Working Paper No. 2018001

PHBS
北京大学汇丰商学院

P H B S

Asymmetric Peer Effects in Capital Structure Dynamics

Hyun Joong Im

Asymmetric peer effects in capital structure dynamics☆

Hyun Joong Im[a,*]

[a] *HSBC Business School, Peking University, University Town, Nanshan District, Shenzhen, 518055, China*

Abstract

Using a semiparametric smooth-coefficient partial adjustment model, this study finds evidence for *asymmetric* peer effects on capital structure adjustment speeds between overlevered and underlevered firms. Overlevered firms' adjustment speeds and peer firm shocks have a U-shaped relationship, while underlevered firms' adjustment speeds monotonically increase with peer firm shocks.

Keywords: Peer effects, Capital structure, Speed of adjustment, Leverage dynamics

1. Introduction

While the roles played by peer firms in various corporate decisions have long been confirmed,[1] such peer firm effects in capital structure choices have largely been understudied partly due to inherent identification challenges. Most of the prior research of peer effects in capital structure decisions has, therefore, provided either exploratory evidence based on survey results (Graham and Harvey, 2001) or indirect evidence based on industry-average leverage ratios (Welch, 2004; Frank and Goyal, 2009). The first direct evidence of peer effects in capital structure choices is provided by Leary and Roberts (2014). Using a novel identification

☆The author thank Steve Bond, Hursit Selcuk Celil, and Chang Yong Ha for insightful comments, and Ya Kang and Terry Lim for research assistance.

*Corresponding author

Email address: hyun.im@phbs.pku.edu.cn (Hyun Joong Im)

[1] Examples include, among many others, Faulkender and Yang (2010) for CEO compensation, Kaustia and Knüpfer (2012) for stock market entry decision, Foucault and Fresard (2014) for corporate investment, and Hunter et al. (2014) for fund performance evaluation.

strategy immune from a particular type of endogeneity bias called the *reflection* problem (Manski, 1993), they show that firms' financing decisions are, in large part, responses to the financing decisions of peer firms.

However, the issue of peer effects in the context of capital structure dynamics still has not been studied widely yet. Fischer et al. (1989) and Hovakimian et al. (2001), among others, show that capital structure adjustment speed is determined by the costs of being off the target as well as the costs of adjusting toward the target. In this spirit, a series of empirical studies have investigated how quickly firms converge to their leverage targets (Fama and French, 2002; Leary and Roberts, 2005; Flannery and Rangan, 2006; Huang and Ritter, 2009; Frank and Goyal, 2009). Recent literature have shown that leverage adjustment speed is influenced by various forces including macroeconomic factors (Cook and Tang, 2010), the gap between cash flows and investment opportunities (Faulkender et al., 2012), and institutional differences across countries (Öztekin and Flannery, 2012). Motivated by the growing attention on the capital adjustment speed in the literature, we aim to provide insight into how peer firms might influence firms' dynamic capital structure decisions—specifically the speed of adjustment, and into the possible interplay between peer effects and firms' current leverage standing.

In this paper, we investigate if the speed of leverage adjustment is influenced by peer firms' financial policies. To identify peer effects in dynamic capital structure decisions, we use peer firms' idiosyncratic equity return shocks as an instrumental variable (IV) to capture exogenous variation in their financial policies.[2] Peer firm equity shocks are an attractive IV to identify peer effects in a firm's capital structure adjustment behavior in a dynamic context because isolating the idiosyncratic component of stock returns is crucial for eliminating underlying sources of common variations and dynamic feedback and spillover effects caused by them. Specifically, we investigate if peer shocks have a significant *asymmetric* impact on a firm's leverage adjustment speed toward its leverage target by examining how differently overlevered and underlevered firms change their leverage adjustment speeds in response to the magnitude of the peer firm idiosyncratic equity shocks. As we do not know the exact functional form describing the relationship between the adjustment speeds and the peer firm shocks, we propose to use a semiparametric smooth-coefficient partial adjustment model.

[2]See Leary and Roberts (2014) for an extensive analysis on the relevance and desirability of the peer firm idiosyncratic equity shocks as a source of exogenous variation in peer firm financial policy.

2. Data and methodology

We use annual accounting data from the CRSP/Compustat Merged Database (CCM) and monthly stock return data from the the Center for Research in Security Prices (CRSP) for the years 1988–2014. Our dataset consists of all manufacturing firms with the two-digit North American Industry Classification System (NAICS) sector code of 31, 32, or 33. We require that each firm have at least 10-year long observations. We exclude firms with missing or negative total assets, negative book equity, or whose stocks are not traded on the three major stock exchanges in the U.S. (i.e., NYSE, NASDAQ, and AMEX). All variables are winsorized at the 1st and 99th percentiles to minimize the effects of outliers. There are a total of 24,827 firm-year observations corresponding to 1,847 firms. Peer groups are defined based on three-digit Standard Industrial Classification (SIC) codes and there are 100 peer groups represented in our sample. On average, we have approximately 9.6 firms per industry-year subsample.

To analyze peer effects in firms' capital structure decisions in a dynamic trade-off framework, we extend the following partial adjustment model of leverage proposed by Flannery and Rangan (2006) and Faulkender et al. (2012):

$$y_{i,t} - y_{i,t-1} = \lambda(y^{\star}_{i,t} - y_{i,t-1}) + \kappa_t + \varepsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is firm i's leverage at the end of year t, $y_{i,t-1}$ is firm i's leverage at the end of year $t-1$, $y^{\star}_{i,t}$ is firm i's target leverage ratio, κ_t is an error component reflecting year fixed effects, and $\varepsilon_{i,t}$ is a white-noise error term. $y_{i,t} - y_{i,t-1}$ measures the leverage adjustment made during year t, and $y^{\star}_{i,t} - y_{i,t-1}$ measures the deviation from the target leverage ratio. Each year, a typical firm closes a proportion λ of the gap between where it stands ($y_{i,t-1}$) and where it wishes to be ($y^{\star}_{i,t}$). As a leverage measure ($y_{i,t}$), we consider both book leverage ratio ($BDR_{i,t}$) and market leverage ratio ($MDR_{i,t}$).

To estimate target leverage ratios, we first model a firm's target leverage ($y^{\star}_{i,t}$) as a linear function of various firm and industry characteristics ($\mathbf{X}_{i,t-1}$) with firm fixed effects ($\eta^{\star}_i$) included: $y^{\star}_{i,t} = \alpha + \eta^{\star}_i + \beta\mathbf{X}_{i,t-1}$. $\mathbf{X}_{i,t-1}$ includes various leverage factors used in Flannery and Rangan (2006): firm size (*LnTA*), market-to-book ratio (*MB*), profitability (*EBIT_TA*), asset tangibility (*FA_TA*), depreciation and amortization (*DEP_TA*), R&D intensity (*RD_TA*), a zero R&D dummy (*D_RD*), and industry median leverage ratios (*INDBDR* or *INDMDR*). Table 1 presents definitions for the main variables used in this study.

Table 1: Variable definitions

Abbreviation	Definition	Calculation
Leverage-related variables		
$BDR_{i,t}$	Book leverage	Total debt ([*dltt*]+[*dlc*]) over book total assets [*at*]
$MDR_{i,t}$	Market leverage	Total debt ([*dltt*]+[*dlc*]) over the sum of total debt ([*dlc*] + [*dltt*]) and market value of equity ([*cshrpi*] * [*prcc_f*])
$BDEV_{i,t}$	Book deviation	Deviation of book leverage from book target at the beginning of year t ($BDR^{\star}_{i,t} - BDR_{i,t-1}$)
$MDEV_{i,t}$	Market deviation	Deviation of market leverage from market target at the beginning of year t ($MDR^{\star}_{i,t} - MDR_{i,t-1}$)
$\Delta BDR_{i,t}$	Book adjustment	Change in book leverage during year t ($BDR_{i,t} - BDR_{i,t-1}$)
$\Delta MDR_{i,t}$	Market adjustment	Change in market leverage during year t ($MDR_{i,t} - MDR_{i,t-1}$)
Idiosyncratic returns		
$\xi_{i,t}$	Idiosyncratic return shock	Annualized idiosyncratic stock returns
$\bar{\xi}_{-i,j,t}$	Peer-firm-average idiosyncratic return shock	Peer-firm average annualized idiosyncratic stock returns
Target leverage determinants		
$LnTA_{i,t}$	Firm size	Natural logarithm of total assets denominated in year-2000 dollars
$EBIT\_TA_{i,t}$	Profitability	Earnings before interests and taxes ([*ib*]+[*xint*]+[*txt*]) over total assets ([*at*])
$MV\_BV_{i,t}$	Market-to-book ratio	Sum of total debt ([*dlc*] + [*dltt*]) and market value of equity ([*cshrpi*] * [*prcc_f*]) over book value of total assets ([*at*])
$FA\_TA_{i,t}$	Tangibility	Total property, plant and equipment net of accumulated depreciation ([*ppent*]) over total assets ([*at*])
$DEP\_TA_{i,t}$	Depreciation	Depreciation and amortization ([*dp*]) over total assets ([*at*])
$RD\_TA_{i,t}$	R&D intensity	R&D expenses ([*xrd*]) over total assets ([*at*]) (0 if missing)
$D\_RD_{i,t}$	Zero R&D indicator	Dummy variable, which equals one if a firm does not report R&D expenses in year t, and zero otherwise.
$INDBDR_{j,t}$	Industry median book leverage	Industry median book leverage, where industry is defined based on three-digit SIC codes
$INDMDR_{j,t}$	Industry median market leverage	Industry median market leverage, where industry is defined based on three-digit SIC codes

Note: This table provides definitions of variables used in this study. The italicized codes in brackets ([]) represent item codes in CRSP/Compustat Merged Database.

Substituting the target leverage equation into Equation (1), we obtain the following model:

$$y_{i,t} = \lambda\alpha + \lambda\eta^{\star}_{i} + (1-\lambda)y_{i,t-1} + \lambda\beta\mathbf{X}_{i,t-1} + \kappa_t + \varepsilon_{i,t}, \tag{2}$$

where $\lambda\eta^{\star}_{i}$ and κ_t represent firm fixed effects and year fixed effects, respectively.

This can be written as the following standard dynamic panel regression model:

$$y_{i,t} = b_0 + b_1 y_{i,t-1} + b_2 \mathbf{X}_{i,t-1} + \text{Year dummies} + \eta_i + \varepsilon_{i,t}, \tag{3}$$

where $b_0 = \lambda\alpha$, $b_1 = (1-\lambda)$, $b_2 = \lambda\beta$, and $\eta_i = \lambda\eta_i^\star$. We include year dummies to control for year fixed effects (κ_t).[3] The speed of adjustment can be estimated as $\widehat{\lambda} = 1 - \widehat{b}_1$. Once we have obtained $\widehat{\lambda}$, it is straightforward to obtain $\widehat{\alpha}$, $\widehat{\beta}$, $\widehat{\eta}_i^\star$, and target leverage estimates.[4] The target book leverage ratio and target market leverage ratio are denoted $BDR^\star$ and $MDR^\star$, respectively.

We then investigate if the speed of leverage adjustment (λ) is influenced by peer firms. If we model λ as a function of peer-firm-average leverage adjustment ($\overline{\Delta y}_{-i,j,t}$), however, the following endogeneity problems could arise: (*i*) there could be a simultaneity bias as firms within the same peer group are exposed to the same or similar financial and business environment; (*ii*) there may be reverse causality running from $\Delta y_{i,t}$ to $\overline{\Delta y}_{-i,j,t}$. To address these endogeneity concerns, we adopt peer-firm-average idiosyncratic return shocks ($\overline{\xi}_{-i,j,t}$) as an IV for $\overline{\Delta y}_{-i,j,t}$ similarly to Leary and Roberts (2014). Unlike Leary and Roberts (2014) who use the shock as an IV for peer-firm-average leverage ($\overline{y}_{-i,j,t}$), we use it as an IV for peer-firm-average leverage adjustment ($\overline{\Delta y}_{-i,j,t}$).[5] See Appendix A.1 for details regarding the instrumental variable. Another issue is that we do not know about the correct functional form describing the relationship between the speed of adjustment and the peer-firm-average return shock. Thus, we employ a semiparametric smooth coefficient model (SPSCM) proposed by Li et al. (2002) and used by Stengos and Zacharias (2006), Sun and Kumbhakar (2013), and Im et al. (2015) among others. Our semiparametric smooth-coefficient partial adjustment

[3]If we replace year fixed effects with year dummies, a caution is required. To restore $\widehat{\lambda}\widehat{\alpha}$, we need to adjust $\widehat{b_0}$ by adding a constant to ensure that the mean of year effects estimated using year dummies is zero. The adjusted $\widehat{b}_0$, or $\widehat{b}_0^\star$, should be equal to $\widehat{\lambda}\widehat{\alpha}$.

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

[5]Conceptually, leverage adjustments are more likely to be correlated with idiosyncratic return shocks than leverage levels are. The correlation analyses confirm this conjecture: Corr(BDR, $\xi_{i,t}$)=-0.0047 (p-value=0.4572); Corr(ΔBDR, $\xi_{i,t}$)=-0.1216 (p-value=0.0000); Corr(MDR, $\xi_{i,t}$)=-0.0536 (p-value=0.0000); Corr(ΔMDR, $\xi_{i,t}$)=-0.3581 (p-value=0.0000).

model (SPSCPAM) can be written as follows:

$$y_{i,t} - y_{i,t-1} = \phi(\overline{\xi}_{-i,j,t}) + \lambda(\overline{\xi}_{-i,j,t})(y^{\star}_{i,t} - y_{i,t-1}) + \varepsilon_{i,t}, \tag{4}$$

where $\phi(\cdot)$ and $\lambda(\cdot)$ are smooth but unknown functions of $\overline{\xi}_{-i,j,t}$. This approach will allow us to know the functional form describing the relationship between the speed of adjustment and the peer-firm-average return shock.

Table 2: Summary statistics

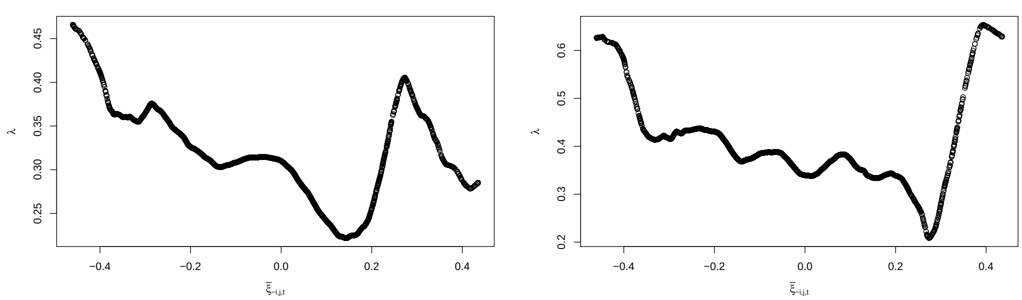
	Full sample (N=24,827)		Overlevered (N=11,553)		Undelevered (N=13,274)	
Variables	Mean	Median	Mean	Median	Mean	Median
Leverage related variables						
$BDR_{i,t}$	0.192	0.178	0.245	0.239	0.146	0.117
$MDR_{i,t}$	0.191	0.136	0.247	0.203	0.141	0.081
$BDEV_{i,t}$	-0.001	0.008	-0.092	-0.070	0.079	0.061
$MDEV_{i,t}$	0.001	0.012	-0.086	-0.065	0.077	0.062
$\Delta BDR_{i,t}$	0.000	-0.001	-0.027	-0.020	0.023	0.000
$\Delta MDR_{i,t}$	0.001	0.000	-0.023	-0.016	0.021	0.000
Idiosyncratic returns						
$\xi_{i,t}$	-0.051	-0.080	-0.013	-0.061	-0.084	-0.095
$\overline{\xi}_{-i,j,t}$	-0.052	-0.057	-0.048	-0.052	-0.056	-0.060
Target leverage determinants						
$LnTA_{i,t}$	5.537	5.389	5.517	5.352	5.555	5.421
$EBIT\_TA_{i,t}$	0.042	0.081	0.048	0.080	0.038	0.084
$MV\_BV_{i,t}$	1.617	1.189	1.489	1.106	1.729	1.285
$FA\_TA_{i,t}$	0.247	0.215	0.254	0.225	0.240	0.205
$DEP\_TA_{i,t}$	0.042	0.039	0.045	0.042	0.040	0.036
$RD\_TA_{i,t}$	0.058	0.024	0.052	0.022	0.063	0.027
$D\_RD_{i,t}$	0.250	0.000	0.257	0.000	0.243	0.000
$INDBDR_{j,t}$	0.160	0.143	0.170	0.158	0.152	0.130
$INDMDR_{j,t}$	0.142	0.114	0.155	0.133	0.130	0.096

Note: This table reports summary statistics for the main variables constructed using a sample of US public firms in the manufacturing industry from 1988 to 2014. The sample consists of firms which have at least 10 years of uninterrupted observations. Overlevered and underlevered firms in this table are defined based on book leverage ratios. All variables are winsorized at the first and 99th percentiles.

3. Results

To test whether peer effects are asymmetric between overlevered and underlevered firms, we construct two subsamples based on the signs of the deviations from leverage targets, $y^{\star}_{i,t} - y_{i,t-1}$. The deviations from book targets and the deviations from market targets are denoted by $BDEV_{i,t}$ and $MDEV_{i,t}$, respectively. Table 2 presents the summary statistics of the main variables for the subsamples of overlevered and underlevered firms as well as for the full sample. First, we find that most key determinants of target leverage (i.e., firm size, profitability, asset tangibility, depreciation, R&D intensity and industry median leverage) are very similar across the subsamples. However, we observe that growth opportunities are somewhat different between the subsamples—underlevered firms tend to have more growth opportunities. Second, we observe notable differences in the annualized idiosyncratic return shocks across subsamples. For example, mean idiosyncratic return shocks are -1.3% and -8.4% for overlevered and underlevered firms, respectively. Nevertheless, peer firm shocks measured as peer-firm-average idiosyncratic return shocks are less noticeably different across the two subsamples. Mean peer firm shocks for overlevered and underlevered firms are -4.8% and -5.6%, respectively. Third, this table suggests that it is very important to investigate overlevered and underlevered firms separately. For the full sample, both mean book deviation and mean book adjustment are close to zero, but they are very different from zero in the two subsamples. Mean book deviation for overlevered (underlevered) firms is -9.2% (7.9%), and mean book adjustment for overlevered (underlevered) firms is -2.7% (2.3%).[6] Therefore, prior empirical results based on the full sample should be interpreted with a caution as they may capture net effects only when the results are asymmetric between the two subsamples.

Figure 1: Semi-parametric estimation of the relationship between peer firm shocks and adjustment speeds: Overlevered firms



(a) Book leverage

(b) Market leverage

Note: Least-squares cross-validation method is used to select smoothing parameters. Epanechnikov kernel function is used.

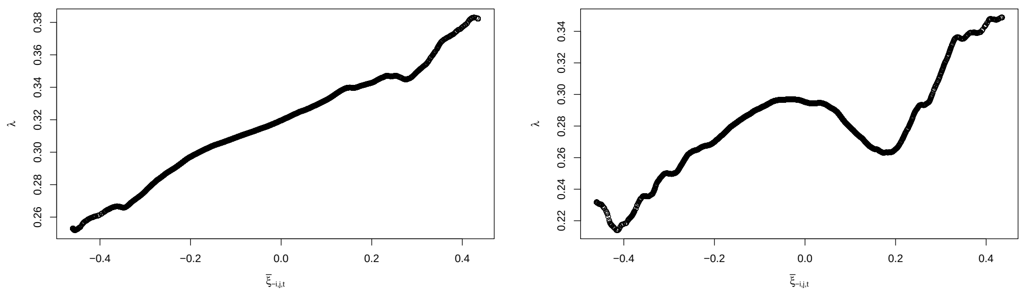
[6]These imply that the speeds of adjustment in both subsamples are approximately slightly less than one third.

Our main empirical results based on the estimation of SPSCPAMs stated in Equation (4) are presented below, separately for overlevered and underlevered firms. Figure 1 reports the estimation results for the relationship between overlevered firms' adjustment speeds (λ) and peer firm shocks ($\bar{\xi}_{-i,j,t}$). Panel (a) shows that overlevered firms' book adjustment speeds and peer firm shocks have a quadratic, specifically U-shaped, relationship. This suggests that overlevered firms adjust their leverage much faster when peer firms experience extremely bad shocks or extremely good shocks compared with when peer firms experience mild shocks. Panel (b) shows that these phenomena are more pronounced for the market leverage measure.

When there are negative equity shocks to peers (e.g., default, scandals, lawsuits, failure in patent applications), peer firms will lower their leverage faster than when there are positive equity shocks to peers. After peer firms' misfortunes such as default or hostile takeover arise, shareholders of overlevered firms will force managers to reduce the deviations from optimal leverage ratios. As influenced by peer firms' failures, firms tend to converge to optima faster in terms of investment, financing, and payout decisions. However, when there are positive shocks to peers, peer firms will increase the speed of leverage adjustment again but for different reasons. When there are positive peer shocks (e.g., grant of patents, appointment of a good CEO, resolution of a legal dispute), firms adjust their leverage more quickly to avoid being financially distressed or being a target of hostile takeovers driven by the loss of competitive advantage. The key assumption is that firms tend to have some "loose nuts and bolts" at times, but firms tend to tighten those nuts and bolts after they observe peer firms' serious misfortunes or when they are worried about the loss of competitiveness arising from peers' fortunes.

Figure 2 reports the estimation results for the relationship between underlevered firms' adjustment speeds (λ) and peer firm shocks ($\bar{\xi}_{-i,j,t}$). Panel (a) shows that underlevered firms' book adjustment speed monotonically increases with peer firm shocks. In fact, the adjustment speed increases monotonically from 25% to 38% as the shock to the peer firm moves away from negative, and becomes positive. Panel (b) shows that a similar pattern is observed when we use market leverage instead of book leverage, although there is more significant variation. This suggests that underlevered firms adjust their leverage very slowly when peer firms experience extremely bad shocks, but tend to adjust their leverage faster when peer firms face better shocks. One possible explanation for the low adjustment speed when peer shocks are negative is that an underlevered firm's leverage is already too low and is immune from this negative event such as default or a hostile takeover, hence we do not observe any significant response from the management

Figure 2: Semi-parametric estimation of the relationship between peer firm shocks and leverage adjustment speeds: Underlevered firms



(a) Book leverage (b) Market leverage

Note: Least-squares cross-validation method is used to select smoothing parameters. Epanechnikov kernel function is used.

team to adjust the firm's leverage. However, when there are positive shocks to peer firms, they are likely to invest more and issue debt to finance their major investment projects (DeAngelo et al., 2011; Elsas et al., 2014; Im et al., 2017). As influenced by peer firms, underlevered firms will also invest more (Facault and Fresard, 2014) by issuing debt to finance their investment projects since underlevered firms can increase their firm value by increasing their leverage ratios. Thus, an underlevered firm will adjust its leverage faster in this case.

4. Conclusion

We investigate whether peer firms play a significant role in capital structure dynamics of US manufacturing firms during the period 1988 to 2014. Unlike Leary and Roberts (2014) who find evidence for peer effects in capital structure in a *static* trade-off framework, we investigate whether peer firms influence a firm's capital structure decisions by extending a dynamic trade-off framework in which there exists a target leverage level (or range) and adjustment benefits and costs affect the speed of leverage adjustment toward the target. Using a semiparametric smooth-coefficient partial adjustment model, we find evidence for *asymmetric* peer effects on capital structure adjustment speeds between overlevered and underlevered firms. Specifically, we find that overlevered firms' adjustment speeds and peer firm shocks have a U-shaped relationship, while underlevered firms' adjustment speeds monotonically increase with peer firm shocks. We provide intuitive explanations to our findings, although we agree that there may be alternative explanations.

Table A.1: Stock return factor regression results

	Mean	S.D.	Q1	Median	Q3
Regression results					
α	0.006	0.023	-0.006	0.005	0.017
β^{MKT}	0.528	1.141	0.034	0.623	1.138
β^{SMB}	0.459	1.436	-0.209	0.439	1.136
β^{HML}	0.104	1.305	-0.540	0.120	0.761
β^{IND}	0.484	0.876	-0.002	0.303	0.828
Observations per regression	56	9	60	60	60
Adjusted R^2	0.217	0.175	0.083	0.191	0.330
Monthly returns					
Avg. monthly return	0.014	0.054	-0.014	0.011	0.036
Avg. expected monthly return	0.016	0.037	-0.003	0.014	0.032
Avg. idiosyncratic monthly return	-0.001	0.039	-0.021	-0.003	0.016
Annualized returns					
Annualized return	0.185	0.957	-0.255	0.042	0.370
Annualized expected return	0.263	1.384	-0.072	0.148	0.405
Idiosyncratic annual return ($\xi_{i,t}$)	-0.078	1.343	-0.321	-0.098	0.117

Note: The sample consists of monthly returns for all manufacturing firms in the CRSP databases between 1988 and 2014. The table presents mean factor loadings and adjusted R^2 from the extended Fama and French three-factor model.

Appendix

A.1. Construction of peer-firm-average idiosyncratic return shocks ($\overline{\xi}_{-i,j,t}$)

To construct peer-firm-average idiosyncratic return shocks ($\overline{\xi}_{-i,j,t}$), we go through the following steps. First, we estimate the following extended Fama and French three-factor model on a rolling annual basis using monthly returns during the previous five-year period (with at least 24 observations):

$$r_{i,j,s} = \alpha_{i,j,s} + \beta^{MKT}_{i,j,s}(r_{MKT,s} - r_{F,s}) + \beta^{SMB}_{i,j,s} r_{SMB,s} + \beta^{HML}_{i,j,s} r_{HML,s} + \beta^{IND}_{i,j,s}(\overline{r}_{-i,j,s} - r_{F,s}) + \nu_{i,j,s},$$

where i, j and s denote firm i, peer group j and month s, respectively. $r_{i,j,s}$ is firm i's monthly stock return, $r_{MKT,s}$ refers to monthly market return, and $r_{F,s}$ refers to monthly risk free rate. $\overline{r}_{-i,j,s}$ is the peer-firm-average monthly return for firm i (excluding firm i's own monthly return), where peer groups are defined by the three-digit SIC codes. The regression is estimated for each firm on a rolling annual basis using historical monthly returns during the five-year period. We require at least 24 months of historical data in the estimation. We compute expected returns using the estimated factor loadings and realized factor returns one year hence. We then compute idiosyncratic returns as the difference between realized returns and expected returns. The regression results are summarized in Table A.1. On average, adjusted R^2 is as high as 21.7%. Mean idiosyncratic monthly return is around -10 basis points, which is comparable to that in Leary and Roberts (2014). Second, we calculate firm i's annualized idiosyncratic shocks in year t ($\xi_{i,t}$) as the difference between annualized actual stock returns and annualized expected stock returns. Finally, we calculate firm i's peer-firm-average idiosyncratic return shocks in year t ($\overline{\xi}_{-i,j,t}$) by taking the average of peer firms' annualized year-t idiosyncratic shocks (excluding firm i's).

A.2. Estimation of target leverage ratios

To implement the semiparametric smooth-coefficient partial adjustment model stated in Equation (4), we first need to estimate target leverage ratios ($y^{\star}_{i,t}$) and calculate the deviations from target leverage ratios ($y^{\star}_{i,t} - y_{i,t-1}$).[7] As mentioned in Section 2, the estimation of leverage targets requires the estimation of a standard dynamic panel regression model stated in Equation (3). Note that there are several estimation issues arising from the simultaneous inclusion of fixed effects and lagged dependent variables. For instance, the ordinary least squares (OLS) and within groups (WG) estimates of the coefficient of the lagged dependent variable tend to be biased upwards and downwards, respectively. This is particularly true when the data have a short panel length (Nickell, 1981; Bond, 2002). Therefore, the coefficients of $\mathbf{X}_{i,t-1}$ in Equation (2) are also likely to be biased. Using simulated panel data, Flannery and Hankins (2013) show that the estimation performance of various econometric methodologies varies substantially depending on data complications, such as fixed effects, the persistence of the dependent variable, endogenous independent variables, and error term autocorrelations. They find that the LSDVC estimator proposed by Bruno (2005) performs the best in the absence of endogenous independent variables whereas the System GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) appears to be the

[7]As in Faulkender et al. (2012), we first estimate target leverage ratios before estimating the speed of leverage adjustment. Unlike Faulkender et al. (2012) who use a parametric partial adjustment model to estimate adjustment speeds, we employ a semiparametric partial adjustment model.

Table A.2: Regression analyses used to estimate target leverage ratios

	Book leverage			Market leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	WG	SYS GMM	OLS	WG	SYS GMM
Variables	$BDR_{i,t}$	$BDR_{i,t}$	$BDR_{i,t}$	$MDR_{i,t}$	$MDR_{i,t}$	$MDR_{i,t}$
$BDR_{i,t-1}$	0.829***	0.637***	0.744***			
	(0.005)	(0.008)	(0.010)			
$INDBDR_{j,t-1}$	0.045***	0.038***	0.030**			
	(0.007)	(0.012)	(0.015)			
$MDR_{i,t-1}$				0.823***	0.613***	0.736***
				(0.005)	(0.008)	(0.009)
$INDMDR_{j,t-1}$				0.054***	0.077***	0.063***
				(0.007)	(0.012)	(0.013)
$LnTA_{i,t-1}$	0.003***	0.010***	0.004***	0.002***	0.021***	0.003**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
$EBIT\_TA_{i,t-1}$	-0.009**	-0.021***	-0.012*	-0.006	-0.023***	-0.004
	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)	(0.007)
$MV\_BV_{i,t-1}$	-0.001**	-0.001**	-0.001	-0.002***	-0.002***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
$FA\_TA_{i,t-1}$	0.028***	0.053***	0.076***	0.032***	0.071***	0.072***
	(0.004)	(0.010)	(0.013)	(0.005)	(0.011)	(0.014)
$DEP\_TA_{i,t-1}$	-0.149***	-0.213***	-0.412***	-0.213***	-0.238***	-0.475***
	(0.027)	(0.048)	(0.062)	(0.031)	(0.051)	(0.069)
$RD\_TA_{i,t-1}$	-0.019**	-0.011	-0.022	-0.036***	-0.006	-0.047***
	(0.009)	(0.016)	(0.019)	(0.008)	(0.014)	(0.017)
$D\_RD_{i,t-1}$	0.005***	0.007**	0.012**	0.009***	0.010**	0.029***
	(0.001)	(0.003)	(0.005)	(0.002)	(0.004)	(0.006)
Constant	0.028***	0.028***	0.036***	0.038***	-0.032***	0.043***
	(0.004)	(0.008)	(0.008)	(0.004)	(0.009)	(0.008)
Firm fixed effects	No	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,617	32,617	32,617	32,617	32,617	32,617
Number of firms	2,127	2,127	2,127	2,127	2,127	2,127
Goodness-of-fit—$Corr(y_{i,t},\widehat{y}_{i,t})^2$	0.742	0.726	0.738	0.748	0.683	0.743
Second-order serial correlation (p-value)			0.655			0.176
Sargan-Hansen test (p-value)			0.923			0.943

Note: This table reports the results of the regression analyses designed to estimate book target leverage ratios and market target leverage ratios using Ordinary Least Squares (OLS), Within Groups (WG), and System GMM (SYS GMM) estimators, respectively. The dependent variables are book leverage (*BDR*) and market leverage (*MDR*) in the first three columns and in the last three columns, respectively. Details for variables included in the models are provided in Table 1. In OLS and WG estimators, standard errors are clustered by firm and displayed in parentheses below. In System GMM, we report two-step GMM coefficients and standard errors that are asymptotically robust to both heteroskedasticity and serial correlation, and which use the finite-sample correction proposed by Windmeijer (2005). Instrument variables used in System GMM are the second to twelfth lags of the dependent variable (*BDR* or *MDR*) and the second to twelfth lags of all target leverage determinants for the equations in first-differences, and the first lag of the first-difference of leverage and the first lags of the first-differences of all target leverage determinants for level equations. Note that year dummies are treated as instruments for the equations in levels only. Overall goodness-of-fit score, $Corr(y_{i,t},\widehat{y}_{i,t})^2$, is calculated as the square of the coefficient of correlation between the dependent variable ($y_{i,t}$) and its predicted value ($\widehat{y}_{i,t}$). Instrument validity is tested using a Sargan-Hansen test of the overidentifying restrictions. Serial correlation is tested using a Lagrange multiplier test on the first-differenced residuals (Arellano and Bond, 1991). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

best choice in the presence of endogeneity and even second-order serial correlation if the dataset includes shorter panels. We reports the results based on the three econometric methodologies to highlight that the results are significantly influenced by the choice of estimation methods, but we use the System GMM results to estimate target leverage ratios.

Our regression results are reported in Table A.2. Columns 1–3 and Columns 4–5 present the estimation results for book and market leverage ratios, respectively. For each leverage measure, we report estimation results based on OLS, WG, and System GMM estimators. We include year fixed effects to account for temporal variations in all three specifications. The System GMM results are satisfactory for the following reasons. First, the coefficients of the lagged dependent variable estimated by the System GMM lies between the OLS and WG estimates, as predicted by Nickell (1981) and Bond (2002). Second, the goodness-of-fit scores of the System GMM model are higher than those of the WG model and slightly lower than those of the OLS model. Note that the goodness-of-fit score should be lower in the WG and System GMM models than in the OLS model as a term reflecting unobserved heterogeneity is a component of the error term in the WG and System GMM models. Third, Arellano and Bond's (1991) serial correlation tests find no significant evidence of the second-order serial correlation in the first-differenced residuals (p-value=0.655 for BDR; p-value=0.176 for MDR). Finally, Sargan-Hansen tests of overidentifying restrictions do not reject these specifications (p-value=0.923 for BDR; p-value=0.943 for MDR). Overall, the signs of the main determinants of leverage targets are consistent with theoretical predictions. Size, asset tangibility, zero R&D indicator, and industry median leverage are positively associated with the target leverage estimates. Profitability, market-to-book, non-debt tax shield proxies, and R&D intensity are all negatively associated with the target estimates generally in all regression models. Most of the relationships are consistent with the findings of the related literature, i.e., Fama and French (2002), Flannery and Rangan (2006), and Faulkender et al. (2012).

References

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. The Review of Economic Studies 58 (2), 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68 (1), 29–51.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87 (1), 115–143.

Bond, S. R., 2002. Dynamic panel data models: a guide to micro data methods and practice. Portuguese Economic Journal 1 (2), 141–162.

Bruno, G. S., 2005. Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. Economics Letters 87 (3), 361–366.

Cook, D. O., Tang, T., 2010. Macroeconomic conditions and capital structure adjustment speed. Journal of Corporate Finance 16 (1), 73–87.

DeAngelo, H., DeAngelo, L., Whited, T. M., 2011. Capital structure dynamics and transitory debt. Journal of Financial Economics 99 (2), 235–261.

Elsas, R., Flannery, M. J., Garfinkel, J. A., 2014. Financing major investments: information about capital structure decisions. Review of Finance 18 (4), 1341–1386.

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

Faulkender, M., Flannery, M. J., Hankins, K. W., Smith, J. M., 2012. Cash flows and leverage adjustments. Journal of Financial Economics 103 (3), 632–646.

Faulkender, M., Yang, J., 2010. Inside the black box: The role and composition of compensation peer groups. Journal of Financial Economics 96 (2), 257–270.

Fischer, E. O., Heinkel, R., Zechner, J., 1989. Dynamic capital structure choice: Theory and tests. The Journal of Finance 44 (1), 19–40.

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 (3), 469–506.

Foucault, T., Fresard, L., 2014. Learning from peers' stock prices and corporate investment. Journal of Financial Economics 111 (3), 554–577.

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

Graham, J. R., Harvey, C. R., 2001. The theory and practice of corporate finance: Evidence from the field. Journal of Financial Economics 60 (2), 187–243.

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

Huang, R., Ritter, J. R., 2009. Testing theories of capital structure and estimating the speed of adjustment. Journal of Financial and Quantitative Analysis 44 (2), 237–271.

Hunter, D., Kandel, E., Kandel, S., Wermers, R., 2014. Mutual fund performance evaluation with active peer benchmarks. Journal of Financial Economics 112 (1), 1–29.

Im, H. J., Mayer, C., Sussman, O., 2017. Investment spike financing.

Im, H. J., Park, Y. J., Shon, J., 2015. Product market competition and the value of innovation: Evidence from US patent data. Economics Letters 137, 78–82.

Kaustia, M., Knüpfer, S., 2012. Peer performance and stock market entry. Journal of Financial Economics 104 (2), 321–338.

Leary, M. T., Roberts, M. R., 2005. Do firms rebalance their capital structures? The Journal of Finance 60 (6), 2575–2619.

Leary, M. T., Roberts, M. R., 2014. Do peer firms affect corporate financial policy? The Journal of Finance 69 (1), 139–178.

Li, Q., Huang, C. J., Li, D., Fu, T.-T., 2002. Semiparametric smooth coefficient models. Journal of Business & Economic Statistics 20 (3), 412–422.

Manski, C. F., 1993. Identification of endogenous social effects: The reflection problem. The Review of Economic Studies 60 (3), 531–542.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica: Journal of the Econometric Society, 1417–1426.

Öztekin, Ö., Flannery, M. J., 2012. Institutional determinants of capital structure adjustment speeds. Journal of Financial Economics 103 (1), 88–112.

Stengos, T., Zacharias, E., 2006. Intertemporal pricing and price discrimination: a semiparametric hedonic analysis of the personal computer market. Journal of Applied Econometrics 21 (3), 371–386.

Sun, K., Kumbhakar, S. C., 2013. Semiparametric smooth-coefficient stochastic frontier model. Economics Letters 120 (2), 305–309.

Welch, I., 2004. Capital structure and stock returns. Journal of Political Economy 112 (1), 106–131.

Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics 126 (1), 25–51.