.026***
	(16.09)	(14.94)	(15.94)
$Mktbk > 1$ *dummy*	0.043***	0.064***	0.084***
	(8.92)	(13.15)	(17.82)
StockReturn	0.008***	0.011***	0.011***
	(3.00)	(4.19)	(4.67)
ROA	0.000	-0.019	-0.040***
	(0.03)	(-1.53)	(-4.28)
NOLC	0.005*	0.007**	0.005**
	(1.80)	(2.19)	(2.00)
LnAssets	-0.005***	-0.012***	-0.017***
	(-3.77)	(-9.24)	(-15.29)
Tangibility	0.021*	0.010	0.020**
	(1.85)	(1.04)	(2.39)
SellingExpense	0.003*	0.003	0.001**
	(1.84)	(1.55)	(2.34)
R&DExpenses	-0.005*	-0.005	-0.003
	(-1.87)	(-1.45)	(-1.59)
Lev_{FDBCP}	0.718***	0.617***	0.372***
	(55.32)	(43.96)	(31.50)
IndustLev	0.007	0.046*	0.066***
	(0.32)	(1.82)	(3.71)
EPSdilutiondummy	0.030***	0.027***	0.017***
	(9.26)	(5.81)	(4.90)
Observations	70,950	70,950	70,950
Year FE	Yes	Yes	Yes
Adjusted R^2	0.0655	0.0618	0.0754
Proportion of Dependent Variable=1	0.617	0.481	0.286

Table 9: Robustness tests

This table presents the following three sets of robustness check results: (1) various specifications to calculate target leverage in columns (1) to (4); (2) controlling for leverage dynamic estimations in columns (5) to (6); (3) CEO fixed effects in column (7); and (4) signed leverage deviations in columns (8) to (10). The dependent variable in columns (1) to (7) is unsigned *LevDev*, which is the squared residuals from the regression of the target leverage equation (eq.1), and is in a natural log form. The key independent variable, $BusinessShock_t$, is the firm-specific stock return variation for firm i in years $t-1$ and t, and it is in a natural log form. Specifically, the first four columns of this table present the regression results of *LevDev* on *BusinessShock* based on various specifications to calculate target leverage. In the regression for column (1), we estimate target leverage using the full sample to obtain the coefficients for all leverage determinants for the whole sample, rather than yearly coefficients for all leverage determinants in our baseline results. In the regression for column (2), we re-estimate target leverage using the full sample, but we further control for GDP in our target leverage estimation. In the regression for column (3), we repeat the step in column (2) and add term spread and default spread to our target leverage estimation. In the regression for column (4), we re-estimate target leverage using the full sample, and we replace time-varying macro-variables such as GDP, term spread and default spread with year fixed effects in the target leverage estimation. Columns (5) and (6) present the regression results of *LevDev* on *BusinessShock* after controlling for leverage dynamic estimations. In the regression for column (5), we include the 1 year lagged leverage ratio as an additional explanatory variable when estimating target leverage. We use the full sample to obtain the coefficient for all debt determinants for the whole sample, rather than yearly coefficients for all debt determinants in our baseline results (Table 3, Panel A). In column (6), we re-estimate the baseline results (Table 3, Panel A, column (6)) by including $LevDev\_(i,t-1)$ in the $LevDev\_(i,t)$ regression. Column (7) re-estimates the baseline settings in column (6) of Panel A Table 3 by replacing firm fixed effects with CEO fixed effects. Columns (8) to (10) present the regression results of estimating the impact of business shocks on signed leverage deviations. Column (8) reports the results of using signed leverage deviation as the dependent variable in the full sample. Columns (9) and (10) report the results in the subsamples with positive and negative leverage deviation observations, respectively. We test the statistical difference in the coefficients of *BusinessShock* in these two subsamples with the χ^2 statistic, which is reported in square brackets. All controls are measured in year $t-1$. The Appendix provides detailed definitions and data sources for these variables. Bootstrapped t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Variables	Dependent variable=$LevDev_{i,t}$									
	Unsigned							Signed	Positive signed	Negative signed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BusinessShock	0.089***	0.098***	0.100***	0.094***	0.183***	0.073***	0.045**	0.029***	0.030***	0.003***
	(5.84)	(6.43)	(5.35)	(5.55)	(13.80)	(5.85)	(2.04)	(16.45)	(16.54)	(3.92)
$LevDev_{i,t-1}$						0.287***				
						(51.72)				
LnAssets	-0.274***	-0.278***	-0.278***	-0.232***	-0.249***	-0.026	-0.223**	-0.018***	-0.041***	-0.018***
	(-3.97)	(-3.50)	(-4.08)	(-2.77)	(-4.44)	(-0.38)	(-2.02)	(-2.77)	(-3.71)	(-4.32)
DeltaAT_AT	-0.080***	-0.088***	-0.094***	-0.087***	-0.175***	-0.110***	-0.238***	0.014***	-0.006*	0.013***
	(-2.82)	(-3.23)	(-3.51)	(-2.95)	(-4.67)	(-3.37)	(-3.82)	(4.80)	(-1.95)	(8.56)
SA	-0.506***	-0.518***	-0.525***	-0.476***	-0.079	-0.177*	-0.653***	-0.039***	-0.064***	-0.017**
	(-4.46)	(-4.15)	(-4.40)	(-3.65)	(-0.94)	(-1.77)	(-3.29)	(-3.42)	(-3.62)	(-2.36)
NonDivPayer_Dum	0.115**	0.133***	0.136***	0.150***	0.137***	0.096**	0.064	0.026***	0.021***	0.000
	(1.97)	(3.55)	(2.61)	(3.67)	(3.50)	(2.47)	(0.73)	(6.17)	(3.96)	(0.12)
AdjMktbk	-0.074***	-0.074***	-0.074***	-0.071***	-0.037***	-0.059***	-0.072***	0.005***	0.001	0.006***
	(-10.04)	(-9.63)	(-8.37)	(-8.41)	(-5.07)	(-7.40)	(-5.34)	(5.79)	(0.43)	(13.32)
AbsOCP	0.304***	0.319***	0.347***	0.315***	0.554***	0.426***	0.647**	-0.002	0.073***	-0.018**
	(2.60)	(2.89)	(2.75)	(2.80)	(3.97)	(3.71)	(2.48)	(-0.17)	(4.36)	(-2.40)
Earns_Vol	0.029**	0.028**	0.029**	0.031**	0.003	-0.004	0.033	-0.000	0.010***	0.000
	(2.16)	(2.19)	(2.29)	(2.09)	(0.22)	(-0.27)	(0.69)	(-0.06)	(3.04)	(0.24)
ROA	-1.456***	-1.461***	-1.444***	-1.451***	-1.208***	-1.015***	-1.657***	0.089***	-0.024	0.143***
	(-11.83)	(-16.45)	(-15.53)	(-17.12)	(-10.33)	(-9.31)	(-7.05)	(8.30)	(-1.42)	(19.55)
Constant	-4.982***	-4.962***	-4.964***	-4.898***	-5.362***	-3.289***	-7.041***	0.106***	0.275***	-0.067***
	(-21.66)	(-22.23)	(-18.31)	(-22.22)	(-15.81)	(-14.02)	(-8.92)	(6.40)	(11.04)	(-5.46)
Observations	78,927	78,927	78,927	78,927	68,319	68,237	20,636	78,927	33,895	45,032
Adjusted R^2	0.0236	0.0236	0.0239	0.0241	0.0234	0.1066	0.02	0.0268	0.0563	0.0991
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEO FE							Yes			
Additional controls in the target leverage regression:										
GDP		Yes	Yes							
Term spread			Yes							
Default spread			Yes							
Year FE				Yes						
LagLev in the target leverage estimation					Yes					
$LevDev_{i,t-1}$						Yes				
Coefficient difference on BusinessShock in Columns (9) and (10)									0.027***	
χ^2									(203.42)	

Table 10: Channel test: Business shocks and the hazard model of investment spikes

This table reports semi-parametric hazard estimates and baseline rates based on large and small business shocks. The sample is firm/years over 1968 - 2015. Firms are assigned to the large (small) business shock sample in column 1 (2) if their business shock is greater than (lower than or equal to) the median of the yearly business shock across all the firms. The dependent variable is the number of years a firm has not exceeded the investment threshold, which is defined as more than twice its own median investment rate (capex/at) over the entire sample period. We follow Whited (2006) and include long-term book leverage, cash flows, sales growth rate, and total assets as control variables that are the main determinants of investment spikes. We suppress the coefficients on these controls for brevity. The variable definitions and data sources are in the Appendix. The log-rank test examines the null hypothesis that the hazards are equal at each time horizon, i.e., 1, 2, ..., 8 years, respectively. The results of the log-rank test are in column (3). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	Large Business Shock (1)	Small Business Shock (2)	Log-rank test (χ^2) (3)=(1)-(2)
1 year Hazard	7.717***	6.073***	6.55**
	(9.14)	(12.87)	
2 year Hazard	5.854***	4.610***	2.57
	(6.90)	(9.48)	
3 year Hazard	4.617***	3.217***	0.03
	(5.54)	(6.22)	
4 year Hazard	3.677***	2.299***	0.36
	(4.33)	(4.12)	
5 year Hazard	2.590***	2.087***	3.41*
	(2.89)	(4.54)	
6 year Hazard	1.853**	0.779	0.00
	(1.99)	(1.22)	
7 year Hazard	1.573*	0.879	0.08
	(1.65)	(1.45)	
8 year Hazard	0.701	0.698	0.72
	(0.56)	(0.98)	
Controls	Yes	Yes	Yes
Log-likelihood	-1177.10	-794.39	
Observations	768	487	
Log-rank test χ^2: (1 to 8 year Hazard)	8.19***		

Table 11: Channel test: Large leverage deviations, business shocks, and investment spikes

This table reports the results for logistic regressions of large leverage deviation on large business shocks and investment spikes. The dependent variable is *LargeLevDev*, which is a dummy variable that takes the value of 1 if a firm leverage deviation in year t is larger than its median leverage deviation throughout the sample period; otherwise it takes a value of zero. Large business shock, *LargeBusShock*, is a dummy variable that takes a value of one if a firm's business shock is greater than its median business shock through its own sample period; otherwise this variable takes a value of zero. $Investmentspike(t)$ ($Investmentspike(t+1)$) is a dummy variable that takes a value of 1 if a firm's investment in year t ($t+1$) exceeds 100% of the firm's average "benchmark" investment over the past three years and is at least 20% of the firm's prior year-end total assets; otherwise it takes a value of 0. Bootstrapped t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	Dependent variable=$LargeLevDev_{i,t}$	
	(1)	(2)
$LargeBusShock_{i,t}$	0.025***	0.019***
	(6.48)	(5.09)
$Investmentspike_{i,t}$	-0.025	
	(-1.51)	
$LargeBusShock_{i,t}$ x $Investmentspike_{i,t}$	0.039*	
	(1.77)	
$Investmentspike_{i,t+1}$		-0.002
		(-0.12)
$LargeBusShock_{i,t}$ x $Investmentspike_{i,t+1}$		0.035
		(1.34)
$LnAssets$	-0.021***	-0.016***
	(-6.84)	(-4.13)
ΔAT_AT	-0.050***	-0.050***
	(-8.66)	(-7.03)
SA	-0.057***	-0.048***
	(-12.89)	(-8.54)
$NonDivPayer\_Dum$	-0.004	-0.012***
	(-0.81)	(-11.49)
$AdjMktbk$	-0.011***	-0.028
	(-8.89)	(-1.26)
$\lvert OperatingCF \rvert$	-0.011	-0.007***
	(-0.66)	(-3.12)
$Earns\_Vol$	-0.007***	-0.230***
	(-3.22)	(-14.19)
ROA	-0.213***	-0.005
	(-11.43)	(-0.86)
Observations	67,681	58,760
Year FE	Yes	Yes
Pseudo R^2	0.0134	0.0134

Table 12: Empirical implications: Business shocks and the estimation of leverage speed of adjustment

This table provides the results of an examination of whether large business shocks influence the estimation of the leverage speed of adjustment (SOA) towards the target leverage. We adopt a two-stage model (Byoun, 2008). In the first stage, we use yearly regression to estimate target leverage for each firm, and in the second stage, we estimate a partial adjustment model. Columns (1) to (3) provide the results of the OLS method, while columns (4) to (6) provide the results of the fixed effects method. The SOA is the coefficient on *LevDev*. The impact of other factors on the SOA is reflected by the coefficients on the interaction terms of *LevDev* and other SOA determinants, including *LnAssets*, ΔAT_AT, *NonDivPayer_Dum*, *AdjMktbk*, $|OperatingCF|$, *Earns_Vol* and *ROA*. Detailed variable definitions are provided in the Appendix. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	Dependent variable=ΔLev					
	OLS			Fixed effect model		
	(1)	(2)	(3)	(4)	(5)	(6)
LevDev	0.157***	0.179***	0.179***	0.362***	0.375***	0.377***
	(68.07)	(58.10)	(58.13)	(108.66)	(97.87)	(98.11)
$LargeBusShock \times LevDev$		-0.049***	-0.045***		-0.032***	-0.030***
		(-10.52)	(-9.50)		(-6.89)	(-6.40)
$LnAssets \times LevDev$			0.002**			-0.003**
			(2.00)			(-2.30)
$\Delta AT\_AT \times LevDev$			0.014***			0.007***
			(5.78)			(2.83)
$SA \times LevDev$			0.004***			-0.001
			(2.75)			(-0.48)
$NonDivPayer\_Dum \times LevDev$			0.010***			0.001
			(6.97)			(0.51)
$AdjMktbk \times LevDev$			-0.001**			-0.000
			(-2.19)			(-0.68)
$\lvert OperatingCF \rvert \times LevDev$			0.017**			0.025***
			(2.33)			(3.20)
$Earns\_Vol \times LevDev$			-0.000			0.004***
			(-0.14)			(3.39)
$ROA \times LevDev$			-0.020***			0.028***
			(-3.24)			(4.11)
Constant	0.007***	0.007***	0.006***	0.002	0.002	0.001
	(13.57)	(14.42)	(8.64)	(0.23)	(0.18)	(0.12)
Firm FE	No	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
Observations	68,237	68,237	68,237	68,237	68,237	68,237
Adjusted R^2	0.064	0.065	0.068	0.171	0.172	0.173