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Firm Financial Behaviour Dynamics and Interactions: A Structural Vector Autoregression Approach

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Abstract

This paper investigates the dynamic interactions of firms' financial behaviours using a five-variable structural vector autoregression (SVAR) framework. We provide empirical evidence that firms' financial behaviours are jointly determined. We demonstrate that a single-equation analysis on one financial behaviour generates biased estimates. We find that firms deviate from the desired level of each financial characteristic to absorb shocks to the other financial characteristics. Following such deviations, the characteristics revert in subsequent periods. Among these inter-related financial behaviours, equity decisions are the most independent, followed by dividend target, investment, and leverage target. Although firms prioritize financial behaviours differently, it appears that there is neither one financial behaviour that firms use only to absorb shocks nor one that never responds to the others.

Keywords: Firm financial behaviours, Interactions, Structural vector autoregression, Priority, Impulse response.

JEL classification: G31, G32, G35

1. Introduction

Although a growing body of literature jointly models investment, dividend payouts and borrowing (e.g., Hennessey and Whited, 2005; DeAngelo et al., 2011; Bolton et al., 2011; Lambrecht and Myers, 2012, 2017), several questions concerning financial behaviour interactions remain unanswered. This paper addresses three such issues. First, the literature lacks a systematic empirical examination of the joint-dependence of firm financial behaviours that addresses whether investment behaviours, dividend behaviours, and financing behaviours help explain each other[1]. Second, if financial behaviours are simultaneously and jointly determined, then the question arises as to whether any financial behaviour has a higher (or lower) priority and tends to be less (more) influenced by the other financial behaviours. Since the firm needs to satisfy its budget constraint and it cannot achieve its financial targets simultaneously (Lambrecht and Myers, 2012; DeAngelo and Roll, 2015), firms must prioritize its financial levers. The question is then which financial policy (i.e., leverage target, dividend target, investment or equity issuance and repurchase) has the highest priority and whether or not the financial policy with the lowest priority is determined residually[2] in order to balance the budget constraint. Third, if firms' financial behaviours are interrelated, then how do they interact with each other? More specifically, how is a shock to one of the financial behaviours absorbed by the other financial behaviours? Do firms use a particular lever as a residual to absorb shocks and to smooth the other financial policies?

Recent studies stress the impact of the budget constraint (Lambrecht and Myers, 2012) and financial frictions (Chang et al., 2014) on firm financial policies, and suggest that firm

[1] In a recent study, Hoang and Hoxha (2016) examine the extent to which debt, investment and dividends absorb profitability shocks. Our work has a more systematic view and can accommodate shocks to any of the financial behaviours, such as how investment shocks lead to responses in profitability.
[2] The residual role indicates that decisions about the financial behaviour depend on decisions about the other financial behaviours. To put it in another way, the residual financial behaviour needs to absorb shocks to the other financial behaviours to balance the budget constraint, but it does not affect the other financial decisions.

investment, dividend and leverage behaviours need to be modelled simultaneously. Lambrecht and Myers (2012) use a budget constraint to explain why shocks to one of the financial behaviours need to be absorbed by the other financial behaviours.[3] In the budget constraint, to avoid affecting investment activities and dividend payouts, firms need to raise or retire debt to absorb any shocks to net income. Cash flow links firms' investment decisions, dividend decisions, and leverage decisions.[4] Adjustments in any of the financial variables are likely to affect the other financial variables. DeAngelo and Roll (2015) point out that firms cannot achieve the desired levels of these financial characteristics at the same time because the system is overdetermined and the budget is limited. The failure to manage these financial behaviours in practice can lead to an increase in agency conflicts. Jensen et al. (1992) note that asymmetric information and misaligned incentives of stakeholders generate agency costs and that firms could minimize these costs by optimizing these aforementioned financial behaviours jointly. Therefore, it is desirable to build a model in which firms' financial behaviours can interact. Gatchev et al. (2010) critique studies focusing on a single financial behaviour and argue that the resulting estimates are biased and misleading due to the lack of variables to capture the interdependent and intertemporal nature of other financial behaviours. Compared to studies examining a single financial behaviour, relatively few studies investigate the interactions between multiple financial behaviours.[5]

To investigate the aforementioned issues, we model firm investment, dividend payouts, profitability, leverage and equity issuance (or repurchase) in a five-variable structural vector

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[3] Lambrecht and Myers (2012) use the following budget constraint equation:

$$\Delta\text{Debt} + \text{Net income} = \text{CAPEX} + \text{Payout},$$

in which firms have internally generated funds (Net income) and funds raised by external debt financing (ΔDebt). Firms allocate the funds between investment (CAPEX) and the distributions to shareholders (Payout). Equity issuance is treated as negative payout in their model.

[4] Apart from the budget constraint, firms' financial behaviours are interrelated in other ways. For example, new investment increases the collateral that is necessary to back up new borrowings. We cover this explanation and other related studies when discussing our empirical results.

[5] Lee et al. (2016) provide a review of the studies applying simultaneous equations.

autoregression (SVAR) framework. The method is developed by Sims (1980) and has been widely used in macroeconomics to study the interactions between a few endogenously determined variables (e.g., Blanchard, 1989; Bernake and Blinder, 1992; Mertens and Olea, 2018; Mumtaz and Theodoridis, 2020). In a corporate finance context, a single equation analysis of investment, leverage or dividend decisions requires controlling for a large number of other variables, most of which are endogenously determined (Gatchev et al., 2010). SVAR can model endogenously determined variables and use lagged values of the variables as IVs (instrumental variables) and use GMM (generalized method of moments) to estimate the coefficients of the lagged endogenous variables. It uses a recursive identification strategy to identify the transmission of shocks between the variables and estimate the impact of a shock to the firm. Using this method, SVAR can overcome the endogeneity problem and isolate the response of financial behaviours to each other respectively. Therefore, it is an appropriate method to study the interactions between financial behaviours.

SVAR models have advantages over other methods. First, compared to theoretical works that typically assume the exogeneity of several factors to limit the model's dimensionality,[6] SVAR models allow all variables to be determined endogenously. Second, compared to the standard regression approach, the results of SVAR models can shed light on which theoretical models align more closely with empirical reality. For example, some theoretical studies use investment, borrowing, and payouts to build models in which debt is residually determined (e.g., Lambrecht and Myers, 2012), whereas others build models in which the dividend is residually determined (e.g., DeAngelo et al, 2011). As there are no strong theoretical arguments for why one financial policy should take priority over another, the SVAR approach allows the data to speak and to determine empirically which decision is given a higher priority. Third, using an SVAR approach avoids the potential bias resulting from the misspecification caused

[6] See Titman and Tsyplakov (2007, Table 1) for a summary of the assumptions.

by the assumed exogeneity in simultaneous equation models (Sims, 1980) and it has the merit of avoiding a complete specification of the models (Bagliano and Favero, 1998).

Our results show that firms' financial behaviours are, indeed, jointly determined. All of the financial behaviour variables are explained by both their previous realisations and the previous realisations of other financial behaviour variables. We use a Granger causality test (Granger, 1969) to evaluate the joint determination of financial behaviours. We find that all of the financial behaviour variables are determined by at least some of the other variables. Therefore, our empirical results are in line with theoretical studies (e.g., Hennessy and Whited, 2005) arguing that firm financial policies are interdependent. We compare the coefficient estimates from single equation models and those from the SVAR model and find that single equation models, without properly controlling other financial behaviours, can generate biased estimates and misleading conclusions.

We then empirically evaluate the priority of firms' financial behaviours by decomposing the forecast error variance of the five financial behaviour variables. Specifically, we analyse the extent to which the forecast error variance in each variable is due to shocks to the other variables. This allows us to conduct a direct comparison of the relative independence of these financial behaviours. We conjecture that the financial behaviour with a higher priority is less exposed to shocks to the other financial behaviours. The results of a forecast error variance decomposition (FEVD) analysis suggest that equity issuance decisions are the most independent, followed by dividend target, investment, and, lastly, leverage target. These results show the relative net cost of deviations from the desired levels of financial characteristics. When there is a shock, firms are most likely to adjust debt decisions to accommodate other financial behaviours and to absorb the shock and are least likely to adjust equity decisions.

Due to the interdependence of firms' financial behaviours, we use orthogonalized impulse response functions (OIRFs) to examine these interactions and to visualize the effect of an orthogonal shock to a single financial behaviour on the other financial behaviours. We find that firms' financial characteristics temporarily deviate from their desired levels to absorb the shocks to other financial characteristics, followed by a reversion to their steady states[7] at varying speeds. Although leverage decisions are given the lowest priority, they are not residually determined. There is clear evidence that the leverage ratio reverts after a shock, although the speed of adjustment (SOA) is low. Although equity issuance and repurchase are given the highest priority, firms also use them to absorb shocks to other financial behaviours. To our knowledge, this is the first study that systematically examines the impulse responses of firms' financial behaviours on each other.

We contribute to the literature in several ways. First, we enrich the literature by empirically demonstrating that firms' financial behaviours are jointly determined. Although a few theoretical works jointly model investment, payouts and borrowing (e.g., Hennessey and Whited, 2005; DeAngelo et al., 2011; Bolton et al., 2011; Lambrecht and Myers, 2012, 2017), the literature lacks a systematic empirical examination of the joint-dependence. Our Granger causality test results show that firms' financial behaviours determine each other. The OIRF results show that firms temporarily deviate from steady states of some financial characteristics to absorb a shock to a single financial characteristic. Thus, financial behaviours interact and firms can optimize over several financial targets (i.e., investment, leverage target, dividend target and equity decisions).

Second, the FEVD results show that firms prioritise among the instruments to absorb a shock. Among these instruments, firms adjust leverage to absorb shocks most often, followed

[7] We borrow the meanings of "shocks" and "steady state" from the macroeconomics literature. The steady state can be interpreted as the equilibrium level of a financial variable, for example, the desired leverage ratio.

by investment, dividends, and equity issuances (or repurchases). Firms appear to use all of the instruments at their disposal to maintain a balance among several financial targets. There is neither one financial behaviour that firms use only to absorb shocks nor one that never responds to the others. When reflecting on our results in light of the theoretical literature, we, therefore, see that our results are in line with, for example, the model in Lambrecht and Myers (2017), in which the debt ratio can remain constant while dividends are smoothed at the same time.

Third, we also provide the empirical evidence to support Acharya and Lambrecht's (2015) assertion that firms do not immediately distribute unexpected profits to shareholders. The results of OIRFs show that firms adjust leverage and investment to absorb part of the profitability shock and to smooth payouts. In this way, firms gradually distribute the extra profits to shareholders in a few years.

The remainder of the paper is organised as follows. Section 2 describes the data and methodology. Section 3 investigates the interdependence of firms' financial behaviours and examines the bias of using a single equation model. Section 4 examines the priority of financial behaviours by decomposing the forecast error variance of each variable. Section 5 uses the OIRFs to illustrate how firms absorb orthogonal shocks to each financial variable. Section 6 discusses the robustness of our results. Section 7 concludes the paper.

2. Data and Methodology

2.1 Data and Descriptive Statistics

We use data collected from the CRSP/Compustat Merged database. Consistent with prior corporate finance studies (e.g., Graham et al., 2015; DeAngelo and Roll, 2015), we exclude financial firms (SIC Codes 6000-6999), utilities (4900-4949), railroads (4000-4100) and telecommunications (4800-4900). We use the firms with a continuous record from 1967 to 2016 to report our main results for two reasons. First, Myers (2015) suggests that the testing of corporate finance theories should focus on large and mature firms. Using those firms with a continuous record helps construct a targeting sample and a stable model.[8] Second, this paper uses a panel time series method, for which a long time series is desirable. We have a balanced panel of 413 firms. For each firm, we have 50 years of data. The base sample accounts for 35% of the market capitalization. Table 1 provides the descriptive statistics and Appendix 1 summarizes the definitions of variables. We apply different sampling criteria and discuss the results in the robustness check section.

[Insert Table 1 here]

Table 1 presents the descriptive statistics for our sample firms. Following Gatchev et al. (2010), we use capital expenditures scaled by total assets to measure firm investment (*Inv*). Investment stands for around 5.3% of total assets, on average. We use the *equity issuance ratio (Equ)* to measure the proportion of net equity issued in year *t* to total assets at the end of year *t*. Net equity issuance makes up 0.7% of total assets at the end of the year, on average. A negative value of *Equ* indicates net equity repurchase. *Return on assets (ROA)* measures firms' ability to generate funds internally, with a mean of 0.054. Following Fama and French (2002), we scale cash dividends by total assets to measure the *dividend payout ratio (Divc)*. Cash dividends equal 0.021 of total assets, on average. The *leverage ratio (Lev)* measures the proportion of total debt to the book value of total assets and the mean is 0.233.

SVAR models require variables to have a stationary time series because unit roots lead to the weak instruments problem (Blundell and Bond, 1998).[9] We perform two unit root tests, the Fisher-type augmented Dicky–Fuller test (Maddala and Wu, 1999; referred to as ADF) and

[8] Shyam-Sunder and Myers (1999) and Fama and French (2002) use similar samples of surviving firms.
[9] Abrigo and Love (2016) cite Blundell and Bond (1998) and explain that the forward orthogonal deviation (FOD) transformation generates white-noise error terms when a unit root exists. In this situation, the moment conditions of the IVs do not provide relevant information.

Phillips and Perron test (1998; referred to as PPerron), to test for unit roots in our variables.[10] The last two columns of Table 1 report the results of these tests, which suggest that we can reject the null hypothesis at the 1% level and indicate that the five financial behaviour variables are stationary.

2.2 Methodology

Sims (1980) developed the SVAR framework, which has since gained wide use in macroeconomics to model the inter-relations between several simultaneously determined variables (e.g., Blanchard, 1989; Bernake and Blinder, 1992; Mertens and Olea, 2018; Mumtaz and Theodoridis, 2020). Sims (1980) argues that the standard assumptions implicit in the identification of simultaneous equation systems, e.g., that a factor impacts one side of the market (the supply or demand side) but not the other, or that monetary variables are exogenous to macroeconomic variables, are too strong to be of practical use. In a corporate finance context this would mean assuming in a simultaneous equation system with, say, dividends and leverage, that a factor influencing dividend payout does not influence leverage and vice versa. Since a fully specified model containing all parameters is, as of now, not available, the method that Sims developed can be useful to estimate a system of simultaneous equations where factors affect multiple variables. Hence, it is possible to examine the interrelated financial policies where one variable affect the others. The model uses the lowest number of assumptions to identify the impulse responses to various shocks and test economic and finance theories; and it uses a logical transmission of shocks among variables to identify the impacts, and hence does not need a complete specification of a structure of models. The absence of a fully specified model makes SVAR a good compromise to provide statistical evidence for comparing

[10] Choi (2001) suggests that the ADF test can accommodate possible lag lengths variation across panels. The ADF test uses lags of a differenced dependent variable to control the serial correlation, while the PPerron test uses Newey-West standard errors. In both tests, the null hypothesis is that unit roots exist, while the alternative hypothesis is that the time series is stationary.

alternative macroeconomic theories. Firms' financial behaviours have the same problem: the variables are endogenously determined and a complete specification of a structure of models is not available. Hence, the SVAR model can be applied to analyse the interactions between financial behaviours. More detailed reviews of the SVAR model and its use are available from, for example, Sims (1989), Bagliano and Favero (1998) and Christiano (2012).

The SVAR framework models an endogenous variable by its own lags and the lags of the other variables in the system. It uses the structure of an appropriate model to capture contemporary effects. In this way, SVAR can model the simultaneously determined financial behaviours. In the SVAR framework, the evolution of a variable in year *t* is a combination of the status of the same variable and the other variables in the previous periods and a shock in year *t*. Holtz-Eakin et al. (1988) develop the method to use lagged variables as IVs to estimate SVAR coefficients in panel data models. Our model has the following form:

$$y_{i,t} = A_1 y_{i,t-1} + \cdots + A_p y_{i,t-p} + u_i + \varepsilon_{i,t}, \quad (1)$$

where $y_{i,t}$ is the vector of the 5 dependent variables of firm *i* at time *t* net of their cross-sectional means to remove year-fixed effects. The five variables capture firms' investment, equity issuance decisions, profitability, dividend payouts and leverage. $y_{i,t-p}$ captures the previous realisations of the financial variables and *p* is the lag order of the SVAR model.[11] u_i is a vector of firm-fixed effects. $\varepsilon_{i,t}$ is a vector of idiosyncratic noise. Estimating a single equation of the dynamic system by OLS or the fixed effects method leads to biased and inconsistent estimates due to the endogeneity in lagged dependent variables and in the other independent variables (Blundell and Bond, 1998; Antoniou et al., 2008). Abrigo and Love (2016) cite Alvarez and Arellano (2003) and suggest that the GMM generates consistent estimates for autoregressive models. Abrigo and Love (2016) propose using a FOD to eliminate the firm-level fixed effects

[11] We follow Holtz-Eakin et al. (1988) and assume that all of the variables have an identical lag length, as this is a typical practice of the SVAR methodology. We test the explanatory power of each lag of the variables.

u_i. We follow these suggestions in estimating model (1). We focus here on a more intuitive description and show more detail of the SVAR methodology in in Appendix 2.

We perform three tests to check the validity of our SVAR model. First, following Enders (2015), we conduct an over-identification test with the null hypothesis that the SVAR model is not over-identified. Second, we test the stability of the SVAR model, as Abrigo and Love (2016) suggest that model stability is a pre-condition for a correct interpretation of the FEVD and OIRF analyses. Third, we check whether the lag structure of our SVAR model is appropriate. Thornton and Batten (1985) and Holtz-Eakin et al. (1988) highlight the importance of using an appropriate lag structure in SVAR models, indicating that an inappropriate choice leads to misspecifications and misleading results from the Granger causality tests. We follow Andrews and Lu (2001) and use the model and moment selection criteria (MMSC) to check the lag structure of our SVAR model.[12]

In the SVAR framework, a shock refers to a deviation from the steady state of a financial variable. Real world shocks, such as a financial crisis, usually have simultaneous impacts on more than one financial variable, but in the SVAR framework we can isolate and examine the impact of a shock to a single variable. We follow Sims (1980) and use a Cholesky decomposition of the covariance matrix (see Appendix 2 for details), which helps show the distinct patterns of movements in the simultaneously determined variables. Cholesky decomposition requires a logical order of the employed variables to identify the transmission of shocks within the firm. Albeit some criticisms on the recursive identification strategy (e.g., Bernanke, 1986), the method is still being used in up-to-date macroeconomic studies (e.g.,

[12] The simulation results in Andrews and Lu (2001) show that, after the selection following the MMSC, SVAR models generate lower-biased estimates and show a more accurate rejection rate. The MMSC requires a greater number of moment conditions than the number of endogenous variables. This indicates that the lag length of the IVs must be larger than the lag order of the SVAR model. In an earlier study, McCabe (1979) finds that financial ratios lagged beyond three years do not convey significant explanatory power, but can lead to multicollinearity. Hence, we test the first-, second- and third-order SVAR models and set the lag length of the IVs to 4.

Auerbach and Gorodnichenko, 2012; Mumtaz and Theodoridis, 2020) to isolate orthogonal shocks. We discuss our choice of the recursive order in Section 4 and check the robustness of our results to alternative orderings in Section 6. Several studies in the monetary economics literature (e.g., Rudebusch, 1998) question the economic sense of shocks in SVAR models. In a corporate finance context, one source of a shock could be unexpected facts (e.g., a variation in sales or tax rate) that managers cannot foresee. Hence, the employed financial variables reflect unforecasted behaviours. Another source could be firms' changing preferences and the timing issue; that is, managers may have time-varying preferences for investment, attempt to maintain a stable dividend payout ratio or leverage ratio, or try to time the securities market. Therefore, managers could make some decisions instantaneously or that market conditions (e.g., investment opportunities) could drive these decisions. These unexpected facts and instantaneous decisions generate shocks to firms. Though different firms may behave differently in reality, we try to understand how an average firm responds.

3. Joint Determination of Firm Financial Behaviours

The literature is ambiguous about the direction of determination among firms' financial behaviours. On the one hand, firm investments need to be funded by using external capital, typically debt financing;[13] on the other hand, financing decisions also impact investments due to capital constraint (Peterson and Benesh, 1983). Lintner (1956) suggests that dividend payments are a targeted proportion of earnings; however, dividends also signal future profitability according to Miller and Modigliani (1961). Jensen et al. (1992) suggest that previous investment has a negative impact on current dividend payments, whereas Hoang and Hoxha (2016) find that firms use the investment to smooth dividend payouts. The mixed

[13] The pecking order theory (Myers and Majluf, 1984) suggests a pecking order among financing sources. Firms tend to use internally generated cash to fund an investment project. If firms need external capital, then they would issue debt first, with the remaining covered by equity issuance.

evidence points to a bi-directional relationship between financial behaviours. Under such a relationship, all of the financial characteristics could be determining factors for the other financial behaviours. In this section, we first present empirical evidence on how each financial behaviour is determined by the other financial behaviours and discuss the validity of the SVAR model. Then, we use the Granger causality test to evaluate the joint determination of financial behaviours. Finally, we examine the difference in coefficient estimates from single equation models and the SVAR model.

[Insert Table 2 here]

Table 2 shows the regression results of the SVAR model, where each column shows the results for one of our model's five equations. *Investment*, *equity issuance*, *ROA*, *dividend*, and *leverage* are all positively associated with their previous realisations, indicating that dynamic effects play an important role. Besides the dynamic effects, all of the variables are explained by other variables, showing evidence of interdependence.

Investment is determined by profitability, dividends, and leverage. Column (1) of Table 2 shows that investment is positively correlated with the previous realisations of *ROA*, suggesting that profitable firms invest more. $Divc_{i,t-2}$ is negatively correlated with $Inv_{i,t}$ (-0.069, z = -4.09), showing that firms possessing a higher dividend payout ratio invest less. This evidence supports Jensen et al.'s (1992) assertion that investments and dividends compete for financing resources. $Lev_{i,t-1}$ has a negative sign (-0.034, z=-7.46), showing that firms with a higher leverage ratio invest less.

Equity decisions are determined by investment and profitability. According to column (2), *Inv* lags have positive signs in the *Equ* equation, showing that investment is a determining factor for equity decisions. $ROA_{i,t-2}$ has a negative sign (-0.038, z = -2.18), showing that firms with higher profitability have lower demand for equity financing or repurchase more equity.

Dividend decisions are determined by investment, profitability and leverage. Unlike the negative sign of $Divc_{i,t-2}$ in the *Inv* equation, the sign of $Inv_{i,t-2}$ is positive in the *Divc* equation (column 4), showing that firms investing more in capital expenditures pay higher dividends. The sign of $Lev_{i,t-1}$ is negative in the *Divc* equation, suggesting that firms with a higher leverage ratio pay lower dividends. The negative signs of $Lev_{i,t-1}$ in the *Inv* and *Divc* equations indicate that financing decisions indeed have a reverse impact on investment and dividend decisions.

Leverage decisions are determined by investment and dividend payouts. According to column (5), $Inv_{i,t-1}$ has a positive sign in the *Lev* equation, suggesting that investments can be used to back up more borrowings and hence firms can have a higher leverage ratio. The effect decreases in the second year. $Divc_{i,t-2}$ has a negative sign in the *Lev* equation, showing that firms paying more dividends tend to use a lower leverage ratio.

The results of the statistical tests suggest that our SVAR model provides a valid representation of the dynamic system. The reported Hansen J-statistic is 284.30, showing that we can reject the null at the 1% level. This result suggests that our SVAR model satisfies the over-identification requirement. The reported maximum modulus (0.85) is less than one, which satisfies the stability condition that all of the moduli be less than unity (Enders, 2015; Abrigo and Love, 2016). Stability suggests that the SVAR model is time-invariant and that the dynamic processes do not explode.

The second-order SVAR model we use in this study is a better specification than a first- or third-order model according to the results of MMSC in Table 3. The model based on the MBIC criterion[14] generates the smallest optimal-order statistic when the number of lags equals

[14] MAIC, MBIC and MQIC are the three criteria based on different trade-offs between model over-identification and model specification. These criteria are analogues of the classic AIC, BIC, and HQIC criteria. The definitions are available in Andrews and Lu (2001, p.136). We also test the first-order SVAR model. Although the MMSC results indicate that we cannot rule out misspecification in a first-order model, we find (in unreported results) that our main prediction of interdependent financial behaviours is not violated.

one, followed by the second-order model. The MAIC and MQIC criteria generate the smallest optimal-order statistic when the number of lags equals two. Comparing these two selections, we find that the first-order SVAR model rejects the Hansen-J over-identification restrictions at the 1% level, indicating misspecification according to Abrigo and Love (2016). Therefore, we use the second-order SVAR model with the Hansen test p-value of 0.799. According to the coefficient of determination (CD), the second-order model explains 48.6% of the variance in the five variables.

[Insert Table 3 here]

[Insert Table 4 here]

We use the Granger causality test to evaluate the joint explanatory power of the two distributed lags of each variable. The null hypothesis is that the coefficients of all lags of one financial variable are jointly equal to zero, which indicates no Granger causality. The results in Table 4 suggest that all financial behaviours are determined by other financial behaviours. *Inv* is Granger caused by *ROA*, *Divc*, and *Lev*. *Equ* is Granger caused by *Inv*, *ROA*, and *Lev*. Although the distributed lags of *Lev* are not statistically significant in the *Equ* equation (column 2 of Table 2), their joint impact is significant at the 1% level. *ROA* is Granger caused by *Inv*, *Divc* and *Lev*. *Divc* is Granger caused by *Inv*, *ROA* and *Lev*. *Lev* is Granger caused by *Inv* and *Divc*. The last row of Table 4 reports the results by testing whether each financial variable is Granger caused by all of the other financial variables. In each column, we can reject the null at the 1% level, indicating that none of the financial behaviours are independently determined.

The Granger causality test results imply that firm financial behaviours are jointly determined. There are also bi-directional relationships, such as those between investment and leverage, and between dividend and ROA. It is difficult to induce a sequence based on a causal relationship from such a jointly determined network. A more appropriate way to interpret these results is that firms jointly optimize over several financial targets rather than optimize each financial variable separately. Gatchev et al. (2010) use simultaneous equations to model firms' financial behaviours and conclude that the regression models without capturing the effects of other financial behaviours may lead to an omitted variable bias. Our Granger causality test results are in line with their assertion.

We use two tests to compare the coefficient estimates from single equation models and the SVAR model to demonstrate the bias. In the first test, we investigate the bias if one estimates a single financial variable without properly controlling other financial behaviours. Specifically, we estimate the coefficients of the five financial variables' own lags in a single equation setting and then compare the coefficients with those from the SVAR model in Table 2. We use one-year and two-year lagged variables because our SVAR model shows that the proper lag structure of financial behaviour variables is 2. Column (1) of Table 5 displays the coefficient estimates of the five variables' own lags in their single equation estimations, respectively. For example, *Inv* is regressed on one-year and two-year lagged *Inv*. Column (2) further controls the lags of the other variables. That is, we also include the lags of *Equ*, *ROA*, *Divc* and *Lev* into the equation of *Inv*. We control firm- and year-fixed effects when estimating the single equations so that the results are comparable with those from the SVAR model in column (3). In columns (4)-(5), we report and test the difference in the coefficient estimates.

[Insert Table 5 here]

Results in Table 5 show that the bias is statistically significant in all of the five equations and is economically more pronounced in the *Equ*, *ROA* and *Divc* equations. For example, single equation models (columns 1 and 2) show that $Equ_{i,t-2}$ has a negative effect on $Equ_{i,t}$. However, the relation is positive and not statistically significant in an SVAR framework and the distributions differ significantly, as shown in columns (4)-(5). $ROA_{i,t-2}$ has a negative coefficient of -0.022 in column (2) but a positive coefficient of 0.078 in the SVAR model (column 3). The coefficient estimates of lagged *Divc* doubles in column (3), compared to those in single equation models. Most of the coefficient estimates reported by single equation models are biased downward, with the exception of $Lev_{i,t-2}$ that is marginally overestimated in column (1). These results show that single equations without controlling other financial behaviour as a system generate biased estimates and that the bias exists even if we control the lags of other variables in the single equation (column 2).

In the second test, we compare coefficient estimates from commonly-used regression specifications in prior studies with those from the SVAR framework to demonstrate the bias of using single equations. A firm's market-to-book ratio (M/B) and size are controlled in almost all empirical corporate finance studies. Hence, we test the effects of M/B and size in determining firm financial behaviours and compare the estimates from a single equation setting and the SVAR framework[15]. First, we estimate the coefficients of one-year lagged M/B and size indicators in a single equation setting, either a static model (column 1 of Table 6) or a dynamic model controlling a one-year lagged dependent variable (column 2). Then, we estimate the effects of these indicators in an SVAR framework (column 3), assuming they are exogenous as we do in the single equations. We define a firm as a high-M/B (or large) firm if its M/B (size) is higher than the annual median value of the sample.[16] We control firm- and year-fixed effects when estimating single equation models so that the results are comparable with those from the SVAR model. In columns (4)-(5), we report and test the difference in the coefficient estimates.

[15] When we include the M/B and size indicators into our SVAR model, the main results are qualitatively same to our 5-variable SVAR model. We do not report the results for the sake of brievity.

[16] We use indicators because our study uses a long time period for which M/B and size can have trends. Otherwise, taking size for an example, we will be testing the difference between early-year observations and recent observations. Using indicators can better capture the cross-sectional variation.

[Insert Table 6 here]

Results in Table 6 suggest that single equation models underestimate the effects of M/B and size in the *Inv* and *Equ* equations but overestimate the effects of M/B and size in the *ROA*, *Divc* and *Lev* equations. For example, single equation models do not show a significant relation between firm size and investment, while the SVAR model in column (3) shows a positive and significant relation (0.034, z=12.35) suggesting that large firms invest more. For another example, single equation models report a positive effect of $High\_M/B_{i,t-1}$ on *Divc* while the SVAR model reports a negative effect. In columns (4)-(5), we test and find significant differences between coefficients of $High\_M/B_{i,t-1}$ and $Large\_size_{i,t-1}$ from single equation models and those from the SVAR model. These results suggest that failing to properly control other financial behaviours may lead to biased estimates and misleading conclusions. Our results illustrate the problems with "bolting together" results from single equation models to obtain an overall picture of firm financial policies. The SVAR framework is superior in simultaneously modeling and estimating financial variables and dealing with the endogeneity issue.

4. The Priority of Firm Financial Behaviours

Since firms target the desired levels of several financial characteristics, they could rank these targets due to a constrained cash flow budget and it is not possible to achieve the targets simultaneously. In this situation, firms would first allocate resources to the target with the highest priority, then to the second, and so on. Empirically, a higher priority financial policy should show less response in the corresponding financial variable to shocks to other financial variables. This section empirically explores the ranking of priority.

By analysing the forecast errors of the five endogenously determined variables, we measure the relative independence of financial behaviours and evaluate which one is the most (or least) easily influenced. Enders (2015) suggests viewing the variable most explained by its own shocks as the most exogenous (independent) variable and viewing the variable most explained by shocks to the other variables as the most endogenous variable. We use this method and regard the financial behaviour for which shocks to the other variables explain the most (or least) of its forecast errors as the financial behaviour with the lowest (highest) priority. Enders (2015) and Abrigo and Love (2016) suggest using a recursive order supported by theory to identify the transmission of shocks and estimate FEVDs.[17] We use the order *Inv – Equ – ROA – Divc – Lev* because the literature suggests this recursive order is reasonable:[18]

Prior studies tend to take investment as the first-move financial behaviour because investment determines firm value (e.g., Fama, 1974; Myers, 2015). These studies suggest that firms make independent investment decisions to take full advantage of positive-NPV projects. Similar to investment decisions, capital market condition is a driving factor for equity issuances and repurchases. Fama and French (2005) find that firms do not issue equity as the last resort, even though the pecking order theory suggests they should. Baker and Wurgler (2002) and Butler et al. (2011) find that firms time the stock market and issue (or repurchase) equity when the stock price is over-valued (under-valued). These findings indicate that firms are likely to issue or repurchase equity when there is a window in the capital market. Therefore, we take *Inv* and *Equ* as the first and the second-order variables, respectively.[19] Firms generate profits from investment activities; therefore, we take the *ROA* as the third-order variable. Firms use their earnings to pay dividends; hence, we take *Divc* as the fourth-order variable. Fama and French (2002) find that firms stick to the dividend target more closely than they do the leverage target. Lambrecht and Myers (2012) suggest that firms issue or retire debt to smooth dividend

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[17] Abrigo and Love (2016) suggest that the recursive order of endogenous variables in FEVD should be based on the theoretical background that states the timing of responses. There is no empirical method, so far, to test the ordering. We discuss the robustness of our results to alternative orderings in Section 6.

[18] Note that the recursive order is not a ranking of priority. The latter is based on the extent that firms deviate from the steady state of each financial variable, while the former is an order of the variables used to identify the transmission of shocks within the system and to estimate FEVDs and OIRFs but not a hypothesis.

[19] In Section 3, we find that investment determines equity issuance. This result suggests giving investment the first order.

payouts. We follow these studies and take *Lev* as the fifth-order variable. Such an order can reasonably identify how a shock is transmitted within the firm and we apply alternative orderings in Section 6 for robustness checks.

Table 7 reports the results of the FEVD analysis. We calculate the proportion of forecast errors in each variable that can be explained by orthogonal shocks to the other financial variables and by its own shocks at each forecast horizon. We present the results for each variable for 6 forecasting horizons, namely the 1^{st}, 2^{nd}, 4^{th}, 6^{th}, 8^{th} and 10^{th} years. The value in each cell reports the percentage of forecast error variation in each panel variable explained by shocks to the column variable.

[Insert Table 7 here]

Shocks to the other financial variables explain a proportion (7.4%) of the forecast error variance in *Inv*. According to Panel A of Table 7, more than 92% of the forecast errors for *Inv* are accounted for by its own innovations at all forecast horizons. The percentage explained by *ROA* shocks and *Lev* shocks are 4.2% and 2.0% at the tenth forecast horizon, respectively, while *Divc* shocks have a little impact (1.1%). These results show that investment is endogenously determined and that firms adjust investment decisions to absorb shocks to other financial behaviours, although to a small extent (7.4%). This can be explained by the high cost to stop and to restart an investment project.

Equity issuance decisions show the highest independence. According to Panel B, *Equ* shocks explain nearly 100% of its forecast errors at the first forecast horizon and 99% at the tenth forecast horizon. The value is higher than those of any other variables, showing that firms are least willing to adjust equity decisions to accommodate other financial targets.

Consistent with the literature (e.g., Fama and French, 2002; Lambrecht and Myers, 2012), we find that the dividend payout ratio is more sticky than the leverage ratio is. According to

Panel D, 97.2% of the forecast errors in *Divc* are explained by its own shocks, which is substantially larger than the 76.9% for the leverage ratio (column 5 of Panel E). This indicates that leverage is more vulnerable than dividends are to absorbing shocks to other financial behaviours. An exogenous shock to *Inv* or *ROA* is more likely to lead to a deviation from the leverage target than a deviation from the dividend target.

Leverage decision appears to be the most endogenous financial decision. According to Panel E, *Lev* shocks explain 73.4% of the forecast errors at the first forecast horizon, and the ratio is 76.9% at the tenth forecast horizon. Apart from *Lev* shocks, *ROA* shocks (19.7% at the tenth forecast horizon) explain the largest proportion, followed by *Divc* (2.1%), *Inv* (0.9%) and *Equ* shocks (0.3%). The percentage of forecast errors explained by *Lev* own shocks is substantially lower than those of the other variables, indicating that firms are more likely to adjust leverage to absorb a shock than to adjust other decisions. Although firms adjust leverage to absorb shocks, over 70% of the variance in leverage forecast errors is due to its own shocks, indicating that debt is not a pure shock absorber.

The extent that shocks to the other financial behaviours explain one financial behaviour reflects the relative net cost of deviation. Our results suggest that equity decisions have the highest deviation cost. Equity decisions reveal managers' inside information to the public, and firms do not want to issue equity and send a signal that the stock price has been overvalued. Hence, firms are reluctant to issue equity to absorb shocks to other financial behaviours. Adjusting dividend payouts signals managers' predictions of future profitability, which is associated with information costs. Therefore, firms absorb profitability shocks mostly by debt and try to smooth dividend payouts. The fact that dividend decisions are more independent than leverage decisions are indicates that the information costs of adjusting dividend payouts are higher than the cost of deviating from the optimal leverage ratio. Firms also adjust investment, to some extent, to absorb shocks to other financial behaviours. The relative net cost of deviation motivates firms to prioritize these financial behaviours differently. In summary, our results suggest that firms give the highest priority to equity issuance decisions, followed by dividend targeting, investment, and leverage targeting. When there is a shock, firms are more likely to use the behaviour with the lowest deviation cost (leverage) to absorb the shock and are least likely to use the one with the highest deviation cost (equity) to absorb the shock.

5. Shocks to Firm Financial Behaviours and Responses

In this section, we use OIRFs to measure how firms absorb an orthogonal shock to one of the financial behaviours and discuss whether a pure residual among them exists. We develop three hypotheses from the literature:

(a) Several studies (e.g., Jensen et al., 1992; Hennessy and Whited, 2005) suggest that firms jointly optimize several financial behaviours when the market is not perfect. In this situation, when a shock to one of the financial behaviours takes place, firms would not tolerate the shock. We hypothesize that *firms temporarily deviate from steady states of several financial characteristics to absorb the shock*. Firms can thus jointly minimize the overall cost of deviations.

(b) Lambrecht and Myers (2012) indicate that debt decisions might play a residual role among financial behaviours and that a change in debt must absorb income shocks in order to smooth dividends. If debt is the shock-absorber, then shocks to investment or net income would not lead to a response in dividend payouts because firms use debt to smooth dividends. In this case, leverage would be the only variable to respond. If the firm's debt capacity constrains its ability to issue debt (Lemmon and Zender, 2010), then firms cannot always use debt to absorb shocks. Debt will not be residually determined. In this case, firms would minimize the costs of deviations jointly. If the second case is correct and debt is not a residual, we hypothesize that *investment or profitability shocks lead to a response in dividend payouts* and that *investments and dividends also absorb leverage shocks to some extent*.

(c) Acharya and Lambrecht (2015) note that managers take advantage of asymmetric information and do not immediately distribute all of the unexpected profits to shareholders because they are reluctant to make dividend changes that they must later reverse. To smooth out dividends, managers would distribute the extra profits gradually. Under this theory, we hypothesize that *firms gradually absorb temporary ROA shocks using dividends. At the same time, leverage and investment also absorb part of the ROA shocks to smooth out dividends.*

We construct the OIRFs based on the estimated SVAR model coefficients. The OIRFs are a quasi-experiment assuming that the firm is at its steady state and we shock the firm in one dimension of the financial behaviours. The orthogonal condition assumes that there is no shock in the subsequent period and that there is no shock to other financial characteristics at the same time. Each row of Figure 1 visualizes how an average firm absorbs a one-standard-deviation of positive shock and how long it takes these financial characteristics to revert to their steady states. Compared to the regression coefficients showing how the variables evolve conditional on the states in the previous two years, the OIRFs show how a firm absorbs an orthogonal shock and how long it takes a variable to revert to the steady state. The grey area covers the 95% confidence interval, which we establish by 2,000 Monte Carlo simulation draws.[20] It indicates a statistically significant response if zero falls outside the 95% confidence interval.

[Insert Figure 1 here]

A. Investment Shocks

[20] The results are robust to the number of Monte Carlo simulation draws. We also tried 200, 500 and 5,000 draws. This does not make a difference to the results. These alternative results are available in the Online Appendix.

The first row of Figure 1 shows how firms absorb an investment shock. The results suggest that firms adjust leverage, equity issuance, and dividend decisions to absorb investment shocks. According to Graph (inv:lev), a positive investment shock is followed by a positive response in leverage. The response of leverage remains statistically significant for 5 years, reflecting a slow SOA. The response in equity issuance seems to be delayed and reached the peak in the second year, showing that debt is the primary tool firms use to absorb investment shocks. Dividends do not have a strong response. According to Graph (inv:divc), dividends respond negatively; however, the response becomes statistically insignificant within two years. This evidence also supports previous studies (e.g., Fama and French, 2002; Lambrecht and Myers, 2012; DeAngelo and Roll, 2015) stating that dividends are more sticky than leverage is.

B. Equity Shocks

The second row of Figure 1 shows that equity shocks lead to negative responses in dividends, ROA and leverage. Cash dividends decline after a positive equity shock, suggesting that firms with net equity issuance are unlikely to maintain their previous dividend payouts. Fama and French (2005) state that issuing stocks to pay dividends decreases the wealth of current shareholders, and hence, firms do not issue equity to pay dividends. The response in dividends vanishes after one year, together with the equity shock.

Equity shocks do not lead to significant responses in investment. Graph (equ:equ) shows that equity shocks diminish rapidly in one year. Investment does not respond, according to Graph (equ:inv). This result shows that although equity shocks (e.g., market timing opportunities) influence available cash in the short term, firms do not immediately set up new investment projects or drop existing ones. As a result, ROA and dividends do not have persistent responses to equity shocks either. Our results provide additional support to Butler et al.'s (2011) finding that firms' market timing behaviours do not influence future returns.

C. Profitability Shocks

Profitability (ROA) shocks lead to persistent responses in leverage, dividends, and investment. In line with our finding in Section 4 that adjusting leverage decisions is less costly than adjusting dividend and investment decisions, the OIRFs show that leverage is more sensitive to profitability shocks than are dividends and investment. According to the third row of Figure 1, dividends and investment respond to profitability shocks to a minor extent, whereas leverage responds more dramatically. This result indicates that firms use a larger proportion of unexpected profits to deleverage than for distributions to shareholders or reinvestment. Both dividends and investment respond to profitability shocks significantly, showing that firms do not only use leverage to absorb shocks. Graph (ROA:lev) shows that it takes over ten years for the leverage ratio to recover from the deviation, showing a low SOA.

Dividend payouts respond smoothly to profitability shocks. Graph (ROA:divc) shows that firms do not use dividends to immediately distribute all of the extra profits to shareholders; rather, firms adjust leverage and investment to smooth dividend payouts. Although profitability shocks diminish in one year, the response in dividends remains statistically significant over ten years according to Graph (ROA:divc). These results are consistent with *hypothesis (c)* that firms gradually distribute extra profits to shareholders.

D. Dividend Shocks

Dividend shocks lead to responses in investment, profitability, and leverage. Graph (divc:inv) shows that investment responds negatively to dividend shocks. Jagannathan et al. (2000) suggest that dividends are an ongoing commitment to shareholders. Lambrecht and Myers (2012) suggest that managers smooth dividend payouts because these are linked to managers' rents. These studies explain why firms decrease investment to pay dividends. Graph (divc:ROA) shows that a dividend shock is followed by a positive response in ROA. Signalling theory can explain this finding; that is, an increase in dividends signals future profitability. Graph (divc:lev) shows that a positive dividend shock is followed by a positive response in leverage. This result indicates that firms adjust leverage to accommodate dividend policy.

Dividend shocks diminish rapidly. According to Graph (divc:divc), the shock reduces dramatically from 0.03 to 0.005 in one year. This result indicates that firms absorb dividend shocks rapidly so that dividend payouts revert quickly to the steady state. Our evidence by studying orthogonal dividend shocks is consistent with the literature (e.g., Lintner, 1956; Fama and French, 2002) that uses the partial adjustment model and finds that the dividend payout ratio is sticky.

E. Leverage Shocks

Leverage shocks lead to responses in investment, equity issuance, profitability, and dividends. This evidence supports our *hypothesis (b)* that debt is not residually determined. If firms use debt as a residual financial decision, then leverage should not impact the other financial behaviours with a higher priority. However, the last row of Figure 1 shows that investment, equity issuance, and dividends all respond to absorb leverage shocks. This evidence suggests that leverage also has an effect on other financial behaviours, and therefore, it is unlikely a residual that is only used to absorb shocks to other financial behaviours.

Leverage shocks persist, showing a low SOA. Graph (lev:lev) shows that leverage shocks decrease from 0.071 to 0.013 after 10 years and remain statistically significant. The average SOA is 15.6%, calculated as $1 - (0.013/0.071)^{1/10}$. Our result is consistent with the literature stating that leverage target adjustment is fairly slow and that it takes a long time for the leverage ratio to fully recover from deviations. Among these studies, Fama and French (2002) use a partial adjustment model and find that leverage reverts at a speed of between 7% and 17%; DeAngelo and Roll (2015) document a speed of around 15% by simulation. We provide additional evidence by examining how an orthogonal leverage shock is absorbed, and the estimated SOA is qualitatively close to theirs.

Overall, our empirical results support *hypothesis (a)* on firm financial behaviour interactions: given a shock to one variable, firms deviate from the desired levels of several variables to absorb the shock. All of the financial variables show a tendency to revert, although the SOA varies. Firms adjust leverage decisions to absorb shocks to other financial variables, but it appears that leverage is not a shock absorber. First, the leverage ratio reverts after deviations. This evidence is in line with Lambrecht and Myers' (2017) finding that firms keep debt ratio constant.[21] Second, equity issuance, dividends, and investment, which have a higher priority, also inversely absorb leverage shocks. The fact that all of the financial behaviour variables deviate from the desired levels to absorb shocks suggests that there is not a pure shock-absorber. Our evidence indicates that firms jointly optimize over several financial behaviours and minimize the overall cost of deviations. We also find that dividends do not immediately and completely absorb a positive profitability shock. Instead, firms deleverage and reinvest to absorb a fraction of the shock, and gradually distribute the extra profits to shareholders. The dividend payout ratio responds smoothly.

To summarize our empirical results of Sections 3 to 5, it appears that firms' financial behaviours are jointly determined rather than independent. Failing to control other financial behaviours may generate biased estimates and misleading conclusions. In this joint relationship, firms' financial behaviours have different priorities. Equity decisions appear to have the highest priority, followed by dividend target, investment, and, lastly, leverage target. Firms appear to use all of the instruments at their disposal to maintain a balance among several financial targets.

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[21] We should note that Lambrecht and Myers (2017) obtain this result assuming that managers have CRRA utility. Under CARA utility, this result does not hold. Although we do not explicitly examine manager's utility in this study, our results could indicate that CRRA utility is a better model for managerial behaviour than CARA is.

When there is a shock, firms deviate from the desired levels of several financial variables to absorb the shock. The deviation is followed by a reversion in subsequent periods. Among the financial decisions, leverage decisions are relatively more responsive, while equity issuance decisions are relatively sticky. These results indicate that firms may jointly minimize the costs of deviating from the desired levels of several financial characteristics.

6. Robustness Checks

We check the robustness of our results against alternative definitions of variables, different sampling criteria, and changing the recursive order of the variables.[22] Our main results hold, suggesting that our findings are not limited to our base model as a particular setting. We summarize these changes and a few interesting points in this section. All empirical results are available in the Online Appendix.

We use alternative definitions of variables to check the robustness of our findings. Although we define the variables following the literature, the variables used in our base model are thin compared to the broad corporate finance literature where there are other definitions. Hence, we use other definitions and see whether our results hold. First, we follow Richardson (2006) and use another definition of investment (Capital expenditures + M&A expenses + R&D expenses – Sale of property, plant, and equipment, and investments) to count more activities as investment. Second, we restrict *Equ* to equity issuance activities only and define dividends as cash dividends plus equity repurchases because equity repurchases are increasingly used as a way of paying dividends. In this case, dividend becomes slightly more exogenous, increasing from 97.2% to 97.9%, while equity issuances remain the most exogenous variable (99.1%). Third, we use dividend per share (Dvpsx) to capture a firm's dividend policy because firms may smooth Dvpsx instead of the sum of dividends paid. Fourth,

[22] We thank the anonymous reviewers for many suggestions included below.

we define profitability as earnings before interest and tax (EBIT) over total assets rather than net income over total assets, because the former definition is a more classical determinant of leverage (e.g., Rajan and Zingales, 1995). We find that using EBIT as the numerator Granger causes *Lev* at the 1% level. Fifth, we use *Cash Flow* (Net income + Depreciation and amortization) scaled by assets to replace ROA, because the former better captures the inflow of cash. Sixth, we use retained earnings (Net income - Cash dividends) to capture the firm's ability to generate funds internally. In this case, the model becomes a 4-factor SVAR model as cash dividends have been included in the calculation of retained earnings and dividend policy is assumed exogenous. Seventh, we follow the literature (e.g., Strebulaev and Whited, 2012; Lambrecht and Myers, 2012, 2017) and replace the leverage ratio with the net debt ratio to capture a firm's cash holdings. Under this definition, leverage is not bounded between 0 and 1. We find that treating cash as negative debt generates similar results. The net debt ratio remains the most vulnerable variable; however, there is clear evidence that net debt ratio reverts from shocks. Eighth, Welch (2011) suggests two alternative measures of leverage policy. One is total liabilities over total assets, to account for non-financial liabilities. The other one is net debt issuance, defined as the net increase in total debt scaled by total assets. We find that using these two measures to capture a firm's debt policy does not alter our findings.[23]

We use alternative sampling criteria to examine the robustness of our results. Our study uses a panel time series method that requires that all firms are a going concern over a long period. Therefore, our base sample has a relatively low number of firms having a long life of 50 years, and it is important to check whether our results hold for narrower or broader firms. We first extend the sample period from 50 years (1967-2016) to 60 years (1957-2016) which has the effect that we use fewer firms. Second, we reduce the sample period used for estimation

[23] Although using net debt issuance can generate the same conclusion of financial behaviour interactions, one drawback is that it is not an autoregressive variable and it does not capture the dynamics of leverage.

to the most recent 40 years (1977-2016) or 30 years (1987-2016). This has an effect that firms used in the estimation had already existed for at least 10 or 20 years, thus ensuring that we only consider mature firms. One interesting difference is that cash dividends become insignificant in Granger causing investment and leverage in the case of 30 years. A possible reason for the difference is that firms pay, on average, lower cash dividends after 1980. Although cash dividends are more sticky in the 40-year (98.4%) and 30-year samples (98.9%) than in the base sample (97.2%), they become less important in determining other financial behaviours. Third, to avoid the potential issue of survivorship bias and to check how the model works for broader firms, we relax the restriction of a 50-year continuous record. In the new sample, firms have a record of at least 7 years, the minimum length to estimate our model[24], among the 50 years. This sample accounts for 99% of market capitalization. While our main results are robust, one noteworthy difference is that, in the larger sample including young firms, equity decisions respond to other financial behaviours more frequently than in the sample of mature firms. The percentage of forecast errors explained by *Equ* own shocks decreases from the 99% of the base sample to 92%. This result is in line with Myers (2015), who states that young firms sell seasoned equity offerings more often than mature firms do.

Finally, we change the recursive order of the variables to see whether our results hold. The recursive order of employed variables is important because it is used to identify the transmission of shocks within the firm and changing it may lead to different results in the FEVD and OIRF analyses (Bernanke, 1986; Enders, 2015; Abrigo and Love, 2016). Therefore, we check whether our results are sensitive to the change of the recursive order by applying other reasonable orderings. First, we change the order of *Equ* and *Inv* because both equity and investment decisions can be driven by market conditions and available opportunities, and it is

[24] Holtz-Eakins et al. (1988) suggest that the sample period T needs to be larger than p (the number of lags in the SVAR model) + q (the number of lags used as IVs) in order to estimate the SVAR model.

not certain that investment opportunities are more valuable than market timing opportunities are. Second, we change the order of *ROA* and *Divc* to reflect the signalling effect of dividends. Third, we change the order of *Divc* and *Lev* to consider the possibility that dividend payout is determined residually, for example, in DeAngelo et al.'s (2011) model. Fourth, we move *Inv* to the end to reflect the effects of debt burden on a firm's investment. Fifth, we place *Equ* at the end of the order to reflect the pecking order theory in which equity financing is the last resort. *Equ* shows a high exogeneity (97.0%) even though it is placed at the end. Leverage remains the most endogenous variable among the five, even if it is not placed at the end of the recursive order. Sixth, we order the variables based on our findings of financial behaviour priority as if firms satisfy those targets one by one. These changes do not make a qualitative difference to the indicated ranking of priority or the impulse responses of shocks.

7. Conclusion

We use a five-variable SVAR framework to investigate the dynamics and interactions of firms' investment, dividends, leverage, equity issuance, and profitability. The empirical results show that none of these financial behaviours is completely independent. Instead, firms' financial behaviours are determined by their previous realisations and the previous realisations of the other financial behaviours. It appears that firms jointly optimize over several financial tasks and that their financial behaviours determine each other.

By decomposing the forecast error variances, we compare the relative exogeneity of the simultaneously determined financial behaviours, and the result reveals a priority ranking that we can think of as reflecting the relative net cost of deviating from the desired levels of these financial characteristics. Our results suggest that adjusting equity decisions to absorb shocks to the other financial behaviours is the most costly, followed by deviating from the target payout ratio, adjusting investment decisions, and, lastly, deviating from the target leverage ratio.

To further examine the interactions, we use OIRFs to visualize how an orthogonal shock to one dimension of the financial characteristics leads to responses in the firm. We find that all of the five financial variables deviate from their desired levels to absorb shocks and that they revert to their desired levels at varying speeds. Our results suggest that firms might jointly minimize the overall cost of deviating from the desired levels of several financial characteristics. There is neither a residually determined financial behaviour, nor a single financial behaviour that never responds to the others.

We have two suggestions for further research. First, we recommend using SVAR models to study corporate financial decisions and deal with the endogeneity issue. In this paper, we demonstrate that single equation models without properly controlling other financial behaviours generate biased estimates, and hence we recommend further studies modelling firm financial behaviours in a system. It would also be interesting to examine whether the findings in prior corporate finance studies using single equations hold in an SVAR framework. Second, we recommend to examine whether and how heterogeneous firm features influence the prioritisation of financial behaviours. While we give a broad overview of financial behaviour interactions based on a large number of firm-year observations and find highly robust results, we do not analyse these interactions at the individual firm level. The net cost of deviating from each financial target may very well vary across firms and institutional backgrounds. Thus, the priority may also differ for individual firm. If the prioritisation varies, managers can choose to adjust a different financial decision to absorb the shock. We anticipate that a study to determine which firm or business environment characteristics influence managerial choices will be a fruitful area of future research.

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Table 1 Descriptive Statistics

Variable	N	Mean	Median	Std. Dev	p5	p95	ADF	PPerron
Inv	20,222	0.053	0.050	0.050	0.011	0.158	79.72***	109.15***
Equ	20,303	0.007	0.001	0.089	-0.049	0.085	128.54***	279.64***
ROA	20,466	0.054	0.059	0.115	-0.229	0.213	65.26***	128.31***
Divc	20,477	0.021	0.016	0.036	0	0.059	34.37***	51.36***
Lev	20,442	0.233	0.217	0.170	0.000	0.520	115.39***	24.77***
M/B	19,843	1.600	1.327	0.983	0.792	3.241	51.87***	53.46***
Size	20,477	6.659	6.826	2.218	2.856	10.298	-6.68	-5.98

This table presents the descriptive statistics of the variables. We collect the data from CRSP/Compustat Merged database. The sample includes all unregulated Compustat firms with a continuous record from 1967 to 2016 on an annual basis. We report the number of firm-year observations (N), mean, median, standard deviation, the values at the 5^{th} and 95^{th} percentiles, and the results of two unit root tests (ADF and PPerron). For the unit root tests, *** indicates significance at the 1% level. Appendix 1 summarises the definitions and explanations of variables.

Table 2 Structural Vector Autoregression Model Results

	(1)	(2)	(3)	(4)	(5)
	Inv	Equ	ROA	Divc	Lev
$Inv_{i,t-1}$	0.491***	0.065**	0.145**	-0.006	0.118**
	(24.74)	(1.99)	(2.35)	(-1.06)	(2.87)
$Inv_{i,t-2}$	0.071***	0.091***	-0.008	0.009**	-0.078***
	(5.20)	(2.99)	(-0.37)	(2.16)	(-3.11)
$Equ_{i,t-1}$	-0.000	0.050**	-0.022	0.000	0.012
	(-0.06)	(2.04)	(-1.30)	(0.25)	(1.52)
$Equ_{i,t-2}$	0.002	0.010	0.005	0.001	0.008
	(0.49)	(0.80)	(0.41)	(0.34)	(0.99)
$ROA_{i,t-1}$	0.029***	0.023	0.074	-0.000	0.037
	(3.82)	(1.28)	(1.35)	(-0.02)	(0.77)
$ROA_{i,t-2}$	0.015***	-0.038**	0.078**	0.009***	-0.006
	(4.56)	(-2.18)	(2.11)	(3.99)	(-0.25)
$Divc_{i,t-1}$	-0.010	-0.001	0.128***	0.186***	-0.064
	(-0.65)	(-0.03)	(4.06)	(7.26)	(-1.45)
$Divc_{i,t-2}$	-0.069***	-0.016	0.167***	0.232***	-0.087**
	(-4.09)	(-0.80)	(5.24)	(7.90)	(-2.30)
$Lev_{i,t-1}$	-0.034***	0.023	-0.046*	-0.023***	0.793***
	(-7.46)	(1.41)	(-1.74)	(-6.43)	(40.19)
$Lev_{i,t-2}$	0.015***	0.010	-0.028	0.002	0.045***
	(3.26)	(0.85)	(-1.22)	(0.66)	(2.78)
N					18,683
Hansen J-stats					284.30***
Maximum Moduli					0.85

This table presents the regression results of SVAR model (1). The sample includes all unregulated Compustat firms with a continuous record from 1967 to 2016. Columns (1) to (5) show the regression results of the 5 equations. We use a second-order model (*p = 2*) and the lag length of IVs is 4.

$$y_{i,t} = A_1 y_{i,t-1} + \cdots + A_p y_{i,t-p} + u_i + \varepsilon_{i,t}, \quad (1)$$

We report the regression coefficients and Z-statistics. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. N reports the number of firm-year observations. Hansen J-statistic reports the over-identification test results. Maximum modulus reports the model stability test results, with a value below one indicating stability.

Table 3 Model and Moment Selection Criteria

Lags(n)	CD	Hansen-J-stats	P	MBIC	MAIC	MQIC
1	0.682	236.19	0.000	-489.39*	86.19	-104.23
2	0.486	41.47	0.799	-442.25	-58.53*	-185.47*
3	-0.631	18.24	0.832	-223.62	-31.76	-95.23

This table presents the results of the MMSC for the SVAR model. For each lag order from 1 to 3, we report the CD (Coefficient of Determination), Hansen J-Statistics, and p-values. MBIC, MAIC and MQIC show the results under different selection criteria. * indicates the best selection.

Table 4 Granger Causality Matrix

	Inv	Equ	ROA	Divc	Lev
Inv	-	19.50***	5.63*	5.03*	14.18***
		(0.00)	(0.06)	(0.08)	(0.00)
Equ	0.25	-	1.87	0.14	2.92
	(0.88)		(0.39)	(0.93)	(0.23)
ROA	30.52***	6.84**	-	16.29***	0.72
	(0.00)	(0.03)		(0.00)	(0.70)
Divc	17.65***	0.64	40.05***	-	7.76**
	(0.00)	(0.73)	(0.00)		(0.02)
Lev	64.74***	8.71**	27.24***	66.07***	-
	(0.00)	(0.01)	(0.00)	(0.00)	
All	116.26***	32.30***	87.24***	119.08***	26.68***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

This table presents the Granger causality matrix of the financial behaviour variables. Each cell shows whether the column variable is Granger caused by the row variable. The last row presents a joint test of whether the column variable is Granger caused by all of the row variables. We report the Chi-square statistics and p-values in brackets. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5 Testing the Effects of Own Lags Using Different Models

		(1)	(2)	(3)	(4)	(5)
Dependent variables (Equations)	Lags	Single equation with own lags	Single equation with own lags and the lags of other variables	SVAR model	Difference (1)-(3)	Difference (2)-(3)
Inv	$Inv_{i,t-1}$	0.484***	0.488***	0.491***	-0.007***	-0.003***
		(67.82)	(67.96)	(24.74)	(-45.23)	(-19.38)
	$Inv_{i,t-2}$	0.066***	0.065***	0.071***	-0.005***	-0.006***
		(9.21)	(9.20)	(5.20)	(-43.80)	(-52.51)
Equ	$Equ_{i,t-1}$	0.031***	0.031***	0.050**	-0.019***	-0.019***
		(3.84)	(3.82)	(2.04)	(-99.12)	(-99.05)
	$Equ_{i,t-2}$	-0.037***	-0.039***	0.098	-0.135***	-0.137***
		(-4.66)	(-4.83)	(0.80)	(-1,287.08)	(-1,303.23)
ROA	$ROA_{i,t-1}$	0.003	0.0000	0.074	-0.071***	-0.074***
		(0.37)	(0.00)	(1.35)	(-174.69)	(-181.55)
	$ROA_{i,t-2}$	0.012	-0.022**	0.078**	-0.066***	-0.100***
		(1.50)	(-2.45)	(2.11)	(-238.56)	(-359.19)
Divc	$Divc_{i,t-1}$	0.110***	0.104***	0.186***	-0.076***	-0.082***
		(15.26)	(13.94)	(7.26)	(-386.3)	(-412.45)
	$Divc_{i,t-2}$	0.108***	0.112***	0.232***	-0.124***	-0.12***
		(14.66)	(14.80)	(7.90)	(-568.88)	(-545.70)
Lev	$Lev_{i,t-1}$	0.738***	0.787***	0.793***	-0.055***	-0.006***
		(102.02)	(90.39)	(40.19)	(-355.65)	(-37.47)
	$Lev_{i,t-2}$	0.053***	0.035***	0.045***	0.008***	-0.01***
		(7.33)	(3.99)	(2.78)	(62.84)	(-74.67)

This table presents the results of testing the effects of own lags using different models. Column (1) presents the results by using single equations with own lags as the only explanatory variables. Column (2) further includes the lags of other financial variables. In columns (1)-(2), we use the base sample and control firm- and year-fixed effects so that the results are comparable with the estimates from the SVAR model (column 3). Column (3) uses the results reported in Table 2. In columns (1)-(3), we report the coefficients and t-values (or z-values) of each equation variable's own lags. Columns (4)-(5) display and test the difference in the estimates from single equation models and those in the SVAR model. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 6 Testing the Effects of M/B and Size in Determining the Financial Variables

		(1)	(2)	(3)	(4)	(5)
Dependent variables (Equations)	Independent Variables	Single equation	Single equation with $Dep_{i,t-1}$	SVAR model	Difference (1)-(3)	Difference (2)-(3)
Inv	$High\_M/B_{i,t-1}$	0.012***	0.007***	0.018***	-0.005***	-0.011***
		(18.13)	(12.00)	(14.52)	(-603.05)	(-1,161.66)
	$Large\_size_{i,t-1}$	0.000	-0.001	0.034***	-0.034***	-0.035***
		(0.42)	(-1.42)	(12.35)	(-1,532.81)	(-1,644.71)
Equ	$High\_M/B_{i,t-1}$	0.003**	0.003**	0.016***	-0.013***	-0.013***
		(2.10)	(1.92)	(4.72)	(-475.62)	(-475.45)
	$Large\_size_{i,t-1}$	-0.006**	-0.006**	0.017***	-0.023***	-0.023***
		(-2.28)	(-2.27)	(2.70)	(-457.15)	(-457.03)
ROA	$High\_M/B_{i,t-1}$	0.047***	0.048***	0.036***	0.011***	0.012***
		(24.67)	(24.75)	(9.23)	(348.92)	(380.55)
	$Large\_size_{i,t-1}$	-0.010***	-0.010***	-0.011	0.001***	0.001***
		(-3.34)	(-3.14)	(-1.41)	(16.55)	(16.47)
Divc	$High\_M/B_{i,t-1}$	0.006***	0.005***	-0.004***	0.010***	0.009***
		(9.80)	(8.38)	(-5.35)	(1,315.20)	(1,224.27)
	$Large\_size_{i,t-1}$	-0.001	-0.000	-0.011***	0.010***	0.011***
		(-0.59)	(-0.39)	(-5.23)	(601.53)	(637.53)
Lev	$High\_M/B_{i,t-1}$	-0.010***	-0.001	-0.021***	0.011***	0.020***
		(-3.94)	(-0.94)	(-5.86)	(364.00)	(697.71)
	$Large\_size_{i,t-1}$	0.011***	-0.001	-0.056***	0.067***	0.055***
		(2.87)	(0.663)	(-8.14)	(1,171.17)	(17.67)

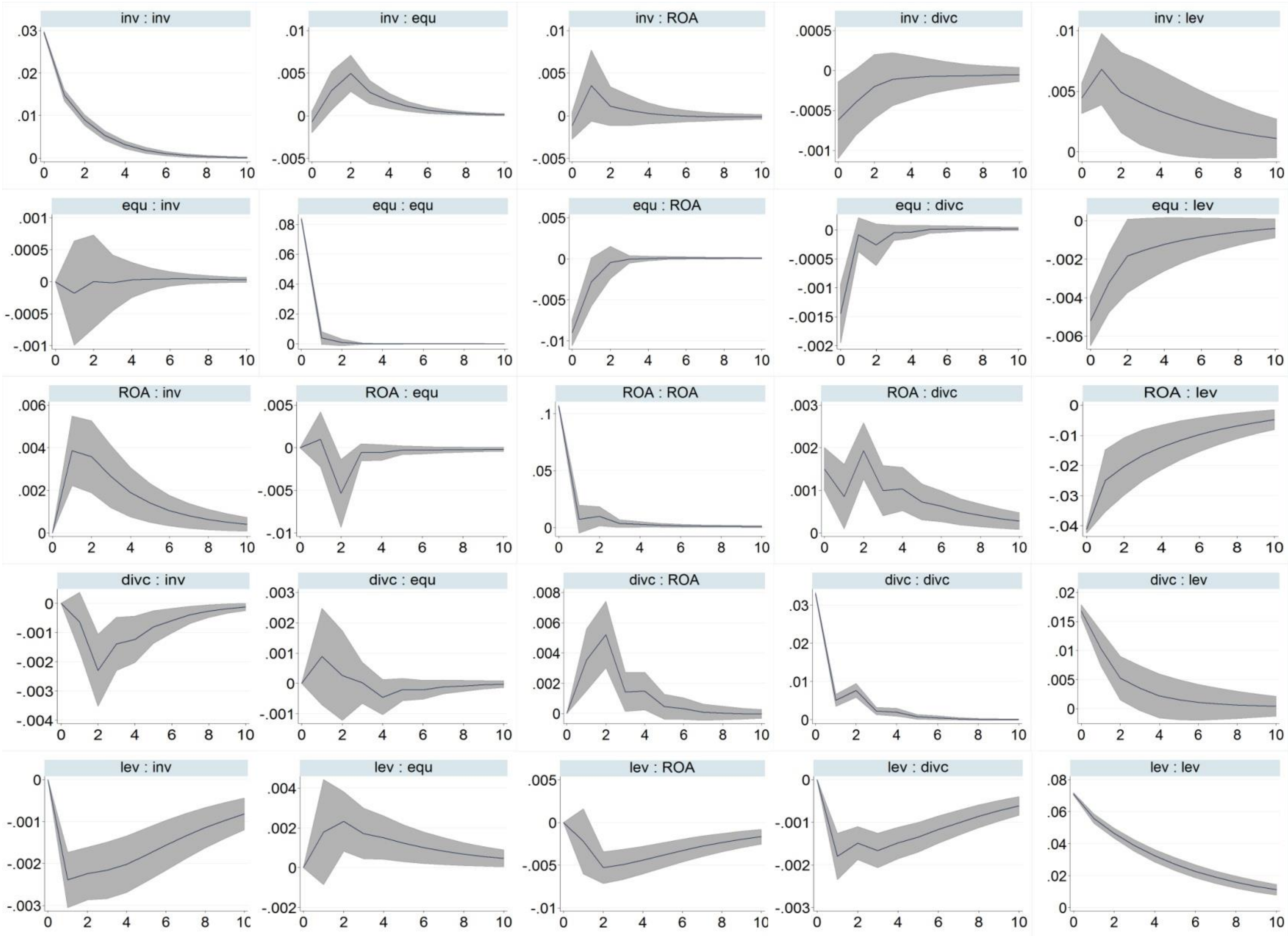
This table presents the results by using different models to test the effects of M/B and Size indicators in determining the financial variables. Column (1) uses static single equations without controlling lags of the dependent (equation) variable. Column (2) uses a dynamic model by controlling a one-year lagged dependent variable. In columns (1)-(2), we control firm- and year-fixed effects so that the results are comparable with those from the SVAR model (column 3). In columns (1)-(3), we report the coefficients and t-values (or z-values) of High_M/B and Large_size. High_M/B is an indicator if the firm's market-to-book ratio is higher than the annual median of the sample. Large_size is an indicator if the firm's book value of assets is larger than the annual median. Columns (4)-(5) display and test the difference in the coefficient estimates from single equation models and those from the SVAR model. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 7 Forecast Error Variance Decomposition

	(1)	(2)	(3)	(4)	(5)
			Panel A: Inv		
Lags(n)	Inv	Equ	ROA	Divc	Lev
1	100%	0	0	0	0
2	97.8%	0	1.6%	0.1%	0.5%
4	94.6%	0	3.5%	0.8%	1.1%
6	93.4%	0	4.0%	1.0%	1.6%
8	92.8%	0	4.2%	1.1%	1.9%
10	92.6%	0	4.2%	1.1%	2.0%
			Panel B: Equ		
Lags(n)	Inv	Equ	ROA	Divc	Lev
1	0	100%	0	0	0
2	0	99.9%	0	0	0
4	0.4%	99.1%	0.3%	0	0.1%
6	0.5%	99.0%	0.3%	0	0.2%
8	0.5%	99.0%	0.3%	0	0.2%
10	0.5%	99.0%	0.3%	0	0.2%
			Panel C: ROA		
Lags(n)	Inv	Equ	ROA	Divc	Lev
1	0	0.6%	99.4%	0	0
2	0.2%	0.6%	99.0%	0.1%	0.1%
4	0.2%	0.6%	98.2%	0.4%	0.6%
6	0.2%	0.6%	97.9%	0.4%	0.9%
8	0.2%	0.6%	97.7%	0.4%	1.1%
10	0.2%	0.6%	97.6%	0.4%	1.3%
			Panel D: Divc		
Lags(n)	Inv	Equ	ROA	Divc	Lev
1	0	0.2%	0.2%	99.6%	0
2	0.1%	0.2%	0.3%	99.2%	0.3%
4	0.1%	0.2%	0.8%	98.3%	0.7%
6	0.1%	0.2%	1.0%	97.7%	1.1%
8	0.1%	0.2%	1.1%	97.4%	1.3%
10	0.1%	0.2%	1.1%	97.2%	1.5%
			Panel E: Lev		
Lags(n)	Inv	Equ	ROA	Divc	Lev
1	0.3%	0.5%	22.1%	3.6%	73.4%
2	0.7%	0.4%	20.6%	3.3%	75.0%
4	0.8%	0.4%	20.0%	2.6%	76.2%
6	0.9%	0.3%	19.8%	2.3%	76.7%
8	0.9%	0.3%	19.7%	2.3%	76.8%
10	0.9%	0.3%	19.7%	2.1%	76.9%

Panels A to E of this table show the percentage of forecast error variance for each panel variable predicted by its own shocks and shocks to the other financial variables. Lags (n) denotes the 1-10-year-ahead forecast horizons.

Figure 1 Othogonalized Impulse Response Functions



This figure illustrates the impulse responses to a one-standard deviation of shock to the financial behaviour variables. The shaded area denotes the 95% confidence interval calculated by 2,000 Monte Carlo draws from SVAR Model (1). The X-axis shows the steps of the forecast horizons in years, and the Y-axis shows the magnitude of the response. Graph (A:B) illustrates the response of variable B to an orthogonal shock to variable A. Graph (A:A) shows how the shock is absorbed.

Appendix 1 Variable Definitions and Explanations

Briefs	Variables	Definitions	Rationale
Inv	Investment to assets ratio	Capital expenditures / Total Assets	We follow Gatchev et al. (2010) and use capital expenditures scaled by total assets to capture investment.
Equ	Equity issuance (repurchase) ratio	(Shareholders' Equity_t – Shareholders' Equity_{t-1} – Retained Earnings_t + Retained Earnings_{t-1}) / Total assets_t	We follow Baker and Wurgler (2002) and scale net equity issuance (or repurchase) by total assets at year *t* to measure equity issuance.
ROA	Return on Assets	Net income / Total assets	We follow Lambrecht and Myers' (2012) budget constraint equation and use net income scaled by total assets to capture internally generated funds.
Divc	Dividend to assets ratio	Cash dividend / Total assets	We follow Fama and French (2002) and scale dividends by total assets rather than earnings in case of the observation problem.
Lev	Leverage ratio	Total debt / Total assets	We follow Graham et al. (2015) and use total debt scaled by total assets to measure the leverage ratio.
M/B	Market-to-book ratio	(Market value of quity - book value of equity + book value of assets)/book value of assets	To demonstrate the bias in single equation estimation because M/B is controlled in almost all empirical corporate finance studies.
	Size	The natural logarithm of book value of assets	To demonstrate the bias in single equation estimation because size is controlled in almost all empirical corporate finance studies.

Appendix 2 More on Methodology

Our model is a panel vector autoregression (pVAR) of the form

$$y_{i,t} = A_1 y_{i,t-1} + \cdots + A_p y_{i,t-p} + u_i + \varepsilon_{i,t}, \;\; i = 1, \dots, N, \;\; t = p+1, \dots, T, \;\; (A.1)$$

where $y_{i,t} \in \mathbb{R}^k$ is the vector of k dependent variables of firm i at time t net of their cross-sectional means, $u_i \in \mathbb{R}^k$ is a vector of firm-specific panel fixed-effects, and $\varepsilon_{i,t} \in \mathbb{R}^k$ is a vector of idiosyncratic noise. Here, N is the total number of firms in the sample and T is the number of time periods for which we have observations. The distributional assumptions on the noise are the usual ones:

$$E\left[\varepsilon_{i,t} = 0\right], E\left[\varepsilon_{i,t}\varepsilon_{i,t}^T\right] = \Sigma, and\ E\left[\varepsilon_{i,t}\varepsilon_{i,s}^T\right] = E\left[\varepsilon_{i,t}\varepsilon_{j,t}^T\right] = 0, all\ t \neq s\ and\ j \neq i,$$

where the $k \times k$ variance-covariance matrix Σ is assumed to be positive-definite and symmetric.

It is well-known that, even for large N, OLS estimates for a model like (A.1) are biased, because of the presence of firm fixed effects (Nickell, 1981). This bias is still present for relatively large T, although it does disappear in the limit (Judson and Owen, 1999). Of course (A.1) could be estimated using OLS. However, OLS treats all the variables on the right-hand side (RHS) as exogenous, which obviously they are not. Therefore, the standard OLS estimator is biased. To deal with that problem we use a GMM estimator that explicitly deals with the endogeneity of the variables on the RHS.

Estimation

Here we follow the estimation procedure suggested by Holtz–Eakin et al. (1988). Throughout, we assume that $T > p + q$ and $N > 1$, for some $q \geq 0$ to be introduced later. Let X_i be a $(T - p - q) \times (pk)$ matrix, with t-th row

$$X_{i,t} := \left[y_{i,t-1}^T \cdots\ y_{i,t-p}^T\right], \;\; t = p+q+1, \dots, T,$$

let Y_i be a $(T-p-q)\times k$-dimensional matrix with t-th row

$$Y_{i,t} := y_{i,t}^T, \quad t = p+q+1, \dots, T,$$

and let Z_i be a $(T-p-q)\times r$ matrix of instruments, where

$$Z_i := \begin{bmatrix} Z_{i,p+1}^T & 0 & \cdots & 0 \\ 0 & Z_{i,p+2}^T & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & Z_{i,T}^T \end{bmatrix}$$

and

$$Z_{i,T}^T := \left[y_{i,t-p-1} \cdots y_{i,t-p-q}\right],$$

so that $r = q(T-p-q)$. Here, q represents the additional lags that are used as instruments.

The firm-fixed effects, u_i , are removed by the forward orthogonal deviation transformation; see, e.g., Hayakawa (2009). For that purpose, define the matrix

$$\mathrm{F} :=$$

$$\begin{bmatrix} \sqrt{\frac{T-p-q-1}{T-p-q}} & 0 & \cdots & 0 \\ 0 & \sqrt{\frac{T-p-q-2}{T-p-q-1}} & \ddots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{\frac{1}{2}} \end{bmatrix} \begin{bmatrix} 1 & -\frac{1}{T-p-q-1} & -\frac{1}{T-p-q-1} & \cdots & \cdots & \cdots & -\frac{1}{T-p-q-1} \\ 0 & 1 & -\frac{1}{T-p-q-2} & \cdots & \cdots & \cdots & -\frac{1}{T-p-q-2} \\ \vdots & \vdots & \vdots & & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & 0 & 0 & \cdots & 0 & 1 & -1 \end{bmatrix}$$

To implement GMM, we use the moment restriction $E[Z_i^T \varepsilon_i] = 0$, where ε_i is the $(T-p-q)\times k$ matrix with t-th row $\varepsilon_{i,t}^T$, and assuming that $E\left[Y_{i,t}^T Z_i\right]$has rank pk, the Arellano–Bond estimator for the $(pk)\times k$ coefficient matrix A, with

$$\mathrm{A} := [A_1^T \cdots A_P^T]^T,$$

is identified and equals

$$\widehat{\mathrm{A}} = [(\sum_{i=1}^{N} X_i^T (F^T Z_i))(\sum_{i=1}^{N} (F^T Z_i)^T (F^T Z_i))^{-1} (\sum_{i=1}^{N} (F^T Z_i)^T X_i)]^{-1} \times$$
$$(\sum_{i=1}^{N} X_i^T (F^T Z_i))(\sum_{i=1}^{N} (F^T Z_i)^T (F^T Z_i))^{-1} (\sum_{i=1}^{N} (F^T Z_i)^T X_i)$$

See, e.g., Arellano and Bond (1991) for details. This estimator is consistent and asymptotically normal, so that parameter restrictions can be tested using, e.g., a Wald test.

Model selection

In order to select the lag parameter p, we follow Andrews and Lu (2001) who base their model of moment selection criteria (MMSC) on Hansen's overidentifying restrictions statistic (cf. Hansen, 1982):

$$J_N(k,p,q) := \frac{1}{N}\left(\sum_{i=1}^{N} \hat{\varepsilon}_i^T (F^T Z_i)\right)\left(\sum_{i=1}^{N} (F^T Z_i)^T (F^T Z_i)\right)^{-1}\left(\sum_{i=1}^{N} (F^T Z_i)^T \hat{\varepsilon}_i\right),$$

where

$$\hat{\varepsilon}_i := Y_i - Z_i^T \hat{A}$$

is the estimated error matrix. The Akaike information criterion (AIC), Bayesian information criterion (BIC) and Hannan–Quinn information criterion (HQIC) are then given by

$$MMSC_{AIC,N}(k,p,q) := J_N(k,p,q) - k^2(|q| - |p|)\log(N),$$

$$MMSC_{BIC,N}(k,p,q) := J_N(k,p,q) - 2k^2(|q| - |p|)k^2,$$

and

$$MMSC_{HQIC,N}(k,p,q) := J_N(k,p,q) - Rk^2(|q| - |p|)\log(\log(N)), \text{ for some } R > 2,$$

respectively. Andrews and Lu (2001) suggest to choose p and q to minimize these criteria within a reasonable set of values for p and q.

Impulse response functions

As is well-known (see, e.g., Hamilton, 1994), a VAR model of order p is stable, in the sense that all variables return to their steady-state after a shock to the system, if all the eigenvalues of the matrix

$$\bar{\mathrm{A}} \coloneqq \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I_k & 0 & \cdots & 0 & 0 \\ 0 & I_k & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_k & 0 \end{bmatrix}$$

(here I_k is the k-dimensional identity matrix), lie inside the unit circle (in the complex plane). If this is the case, then the panel VAR is invertible and has an infinite-order vector moving average (VMA) representation

$$y_{i,t} = \mu_i + \sum_{s=0}^{\infty} \Psi_s \varepsilon_{i,t-s},$$

where

$$\mu_i = (I_k - A_1 - \cdots A_P)^{-1}\, u_i,$$

And Ψ_s is the upper left block of $\bar{A}^s$.

The VMA representation allows for the interpretation

$$\frac{\partial y_{i,t+s}}{\varepsilon_t^T} = \Psi_s$$

If we shock the system by $\delta = (\delta_1, \ldots, \delta_k)$ in the current (and only the current) time, then these shocks get propagated through the system as

$$\Delta y_{t+s} = \Psi_s \delta.$$

This is called the *impulse response function* (IRF) and has been used in many applications in micro and macroeconometrics to explore the impact of shocks to particular variables on the entire system over time.

It should be noted that IRFs can't be used to establish causality, because the *k* terms in the vector $\varepsilon_{i,t}$ are correlated. Therefore, we can't just give a shock to one variable only, because that would be a null event due to mutual correlation. Fortunately, every symmetric positive definite matrix – like the variance-covariance matrix Σ – admits a decomposition $= PDP^T$, where *D* is a diagonal matrix and *P* is a lower-triangular matrix with 1s on the diagonal. This decomposition of the matrix Σ, called the Cholesky decomposition, can be used to *orthogonalize* the impulse responses, i.e., to "switch off" the mutual correlation between the variables. The price for this disentangling of shocks is that one has to impose an order in which a shock to one variable affects the other variables, the *recursive order* mentioned in the paper. The recursive order is codified by the lower triangular matrix *P*.

Technically speaking, from the decomposition PDP^T we can now construct a k-dimensional vector

$$v_{i,t} = P^{-1}\varepsilon_{i,t}.$$

It then follows that

$$E\left[v_{i,t}v_{i,t}^T\right] = D.$$

This shows that the elements of $v_{i,t}$ are mutually uncorrelated. It can then be shown that

$$\frac{\partial E\left[y_{i,t+s} | y_{i,t}(j), y_{i,t}(j-1), \dots, y_{i,t}(1)\right]}{\partial y_{i,t}(j)} = \Psi_s P_j$$

where P_j is the *j*-th column of the lower-triangular matrix P and $y_{i,t}(j)$ is the *j*-th element of the vector $y_{i,t}$.

Our GMM estimates for $A_1, \ldots, A_p, \Sigma$ can be used to estimate these *orthogonalized impulse response functions* (OIRFs). That is, we assume that the system is in steady-state before a shock and we report deviations $\hat{y}_t$ from that steady-state at year *t* by recursively calculating

$$\hat{y}_0 = \delta,$$

$$\hat{y}_t = (\Psi_t P)^T diag(\delta), \ \ \mathrm{t} > 0,$$

where δ is the initial shock and $diag(\delta)$ is obtained by diagonalizing the vector δ. In our analysis we set, for each variable *k* separately, δ_k equal to 1 standard deviation with 0s for all other variables. Confidence intervals are obtained using Monte Carlo-based bootstrapping techniques. By imposing this structure we find that the error terms have a recursive orthogonal decomposition:

$$\mathrm{E}\left[\varepsilon_{i,t}(j) | v_{i,t}(j-1), \ldots, v_{i,t}(1)\right] = A_{j,1} v_{i,t}(1) + \cdots + A_{j,j-1} v_{i,t}(j-1).$$

We use OIRFs to isolate and examine the effects of shocks to individual variables, but this comes at the price of imposing a recursive order. Note that this order is not linked to a time period. That is, if there is an orthogonal shock to y_1 at time *t* and the recursive order is y_1, y_2, y_3, ... , y_k, then this does not mean that that y_2 changes from year $t + 1$ onward, y_3 from $t + 2$ onward, etc. Rather, y_2, ..., y_k are all affected from *t* onward. We discusses our choice of the ordering in the manuscript and test the robustness of our results to alternative orderings in the robustness check section.

Forecast Error Variance Decomposition

The *h*-step ahead forecast error of our model is (using the VMA)

$$y_{i,t+h} - \hat{y}_{i,t+h} = \sum_{s=0}^{h-1} \Psi_s \varepsilon_{i,t+h-s},$$

where $y_{i,t+h}$ is the observed vector at time $t + h$ and $\hat{y}_{i,t+h} = E[y_{i,t+h}]$ is the vector of predicted values for time $t + h$ based on observations up to, and including, time t.

To isolate each variable's contribution to the forecast error, we orthogonalize the errors as before by using $v_{i,t} = P^{-1}\varepsilon_{i,t}$, which has the variance-covariance matrix D. So, the contribution of variable m to the h-step forecast-error variance of variable j can then be calculated as

$$\sum_{s=0}^{h-1}\left(D_j^T P \Psi_s^T D_m\right)^2,$$

where D_j is the j-th column of the diagonal matrix D.