

What Moves Investment Growth?*

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Abstract

We use accounting identities to decompose unexpected changes in investment growth into surprises to current cash flow growth and stock returns, and revisions of expectations about future cash flow growth and future discount rates. Using a vector autoregressive model we find that current cash flow surprises account for the largest component in the variance of investment growth. Investment growth is negatively correlated with news about future cash flow growth, something that can be expected from persistent productivity shocks and decreasing returns to scale. Return terms are of second order importance and have unintuitive signs. Thus, the market looks like a side show for understanding investment growth.

JEL Classification: E22, G12

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Business investment is perennially important for economics: it creates current employment and it leads to long-run growth; at the same time large swings in investment are a primary contributor to business cycle volatility. Intuitively, investment is a trade-off between the present and the future. When making investment decisions managers should consider the prospect of future profits created by the new investment, and the present cost of such profits. But what really moves investment? Does the stock market affect investment over and above cash flows? Is investment driven by expected future profits or by current cash flows? These are some of the most fundamental questions in financial economics.

Many papers study the relationship between investment growth, stock returns, and measures of “fundamentals” (see, for example, Barro (1990), Blanchard, Rhee, and Summers (1993), Campello and Graham (2012), Cochrane (1991), Lamont (2000), Lettau and Ludvigson (2002), and Morck, Shleifer, and Vishny (1990)). While in general returns are found to have limited explanatory power for investment, a debate remains regarding the interpretation of this finding since it is hard to disentangle the effect of returns from the effect of cash flows. At the same time economists have long been puzzled by a strong relation between investment and *current* cash flows (see Eisner (1978) for an early summary). Fazzari, Hubbard, and Petersen (1988) interpret this investment-cash flow sensitivity as evidence in favor of financial constraints (see also Almeida, Campello, and Weisbach (2004) among others), although others argue that current cash flow may contain long-run information not captured by other variables (see Abel and Eberly (2012) among others). The difficulty in this second strand of the literature is on how to separate information about long-run cash-flow dynamics from short-run cash windfalls.

Borrowing the asset pricing techniques developed by Campbell and Shiller (1988), we propose a simple methodology to address the above-mentioned issues in the previous literature. Our novel methodology has several advantages. First, investment in our framework is related to its four drivers —current cash flows, expectations of future cash flows, current returns, and expectations of future discount rates— through present-value identities before any theoretical consideration is brought to the table. Second, we estimate the relation between investment and each of its four drivers simultaneously and within a consistent framework, allowing us to directly compare the

magnitudes of the different effects. Finally, we allow for time-variation in discount rates, which as emphasized by Abel and Blanchard (1986) accounts for most of the movements in q (the present value of marginal profits) and potentially also investment (see Lettau and Ludvigson (2002)).

Specifically, we start from the intertemporal budget constraint of the firm that links cash flows, investment, equity values, and stock returns. The budget equation identifies the sources of variation in investment growth, but is model-free in the sense that any theory that obeys basic identities can be expressed in this form. Different theories about investment put emphasis on different elements of the decomposition. Our approach allows us to estimate empirically the relative contribution of each element without recourse to a particular theory, and in this way deliver a set of quantitative stylized facts for all potential theories to match. This can be done without taking a stand with respect to the underlying mechanisms because some basic relations –especially those enforced through accounting identities– must hold regardless of economic interpretation and modeling. The appeal of this approach can be summarized by going back to Brainard and Tobin (1968):

We argue for the importance of explicit recognition of the essential interdependencies of markets in theoretical and empirical specifications of financial models. Failure to respect some elementary interrelationships—for example, those enforced by balance-sheet identities—can result in inadvertent but serious errors of econometric inference and of policy. This is true equally of equilibrium relationships and of dynamic models of the behavior of the system in disequilibrium (Page 99).

We estimate current surprises and long-run news through a vector autoregressive (VAR) system in the style of variance decompositions that followed Campbell and Shiller (1988). This system of predictive regressions imposes minimal structure on expectations and on the information set available to economic agents when they make forecasts. Some of its advantages are simplicity and the flexibility to condition on alternative information sets. Another advantage of using a predictive system instead of a single regression model is that all simultaneous effects, which can in principle offset each other, are accounted for. Chirinko and Schaller (1996) and Gatchev, Pulvino, and Tarhan (2010) make a similar point in favor of predictive systems vis-a-vis single equation models

of investment. However, they do not compute news terms like we do, and Gatchev, Pulvino, and Tarhan (2010) do not consider equity values as endogenous to the system.

Predictive regressions provide estimates of short-run and long-run effects without relying on direct measures of q . Empirical proxies for q typically require particular modelling assumptions such as the equivalence theorem between average and marginal q (Hayashi (1982)), and are prone to measurement error (Almeida, Campello, and Galvao (2010)). Much debate in the literature is focused on whether q fails as a sufficient statistic for long-run information, and on how cash flow variables may contain long-run information that q does not capture (see, for instance, Abel and Eberly (2012)). Our measures sidestep this problem by computing long-run news that are based solely on identities and predictive regressions. To be sure, our methodology has its own shortcomings, but it represents a reasonable alternative way to estimate long-run information that is rooted in the asset pricing tradition.

Our main results refer to aggregate U.S. data starting from 1952, and industries or other portfolios of U.S. listed firms starting from 1970. We also perform our decomposition at the firm level, although our framework is, admittedly, best suited to study investment series that are less lumpy. The main findings are as follows. First, the lion's share of variation in investment growth is strongly related to surprises to current cash flow growth. Second, we find that investment growth is negatively correlated with news about long-run cash flow growth, although this component is smaller than the one attributable to current cash flow surprises. The differences in sign and magnitude reveal interesting dynamics in investment and cash flows that cannot be captured by a static model. Finally, we find that, when compared to the magnitude of cash-flow terms, return terms are of second order importance for understanding investment dynamics, and crucially, they correlate with investment in unintuitive directions. Current return surprises are negatively correlated with investment growth as also found by Lamont (2000). More importantly, the correlation of investment growth and discount rate news is positive, which is unintuitive in a present-value sense since it implies that investment growth increases when discount rates go up.

The previous literature deals primarily with investment levels (i.e., the investment-to-capital ratio) and not investment growth. Focusing on growth rates is arguably better than working with

levels, because first differences can remove low frequency aspects of the data (see Barro (1990), Cochrane (1991), Morck, Shleifer, and Vishny (1990) along these lines). Since the theoretical implications for investment growth are not always explicit in the previous literature, we include a simple, stripped-down model where we derive some basic implications for our decomposition. The model does surprisingly well in matching the positive covariance of investment and cash flow surprises, and the negative covariance of investment with long-run cash flow news. Persistent productivity shocks and decreasing returns to scale are the key features of the model that allow us to match the joint dynamics of cash flows and investment. It is important in this respect that we deal with growth rates and not levels. Future investment *levels* are positively correlated to current (and persistent) productivity shocks, but future investment *growth rates* can be negatively correlated to current shocks because growth rates fall as the effect of the shock decays into the future. The future fall in growth rates is stronger when decreasing returns to scale are stronger. The model with constant returns to scale does worse in all dimensions. The problem with all versions of the model (with and without decreasing return to scale) is that the model produces a counterfactually high comovement of investment and returns, and typically a strong negative effect of discount rates. The model that we present allows us to digest the empirical results in an orderly fashion, making explicit the connection between earnings, investment and returns. We cannot do justice to the richness and diversity of investment models. In particular, we do not claim that all investment theories and their multiple incarnations are beyond repair. However, we highlight where the main challenges lie in the data.

Our results are relevant in several ways, most obviously for the long-standing debate about the relationship between stock markets and investment. Paraphrasing Morck, Shleifer, and Vishny (1990), we can say that the stock market seems to be a side show for investment decisions. Blanchard, Rhee, and Summers (1993) arrive at a similar conclusion stating that “market valuation appears to play a limited role, given fundamentals, in the determination of investment decisions (p. 132).” A related debate concerns the real effects of market inefficiency and mispricing (see, for example, Baker, Stein, and Wurgler (2003), Campello and Graham (2012), Chirinko and Schaller (1996), Gilchrist, Himmelberg, and Huberman (2005), Polk and Sapienza (2009), and Stein (1996)).

Our results suggest that the impact of market mispricing is at best limited, at least when studying aggregate investment, large groups of firms such as industries, or a long time-series. The effects of mispricing are potentially easier to detect in narrow subsets of firms more exposed to stock market fluctuations (as in Baker, Stein, and Wurgler (2003) for example) or in particular time periods with notable deviations of prices from fundamentals (as in the 1990’s technology bubble studied by Campello and Graham (2012)). Finally, the large effect of current cash flow shocks is reminiscent of the investment-cash flow sensitivity literature started by Fazzari, Hubbard, and Petersen (1988). However, the connection between short-run and long-run cash flow terms, and the different response of investment to these terms, highlights the fact that there are non-trivial dynamics between cash flows and investment that can go unnoticed in a purely static model. We emphasize that these results come from applying an estimation technique that: (i) puts all potential drivers of investment on equal footing, and (ii) does not rely on assuming, for instance, the existence of financial constraints, mispricing, adjustment costs in investment, or others. Like Campbell and Shiller (1988) in the asset pricing literature, we solely rely on budget constraints that can be recast in terms of present-value relationships.

The rest of the paper proceeds as follows. Section 1 develops the present value relationship between investment and discounted cash flows starting from the intertemporal budget constraint of the firm. Section 2 presents the various data sources and empirical methodology. Section 3 shows the results for aggregate investment growth and discusses portfolio- and firm-level results. Section 4 presents a simple log-linear model to digest the empirical findings. Section 5 concludes.

1 Investment and the present value of cash flows

1.1 The firm’s intertemporal budget constraint

The intertemporal budget constraint for equity is:

$$E_{t+1} = E_t \times R_{t+1} + NI_{t+1}^E - DIV_{t+1}, \quad (1)$$

where E_t is total equity value at the end of period t , R_t is gross equity return in period t , NI_t^E is net equity issuance in period t , and DIV_t is total dividends during period t . The difference $DIV_{t+1} - NI_{t+1}^E$ is net equity payout as in Boudoukh, Michaely, Richardson, and Roberts (2007) or Larrain and Yogo (2008). Equation (1) says that equity in the current period is equal to equity last period, which has grown at the realized rate of return, plus the amount contributed by shareholders (i.e., net equity issuance), minus the dividend payout.

The flow of funds identity is:

$$I_{t+1} + DIV_{t+1} = EARN_{t+1} + CFADJ_{t+1} + NI_{t+1}^D + NI_{t+1}^E, \quad (2)$$

where I_{t+1} is investment, $EARN_{t+1}$ is earnings (after interest expense), $CFADJ_{t+1}$ is cash flow adjustments to earnings, and NI_{t+1}^D is net debt issuance. Equation (2) states that the uses of funds (investment and payout) must be equal to the sources of the funds (cash flow plus net securities issuance).¹

We define Y_{t+1} or *equity cash flow* as:

$$\begin{aligned} Y_{t+1} &= EARN_{t+1} + CFADJ_{t+1} + NI_{t+1}^D \\ &= I_{t+1} + DIV_{t+1} - NI_{t+1}^E, \end{aligned} \quad (3)$$

The term equity cash flow is meant to refer to the total amount of cash that the firm can allocate to either investment or net equity payout. Combining equations (1) and (3) yields the intertemporal budget constraint for equity in terms of investment and equity cash flow:

$$E_{t+1} = E_t \times R_{t+1} + I_{t+1} - Y_{t+1}. \quad (4)$$

¹The appendix provides additional details by relating our identities to the firm-level flow of fund identity discussed in Gatchev, Pulvino, and Tarhan (2010).

Similarly, we define Y_{t+1}^A or *asset cash flow* as:

$$\begin{aligned} Y_{t+1}^A &= EARN_{t+1} + INT_{t+1} + CFADJ_{t+1} \\ &= I_{t+1} + DIV_{t+1} - NI_{t+1}^E + INT_{t+1} - NI_{t+1}^D, \end{aligned} \quad (5)$$

where INT_{t+1} is interest expense. Equation (5) shows that asset cash flow is the amount of cash the firm can allocate to either investment or net payout of equityholders and debtholders together. As in the case of equity, the intertemporal budget constraint for assets (equity plus debt) can be written as:

$$A_{t+1} = A_t \times R_{t+1}^A + I_{t+1} - Y_{t+1}^A. \quad (6)$$

where A_t is the value of total assets (equity plus debt), R_{t+1}^A is asset return, and Y_{t+1}^A is asset cash flow.

The intertemporal constraints for equity and assets are very similar. We focus primarily on the one for equity because the connection between equity returns and investment has dominated much of the literature. The budget constraint for assets relates investment with returns that combine equity and debt. On the other hand, asset cash flow only captures internally generated funds, while equity cash flow includes debt financing. Ultimately, the difference between both constraints is whether debt is included in returns (as in the case of assets) or in cash flows (as in the case of equity). Investment is the same in both cases.

1.2 Present-value relation involving cash flow, investment, and discount rates

In the same style of Campbell and Shiller (1988), we log-linearize the intertemporal budget constraint for equity in equation (4). The derivation for the case of total assets is analogous. In the following derivations small letters represent the log of the original variables (in capital letters). The notation Δ_{t+1} refers to the log-difference between $t+1$ and t for a given variable. As is explained in detail in the appendix, the loglinearization of equation (4) gives us (ignoring constants):

$$v_t \approx r_{t+1} - \theta \Delta y_{t+1} + (\theta - 1) \Delta i_{t+1} + \rho v_{t+1}, \quad (7)$$

where we define,

$$v_t \equiv \theta y_t - (\theta - 1) i_t - e_t, \quad (8)$$

The variable v_t is the log version of the net payout yield for equity, which in levels is $(Y_t - I_t)/E_t$. Equation (7) is similar to equation (4) in Larrain and Yogo (2008); however, we dig deeper into the determinants of net payout growth in our specification. In the appendix we discuss the log-linearization in detail, including its accuracy, and the choice of parameters ($\theta = 1.77$ and $\rho = 0.99$).

Solving Equation (7) forward and taking expectations, we get a present value equation for the net payout ratio:

$$v_t = \sum_{j=1}^{\infty} \rho^{j-1} E_t[r_{t+j} - \theta \Delta y_{t+j} + (\theta - 1) \Delta i_{t+j}]. \quad (9)$$

The net payout ratio is higher because expected returns are higher, or expected cash flow growth is lower, or expected investment growth is higher.

In a way analogous to the decomposition of unexpected returns of Campbell (1991), we decompose unexpected investment growth from equation (9) into four elements:

$$\begin{aligned} \Delta i_{t+1} - E_t \Delta i_{t+1} &= \underbrace{-\frac{1}{\theta - 1} (r_{t+1} - E_t(r_{t+1}))}_{C_{r,t+1}} + \underbrace{\frac{\theta}{\theta - 1} (\Delta y_{t+1} - E_t(\Delta y_{t+1}))}_{C_{y,t+1}} \\ &\quad - \underbrace{\frac{1}{\theta - 1} \Delta E_{t+1} \sum_{j=2}^{\infty} \rho^{j-1} r_{t+j}}_{N_{r,t+1}} \\ &\quad + \underbrace{\frac{\theta}{\theta - 1} \Delta E_{t+1} \sum_{j=2}^{\infty} \rho^{j-1} \Delta y_{t+j} - \Delta E_{t+1} \sum_{j=2}^{\infty} \rho^{j-1} \Delta i_{t+j}}_{N_{cf,t+1}}. \\ &= -C_{r,t+1} + C_{y,t+1} - N_{r,t+1} + N_{cf,t+1}. \end{aligned} \quad (10)$$

The equation says that unexpected investment growth can be understood as the sum of four components: (i) unexpected current return ($C_{r,t+1}$), (ii) unexpected current cash flow growth ($C_{y,t+1}$), (iii) discount rate news ($N_{r,t+1}$), and (iv) cash flow news ($N_{cf,t+1}$). The first two components are current realizations that deviate from prior expectations. The last two components are revisions of

expectations about the future. Equation (10) does not imply that the four right-hand-side elements *cause* investment growth. To the contrary, these are all potentially endogenous pieces that simply add up to total unexpected investment growth. They tell us about the different pieces into which we can decompose investment growth.

It is important to note that the investment decomposition holds by definition. Therefore, without resorting to any particular investment theory, one can see how each element contributes to investment. For example, holding constant current cash flow and expectations on future returns and cash flows, higher investment today must imply lower stock return today because of the substitution between investment and payout. This explains the negative sign before $C_{r,t+1}$. It does not mean, however, that unexpected investment and stock returns have to be negatively correlated in the data, because the other three terms can move around and affect investment at the same time. After these other effects are taken into account, investment and returns could very well be positively correlated.

Similarly, holding everything else constant, investment can be financed through a positive cash flow shock, which explains the positive sign before $C_{y,t+1}$. This does not mean, however, that investment has to be positively correlated with cash flow shocks. Forward-looking managers could react to a transitory cash flow shock by adjusting current payout and leaving investment intact. That is, $C_{r,t+1}$ and $C_{y,t+1}$ can change at the same time without impacting investment.

We study the contribution to investment variation of each element by computing the covariance of $\Delta i_{t+1} - E_t \Delta i_{t+1}$ with each side of equation (10):

$$\begin{aligned}
 \text{var}(\Delta i_{t+1} - E_t \Delta i_{t+1}) &= \text{cov}(\Delta i_{t+1} - E_t \Delta i_{t+1}, -C_{r,t+1}) + \text{cov}(\Delta i_{t+1} - E_t \Delta i_{t+1}, C_{y,t+1}) \\
 &\quad + \text{cov}(\Delta i_{t+1} - E_t \Delta i_{t+1}, -N_{r,t+1}) \\
 &\quad + \text{cov}(\Delta i_{t+1} - E_t \Delta i_{t+1}, N_{cf,t+1}).
 \end{aligned} \tag{11}$$

The variance of investment can be decomposed into four covariance terms. Intuitively, not all variation of the items in the right hand side of equation (10) matters for the variation of investment. What matters is the portion of variation that is related to investment, which is precisely what the

covariance captures.²

If we divide both sides of equation (11) by $var(\Delta i_{t+1} - E_t \Delta i_{t+1})$ we get:

$$1 = \beta_{C_r} + \beta_{C_y} + \beta_{N_r} + \beta_{N_{cf}}, \quad (12)$$

where each β is a covariance divided by the variance of investment. Each β can be interpreted as the regression coefficient from running one of the terms, say $C_{r,t+1}$, on unexpected investment growth. In other words, if investment moves unexpectedly today this movement must come from either current returns, current cash flow, future returns, or future cash flow growth. These regression coefficients have to add up to one if the budget constraint holds.

One can use this decomposition to give content to different theories about investment behavior. For example, if current shocks are purely transitory and managers are forward-looking we expect to find small β_{C_r} and β_{C_y} , but large β_{N_r} and $\beta_{N_{cf}}$. Of course, the identity by itself cannot tell us about the relative importance of investment components. The economic content of the identity comes down entirely to estimation, which is what we do in the next section.

2 Data and Empirical Methodology

2.1 Data Sources

Our primary source for aggregate data is the seasonally-adjusted quarterly data from the Flow of Funds Accounts of the United States, 1952:01-2010:03. We construct the variables for the nonfarm, nonfinancial corporate sector. All flows are expressed at the quarterly frequency and not at the annual frequency. From Table F.102 we obtain earnings ($EARN_t$, Line 1), dividends (DIV_t , Line 3), capital expenditure (I_t , Line 11) which includes fixed investment and inventory change, net equity issues (NI_t^E , Line 39), and net debt issues (NI_t^D , Line 41 plus Line 43). Interest expense (INT_t) is not reported by the Flow of Funds so we obtain it from the NIPA Table 1.14. With these elements we compute equity cash flow (Y_t) and asset cash flow (Y_t^A) as defined in equations

²We emphasize that the four elements in the right-hand side of equation (10) are not assumed to be independent or orthogonal to each other. See Campbell and Ammer (1993) for a similar treatment regarding return decompositions.

(3) and (5) respectively. From Table B.102 we obtain the book value of debt (Line 21) and the market value of equity (E_t , Line 35), which together represent our measure of total assets (A_t) as in Larrain and Yogo (2008). Stock returns (R_t) and asset returns (R_t^A) are computed with the above elements from equations (1) and (6) respectively. All data are deflated using the end-of-quarter CPI from the *Bureau of Labor Statistics*.

Our secondary data source is a merge of the Compustat Annual Industrial File and the Center for Research in Security Prices (CRSP) Database. When constructing the variables, we follow the variable definitions and procedures in Larrain and Yogo (2008) and Gatchev, Pulvino, and Tarhan (2010) closely. Due to the requirement for the statement of cash flows, the data are available at annual frequency only since 1971 and up to 2009. We exclude SIC codes 6000-6799 to focus on the nonfinancial firms. The Compustat-CRSP dataset covers only publicly traded companies, while the Flow of Funds includes public and private companies. From Compustat we collect earnings (NI), dividends (DV), share repurchases (PRSTKC) and share issuance (SSTK). Investment is defined as capital expenditure (CAPX) minus the reduction in inventory (INVCH).³ The market capitalization at the end of each year (E_t) and annual stock returns are computed using the CRSP database. Firm-level variables are aggregated to the market level. The main variables of interest during year t are then scaled with the total market capitalization at the end of year t . Individual stock returns (ret) and capital appreciation components ($retx$) are also aggregated to the market level using value-weighting. Finally, annual log growth rate in variable X is computed as $\Delta x = \ln((\frac{X}{E})_t) - \ln((\frac{X}{E})_{t-1}) + \ln(1 + retx_t)$.

2.2 Descriptive Analysis of Quarterly Sample

Figure 1 plots investment growth against equity cash flow growth (top) and earnings growth (bottom). Growth rates are computed as log differences. For visual clarity, we first compute the average across quarters in each year, and then plot the time series of annual averages. Most importantly, investment growth tends to follow cash flow and earnings growth closely. For example, investment

³In other words, the increase in inventory is categorized as investment. We do this in order to match the definition in the Flow of Funds sample. This treatment, however, does not drive our results. We obtain very similar results using a simpler definition of investment that only includes capital expenditures.

growth, cash flow growth, and earnings growth reach their lowest points during the 2001 recession. Overall, investment growth and cash flow or earnings growth behave like close cousins (if not twins), going wildly up and down together.

Table 1 reports summary statistics for the quarterly sample. Average investment growth, earnings growth, and cash flow growth are below 1%, but average stock returns are about 2% quarterly, which implies an average annual return of approximately 8%. Investment growth is about as volatile as stock returns, earnings growth, and slightly less volatile than cash flow growth. The correlations of investment growth with cash flow growth and with earnings growth are positive and high (0.73 and 0.47 respectively). These strong correlations are consistent with previous results in this literature (see Blanchard, Rhee, and Summers (1993), Hassett and Hubbard (1997), and Caballero (1999)).

Some correlations are puzzling. Stock returns are negatively related to investment growth (-0.04), although the correlation is small in magnitude. Lamont (2000) argues that this result is counter-intuitive, since both investment and returns supposedly reflect the same forward-looking information. Lamont (2000) further argues that the lack of a proper correlation between investment and returns is caused by lags in the implementation of investment plans. Stock returns are also negatively correlated to cash flow growth (-0.08) and earnings growth (-0.03). This seems to suggest that discount rates go up precisely when there are positive shocks to cash flows or earnings. As Kothari, Lewellen, and Warner (2006) point out, this would be against the predictions of standard asset pricing models.

Dividend growth appears more volatile than investment solely because of seasonality.⁴ Most of the volatility in dividends disappears when taking annual averages, while the volatility of earnings and investment growth remains high. This can also be seen in the large and negative autocorrelation of dividends at the quarterly frequency. Dividend growth is essentially uncorrelated with either earnings growth or cash flow growth.

Figure 2 shows the time series of the net payout yield for equity (i.e., $(Y_t - I_t)$ over E_t) and the dividend yield. The net payout ratio looks more stationary than the dividend yield, a variable

⁴For this table dividends are taken from CRSP, and not from the Flow of Funds as in the rest of the paper, in order to facilitate comparisons with the asset pricing literature.

that is commonly used to predict returns. The autocorrelation of net payout yield is 0.84, while the autocorrelation of the dividend yield is 0.92. In fact, the dividend yield exhibits a downward trend during much of the 1952-2010 period.

2.3 VAR Estimation of the Variance Decomposition

A direct approach for computing the variance decomposition is to run regressions of long-run returns or cash flow growth onto current investment shocks. As seen in equation (12), the coefficients of these different regressions are interrelated and should add up to one. However, it has been documented that long-horizon regressions have poor finite-sample properties (e.g., Boudoukh, Michaely, Richardson, and Roberts (2007), Hodrick (1992), and Valkanov (2003)). Therefore, we estimate expectations and surprises to the different variables through a VAR model as is typical in the asset pricing literature (e.g., Campbell (1991)). Consider a vector of demeaned variables $x_t = (r_t, \Delta y_t, \Delta i_t, v_t)'$ such that:

$$x_{t+1} = \Phi x_t + \varepsilon_{t+1}, \quad (13)$$

where $E[\varepsilon_{t+1}] = 0$ and $E[\varepsilon_{t+1}\varepsilon_{t+1}'] = \Sigma$. The first three equations of this VAR can be interpreted as a vector error-correction model where the payout ratio v_t is the cointegrating vector. This is perhaps the best way to justify our VAR specification and thus the information set we use to estimate long-run news. As shown by Chen and Zhao (2009), changes in the VAR specification can lead to different conclusions about the importance of cash flow news and return news when the information set is arbitrarily chosen, at least in the case of return decompositions. The forecasting variables typically used in investment regressions (e.g., Barro (1990)) are precisely the ones we consider: investment lags, earnings or profitability growth, stock returns, and scaled stock prices (i.e., the net payout ratio). In robustness checks we also include other variables (e.g., the market-to-book ratio) to the information set without any material impact on the results as we report later on.

The intertemporal budget constraint in equation (7) implies the following restriction on the

VAR coefficients:

$$[e'_1 - \theta e'_2 + (\theta - 1)e'_3 + \rho e'_4]\Phi = e'_4, \quad (14)$$

where e_i is the i th column of the 4×4 identity matrix I . The VAR model implies that the dynamics of unexpected investment in Equation (10) can be written as:

$$\begin{aligned} e'_3 \varepsilon_{t+1} &= \underbrace{-\frac{1}{\theta-1} e'_1 \varepsilon_{t+1}}_{C_{r,t+1}} + \underbrace{\frac{\theta}{\theta-1} e'_2 \varepsilon_{t+1}}_{C_{y,t+1}} \\ &\quad - \underbrace{\frac{1}{\theta-1} e'_1 \rho \Phi (I - \rho \Phi)^{-1} \varepsilon_{t+1}}_{N_{r,t+1}} \\ &\quad + \underbrace{\left(\frac{\theta}{\theta-1} e'_2 - e'_3 \right) \rho \Phi (I - \rho \Phi)^{-1} \varepsilon_{t+1}}_{N_{ef,t+1}}. \end{aligned} \quad (15)$$

Define:

$$A = \rho \Phi (I - \rho \Phi)^{-1}. \quad (16)$$

The variance decomposition of unexpected investment becomes:

$$\begin{aligned} e'_3 \Sigma e_3 &= -\frac{1}{\theta-1} e'_1 \Sigma e_3 + \frac{\theta}{\theta-1} e'_2 \Sigma e_3 \\ &\quad - \frac{1}{\theta-1} e'_1 A \Sigma e_3 + \left(\frac{\theta}{\theta-1} e'_2 - e'_3 \right) A \Sigma e_3 \end{aligned} \quad (17)$$

We estimate the VAR using OLS equation-by-equation. An alternative way, similar to what Campbell and Shiller (1988) do, is to obtain the coefficients of the fourth regression (the net payout yield regression) by imposing the constraints in equation (14). The unrestricted OLS regression for the net payout yield gives very similar coefficients, which only attests to the underlying connection between the different coefficients through a budget constraint and the accuracy of the log-linear approximation. The results of the variance decomposition are not affected in a material way by imposing the restrictions in equation (14). We report Newey-West corrected standard errors for the coefficients of the VAR.

3 Results

3.1 Baseline Case with Aggregate Data

The left half of Table 2 reports the VAR results using the quarterly sample for 1952:02-2010:03 and terms in the equity budget constraint. Consistent with the current literature (see Boudoukh, Michaely, Richardson, and Roberts (2007) and Larrain and Yogo (2008)), the net payout yield significantly predicts stock returns (0.032, t -statistic 2.17). The payout yield also predicts cash flow growth (-0.069 , t -statistic -3.61) and investment growth (-0.053 , t -statistic -3.61). Importantly, the ability of the payout yield to predict cash flow growth and investment growth is stronger than its ability to predict returns; this is clear from both the size of the coefficients and the t -statistics. In addition, and not surprisingly, the lagged payout ratio strongly predicts the current payout ratio (0.897, t -statistic 30.4).

As the cointegration vector, the ability of the net payout yield to predict each variable largely determines the long-run expectation of that variable. Since the payout yield is the key variable, one common practice in the literature is to estimate a reduced-form VAR, in which the only independent variable is the payout yield (see, among others, Cochrane (2008), and Chen (2009)). When we do so, the coefficient on the return equation becomes significant only at the 10% level (t -statistic 1.72), but the coefficient on the cash flow equation (-0.085 , t -statistic -4.56) and on the investment equation (-0.056 , t -statistic -3.99) become slightly larger and more significant. In the language of cointegration, the results of the VAR can be summarized as follows. When the net payout ratio is high, and in order for the payout ratio to go back to its mean, it has to be the case that either future returns are high or future payout growth is low. The VAR shows that part of the adjustment is achieved through future returns, but more importantly through future payout growth.

These results are basically unchanged if we run a “kitchen-sink” VAR that includes a host of predictive variables studied in the literature and reviewed by Goyal and Welch (2008).⁵ Adding more variables allows us to check how robust the predictive relationships are to changes in the information set. In particular, the kitchen-sink VAR (not reported) includes the following variables

⁵The data for the kitchen-sink VAR from Goyal and Welch (2008) ends in 2008.

besides those already presented in Table 2: the book-to-market ratio, the earnings-price ratio, the dividend-payout ratio, the term spread, the default yield spread, Lettau and Ludvigson (2001)'s *cay*, inflation, net equity issuance, stock return variance, and the investment-to-capital ratio. We find that the predictive relationships presented in Table 2 are robust to including all or subsets of these variables.

The R-squared of the regressions in Table 2, though not very high, is on par with (or even better than) typical studies on return and cash flow predictability (e.g., Campbell and Shiller (1988) and Cochrane (2008)). The R-squared for cash flow growth and for investment growth, around 10%-15%, is actually impressive compared to the literature. In the case of the kitchen-sink VAR the R-squared goes up to approximately 25%, but never higher than that.⁶

The right half of Table 2 shows the annual VAR with aggregate Compustat-CRSP data. The main difference with the quarterly sample is that the power of the net payout yield to predict cash flow growth and investment growth is reduced in significance. Different firms in Compustat are associated with different fiscal year ends, resulting in a non-synchronicity problem that partially explains the reduction in significance. The R-squared for the cash flow regression and investment regression is still higher than in the return regression since the other lags of returns, cash flow growth, and investment growth provide substantial predictive power.

Table 3 reports the variance decompositions that follow from the quarterly VARs. In Panel A, we present the results for the full VAR, the reduced-form VAR, and the kitchen-sink VAR with all the predictive variables, all using the quarterly FOF data. For the full VAR, the variance of unexpected investment growth is 0.0063 per quarter, which implies a standard deviation of 7.9% per quarter. The standard deviation of raw investment growth is 8.5% per quarter (see Table 1). Therefore, raw investment volatility and unexpected investment volatility are quite close.

The covariance between unexpected investment growth and current cash flow surprises is 0.0132 or 210% of the variance of unexpected investment growth. This number represents the largest element in the variance decomposition. In the lower panel of the table we report the correlation of

⁶Again, the limited predictive power is standard in regressions with growth rates. Very different are the regressions that use earnings and investment in levels (i.e., as fraction of assets), which tend to have higher R-squared because levels move more slowly. Regressions in levels also typically rely on cross-sectional differences and not solely on the time series like we do.

investment surprises and cash flow surprises, which is above 0.70 in the three VAR specifications. Therefore, the high covariance is not simply an artifact of the volatility of cash flow, but it comes from the synchronization of unexpected movements in both investment and cash flow growth. We obtain very similar results using both the reduced-form and the kitchen-sink VARs, suggesting that the results are not driven by potentially strange combinations of VAR coefficients or the autocorrelation of the variables.

The second largest element (in absolute terms) in the decomposition is the covariance of long-run cash flow growth and unexpected investment growth. The negative covariance implies that *higher* than expected current investment growth goes hand in hand with *lower* than expected long-run cash flow growth. If we were to run a regression of long-run cash flow growth on past investment surprises we would get a *negative* coefficient (i.e., $\beta_{N_{cf}} < 0$). As explained in detail in Section 4, future cash flow *growth* can be negatively correlated to the current increase in the capital stock as a product of diminishing returns in production.

The other two covariances –of unexpected investment growth with current return surprises and with discount rate news– are small in magnitude. The covariance with discount rate news is the largest of the two, but still smaller than 36% of investment variance. Return dynamics seem to be disconnected from investment growth or they are of second order importance. Compared to Lamont (2000), we do not only estimate the covariance of current investment and current returns, but we simultaneously estimate the covariance of current investment and long-run discount rate news. In this last case we also find a result that seems to defy the present-value logic: the positive covariance implies that investment growth increases when long-run discount rates go up.

Panel B in Table 3 shows the variance decomposition based on the annual Compustat-CRSP sample. Given the shorter sample length, we do not run the Kitchen-sink VAR. The estimates of the cash flow related terms are similar to the ones in the quarterly sample. The return-related terms are, however, larger than in the quarterly sample. Both terms are about 100% of investment variance in the case of the full VAR. Still, the covariance of investment and current returns is estimated to be negative, while the covariance of investment and discount rate news is positive. In a sense, the Compustat-CRSP results only deepen the puzzle.

3.2 Robustness Checks with Aggregate Data

We explore the robustness of our results to several modifications of the baseline framework. None of the modifications changes the overall picture.

Using Earnings instead of Cash Flows The difference between earnings and equity cash flow lies in the cash flow adjustment term and net debt issuance (see equation (3)). Earnings growth and equity cash flow growth have similar volatility and a relatively high correlation (0.38 in Table 1). Although the budget constraint of the firm does not hold exactly if we substitute equity cash flow for earnings, we run the basic VAR and decomposition using earnings growth instead of cash flow growth in Table 4.⁷ The results are very similar as to the baseline case, showing that the high covariance between investment and cash flow growth is not an artifact of cash flow adjustments or debt financing.

Asset Decomposition In Table 4 we present the results from the decomposition of investment variance based on the asset budget constraint of equation (6). The procedure is analogous to the case of equity, although using asset cash flow, asset returns, and the asset net payout yield (i.e., $(Y_t^A - I_t)$ over A_t). As seen in Table 1, asset cash flow growth is slightly more volatile than equity cash flow growth, but both are highly correlated (0.88). Similar to the case of equity, asset cash flow growth is still highly correlated with investment growth (0.68). Asset returns are lower on average than equity returns (1.5% vs 2% quarterly), and less volatile (4.8% vs 8.9% quarterly). The net payout yield for assets is also highly correlated with the net payout yield for equity (0.84).

The results in Table 4 show that the decomposition of investment based on the asset budget constraint is very similar. The covariance with cash flow growth is still the largest term in the decomposition at 232% of investment variance. Long-run cash flow growth is negatively correlated with current investment growth surprises. The covariances with current and long-run returns are both small: none is larger than 10% of investment variance in absolute value. In the last panel of Table 4 we use earnings growth instead of cash flow growth and the results do not vary much as in

⁷In this case, and the other cases in Table 4, we derive the coefficients on the net payout yield equation by imposing the restrictions in equation (14).

the case of equity.

Five-Term Decomposition We can write equity cash flow as:

$$Y_{t+1} = EARN_{t+1} \left(1 + \frac{CFADJ_{t+1} + NI_{t+1}^D}{EARN_{t+1}} \right), \quad (18)$$

which after taking logs and first differences is:

$$\Delta y_{t+1} = \Delta earn_{t+1} + \Delta adj_{t+1},$$

where $\Delta adj_{t+1} = \Delta \ln \left(1 + \frac{CFADJ_{t+1} + NI_{t+1}^D}{EARN_{t+1}} \right)$. Therefore, equity cash flow growth can be decomposed into earnings growth and the growth rate of the adjustment term defined above. Current cash flow shocks in equation (10) can then be split into earnings shocks and adjustment shocks:

$$C_{y,t+1} = C_{earn,t+1} + C_{adj,t+1}. \quad (19)$$

In Table 5 we report the variance decomposition, now with five components, using the aggregate samples. The five-term decomposition is derived from a VAR with five variables $x_t = (r_t, \Delta earn_t, \Delta adj_t, \Delta i_t, v_t)'$. The covariance of investment growth and earnings growth still accounts for the largest share of the investment decomposition. Unexpected earnings growth and unexpected investment growth are positively correlated in the Flow of Funds and Compustat (the correlation coefficient is around 0.40). The covariance of investment growth and the adjustment term flips signs depending on whether we look at the Flow of Funds or Compustat-CRSP. A positive covariance, as seen in the Flow of Funds sample, implies that investment growth is unexpectedly high when the ratio of cash flow adjustments and debt issuance to earnings is growing fast. In the Compustat-CRSP sample we obtain a negative correlation instead.

Notice that by adding the first two terms in the 5-term decomposition we get approximately the term $cov(\Delta i_{t+1} - E_t \Delta i_{t+1}, C_{y,t+1})$ of our original decomposition. The only difference lies in that the VAR for the 5-term decomposition includes five variables instead of four, which modifies

a bit the predictive power of each regression. Since the differences are small, and the 5-term decomposition provides more information, we report only the 5-term decomposition in the tables that follow.

3.3 Evidence with Disaggregated Data

3.3.1 Portfolio Results

Table 6 reports the variance decomposition of unexpected investment growth for 10 industry portfolios formed with Compustat data. We used the Fama-French ten industrial classifications. Figure 3 gives a visual impression of the evolution of the variance decomposition from the least volatile industry (healthcare and medical equipment) to the most volatile industry (consumer durables). For visual clarity we add the covariances of investment growth with earnings and adjustment growth into a single term. A first thing to note is that investment surprises are almost ten times more volatile in the most volatile industry compared to the least volatile industry. Despite this variation in the level of investment variance, the composition of investment surprises is less heterogeneous across industries. This covariance with current cash flow growth is always the largest element in the variance decomposition (in absolute value). On average this covariance is about 200% of the variance of investment, confirming the main finding in the aggregate data. The covariance of unexpected investment growth with long-run cash-low news is mostly negative, but smaller in magnitude than the covariances in previous cases. The covariances of unexpected investment growth with return surprises and long-run return news are generally the smaller elements of the variance decomposition for each industry.

In Table 7 we form portfolios according to firm characteristics: the book-to-market ratio and size (total market capitalization). Across portfolios the signs and relative magnitudes of the different covariance terms across are mostly maintained, and also coincide with the aggregate results. Cash flow terms are typically the largest terms in the variance decomposition across all portfolios. Direct earnings growth is relatively more important for value and small stocks. The large and positive covariance with current earnings growth is partly offset with a negative covariance of investment growth and long-run cash flow news. Discount rate news are almost always positively correlated

with investment surprises as in the aggregate sample.

3.3.2 Firm-by-Firm Results

Applying our decomposition to individual firms presents some technical challenges. The most immediate problem is that some elements in the flow of funds identity in equation (4) can be negative in some periods, which makes it impossible to use logs. For instance, the fraction of firm-year observations with negative earnings in our Compustat sample is 20%. Recall that the annual log growth rate in variable X is computed as $\Delta x = \ln((\frac{X}{E})_t) - \ln((\frac{X}{E})_{t-1}) + \ln(1 + retx_t)$. When X is negative, the log growth rate is undefined. To circumvent this problem, in those firm-year observations with negative X 's, we increase both $(\frac{X}{E})_t$ and $(\frac{X}{E})_{t-1}$ by the same amount. To ensure the flow of fund identity, we apply the same constant upward shift to investment (I), earnings ($EARN$), and equity cash flow (Y) –all scaled by market capitalization– so their minimum is 5%. This procedure, albeit ad-hoc, avoids negative numbers and at the same time preserves the relative magnitudes of different growth rates.

Table 8 shows results for two different VARs using firm-by-firm data. First we run a panel VAR that includes all the cross-sectional and time-series variation. Second, we run a VAR for each firm, and then we average coefficients and t -statistics across all firms for each variable (a "reverse" Fama-MacBeth procedure). For both VARs, we use the same panel containing firms with at least 18 years of data. The panel contains 1855 firms, each with an average of 27 years of data.

The magnitude of coefficients is similar across both VARs (see Panels A1 and B1). The main predictive relationships observed in the aggregate data are seen here. For example, the net payout ratio predicts returns with a positive sign, and earnings and investment growth with a negative sign. The autocorrelation coefficient of the net payout yield is smaller than at the aggregate level (e.g., 0.42 in the panel VAR). The R-squared is higher than in the case of aggregate data, but still around 20% – 30%.

The results for the variance decomposition in Panels A2 and B2 show that investment is naturally more volatile at the firm level than at the aggregate level or industry level. Current earnings growth accounts for close to 100% the variation in investment, while the other elements of the

variance are quite small. Both cash flow news and discount rate news seem practically irrelevant at the firm level.

3.4 Are cash flow surprises forward-looking?

Our findings show that cash flow surprises account for the lion’s share of variation in unexpected investment growth. Therefore, a natural question to ask is whether these shocks are transitory surprises or if they represent signals about the future. This is important since in many models cash flow surprises affect investment because they are signals about future profitability (e.g., Abel and Eberly (2012)). In terms of our previous notation, this question boils down to estimating the covariances between cash flow surprises and news terms, i.e., $Cov(C_{y,t+1}, N_{cf,t+1})$ and $Cov(C_{y,t+1}, N_{r,t+1})$. Remember that the four terms in the decomposition shown in equation (10) are not assumed to be orthogonal, hence these covariances can be positive, negative, or zero. Intuitively one can understand these covariances as coming from predictive regressions of future long-run cash flow growth or returns on current cash flow surprises:

$$\begin{aligned} \sum_{j=2}^T \Delta y_{t+j} &= a + bC_{y,t+1} + \epsilon, \\ \sum_{j=2}^T r_{t+j} &= c + dC_{y,t+1} + \epsilon. \end{aligned}$$

While we can also estimate the covariances of interest directly from the VAR, the predictive regressions are more intuitive and they show that the results do not rely on a particular VAR structure.

Panel A of Table 9 reports results for long-horizon regressions in the Flow of Fund quarterly sample. A positive surprise to cash flow growth is a strong predictor of future lower cash flow growth at least up to twelve quarters after the shock. The effects are long lasting and do not correspond simply to short-run mean reversion. The same predictive power is seen in net cash flow growth, which following the logic of cash flow news in equation (10) is defined as $[\theta/(\theta - 1)]\Delta y_t - \Delta i_t$. Cash flow surprises have no predictive power for returns at any horizon. Panel B of Table 9 shows similar

results using the aggregate Compustat-CRSP annual sample. The negative relationship between current cash flow surprises and future cash flow growth appears with all alternative measures of cash flow. There is some predictive power for returns in the short-term, but no predictive power in the long term as in the Flow of Funds sample.

We conclude that cash flow growth shocks have predictive power for future cash flow growth, although not for discount rates. Considering long horizons we can say that a positive cash flow surprise implies *lower* future cash flow growth, i.e., $Cov(C_{y,t+1}, N_{cf,t+1}) < 0$, although no change in discount rates, i.e., $Cov(C_{y,t+1}, N_{r,t+1}) \approx 0$.

These regressions help us to complete the picture, although they only reiterate our previous findings. If the argument is that current cash flow surprises are correlated with investment growth because current cash flow signals something about the future, then that forward looking component of investment is already captured by the terms $Cov(\Delta i_{t+1} - E_t \Delta i_{t+1}, N_{cf,t+1})$ and $Cov(\Delta i_{t+1} - E_t \Delta i_{t+1}, -N_{r,t+1})$ in our decomposition. The advantage of estimating all the pieces of the identity together is precisely to impose discipline on the stories one can tell about the different factors that move investment.

3.5 Investment Lags

Lamont (2000) argues that although investment and returns respond to the same forward-looking information, investment decisions are implemented with lags while prices reflect the information instantaneously. This can in principle explain the puzzling negative correlation between investment and return surprises. Consistent with this argument, Lamont (2000) shows that investment plans (rather than actual investment) and returns are positively correlated. Similarly, Lettau and Ludvigson (2002) show that some financial variables that predict returns also predict investment in the long run, although not in the short run.

Can investment lags explain (i) the strong correlation between investment shocks and current cash flow surprises, and (ii) the wrong sign in the correlation of investment shocks and return surprises? The answer to the first question is likely no. This is because, contrary to the existence of lags, the response of investment to current cash flow shocks is not delayed. The fact that current

cash flow shocks are strongly related to investment suggests that the bulk of investment is not implemented with lags.

Investment lags have more potential to answer the second question, i.e., the disconnection that we observe between investment and stock returns. We explore this issue in Table 10 where we regress future investment growth on lagged return surprises. Consistent with investment lags, returns predict two- and three-quarter ahead investment growth with the correct (positive) sign. After three quarters the predictive power disappears.

The predictive power is, however, quite small. The R-squared (the fraction of future investment variance explained by the variable) is at best 5% in these regressions. Therefore, even if investment lags can salvage the role of returns, they still do not explain the bulk of investment variation. This is because most of investment variation corresponds to a simultaneous response – without a lag – to cash flow shocks. In particular, the right-hand side panel in Table 10 shows that the R-squared increases up to about 50% when contemporaneous cash flow shocks are included in each regression. Contemporaneous cash flow shocks also seem to reduce the predictive power of past returns.

4 Understanding the Variance Decomposition of Investment Growth with a Simple Model

Having summarized the empirical patterns regarding the variance decomposition of investment growth, in this section we explore whether these patterns can be understood in a simple model.

4.1 Production and Capital Accumulation

Assume that there is a single good in the economy. Earnings can be used for consumption or for investment, which increases the stock of capital next period. Assume that earnings (Y_{t+1}), productivity (Z_{t+1}), and the capital stock (K_{t+1}) are related through a Cobb-Douglas production function:⁸

⁸One can also understand this production function as having fixed unit labor. We express the production function in terms of earnings and not output, but since we later on work with logs and abstracting from constants, this is irrelevant. In a Cobb-Douglas framework, earnings (output minus wage) are simply a constant fraction of output.

$$Y_{t+1} = Z_{t+1}K_{t+1}^\alpha. \quad (20)$$

The parameter α captures the degree of decreasing returns. If $\alpha = 1$ the model exhibits constant returns to scale. We assume the existence of adjustment costs in the process of capital accumulation. Following Abel (2003) we propose a characterization of adjustment costs that fits easily into a log-linear framework. In particular, the stock of capital next period is given by:

$$K_{t+1} = (I_t^\nu I_{t-1}^{1-\nu})^\phi K_t^{1-\phi}. \quad (21)$$

Where $0 \leq \nu \leq 1$ and $0 \leq \phi \leq 1$. Our parameterization of adjustment costs implies that there are standard capital adjustment costs (as in Abel (1979) and Hayashi (1982)), and simultaneously investment adjustment costs (as in Christiano, Eichenbaum, and Evans (2005)). This equation also encompasses the loss of capital due to depreciation. If $\phi = 0$ we are in a Lucas' tree model with constant capital stock and no depreciation. If $\phi = 1$ (and $\nu = 1$) we are in the neoclassical model with full depreciation.

To see more clearly how the different adjustment costs enter the model, define Q_t as the price of a unit of installed capital in terms of consumption foregone today (see Abel (2003)):

$$Q_t = \left(\frac{dK_{t+1}}{dI_t} \right)^{-1} = \frac{1}{\nu\phi} \left(\frac{I_t}{K_t} \right)^{1-\phi} \left(\frac{I_t}{I_{t-1}} \right)^{\phi(1-\nu)}. \quad (22)$$

Installed capital becomes more expensive as the investment-to-capital ratio increases, which is a standard result in the q -theory. In this model, capital also becomes more expensive when current investment increases relative to past investment.

Investment in this model is proportional to the market value of the capital stock, $Q_t K_{t+1}$, which is equal to:

$$Q_t K_{t+1} = \frac{1}{\nu\phi} I_t \quad (23)$$

In other words, the market value of the capital stock should be a sufficient statistic for investment. This simple model gives the usual prediction that if we account for the price of installed

capital relative to its replacement cost (i.e., Q_t), earnings should have no additional predictive value for investment-to-capital ratios.

4.2 Equilibrium Condition

In order to link investment to primitive parameters we close the model with an equilibrium condition derived from the optimal behavior of a representative equityholder who holds the capital stock in the economy. The standard equilibrium condition used in consumption-based asset pricing is derived from the consumer's first order condition, i.e., $1 = E_t[M_{t+1}R_{t+1}]$, where M_{t+1} is the stochastic discount factor (SDF) and R_{t+1} is the return on any given asset. This equilibrium condition applied to the capital stock of the economy implies that:

$$\begin{aligned} 1 &= E_t \left[M_{t+1} \left(\frac{Y_{t+1} - I_{t+1} + Q_{t+1}K_{t+2}}{Q_t K_{t+1}} \right) \right] \\ &= E_t \left[M_{t+1} \left(\frac{Y_{t+1} - I_{t+1} + \frac{1}{\nu\phi} I_{t+1}}{\frac{1}{\nu\phi} I_t} \right) \right]. \end{aligned} \quad (24)$$

Intuitively, the return on capital has a cash flow piece, which corresponds to consumption ($Y_{t+1} - I_{t+1}$), and a capital gain piece. Since market values are proportional to investment, capital gains can be expressed in terms of investment growth.

4.3 Log-linear Model

We now make functional assumptions and take approximations in order to match the log-linear framework we developed in the first part of the paper. First, we log-linearize the return on capital, which abstracting from constants is equal to:⁹

$$\begin{aligned} r_{t+1} &= \log \left(\frac{Y_{t+1} - I_{t+1} + \frac{1}{\nu\phi} I_{t+1}}{\frac{1}{\nu\phi} I_t} \right) \\ &\approx (1 - \rho_r)(y_{t+1} - i_{t+1}) + \Delta i_{t+1}. \end{aligned} \quad (25)$$

⁹The log-linearization parameter is $\rho_r = \frac{1-\nu\phi}{(1-\nu\phi)+\nu\phi \exp\{E[y_t - i_t]\}}$.

Log productivity shocks (z_{t+1}) are assumed to be exogenous and follow a simple AR(1) process:

$$z_{t+1} = \phi_z z_t + \varepsilon_{z,t+1}, \quad (26)$$

where $\varepsilon_{z,t+1}$ is a standard normal shock, with mean zero and standard deviation σ_z . Subtracting z_t from both sides of (26) and taking expectations:

$$\begin{aligned} E_t[\Delta z_{t+1}] &= E_t[(\phi_z - 1)z_t + \varepsilon_{z,t+1}] \\ &= (\phi_z - 1)(\phi_z z_{t-1} + \varepsilon_{z,t}). \end{aligned} \quad (27)$$

When ϕ_z is between zero and one, a positive productivity shock ($\varepsilon_{z,t}$) today leads to lower expected productivity growth ($E_t[\Delta z_{t+1}]$) for tomorrow.

The log version of the intertemporal equilibrium condition is $1 = E_t[\exp(m_{t+1} + r_{t+1})]$, hence we need to define the log stochastic discount factor. The functional form that we assume is:

$$m_{t+1} = -r_f - \frac{1}{2}x_t^2\sigma_z^2 - x_t\varepsilon_{z,t+1}. \quad (28)$$

This specification of the SDF follows Jermann (1998) and Lettau (2003) in the sense that only productivity shocks are priced in this production economy. The shock x_{t+1} works as a taste shifter that captures changes in investor preferences (i.e., risk aversion). We also assume it follows an AR(1) process:

$$x_{t+1} = \phi_x x_t + \varepsilon_{x,t+1}, \quad (29)$$

where $\varepsilon_{x,t+1}$ is a standard normal shock, with mean zero and standard deviation σ_x . The correlation between the two shocks is ρ_{xz} .

4.4 Model Solution

Using the equilibrium condition and the other assumptions one can show that (log) investment is of the following form:

$$i_t = B + B_z z_t + B_x x_t + B_k k_t + B_i i_{t-1}. \quad (30)$$

We expect to find that investment responds positively to productivity ($B_z > 0$) since investment is procyclical in the data. On the other hand, we expect investment to respond negatively to a higher price of risk ($B_x < 0$). Finally, a higher capital stock and higher past investment imply that adjustment costs are proportionally lower, leading to higher investment ($B_k > 0$ and $B_i > 0$).¹⁰ The equations that define the relevant parameters are given in the appendix.

We can now express the items in the variance decomposition as functions of the primitive parameters and shocks in this economy. Shocks to earnings, investment, and returns are all driven by shocks to productivity and the price of risk. Unexpected investment can be decomposed as follows:

$$\Delta i_{t+1} - E_t \Delta i_{t+1} = B_z \varepsilon_{z,t+1} + B_x \varepsilon_{x,t+1} \quad (31)$$

$$C_{r,t+1} = \frac{1}{\theta - 1} \{[(1 - \rho_r) + \rho_r B_z] \varepsilon_{z,t+1} + \rho_r B_x \varepsilon_{x,t+1}\}, \quad (32)$$

$$C_{y,t+1} = \frac{\theta}{\theta - 1} \varepsilon_{z,t+1}, \quad (33)$$

$$N_{cf,t+1} = \left\{ \frac{\theta}{\theta - 1} \left[\frac{\rho(\phi_z - 1)}{1 - \rho\phi_z} + \alpha\lambda\kappa_z \right] - (\kappa_z - B_z) \right\} \varepsilon_{z,t+1} \\ + \left\{ \frac{\theta}{\theta - 1} \alpha\lambda\kappa_x - (\kappa_x - B_x) \right\} \varepsilon_{x,t+1}, \quad (34)$$

$$N_{r,t+1} = -(B_z \varepsilon_{z,t+1} + B_x \varepsilon_{x,t+1} + C_{r,t+1} - C_{y,t+1} - N_{cf,t+1}), \quad (35)$$

where $\lambda = \rho\phi[\nu + \rho(1 - \nu)]/[1 - \rho(1 - \phi)]$, $\kappa_z = \frac{1}{1 - \lambda B_k - \rho B_i} \frac{1 - \rho}{1 - \rho\phi_z} B_z$, and $\kappa_x = \frac{1}{1 - \lambda B_k - \rho B_i} \frac{1 - \rho}{1 - \rho\phi_x} B_x$.¹¹

A couple of conclusions can be quickly drawn. First, the shock to current earnings $C_{y,t+1}$ in

¹⁰We also expect to find $B_k < 1$ since the unit price of capital (q_t) should be decreasing in the stock of capital from the assumption of diminishing returns (Romer 1996).

¹¹We define discount rate news in (35) as the residual from the budget constraint to ensure that the variance decomposition holds. There is an alternative way to define discount rate news directly from the definition of returns. However, the partial equilibrium nature of the model, given that the SDF is defined exogenously, does not enforce the aggregate budget constraint on which our decomposition is based.

equation (33) is basically the shock to productivity. On the other hand, unexpected investment growth in equation (31) is a response to both the shock to productivity and the shock to the price-of-risk. As conjectured by Lamont (2000), earnings shocks and investment shocks can be positively correlated as long as the shock to the price-of-risk does not offset the effect of productivity shocks.

Second, from (31) and (32) it is easy to see that unexpected returns behave essentially like unexpected investment growth, particularly since $\rho_r \approx 1$ (see also Cochrane (1991)). Intuitively, unexpected investment responds to the same shocks that affect market values, therefore they must be highly correlated. It follows immediately that whatever correlation there is between earnings surprises and investment surprises, the model predicts a similar correlation between earnings surprises and return surprises. If surprises to investment and earnings are highly correlated, then it has to be the case that surprises to earnings and returns are highly correlated as well in the model.

4.5 Calibration

We calibrate most parameters by taking standard values in the literature. The share of capital α is set at 0.30 in the baseline case although we also show results for the case of constant returns to scale ($\alpha = 1$). For the adjustment cost function we set $\phi = 0.10$ and $\nu = 0.75$ as the baseline numbers. We get $\rho_r = 0.93$ using these numbers and an average earnings-investment ratio ($E[Y_t/I_t] \simeq \exp(E[y_t - i_t])$) of 1.377 from our quarterly data.

Following Lettau and Wachter (2007) we set $\sigma_x = 0.12$ and $\phi_x = 0.95$ in order to match the autocorrelation of the dividend yield. The persistence of productivity is $\phi_z = 0.99$. As is standard in the macro literature, productivity is close to a random walk (see, for example, Campbell (1994) and Lettau (2003)). This implies that productivity shocks are highly persistent instead of transitory noise. In the benchmark case productivity shocks and shocks to the price of risk are assumed to be perfectly and negatively correlated ($\rho_{xz} = -1$) as in Campbell and Cochrane (1999). We calibrate the volatility of productivity shocks from the volatility of cash flows, which are equivalent in this model. We set $\sigma_z = 0.134$ from the volatility of asset cash flow growth in the benchmark quarterly sample.¹²

¹²This number is quite high when compared to typical assumptions for the standard deviation of technology shocks

Table 11 shows the variance decomposition for various parameter choices of adjustment costs, and the volatility and correlation of shocks. The left-hand side panel shows results for the case with $\alpha = 0.3$. The level of investment is higher than the one seen in the data, except when ϕ is low (i.e., when capital adjustment costs are severe). For instance, when $\phi = 0.01$ the variance of investment is 0.0069 which is roughly the same as in the Flow of Funds sample. Capital adjustment costs have a larger impact on the level of investment volatility than investment adjustment costs (i.e., variation in ν). Across the different cases with $\alpha = 0.3$ the covariance between shocks to earnings and investment growth is about twice the variance of investment growth, and it corresponds to the largest element in the variance decomposition. Therefore, the model is capable of matching this key feature of the data.

The cases reported with $\alpha = 0.3$ also match the negative covariance between investment surprises and long-run cash flow news seen in the data, although the magnitudes are smaller than in the data. This contrasts sharply with the case of constant returns to scale ($\alpha = 1$) where the covariance of investment surprises and long-run cash flow news is positive and, in most cases, the largest element in the variance decomposition.

To better understand the intuition behind these comovements, we examine the impulse responses to a positive productivity shock in our simple model. Figure 4 plots the contemporaneous response in investment (i), output (y), and returns (r). Figure 5 plots the future dynamics of capital (k), investment (i), investment growth (Δi), output growth (Δy), and returns (r) from year 2 to year 500. In both figures, the first row corresponds to the case where $\alpha = 1$ and $\nu = 1$; the second row corresponds to the case where $\alpha = 0.3$ and $\nu = 1$; and the third row corresponds to the case where $\alpha = 0.3$ and $\nu = 0.5$.

For constant return to scale ($\alpha = 1$), the positive productivity shock pushes up investment, output, and returns contemporaneously (see the first row in Figure 4). Beyond the current year, the good shock slowly decays into the future according to equation (27), so both capital and investment keep increasing but at a declining rate. As a result, future investment growth and output growth converge to zero from above (see the first row in Figure 5). This implies that future

in the macro literature (see, for example, King and Rebelo (1999)).

cash-flow news is positive. In this case, the covariance between current investment growth and future cash-flow news is positive ($Cov(\Delta i, N_{cf}) > 0$).

With decreasing returns to scale ($\alpha = 0.3$), the impact of the positive productivity shock on current investment and output is smaller (see second row in Figure 4). The impact on future capital and investment is also less pronounced. In fact, the optimal level of capital peaks very soon and then starts declining. As a result, investment growth and output growth are both negative in the long run and future cash-flow news is negative (see second row in Figure 5). In this case, the covariance between current investment growth and future cash-flow news is negative ($Cov(\Delta i, N_{cf}) < 0$). Finally, the third row in Figures 4 and 5 suggest that introducing investment adjustment cost ($\nu < 1$) into our model has little impact on these dynamics.

The second largest element in the decomposition in the case of $\alpha = 0.3$ is the positive covariance between investment growth and returns. This result is almost hard-wired into our model. Unfortunately, it is strongly counterfactual as we saw in the data. The third largest element is the covariance of investment with discount rate news. Discount rate news is strongly and negatively correlated with investment in most cases. In other words, positive updates to future discount rates typically lead to lower current investment in the model. When $\alpha = 1$ the covariance of investment surprises and return surprises is also negative and large. The covariance with discount rate news is mostly positive, which fits the data. However, there are other counterfactual results when $\alpha = 1$. First, the covariance of investment and earnings surprises is much reduced and it even turns negative in some cases. Second, investment is much more volatile in the case of constant returns to scale.

Overall, the model with decreasing returns to scale fits the data better. First, the level of investment volatility is closer to the one observed in the data. Second, the model is able to reproduce the large covariance of investment and earnings surprises. It seems as if the importance of earnings surprises in the case of decreasing returns is substituted for an increased importance of long-run news in the case of constant returns to scale. Finally, when there are constant returns to scale and under several parameter combinations, investment surprises and earnings surprises are negatively correlated, which is highly counterfactual.

The main challenge to this simple model lies in the behavior of returns in connection to investment growth. In the model the correlation between investment and return surprises is positive and high irrespective of the degree of returns to scale or other parameter choices. From an asset pricing perspective, and given that investment growth and returns are basically the same in this model, one can imply that return surprises are highly correlated with current cash-flow surprises and that discount rate news are relatively unimportant for returns. This is in contrast with many asset pricing results (for instance, Campbell (1991) and Cochrane (2008), although see Chen and Zhao (2009) for a dissenting view).

The model also illustrates that one can match the cash flow side of the variance decomposition without matching the return side. However, and precisely for this reason, the model is only a partial answer to what moves investment. Looking at the entire variance decomposition imposes discipline on the precise mechanism one can argue to be working behind the observed dynamics of investment.

5 Conclusions

Starting from the intertemporal budget constraint of the firm, we show that unexpected investment growth can be decomposed into four elements: unexpected current cash flow growth, unexpected current returns, revisions to expectations of future cash flow growth, and revisions to expectations of future discount rates.

We find that aggregate investment variation is predominantly related to current cash flow shocks. The terms related to current and future returns play only a secondary role for investment movements. In a simple forward-looking model we are able to explain the high correlation between investment and cash flow surprises, although at the cost of producing a counterfactually high comovement of investment and return surprises.

A Flow of fund identity: firm level vs. aggregate level

The sources of funds must be equal to uses of funds for each individual firm, which leads to the following two equations (see equation (2) and (3) in Gatchev, Pulvino, and Tarhan (2010)):

$$CF_t = \Delta Cash_t + RP_t + DIV_t + INV_t + ACQUIS_t - \Delta LTD_t - \Delta STD_t - EQUISS_t - ASALES_t,$$

$$CF_t = EBITDA_t - INTEXP_t - TAX_t - \Delta NWC_t,$$

where CF denotes internally available cash flow for investment and financing; $\Delta Cash$ denotes change in cash balance; RP denotes shares repurchase; DIV denotes dividends; INV denotes investment; $ACQUIS$ denotes acquisitions; ΔLTD denotes changes in long-term debt; ΔSTD denotes changes in short-term debt; $EQUISS$ denotes equity issuance; $ASALES$ denotes asset sales; $EBITDA$ denotes earnings before interest, taxes, and depreciation; $INTEXP$ denotes interest expenses; TAX denotes cash taxes; ΔNWC denotes change in net working capital.

Combining the above two equations and aggregating across all firms (public and private) in the economy, we have:

$$EBITDA_t - INTEXP_t - TAX_t - \Delta NWC_t - \Delta Cash_t + EQUISS_t - RP_t = DIV_t + INV_t - \Delta LTD_t - \Delta STD_t.$$

Note $ASALES_t$ and $ACQUIS_t$ do not appear since they cancel out each other in aggregate. To map to our aggregate flow of fund identity (equation (2)), we define:

$$EARN_t = EBITDA_t - INTEXP_t - TAX_t,$$

$$CFADJ_t = -\Delta NWC_t - \Delta Cash_t,$$

$$NI_t^E = EQUISS_t - RP_t,$$

$$NI_t^D = \Delta LTD_t + \Delta STD_t$$

$$I_t = INV_t.$$

B Log-linear approximation

Assume that $y_t - e_t$ and $i_t - e_t$ are stationary. The parameters used in the log-linearization are:

$$\rho = \frac{1}{1 + \exp\{E[y_t - e_t]\} - \exp\{E[i_t - e_t]\}} \quad (36)$$

$$\theta = \frac{\exp\{E[y_t - e_t]\}}{\exp\{E[y_t - e_t]\} - \exp\{E[i_t - e_t]\}} \quad (37)$$

A first-order Taylor approximation of the log of both sides of equation (4) around $E[y_t - e_t]$ and $E[i_t - e_t]$ give equation (7) in the text.

Empirically, $E[y_t - e_t] > E[i_t - e_t]$ so that $\rho < 1$ and $\theta > 1$ are the relevant cases. In the literature on present-value relationships it is standard to set $\rho = 0.99$. For our application we also arrive to $\rho = 0.99$ by substituting the average cash flow-to-equity and investment-to-equity ratios observed in the sample period 1952:01-2010:03 (3.98% and 3.04% respectively) into equation (36). In order to obtain a consistent estimate of θ we note that the stationarity of returns, earnings growth, and investment growth imply that earnings, investment, and equity values are cointegrated. The parameter θ is part of the cointegrating vector between these variables. The ratio v_t is basically the cointegrating relationship. We run the DLS regression of Stock and Watson (1993) to estimate θ .

$$e_t = \alpha + \beta y_t + \gamma i_t + \sum_{j=-k}^k [\delta_j \Delta y_{t+j} + \lambda_j \Delta i_{t+j}] + \epsilon_t$$

Our analysis implies that $\beta = \theta$ and $\gamma = -(\theta - 1)$. In the sample period 1952:01-2010:03 and with $k = 4$ (i.e., one year), we obtain $\beta = 1.77$ and $\gamma = -0.90$ in the baseline case. The coefficient β is estimated with slightly higher precision since its standard error is 0.20, while the standard error of γ is 0.23. We set $\theta = 1.77$ for our analysis. Our results are virtually unchanged for similar values of θ .

In order to assess the accuracy of the loglinear approximation we compare investment growth with its log-linear equivalent, i.e., we compare both sides of the following equation that is derived

from equation (7) in the main text:

$$\Delta i_{t+1} = \frac{1}{\theta - 1} \underbrace{(v_t - r_{t+1} + \theta \Delta y_{t+1} - \rho v_{t+1})}_{\text{approximate investment growth}} \quad (38)$$

	Exact investment growth (1)	Approximate investment growth (2)	Approximation error (1)-(2)
Std. deviation	0.0846	0.0852	0.0045
Correlation with (1)	1.0000	0.9986	-0.0956

As reported in the above table, the correlation between investment growth and its approximate version is 0.99 in the main quarterly sample. The approximation error has a standard deviation of only 0.0045. The correlation between investment growth and the approximation error is -0.09 .

C Model solution

The coefficients on the investment equation are defined by:

$$0 = \rho_r \phi \nu B_k^2 + \rho_r B_k B_i + [(1 - \rho_r) \phi \nu \alpha - 1 + \rho_r (1 - \phi)] B_k + (1 - \rho_r)(1 - \phi) \alpha, \quad (39)$$

$$0 = \rho_r B_i^2 + \rho_r \phi \nu B_k B_i + [(1 - \rho_r) \phi \nu \alpha - 1] B_i + \rho_r \phi (1 - \nu) B_k + (1 - \rho_r)(1 - \nu) \phi \alpha, \quad (40)$$

$$B_z = \frac{(1 - \rho_r) \phi_z}{1 - (1 - \rho_r) \phi \nu \alpha - \rho_r \phi_z - \rho_r \phi \nu B_k - \rho_r B_i}, \quad (41)$$

$$B_x = -\frac{[(1 - \rho_r) + \rho_r B_z] \sigma_z^2}{1 - (1 - \rho_r) \phi \nu \alpha - \rho_r \phi_x - \rho_r \phi \nu B_k - \rho_r B_i + \rho_r \sigma_{xz}}. \quad (42)$$

Out of the roots for B_k that follow from equations (39) and (40) we pick the root that lies between zero and one.

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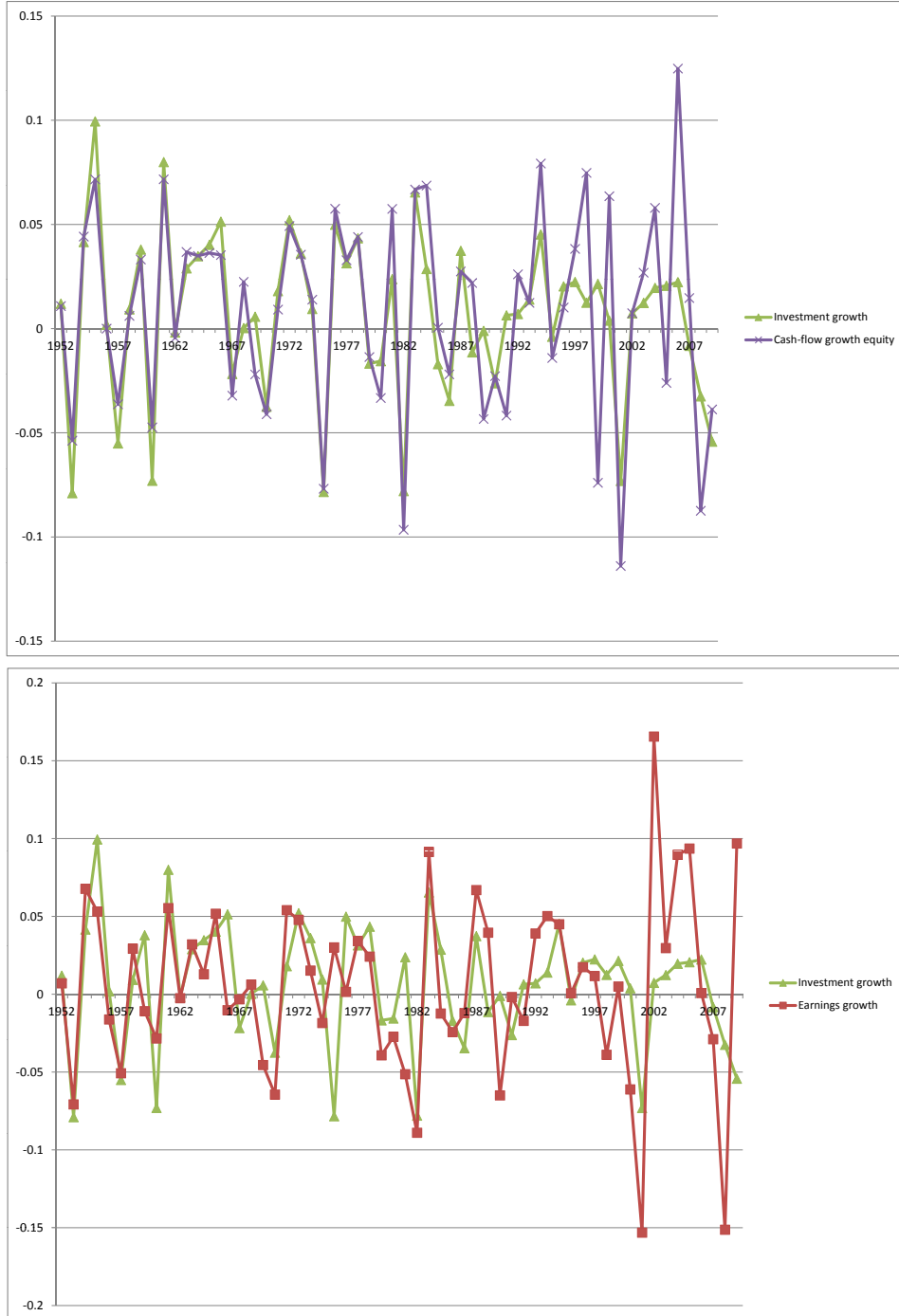


Figure 1. Cash Flow and Investment Growth We plot investment growth against equity cash flow growth (top) and earnings growth (bottom). Growth rates are computed as log differences. For visual clarity, we first compute the average across quarters in each year, and then plot the time series of annual averages. The annual time series cover the period from 1952 to 2010.

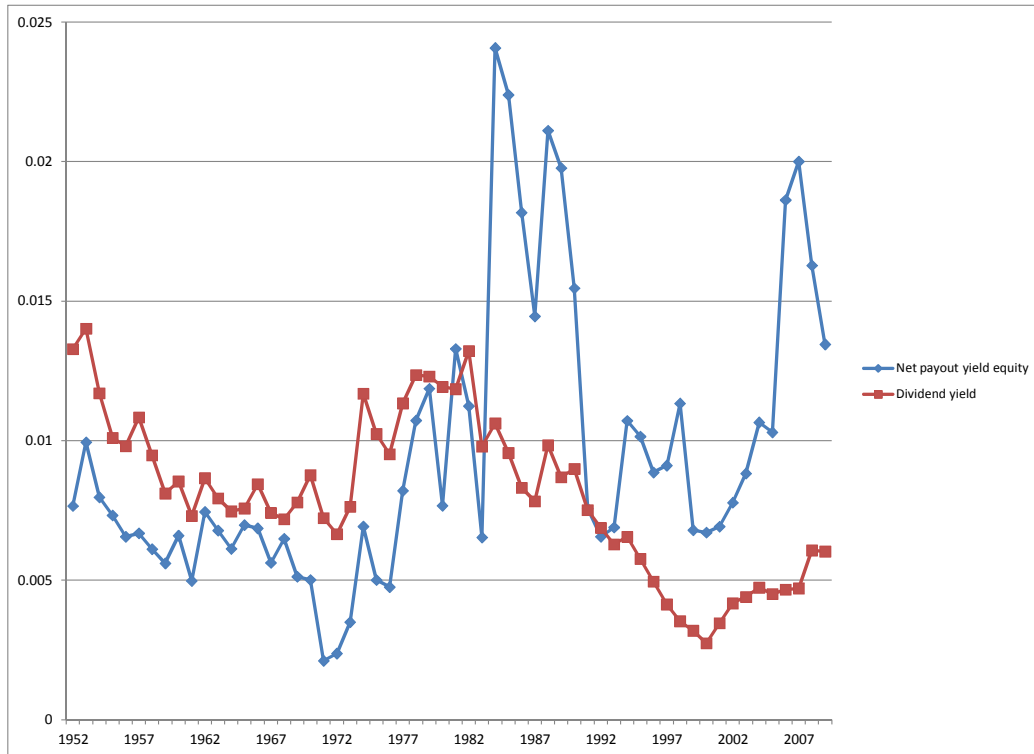


Figure 2. Net Payout Yield and Dividend Yield Quarterly net payout yield is constructed using data from the Flow of Funds for the Non-financial Non-farm Corporate Sector. Quarterly dividend yield is taken from CRSP. We first calculate the average number for each year and then plot the time series at annual frequency from 1952 to 2010.

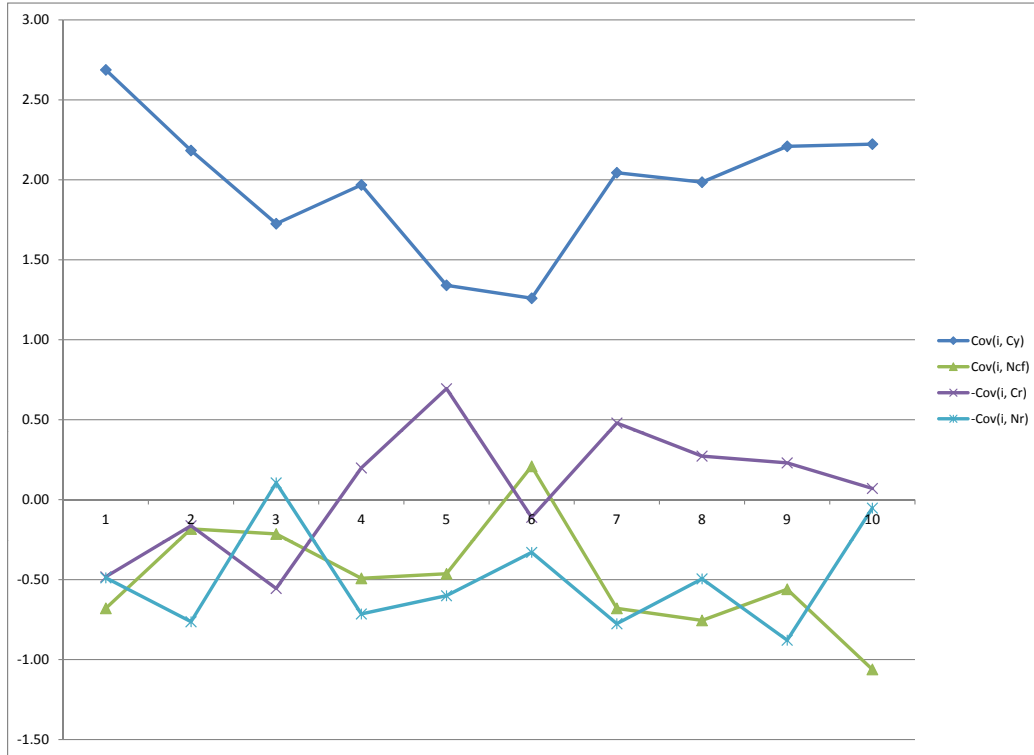


Figure 3. Variance Decomposition Across Industries We plot the four components of unexpected investment growth variance from the least (left) to the most (right) volatile industry. Annual data is obtained from COMPUSTAT-CRSP merged database. The sample covers the period 1972-2009 and excludes financial firms. We decompose the variance of unexpected investment growth rate into covariances with each of its five components: (1) Cy: current cash flow news, (2) Ncf: future cash flow news, (3) Cr: current return surprises, and (4) Nr: future discount rate news. We use the Fama-French ten industry classification. The log-linearization parameters are $\theta = 1.77$ and $\rho = 0.99$.

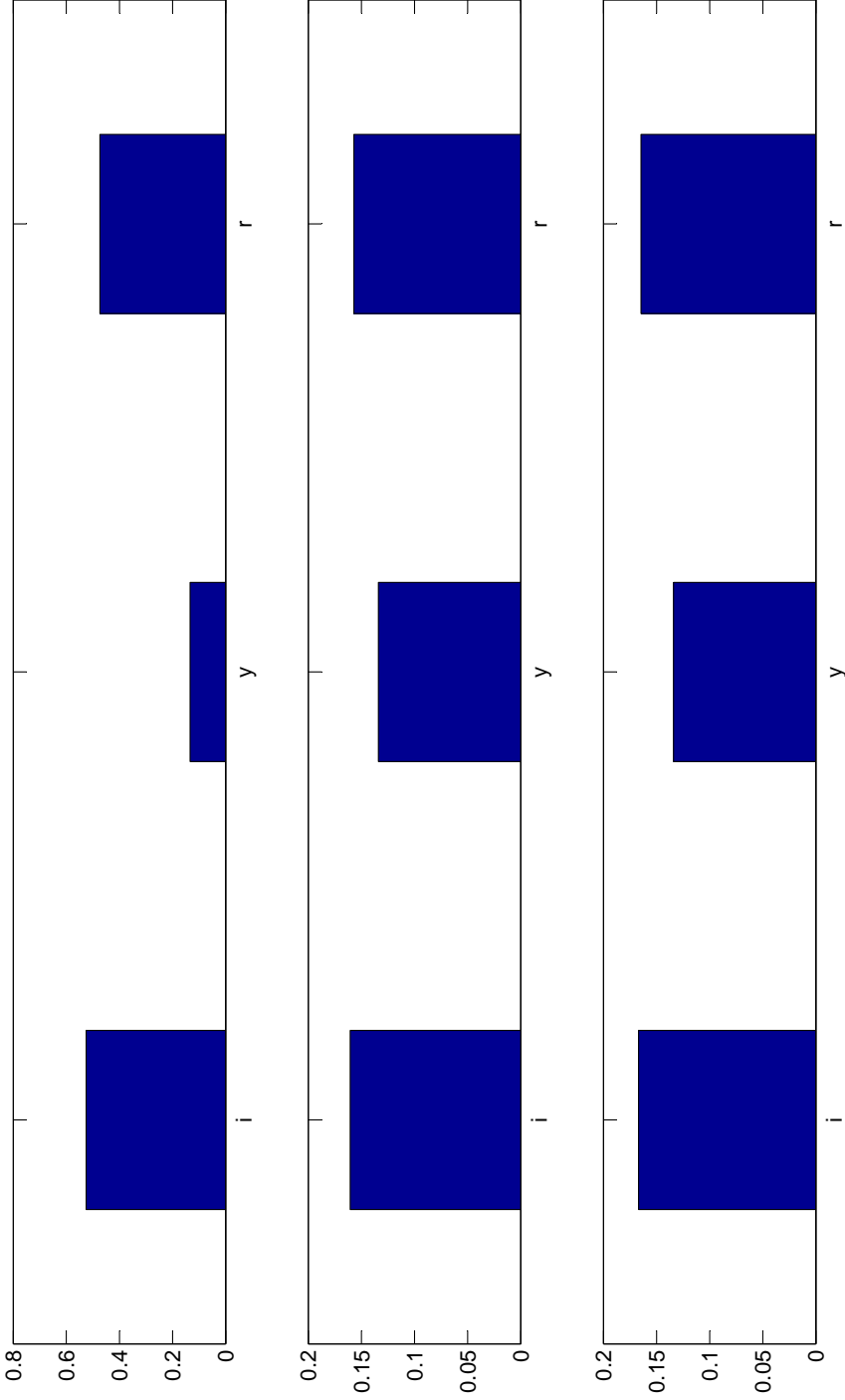


Figure 4. Contemporaneous Response to a Productivity Shock We introduce a positive productivity shock to our calibrated simple model for investment growth and examine the optimal response in investment (i), output (y), and return (r) contemporaneously. The first row corresponds to the case where $\alpha = 1$ and $\nu = 1$; the second row corresponds to the case where $\alpha = 0.3$ and $\nu = 1$; the third row corresponds to the case where $\alpha = 0.3$ and $\nu = 0.5$. All other calibration parameters are described in Section 4.5.

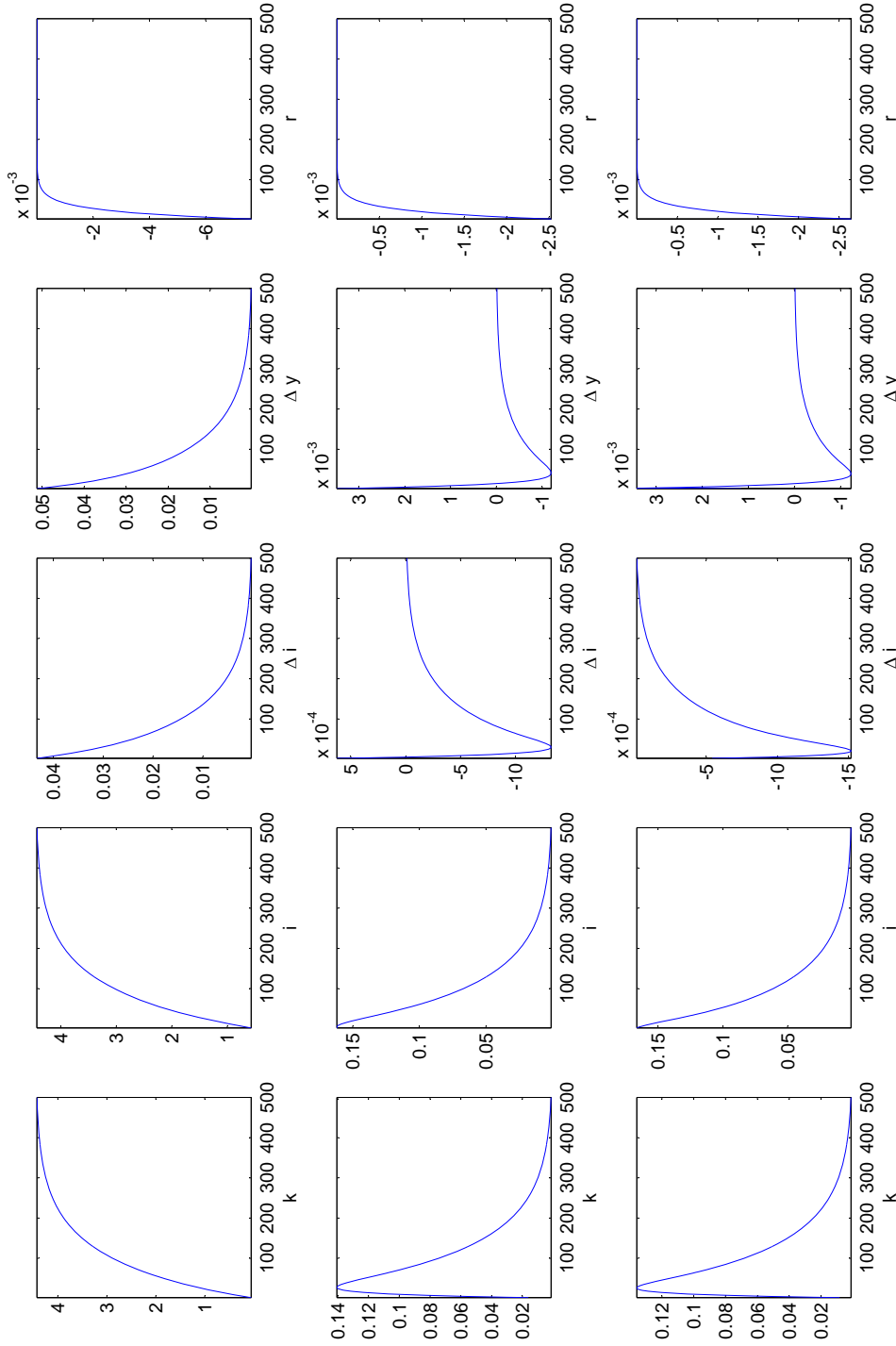


Figure 5. Future Responses to a Productivity Shock We introduce a positive productivity shock to our calibrated simple model for investment growth and examine the future responses in capital (k), investment (i), investment growth (Δi), output growth (Δy), and return (r) from year 2 to year 500. The first row corresponds to the case where $\alpha = 1$ and $\nu = 1$; the second row corresponds to the case where $\alpha = 0.3$ and $\nu = 1$; the third row corresponds to the case where $\alpha = 0.3$ and $\nu = 0.5$. All other calibration parameters are described in Section 4.5.

Table 1: Summary statistics

Quarterly data 1952:02-2010:03. All variables are expressed in real terms using the Consumer Price Index from the BLS. All data is taken from the Flow of Funds for the Non-financial Non-farm Corporate Sector, except for dividend growth and dividend yield which are taken from CRSP. Growth rates are computed as log differences and returns are in log form. The net payout yields and the dividend yield are in levels, not logs.

A) Summary Stats

	Obs	Mean	Std. Dev.	Min	Max	1st Autocorr
Investment growth	234	0.007	0.085	-0.422	0.204	-0.028
Returns equity	234	0.020	0.089	-0.313	0.214	0.074
Returns assets	234	0.015	0.048	-0.156	0.248	0.056
Cash flow growth equity	234	0.009	0.106	-0.365	0.347	-0.144
Cash flow growth assets	234	0.009	0.134	-0.496	0.373	-0.287
Earnings growth	234	0.006	0.091	-0.424	0.231	0.142
Dividend growth	231	0.010	0.118	-0.354	0.697	-0.591
Net payout yield equity	235	0.010	0.005	0.001	0.030	0.836
Net payout yield assets	235	0.005	0.002	0.000	0.012	0.717
Dividend yield	232	0.008	0.003	0.003	0.017	0.917

B) Correlation matrix

	Inv.	R. eq.	R. as	CF g. eq.	CF g. as.	Prof. g.	Div. g.	NP yield eq.	NP yield as.	Div. yield
Investment growth	1.00									
Returns equity	-0.04	1.00								
Returns assets	-0.07	0.95	1.00							
Cash flow growth equity	0.73	-0.08	-0.07	1.00						
Cash flow growth assets	0.68	-0.10	-0.09	0.88	1.00					
Earnings growth	0.47	-0.03	-0.02	0.38	0.41	1.00				
Dividend growth	0.03	0.11	0.16	0.14	0.04	0.01	1.00			
Net payout yield equity	-0.09	-0.07	-0.06	0.12	0.10	-0.15	0.06	1.00		
Net payout yield assets	0.05	-0.09	-0.08	0.23	0.30	-0.02	0.02	0.84	1.00	
Dividend yield	-0.09	-0.11	-0.08	-0.06	-0.06	-0.13	0.15	0.08	-0.06	1.00

Table 2: VAR Results

Quarterly data (1952:02-2010:03) are obtained from the Flow of Funds for the Non-financial Non-farm Corporate Sector. Annual data (1971-2009) are obtained from COMPUSTAT-CRSP merged database excluding financial firms. All variables are expressed in real terms using the Consumer Price Index from the BLS. Growth rates are computed as log differences and returns and the net payout yield are in log form. Newey-West t -statistics with 4 lags are reported in parenthesis below the coefficients. The log-linearization parameters are $\theta = 1.77$ and $\rho = 0.99$.

Lagged regressor	FLOW OF FUNDS QUARTERLY 1952-2010				COMPUSTAT ANNUAL 1971-2009			
	Dependent Variable				Dependent Variable			
	Return Equity	CF growth Equity	Investment growth	Net payout yield	Return Equity	CF growth Equity	Investment growth	Net payout yield
Full VAR:								
Return equity	0.090 (1.40)	0.048 (0.47)	0.130 (1.72)	-0.103 (-0.73)	0.038 (-0.26)	0.280 (-2.89)	0.270 (-2.76)	0.255 (-1.07)
Cash flow growth equity	-0.062 (-0.84)	-0.315 (-3.14)	0.070 (1.33)	-0.552 (-3.78)	0.844 (-1.90)	1.127 (-2.78)	0.962 (-2.89)	0.368 (-0.46)
Investment growth	-0.043 (-0.48)	0.349 (2.53)	-0.092 (-0.73)	0.737 (4.18)	-0.801 (-1.65)	-0.976 (-2.51)	-0.705 (-2.17)	-0.366 (-0.42)
Net payout yield equity	0.032 (2.17)	-0.069 (-3.61)	-0.053 (-3.61)	0.897 (30.41)	0.168 (-2.18)	-0.101 (-1.64)	-0.075 (-1.28)	0.738 (-6.07)
Obs	233	233	233	233	37	37	37	37
R-squared	3%	13%	8%	78%	15%	39%	34%	52%
Reduced VAR:								
Net payout yield equity	0.026 (1.72)	-0.085 (-4.56)	-0.056 (-3.99)	0.876 (29.14)	0.160 (-2.51)	-0.141 (-1.59)	-0.104 (-1.40)	0.695 (-5.46)
Obs	233	233	233	233	37	37	37	37
R-squared	1%	8%	6%	77%	10%	14%	9%	50%

Table 3: Variance Decomposition

We decompose the variance of unexpected investment growth rate (i) into covariances with each of its four components: (1) Cy: current cash flow surprises, (2) Ncf: future cash flow news, (3) Cr: current return surprises, and (4) Nr: future discount rate news. The log-linearization parameters are $\theta = 1.77$ and $\rho = 0.99$. In Panel A, quarterly data are obtained from the Flow of Funds for the Non-financial Non-farm Corporate Sector. The sample covers the period 1952:02-2010:03 except for the Kitchen-sink VAR where the sample ends in 2008. In Panel B, annual data are obtained from COMPUSTAT-CRSP merged database excluding financial firms. The sample covers the period 1972-2009.

Full VAR			Reduced VAR			Kitchen-sink VAR		
	Levels	frac. of Var(i)	Levels	frac. of Var(i)	Levels	frac. of Var(i)	Levels	frac. of Var(i)
Var(i)	0.0063	1.00	0.0068	1.00	0.0058	1.00		
Variance Decomposition:								
Cov(i, Cy)	0.0132	2.10	0.0136	2.02	0.0117	2.01		
Cov(i, Ncf)	-0.0050	-0.80	-0.0057	-0.84	-0.0055	-0.94		
-Cov(i, Cr)	0.0002	0.04	0.0001	0.02	0.0005	0.08		
-Cov(i, Nr)	-0.0022	-0.36	-0.0014	-0.21	-0.0009	-0.15		
Sum	0.0062	0.99	0.0067	0.99	0.0200	1.00		
Corr(i, Cy)	0.7405		0.7108		0.7367			
Corr(i, Cr)	-0.0268		-0.0156		-0.0591			
Corr(Cy, Cr)	-0.0592		-0.0477		-0.1189			
B) Annual Compustat data: 1972-2009								
Full VAR			Reduced VAR			Kitchen-sink VAR		
	Levels	frac. of Var(i)	Levels	frac. of Var(i)	Levels	frac. of Var(i)	Levels	frac. of Var(i)
Var(i)	0.011	1.00	0.016	1.00				
Variance Decomposition:								
Cov(i, Cy)	0.026	2.25	0.035	2.26				
Cov(i, Ncf)	-0.015	-1.29	-0.015	-0.93				
-Cov(i, Cr)	0.012	1.03	0.009	0.56				
-Cov(i, Nr)	-0.011	-0.96	-0.014	-0.88				
Sum	0.012	1.03	0.016	1.01				
Corr(i, Cy)	0.9075		0.9270					
Corr(i, Cr)	-0.4755		-0.3044					
Corr(Cy, Cr)	-0.4365		-0.2572					

Table 4: Variance Decomposition: Other Cases

The Flow of Funds data corresponds to the Non-financial Non-farm Corporate Sector. The quarterly sample covers the period 1952:02-2010:03. For Case II, we use investment, direct earnings growth, and equity returns. For Case III, we use investment, asset cash flow growth, and asset returns. For Case IV: we use investment, direct earnings growth, and asset returns. We decompose the variance of unexpected investment growth rate (i) into covariances with each of its four components: (1) Cy: current earnings surprises, (2) Ncf: future cash flow news, (3) Cr: current return surprises, and (4) Nr: future discount rate news. The log-linearization parameters are $\theta = 1.77$ and $\rho = 0.99$.

	Case II		Case III		Case IV	
	Levels	frac. of Var(i)	Levels	frac. of Var(i)	Levels	frac. of Var(i)
Var(i)	0.0060	1.00	0.0062	1.00	0.0059	1.00
Variance Decomposition:						
Cov(i, Cy)	0.0071	1.18	0.0143	2.32	0.0070	1.17
Cov(i, Ncf)	-0.0015	-0.25	-0.0080	-1.30	-0.0010	-0.17
-Cov(i, Cr)	0.0006	0.10	0.0004	0.06	0.0004	0.07
-Cov(i, Nr)	-0.0001	-0.02	-0.0004	-0.07	-0.0004	-0.07
Sum	0.0061	1.01	0.0062	1.01	0.0059	1.00
Corr(i, Cy)	0.4557		0.6810		0.4525	
Corr(i, Cr)	-0.0691		-0.0781		-0.0899	
Corr(Cy, Cr)	-0.0281		-0.0952		-0.0248	

Table 5: Variance Decomposition: Five terms

We decompose the variance of unexpected investment growth rate (i) into covariances with each of its five components: (1) earn: current direct earnings surprises, (2) adj: current surprises about cash flow adjustment, (3) Ncf: future cash flow news, (4) Cr: current return surprises, and (5) Nr: future discount rate news. The Flow of Funds data corresponds to the Non-financial Non-farm Corporate Sector. The quarterly sample covers the period 1952:02-2010:03. Annual data is obtained from COMPUSTAT-CRSP merged database. The sample covers the period 1972-2009 and excludes financial firms. The log-linearization parameters are $\theta = 1.77$ and $\rho = 0.99$.

	Flow of Funds (Full VAR) Quarterly 1952-2010		COMPUSTAT (Full VAR) Annual 1971-2009		COMPUSTAT (Reduced VAR) Annual 1971-2009	
	Levels	frac. of Var(i)	Levels	frac. of Var(i)	Levels	frac. of Var(i)
Var(i)	0.006	1.00	0.009	1.00	0.015	1.00
Variance Decomposition:						
Cov(i, earn)	0.006	1.09	0.028	3.16	0.042	2.85
Cov(i, adj)	0.005	0.94	-0.010	-1.08	-0.009	-0.61
Cov(i, Ncf)	-0.004	-0.71	-0.011	-1.28	-0.013	-0.89
-Cov(i, r)	0.000	0.06	0.011	1.20	0.008	0.55
-Cov(i, Nr)	-0.002	-0.38	-0.009	-1.00	-0.014	-0.92
Sum	0.006	0.99	0.009	1.00	0.015	1.00
Corr(i, earn)	0.425		0.390		0.427	
Corr(i, adj)	0.295		-0.133		-0.101	
Corr(i, r)	-0.039		-0.541		-0.290	
Corr(earn, r)	-0.011		0.185		0.252	
Corr(adj, r)	-0.056		-0.360		-0.376	

Table 7: Variance Decomposition: Other Portfolios

This table shows the variance decomposition results across portfolios sorted on book-to-market ratios (BM) and market capitalization (Size). Annual data is obtained from COMPUSTAT-CRSP merged database. The sample covers the period 1972-2009 and excludes financial firms. We decompose the variance of unexpected investment growth rate (i) into covariances with each of its five components: (1) $earn$: current direct earnings surprises, (2) adj : current surprises about cash flow adjustment, (3) Ncf : future cash flow news, (4) Cr : current return surprises, and (5) Nr : future discount rate news. The log-linearization parameters are $\theta = 1.77$ and $\rho = 0.99$.

BM	Low		Mid		High	
	Level	Frac	Level	Frac	Level	Frac
Var(i)	0.023	1.00	0.028	1.00	0.017	1.00
Cov(i, earn)	0.016	0.69	0.032	1.12	0.044	2.64
Cov(i, adj)	0.024	1.05	0.023	0.82	-0.011	-0.68
Cov(i,Ncf)	-0.013	-0.57	-0.029	-1.04	-0.004	-0.24
-Cov(i, r)	0.003	0.14	0.002	0.08	-0.010	-0.58
-Cov(i, Nr)	-0.007	-0.29	0.001	0.04	0.000	-0.02

Size	Low		Mid		High	
	Level	Frac	Level	Frac	Level	Frac
Var(i)	0.023	1.00	0.029	1.00	0.009	1.00
Cov(i, earn)	0.109	4.80	0.095	3.30	0.020	2.10
Cov(i, adj)	-0.046	-2.01	-0.030	-1.06	-0.002	-0.22
Cov(i,Ncf)	-0.022	-0.95	-0.029	-1.00	-0.010	-1.04
-Cov(i, r)	-0.005	-0.22	0.002	0.07	0.009	0.94
-Cov(i, Nr)	-0.015	-0.64	-0.009	-0.30	-0.007	-0.74

Table 8: Variance Decomposition: Individual Firms

We show results for two different VARs using firm level data. Annual data is obtained from COMPUSTAT-CRSP merged database. The sample covers the period 1972-2009 and excludes financial firms. We include firms with at least 18 years of data. The panel contains 1855 firms, each with an average of 27 years of data. In Panel A1, we run a panel VAR that includes all the cross-sectional and time-series variations. In Panel B1, we run the VAR for each firm, and then average coefficients and t -statistics across all firms for each variable. In Panel A2 and B2, we decompose the variance of unexpected investment growth rate (i) into covariances with each of its five components: (1) earn: current direct earnings surprises, (2) adj: current surprises about cash flow adjustment, (3) Ncf: future cash flow news, (4) Cr: current return surprises, and (5) Nr: future discount rate news. The log-linearization parameters are $\theta = 1.77$ and $\rho = 0.99$.

A1) Panel VAR

Lagged regressor	Dependent Variable				
	Return	Earnings growth	CF adj growth	Investment growth	Net payout yield
Return	-0.002 (-0.24)	0.449 (32.49)	-0.343 (-25.04)	0.289 (32.80)	-0.264 (-13.92)
Earnings growth	-0.002 (-0.34)	-0.321 (-29.75)	0.250 (24.36)	0.154 (21.16)	-0.530 (-32.32)
Adjustment growth	-0.009 (-1.66)	0.096 (10.09)	-0.220 (-23.40)	0.114 (17.57)	-0.605 (-38.48)
Investment growth	-0.022 (-3.92)	-0.087 (-8.53)	-0.070 (-6.36)	-0.434 (-51.08)	0.428 (26.29)
Net payout yield	0.014 (7.00)	-0.079 (-19.08)	-0.167 (-40.05)	-0.085 (-34.67)	0.427 (62.17)
Obs	49857	49857	49857	49857	49857
No. of Firms	1855	1855	1855	1855	1855
R-squared	1%	17%	27%	23%	13%

A2) Variance decomposition

	Levels	frac of Var(i)
Var(i)	0.305	1.00
Cov(i, earn)	0.316	1.03
Cov(i, adj)	0.043	0.14
Cov(i, Ncf)	0.005	0.02
-Cov(i, r)	-0.056	-0.18
-Cov(i, Nr)	0.004	0.01

B1) Firm-by-firm VAR

Lagged regressor	Dependent Variable				
	Return	Earnings growth	CF adj growth	Investment growth	Net payout yield
Return	0.007 (0.62)	0.449 (20.58)	-0.385 (-19.12)	0.259 (18.61)	-0.343 (-14.50)
Earnings growth	0.011 (0.90)	-0.311 (-10.99)	0.421 (13.94)	0.244 (14.22)	-0.174 (-6.92)
Adjustment growth	-0.041 (-3.86)	0.055 (2.54)	-0.044 (-2.05)	0.144 (9.42)	-0.218 (-10.25)
Investment growth	-0.015 (-1.09)	-0.059 (-1.85)	-0.165 (-5.18)	-0.396 (-23.53)	0.139 (5.54)
Net payout yield	0.042 (13.45)	-0.088 (-14.84)	-0.216 (-35.81)	-0.110 (-24.70)	0.274 (31.91)
Average No. of Periods	27	27	27	27	27
No. of Firms	1855	1855	1855	1855	1855
R-squared	22%	32%	41%	36%	27%

B2) Variance decomposition

	Levels	frac of Var(i)
Var(i)	0.251	1.00
Cov(i, earn)	0.279	1.09
Cov(i, adj)	0.016	0.02
Cov(i, Ncf)	0.007	0.10
-Cov(i, r)	-0.049	-0.19
-Cov(i, Nr)	0.002	0.01

Table 9: Predictive Power of Current Earnings Shocks

We regress long-run (accumulated) cash flow growth, investment growth, earnings growth, and returns on lagged earnings surprises (VAR residuals from VARs in Table 3). Cash flow growth is defined as $(\theta/(\theta-1))$ earnings growth-investment growth. Newey-west t -stats are reported. Sample period is 1952:02-2010:03 for flow of funds data and 1972 to 2009 for Compustat data.

<i>A) Flow of Funds data</i>						
Future Horizon (quarter)	1	2	3	4	8	12
Cash flow growth equity	-0.211 (-2.53)	-0.179 (-2.35)	-0.274 (-2.58)	-0.315 (-2.54)	-0.560 (-4.10)	-0.703 (-4.14)
Net cash flow growth equity	-0.530 (-2.64)	-0.440 (-2.62)	-0.653 (-2.77)	-0.638 (-2.63)	-1.153 (-4.55)	-1.379 (-4.39)
Earnings growth	-0.040 (-0.65)	-0.130 (-1.20)	-0.174 (-1.18)	-0.413 (-2.65)	-0.659 (-2.55)	-0.833 (-3.64)
Returns	-0.050 (-0.93)	-0.009 (-0.09)	-0.037 (-0.30)	0.045 (0.37)	0.201 (1.25)	0.272 (1.12)

<i>B) Compustat data</i>						
Future Horizon (year)	1	2	3	4	5	6
Cash flow growth equity	-0.345 (-1.63)	-0.299 (-0.96)	-0.182 (-0.60)	-0.607 (-2.15)	-0.618 (-1.60)	-0.940 (-4.14)
Net cash flow growth equity	-0.816 (-1.92)	-0.727 (-1.23)	-0.533 (-0.99)	-1.346 (-2.63)	-1.338 (-1.90)	-1.991 (-3.56)
Earnings growth	-0.245 (-0.50)	-0.342 (-0.48)	-0.272 (-0.24)	-1.832 (-2.66)	-1.943 (-2.48)	-1.687 (-2.26)
Returns	0.906 (4.96)	0.949 (2.95)	0.706 (1.29)	0.884 (1.88)	0.639 (1.71)	0.247 (0.40)

Table 10: Regressions of Future Unexpected Investment Growth

We regress the future unexpected investment growth (F.i) on the current Cr (current return surprise). Unexpected investment growth is measured at least one quarter, and up to 8 quarters, after Cr. In the right hand side panel, we also control for Cy (current earnings surprise) during the same quarter as unexpected investment growth. The quarterly sample covers the period 1952:02-2010:03. *t*-statistics are reported below the coefficients.

F.i	Cr	R2/AR2	Cr	F.Cy	R2/AR2
1	-0.011 (-0.24)	0.0% -0.4%	-0.004 (-0.12)	0.258 (16.40)	54.0% 53.6%
2	0.153 (3.44)	4.9% 4.5%	0.043 (1.35)	0.252 (15.76)	54.5% 54.1%
3	0.129 (2.86)	3.5% 3.0%	0.051 (1.64)	0.253 (16.01)	54.7% 54.3%
4	0.020 (0.43)	0.1% -0.4%	0.032 (1.03)	0.258 (16.37)	54.3% 53.9%
5	0.023 (0.51)	0.1% -0.3%	-0.008 (-0.24)	0.257 (16.27)	54.1% 53.7%
8	-0.007 (-0.16)	0.0% -0.4%	-0.009 (-0.28)	0.251 (15.95)	53.4% 53.0%

Table 11: Variance Decomposition: Model Implied

This table shows the variance decomposition results using the simple log-linear q -theory model for various parameter choices. The left hand side panel assumes decreasing returns to scale, and the right hand side panel assumes constant returns to scale. We decompose the variance of unexpected investment growth rate into covariances with each of its four components: (1) Cy: current earnings surprises, (2) Ncf: future cash flow news, (3) Cr: current return surprises, and (4) Nr: future discount rate news. The table also shows correlation coefficients between the different terms. All other calibration parameters are described in Section 4.5.

		$\alpha=0.3$				$\alpha=1$							
		ν		ϕ		ν		ϕ					
		0.25	0.75	1	0.01	0.05	0.1	0.25	0.75	1	0.01	0.05	0.1
Var(i)		0.0262	0.0268	0.0258	0.0069	0.0238	0.0279	0.0019	2.5746	0.2763	0.0414	2.4726	9.2238
		as % of investment variance											
Cov(i, Cy)		191%	180%	2%	370%	200%	185%	-702%	19%	59%	151%	-20%	-10%
Cov(i, Ncf)		-12%	-14%	-16%	-113%	-20%	-11%	1397%	563%	591%	35%	296%	361%
-Cov(i, Cr)		-129%	-128%	-127%	-130%	-130%	-128%	-112%	-118%	-117%	-130%	-125%	-121%
-Cov(i, Nr)		51%	53%	52%	-27%	50%	55%	-483%	-364%	-433%	43%	-51%	-130%
		correlations											
Corr(i, Cy)		1.00	1.00	1.00	1.00	1.00	1.00	-1.00	1.00	1.00	1.00	-1.00	-1.00
Corr(Cy, Cr)		1.00	1.00	1.00	1.00	1.00	1.00	-1.00	1.00	1.00	1.00	-1.00	-1.00
Corr(i, Cr)		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		level											
		ρ_{xz}		σ_x/σ_z		ρ_{xz}		σ_x/σ_z					
		-1	0	1	0.5	1	2	-1	0	1	0.5	1	2
Var(i)		0.0279	0.0203	0.0147	0.0237	0.0291	0.0464	9.2238	0.3507	0.0624	0.7038	88.167	0.2321
		as % of investment variance											
Cov(i, Cy)		185%	214%	254%	200%	181%	143%	-10%	-40%	-123%	-37%	-3%	64%
Cov(i, Ncf)		-11%	-27%	-50%	-20%	-9%	12%	361%	549%	1073%	528%	318%	-105%
-Cov(i, Cr)		-128%	-129%	-131%	-129%	-130%	-127%	-121%	-120%	-116%	-120%	-121%	-124%
-Cov(i, Nr)		55%	43%	27%	48%	57%	71%	-130%	-289%	-734%	-272%	-94%	265%
		correlations											
Corr(i, Cy)		1.00	0.99	1.00	1.00	1.00	1.00	-1.00	-0.77	-1.00	-1.00	-1.00	1.00
Corr(Cy, Cr)		1.00	0.99	1.00	1.00	1.00	1.00	-1.00	-0.76	-1.00	-1.00	-1.00	1.00
Corr(i, Cr)		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00