

What drives Q and investment fluctuations?

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Abstract

A dynamic present-value relation implies that variations in the ratio of the marginal profitability of capital to marginal Q are driven by shocks to the expected growth of the marginal profitability of capital or discount rate shocks, or both. We find that this ratio predicts future marginal profitability of capital growth at horizons of up to 20 years, but not investment returns. Thus, in contrast to stock prices, the primary source of fluctuations in marginal Q as well as of aggregate investment is expected profit growth shocks, whereas the role of discount rate shocks is negligible. The results indicate that managers' real investment decisions are strongly related to economic fundamentals.

Keywords: Asset pricing, Tobin's q , Present-value model, Investment returns, Long-horizon regressions, VAR implied predictability

JEL classification: G10; G12

1 Introduction

The neoclassical Q-theory of investment implies that under linearly homogenous technologies the marginal value of capital, termed marginal Q ([Tobin \(1969\)](#)), is a sufficient statistic to describe investment behavior ([Hayashi \(1982\)](#)). Marginal Q is the present value of all future marginal profitability entailed by installing an additional unit of capital. Thus, similar to stock prices, variations in marginal Q are driven by shocks to expected cash flows as well as by discount rate shocks.

In this paper we explore the sources of variation in marginal Q and aggregate investment. This is important for at least two reasons. First, aggregate investment is highly procyclical and one of the main drivers of the business cycle. Thus, uncovering its sources of variation will enhance our understanding of the business cycle.

Second, a large literature explores the sources of variation in stock prices (see [Campbell and Shiller \(1988\)](#), [Fama and French \(1988\)](#), [Cochrane \(2011\)](#)). While stock prices are determined by investors in the stock market, it is company managers who ultimately assess the marginal value of capital and base investment decisions on their assessment. Stock market investors are susceptible to the influence of investor sentiment and several other behavioral biases. Managers, however, may be less susceptible to these biases because they have more information about their firms.¹ Thus, fluctuations in marginal Q and investment could originate from different sources than stock prices. For example, the finding that discount rate shocks are the sole determinant of variation in the aggregate dividend yield ([Cochrane \(2008\)](#)) are consistent with time-variation of risk or risk aversion but also with waves of investor sentiment leading to mispricing of stocks. It might be, therefore, reassuring if the source of fluctuations in marginal Q and investment is different.

To identify marginal Q, we refrain from using observable measures of Q (such as the market-to-book ratio) that could be contaminated with measurement errors (see [Erickson](#)

¹For example, [Hribar and Quim \(2013\)](#) find that managers' trades are negatively related to investor sentiment, and especially so with stocks that are difficult to value.

and Whited (2000)). Instead, we employ the Euler equation from the firm’s optimization that equates the marginal value of capital to the marginal cost of investment. Assuming a (standard) functional form of the adjustment cost of investment (as in Liu, Whited, and Zhang (2009)) enables us to identify the marginal cost of investment and thereby the marginal value of capital, namely marginal Q. We note that the model-implied marginal Q is a function of investment. Our approach is therefore a supply approach to identifying Q, and is similar to that of Belo, Xue, and Zhang (2013) who use the supply side, that is, the firm’s optimization conditions, to identify Q.

We use generalized method of moments (GMM) to match the mean of levered investment returns to the mean of stock returns (as in Liu, Whited, and Zhang (2009)) and to match observed marginal Q in the data to model-implied marginal Q (as in Belo, Xue, and Zhang (2013)). We conduct the GMM estimation at the aggregate level for all firms on Compustat for both value-weighted and equal-weighted aggregate portfolios.²

We derive a dynamic present value relation, according to which fluctuations of the log ratio of the marginal profitability of capital to marginal Q (which we intermittently refer to as mq) emanate from shocks to the expected growth rate of the marginal profitability of capital, or discount rate shocks, that is, shocks to expected investment returns, or both. This present value relation is reminiscent of the Campbell and Shiller (1988), where mq plays the role of the log dividend-to-price ratio.

We estimate weighted long-horizon regressions (as in Cochrane (2008, 2011) and Maio and Santa-Clara (2015)) as well as conduct a variance decomposition for mq based on a first-order VAR (following Cochrane (2008)). We find that the ratio of the marginal profitability of capital to marginal Q is a strong predictor of the growth rate of the marginal profitability of capital at horizons between one year and twenty years. mq does not have any predictive power for investment returns though. Noticing that marginal Q is three times more volatile than marginal profit, much of the variation in mq stems from variations in the log marginal

²As a robustness check, we also estimate the parameters using decile portfolios sorted on Q.

Q. We conclude that the main source of fluctuations in both marginal Q and aggregate investment are shocks to expected growth of the marginal profitability of capital.

In the last part of the paper, we conduct a variance decomposition for the log Q (q) in terms of future log investment returns and the level of log marginal profits. The results indicate that the cash-flow channel plays a much more important role in driving the variation in q than in the case of mq . Nevertheless, the return channel continues to play an important role, especially in the case of the value-weighted index.

[Abel and Blanchard \(1986\)](#) calculate an approximation for the two components of marginal Q, namely expected returns and expected marginal profitability. They find that most of the variability in marginal Q is generated by variability in the cost of capital, whereas the marginal profit component of marginal Q is more closely related to aggregate investment. [Abel and Blanchard \(1986\)](#) argue that a possible explanation to their finding regarding a weak relation between aggregate investment and discount rates is that they have been less successful in constructing the cost of capital component of marginal Q than the marginal profitability component.

[Cochrane \(1991\)](#) finds that the aggregate investment to capital ratio predicts the future stock market return as well as future investment returns. Cochrane's result suggests that the cost of capital is a driver of investment, which seems to be somewhat at odds with the conclusion reached by [Abel and Blanchard \(1986\)](#). Our methodology does not require the construction of any approximation, although it does require parameter estimation. Thus, we provide an independent test of the drivers of marginal Q and investment. Our results regarding the link between expected marginal profitability shocks and investment are overall consistent with those of [Abel and Blanchard \(1986\)](#). Given that we take the supply approach to valuation (as in [Belo, Xue, and Zhang \(2013\)](#)), that is, we identify marginal Q using investment, our results are very different from those of [Abel and Blanchard \(1986\)](#) regarding the sources of fluctuations in marginal Q. That is, we find that shocks to the marginal profitability of capital are the sole drivers of variation in marginal Q.

Lettau and Ludvigson (2002) show theoretically and confirm empirically that predictive variables for excess stock returns over long horizons can also predict future investment growth. Chen, Da, and Larrain (2016) use accounting identities to decompose unexpected investment growth to surprises to current cash flow growth and stock returns, shocks to expected cash flow growth, and discount rate shocks. They use a VAR to extract unexpected components, and find that current cash flow shocks account for the bulk of unexpected aggregate investment growth. Chen, Da, and Larrain (2016) also find that discount rate shocks are unimportant for unexpected aggregate investment growth. They find a negative covariance between unexpected investment and expected cash flow shocks. This finding is very different from our finding that variations in aggregate investment predict positively the future marginal profitability of capital. Moreover, Chen, Da, and Larrain's (2016) result crucially depend on their VAR specification.

Our work also relates to the growing literature that studies stock return predictability by financial ratios in association with present-value relations. This literature emphasizes the benefits of analyzing jointly the predictability of future stock returns and cash flows by computing variance decompositions for the financial ratios. Most of the work is concentrated on the predictability from the dividend yield (e.g., Cochrane (1992, 2008, 2011), Lettau and Van Nieuwerburgh (2008), Chen (2009), Binsbergen and Koijen (2010), Engsted, Pedersen, and Tanggaard (2012), Asimakopoulos et al. (2014), Rangvid, Schmeling, and Schrimpf (2014), Maio and Santa-Clara (2015)). On the other hand, several studies compute variance decompositions for other financial ratios like the earnings yield, book-to-market ratio, or net payout yield (e.g., Cohen, Polk, and Vuolteenaho (2003), Larrain and Yogo (2008), Chen, Da, and Priestley (2012), Maio (2013)). Koijen and Van Nieuwerburgh (2011) provide a survey.

The rest of the paper is organized as follows. In section 2 we present a model of a firm's optimal investment decisions. Section 3 describes the data and the econometric methodology for estimating the production and adjustment costs parameters. We derive the present value

relation linking mq to future cash flows and discount rates in Section 4. Section 5 presents the benchmark empirical results when using weighted long horizon regressions, while Section 6 presents an alternative variance decomposition based on a first-order VAR. Finally, in Section 7 we estimate a variance decomposition for q . The paper concludes in Section 8.

2 Model

We follow [Liu, Whited, and Zhang \(2009\)](#) and derive a model of the firm with linearly homogenous production and adjustment cost technologies. The factors of production are capital, as well as costlessly adjustable inputs, such as labor. The firm is a price taker, and in each period chooses optimally the costlessly adjustable inputs to maximize operating profits, defined as revenues minus the cost of the costlessly adjustable inputs. Taking operating profits as given, the firm chooses optimal investment and debt to maximize the value of equity.

Let $\Pi(K_{it}, X_{it})$ denote the maximized operating profits of firm i at time t , where K is the stock of capital and X is a vector of aggregate and idiosyncratic shocks. The firm is assumed to have a Cobb-Douglas production function with constant returns to scale. The marginal product of capital is given by

$$\partial\Pi(K_{it}, X_{it})/\partial K_{it} = \alpha Y_{it}/K_{it}, \tag{1}$$

where $\alpha > 0$ is the share of capital in production and Y is sales.

The law of motion of capital is given by

$$K_{i,t+1} = (1 - \delta) K_{it} + I_{it}, \tag{2}$$

where I_{it} is investment and δ is the capital depreciation rate.³ Investment entails adjustment

³The assumption of a constant depreciation rate is necessary for the derivation of the present value relations in Section 4.

costs. As in [Liu, Whited, and Zhang \(2009\)](#) we assume standard quadratic functional form for the adjustment cost function:

$$\Phi(I_{it}, K_{it}) = a/2 (I_{it}/K_{it})^2 K_{it}, \quad (3)$$

where $a > 0$ is the adjustment cost parameter. Following [Hennessy and Whited \(2007\)](#) we assume only one period debt. Taxable profits equal operating profits minus capital depreciation minus interest expenses.

The firm's payout is given by

$$D_{it} = (1 - \tau_t) [\Pi(K_{it}, X_{it}) - \Phi(I_{it}, K_{it})] - I_{it} + B_{i,t+1} - R_{it}^B B_{it} + \tau_t \delta K_{it} + \tau_t (R_{it}^B - 1) B_{it}, \quad (4)$$

where τ_t is the corporate tax rate, B_{it} is bonds issued at time $t - 1$ and paid at the beginning of time t , and R_{it}^B is the gross corporate bond returns. $\tau_t \delta K_{it}$ represents the interest tax shield.

The firm maximizes its cum-dividend market value of equity

$$V_{it} = \max_{(I_{i,t+s}, K_{i,t+s+1}, B_{i,t+s+1})} E_t \left[\sum_{s=0}^{\infty} \widetilde{M}_{t+s} D_{i,t+s} \right], \quad (5)$$

where \widetilde{M}_{t+1} is the stochastic discount factor from t to $t + 1$ and which is correlated with the aggregate component of $X_{i,t+1}$, subject to a transversality condition:

$$\lim_{T \rightarrow \infty} E_t \left[\widetilde{M}_{t+\tau} B_{it+T+1} \right] = 0. \quad (6)$$

Proposition 1 in [Liu, Whited, and Zhang \(2009\)](#) states that firms' equity value maximization implies that

$$E_t \left[\widetilde{M}_{t+1} R_{i,t+1} \right] = 1, \quad (7)$$

in which the investment return is given by

$$R_{i,t+1} = \frac{(1 - \tau_{t+1}) \left[\alpha \frac{Y_{i,t+1}}{K_{i,t+1}} + \frac{a}{2} \left(\frac{I_{i,t+1}}{K_{i,t+1}} \right)^2 \right] + \tau_{t+1} \delta + (1 - \delta) \left[1 + (1 - \tau_{t+1}) a \left(\frac{I_{i,t+1}}{K_{i,t+1}} \right) \right]}{\left[1 + (1 - \tau_t) a \left(\frac{I_{i,t}}{K_{i,t}} \right) \right]}. \quad (8)$$

The marginal value of an additional unit of capital appears in the numerator, whereas the marginal cost of investment is in the denominator.

We define marginal profitability of capital, M , as follows:

$$M_{i,t+1} \equiv (1 - \tau_{t+1}) \left[\alpha \frac{Y_{i,t+1}}{K_{i,t+1}} + \frac{a}{2} \left(\frac{I_{i,t+1}}{K_{i,t+1}} \right)^2 \right] + \tau_{t+1} \delta. \quad (9)$$

Thus, the marginal profitability of capital is the sum of the after tax marginal product of capital and reduction in adjustment costs due to the existence of the extra unit of capital, plus the interest tax shield.⁴

Therefore, the investment return for firm i can be rewritten as

$$R_{i,t+1} = \frac{(1 - \delta)(1 + Q_{i,t+1}) + M_{i,t+1}}{1 + Q_{it}}, \quad (10)$$

where Q represents Tobin's marginal Q and M stands for marginal profits.⁵

3 Data and methodology

In this section, we estimate aggregate measures of the investment return and the respective components.

⁴The additional unit of capital reduces tax liabilities as it depreciates.

⁵Note that marginal Q is net of corporate tax.

3.1 Methodology

Since the investment return and its components are not directly observable, we use the approach conducted in [Liu, Whited, and Zhang \(2009\)](#) to estimate these variables. To estimate the aggregate capital share (α) and the adjustment cost parameter (a) we use GMM to fit both the investment Euler equation and the valuation equation moments. Because we estimate the parameters at the aggregate level using only the investment Euler equation, this leads to an unidentified estimation (we only have one moment but two parameters: the capital share and the adjustment cost parameter). With two moments and two parameters, the estimation is exactly identified and the two moments fit perfectly. We use the investment model specified in [Liu, Whited, and Zhang \(2009\)](#) with one adjustment, that is, we include the valuation moment in the estimation.⁶ Specifically, the first set of moment conditions correspond to testing whether the average unlevered investment return equals the weighted average of the stock return and the after-tax bond return,

$$e_i^r \equiv E_T[(w_{i,t}R_{i,t+1}^{Ba} + (1 - w_{i,t})R_{i,t+1}^S) - R_{i,t+1}] = 0, \quad (11)$$

where $R_{i,t+1}^{Ba} \equiv R_{i,t+1}^B - (R_{i,t+1}^B - 1)\tau_{t+1}$, $w_{it} \equiv \frac{B_{i,t+1}}{(P_{i,t} + B_{i,t+1})}$, and $E_T(\cdot)$ denotes the sample moment.

The second set of moment conditions tests whether the average Tobin's Q in the data equals the average Q predicted by the model:

$$e_i^q \equiv E_T \left[Q_{i,t} - \left(1 + (1 - \tau_t)a \left(\frac{I_{i,t}}{K_{i,t}} \right) \right) \frac{K_{i,t+1}}{A_{i,t}} \right] = 0. \quad (12)$$

We estimate the parameters, $\mathbf{b} \equiv (\alpha, a)$, by minimizing a weighted combination of the sample moments (3) and (5), denoted by \mathbf{g}_T . The GMM objective function is a weighted

⁶Similarly, [Belo, Xue, and Zhang \(2013\)](#) base their tests on both the investment Euler equation and the valuation equation. However, we assume that the adjustment cost function has a quadratic form in contrast to [Belo, Xue, and Zhang \(2013\)](#) who consider a smoother adjustment cost function. We motivate our choice with the evidence in [Cooper and Haltiwanger \(2006\)](#) who show that a model with quadratic adjustment costs at the plant-level fits well aggregate investment data.

sum of squares of the model errors, that is, $\mathbf{g}'_T \mathbf{W} \mathbf{g}_T$, in which we use $\mathbf{W} = \mathbf{I}$, the identity matrix. Let $\mathbf{D} = \frac{\partial \mathbf{g}_T}{\partial \mathbf{b}}$ and \mathbf{S} equal a consistent estimate of the variance-covariance matrix of the sample errors \mathbf{g}_T . We estimate \mathbf{S} using a standard Bartlett kernel with a window length of five. The estimate of \mathbf{b} , denoted $\hat{\mathbf{b}}$, is asymptotically normal with variance-covariance matrix given by

$$\text{var}(\hat{\mathbf{b}}) = \frac{1}{T} (\mathbf{D}' \mathbf{W} \mathbf{D})^{-1} \mathbf{D}' \mathbf{W} \mathbf{S} \mathbf{W} \mathbf{D} (\mathbf{D}' \mathbf{W} \mathbf{D})^{-1}. \quad (13)$$

To construct standard errors for the model errors, we use

$$\text{var}(\mathbf{g}_T) = \frac{1}{T} [\mathbf{I} - \mathbf{D} (\mathbf{D}' \mathbf{W} \mathbf{D})^{-1} \mathbf{D}' \mathbf{W}] \mathbf{S} [\mathbf{I} - \mathbf{D} (\mathbf{D}' \mathbf{W} \mathbf{D})^{-1} \mathbf{D}' \mathbf{W}], \quad (14)$$

which is the variance-covariance matrix for the model errors, \mathbf{g}_T .

As a robustness check, we estimate the aggregate capital share (α) and the adjustment cost parameter (a), using as testing portfolios deciles formed on Tobin's Q . We largely follow [Belo, Xue, and Zhang \(2013\)](#) and sort all stocks on Tobin's Q at the end of June of year t into deciles based on the NYSE breakpoints. We compute annual equal- and value-weighted portfolio returns from July of each year t to June of year $t + 1$. These portfolios are rebalanced at the end of each June.

3.2 Data

We construct annual levered investment returns to match with annual stock returns and annual valuation ratios to match with annual Tobin's q . Data are from the merged CRSP and COMPUSTAT industrial database. The sample is from 1961 to 2014.

We follow [Liu, Whited, and Zhang \(2009\)](#) and [Belo, Xue, and Zhang \(2013\)](#) in measuring the variables. We include all firms with fiscal year ending in the second half of the calendar year. We exclude firms with primary standard industrial classifications between 4900 and 4999 (utilities) and between 6000 and 6999 (financials). We also delete firm-year observations for which total assets, capital stock, debt, or sales are either zero or negative. Capital

stock, K_{it} , is net property, plant, and equipment (item PPENT). Investment, I_{it} , is capital expenditures (item CAPX) minus sales of property, plant, and equipment (item SPPE, if not available, we set it to zero). Tobin's q , Q_{it} , is market value of equity plus debt to total assets (item AT). Total debt, $B_{i,t+1}$, is long-term debt (item DLTT) plus short-term debt (item DLC) for the fiscal year ending in the calendar year $t - 1$. We follow [Cochrane \(1991\)](#) and assume a depreciation rate, δ , equal to 0.1.⁷ Output, Y_{it} , is sales (item SALE). Market leverage, w_{it} , is the ratio of total debt to the sum of total debt and the market value of equity. We aggregate firm-specific characteristics to aggregate- and portfolio-level characteristics as in [Fama and French \(1995\)](#). For example, Y_{it+1}/K_{it+1} is the sum of sales in year t of all the firms in our sample divided by the sum of capital stocks at the beginning of year $t + 1$ for the same set of firms. We proceed in a similar way for the aggregation of the remaining characteristics. The corporate tax rate is the statutory corporate income tax rate. We equal- and value-weight corporate bond returns and stock returns.

Firm-level corporate data are limited. Hence, we follow [Blume, Lim, and MacKinlay \(1998\)](#) to impute the credit ratings for the Compustat firms that have no such ratings. Specifically, we first estimate an ordered probit model that relates credit ratings to observed explanatory variables. To this end we use all the Compustat firms that have credit ratings data (item SPLTICRM). We use the fitted values produced by the probit ordered model to calculate the cutoff value for each credit rating. We compute the credit scores for all Compustat firms and next assign the corporate bond returns for a given credit rating from Ibbotson Associates to all firms with the same credit rating. The explanatory variables in the probit ordered model are: interest coverage, the ratio of operating income after depreciation (item OIADP) plus interest expense (item XINT) to interest expense; operating margin, the ratio of operating income before depreciation (item OIBDP) to sales (item SALE); long-term leverage, the ratio of long-term debt (item DLTT) to total assets (item AT); total leverage, the ratio of long-term debt plus debt in current liabilities (item DLC) plus short-

⁷In the data, the mean value of aggregate depreciation rate is equal to 0.1089.

term borrowing (item BAST) to total assets; the natural logarithm of the market value of equity (item PRCC-C times item CSHO) deflated to 1973 by the consumer price index; the market beta and residual volatility form the market regression. For each calendar year we estimate the beta and residual volatility for firms with at least 200 daily observations. To adjust for nonsynchronous trading we use the lead and lagged values of market return.

3.3 Structural parameter estimates

Table 1 reports the estimates of capital share (α) and adjustment costs (a) along with the corresponding standard errors. The estimates of the two parameters have small standard errors both in the benchmark estimation and the robustness estimation with the Tobin's Q deciles as testing portfolios. The size of the estimates of both parameters is not very different across the two estimations.

To interpret the magnitude of the adjustment costs, we follow [Belo, Xue, and Zhang \(2013\)](#) and report in Table 1 the fraction of lost sales due to adjustment costs $\frac{C}{Y}$, where $C(I_{it}, K_{it}) = \frac{a}{2} \left(\frac{I_{it}}{K_{it}}\right)^2 K_{it}$ is the adjustment cost function, $a > 0$ is the adjustment cost parameter, and Y is sales. To compute the fraction of sales lost, we aggregate the investment, capital, and sales across all the firms, compute the time series of the adjustment costs by plugging these aggregates in the adjustment cost specification, and report the average. The estimated magnitude of the adjustment costs is 10.49% and 13.88% of sales when using the aggregate and the portfolio-level estimate of the adjustment cost parameter. These estimates are in line with those reported in prior studies. For example, [Cooper and Priestley \(2016\)](#) find that implied adjustment costs represent 12.21% of sales across a host of manufacturing industries. [Bloom \(2009\)](#) surveys the estimates of convex adjustment costs to be between zero and 20% of revenue.

[Erickson and Whited \(2000\)](#) and [Liu, Whited, and Zhang \(2009\)](#) express the economic magnitude of the estimates of adjustment costs in terms of the elasticity of investment with respect to marginal Q . This elasticity is given by $\frac{1}{a}$ multiplied by the ratio of the average

Q to average $\frac{I_{it}}{K_{it}}$. The estimates of adjustment cost in Table 1 imply elasticities of 0.25 and 0.19 using the aggregate and portfolio estimates, respectively, suggesting that investment responds to Q inelastically. This inference is in line with the results in Erickson and Whited (2000) and Liu, Whited, and Zhang (2009).

Table 1 also reports two overall performance measures, the mean absolute error for both the investment Euler equation, $|e_i^R|$, and the valuation equation, $|e_i^Q|$, and the χ^2 test. We report these performance measures only for the Tobin's Q deciles. At the aggregate model, the estimation is exactly identified and the two moments fit perfectly. The model is not rejected by the χ^2 test with a high p -value of 96% for both equal- and value-weighted Tobin's Q deciles. Although the model is not rejected, the mean absolute errors represent roughly 50% of the average returns across the deciles and 40% of the average Q across the deciles.⁸ The magnitude of these errors is to be expected because we ask the model to fit both moments simultaneously. Liu, Whited, and Zhang (2009) also report larger mean absolute errors when they ask the model to match expected returns and variances simultaneously.

4 A present-value relation

In this section, we derive a dynamic present-value relation, which represents the basis for the main empirical results in the paper.

Our methodology relies on the definition of the aggregate realized gross investment return (R),

$$R_{t+1} = \frac{(1 - \delta)(1 + Q_{t+1}) + M_{t+1}}{1 + Q_t}, \quad (15)$$

where Q represents the aggregate Tobin's q and M stands for aggregate marginal profits. This definition is analogous to the usual definition of the gross stock return with $1 + Q$ playing the role of the stock price and M mimicking dividends.

⁸We have also considered the specification with non-quadratic adjustment costs. In terms of valuation equation errors, both specifications produce mean absolute errors of similar magnitude. However, in terms of investment return equation errors, the quadratic specification produces a mean absolute error half the size of that produced by the non-quadratic specification.

By conducting a log-linear transformation of the return equation in Eq. (15), and proceeding along the lines of Campbell and Shiller (1988), we derive the following difference equation in the log profits-to- q ratio,

$$mq_t = \text{const.} + \rho mq_{t+1} + r_{t+1} - \Delta m_{t+1}, \quad (16)$$

where $mq_t \equiv \ln(M_t) - \ln(1 + Q_t) = m_t - q_t$ is the log of the profits-to- Q ratio at time t ; $r_t \equiv \ln(R_t)$ represents the log investment return at time t ; and $\Delta m_{t+1} \equiv m_{t+1} - m_t$ denotes the log growth in marginal profits. In this setting, variables denoted with lower-case letters represent the logs of the corresponding variables in upper-case letters. ρ is a (log-linearization) discount coefficient that depends on the mean of mq_t (\overline{mq}):

$$\rho \equiv \frac{e^{\ln(1-\delta) - \overline{mq}}}{1 + e^{\ln(1-\delta) - \overline{mq}}}. \quad (17)$$

By iterating this equation forward and assuming no-bubbles, we obtain the following present-value dynamic relation for mq at each forecasting horizon K :

$$mq_t = \text{const.} + \sum_{j=1}^K \rho^{j-1} r_{t+j} - \sum_{j=1}^K \rho^{j-1} \Delta m_{t+j} + \rho^K mq_{t+K}. \quad (18)$$

Under this present-value relation, the current log profits-to- Q ratio is positively correlated with both future multi-period log investment returns (r_{t+j}) and the future profitability ratio at time $t + K$, and negatively correlated with future multi-period log growth in marginal profits (Δm_{t+j}). This dynamic relation is similar to the present-value relation for the log dividend yield developed in Campbell and Shiller (1988): the log profits-to- Q ratio plays the role of the log dividend-to-price ratio, the log growth in marginal profits is the analogous of log dividend growth, and the investment return plays the role of the stock return.

At an infinite horizon, by assuming the following terminal condition,

$$\lim_{K \rightarrow \infty} \rho^K m_{t+K} = 0, \quad (19)$$

we obtain the following present-value relation:

$$m_{q_t} = \text{const.} + \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} - \sum_{j=1}^{\infty} \rho^{j-1} \Delta m_{t+j}. \quad (20)$$

Hence, at very long horizons, only predictability of future investment returns and profits growth drives the variation in the current log profits-to- Q ratio.⁹

Table 2 presents the descriptive statistics for the variables of the present value relation we derive when portfolios are value-weighted. The average estimated annual investment return is 8%, which is similar to the average investment returns of the manufacturing industries reported in Cooper and Priestley (2016). The standard deviation of 7% is considerably lower than the cross-sectional volatility of the 459 manufacturing industries studied in Cooper and Priestley (2016). The first-order autocorrelation is 0.15, rather large relative to stock returns. The log growth rate of marginal profits, Δm , has a mean around 0%, a rather high volatility with a standard deviation of approximately 10%, and a first-order autocorrelation of 0.22. The log of the marginal profit of capital to marginal Q ratio has a negative mean (-1.72), reflecting the fact that marginal Q is on average larger than the marginal profitability of capital. We note that the first-order autocorrelation of m_q (0.90) indicates that this ratio is relatively persistent.

Panel B of Table 2 describes the correlations between the three variables. The correlation between Δm and r is very high, at 0.95. The reason is that shocks to profitability are also shocks to returns, as seen in the definition of the investment return (see equation 15). Investment returns and m_q are also positively correlated, with a correlation coefficient of 0.20. This is so also because shock to profits are also shocks to contemporaneous returns.

⁹Lettau and Ludvigson (2002) derive a related dynamic accounting decomposition for the log Tobin's Q .

Table 3 presents the descriptive statistics for the equal-weighted market average. The results are largely similar to the value-weighted index, although the mean investment returns is higher at 11% per year. mq is slightly larger than in the case of the value weighted average, and the correlations are very similar to those in Panel B of Table 3.

Figure 1 plots the time series of the marginal profit to marginal Q ratio for value weighted and equal weighted portfolios. The ratio appears to be mean-reverting and somewhat countercyclical. It spikes during the financial crisis in 2007-2008, as well as during the mid-1970s and early 1980s recessions. In untabulated estimation, we find that the correlation of the ratio of marginal profit to marginal Q with real GDP growth is -0.47 , confirming the countercyclical nature of the ratio.

Figure 2 depicts the time series of investment returns. Investment returns exhibits a somewhat procyclical behavior, and its correlation with real GDP growth is 0.26. The correlation between investment returns and the value weighted aggregate stock returns in our sample is 0.09.¹⁰ Figure 3 shows the growth rate of the marginal profitability of capital. The behavior of marginal profitability growth rate is procyclical, and its correlation with real GSP growth is 0.24.

5 Long-horizon regressions

In this section, we evaluate the predictability of the log profits-to- Q ratio for future investment returns and growth in marginal profits by deriving and estimating a variance decomposition.

¹⁰Liu, Whited, and Zhang (2009) explain that while the model predicts that investment return should equal stock return period by period and state by state (as in Cochrane (1991)), no set of parameters can generate this equality and the equality condition is rejected at any level of significance.

5.1 Methodology

Following Cochrane (2008, 2011) and [Maio and Santa-Clara \(2015\)](#), we estimate weighted long-horizon regressions of future log investment returns, log profits growth, and log profits-to- Q ratio on the current profitability ratio:

$$\sum_{j=1}^K \rho^{j-1} r_{t+j} = a_r^K + b_r^K m q_t + \varepsilon_{t+K}^r, \quad (21)$$

$$\sum_{j=1}^K \rho^{j-1} \Delta m_{t+j} = a_m^K + b_m^K m q_t + \varepsilon_{t+K}^m, \quad (22)$$

$$\rho^K m q_{t+K} = a_{mq}^K + b_{mq}^K m q_t + \varepsilon_{t+K}^{mq}. \quad (23)$$

The t -statistics for the direct predictive slopes are based on [Newey and West \(1987\)](#) standard errors with K lags, which incorporate a correction of the bias induced by using overlapped observations in the regressions above.

Similarly to [Cochrane \(2011\)](#), by combining the present-value relation presented in the previous section with the predictive regressions above, we obtain an identity involving the predictability coefficients associated with $m q_t$, at each horizon K :

$$1 = b_r^K - b_m^K + b_{mq}^K. \quad (24)$$

This equation can be interpreted as a variance decomposition for the log profits-to- Q ratio. The predictive coefficients b_r^K , $-b_m^K$, and b_{mq}^K represent the fraction of the variance of current $m q$ attributable to the predictability of future investment returns, marginal profits growth, and profits-to- Q ratio, respectively. Hence, these slopes measure the weight (of the predictability) of each of these variables ($\sum_{j=1}^K \rho^{j-1} r_{t+j}$, $\sum_{j=1}^K \rho^{j-1} \Delta m_{t+j}$, and $\rho^K m q_{t+K}$) in driving the variation in the current profitability ratio. Such relation also imposes a constraint on the predictability from the log profits-to- Q ratio: if at some forecasting horizon K , $m q_t$ does not forecast future investment returns or profit growth, then it must forecast its own

future values, otherwise the profitability ratio would not vary over time.

5.2 Results

The results for the variance decomposition in the case of the value-weighted market average are shown in Figure 4. At the one-year horizon the dominant source of variation in current mq is its own predictability, and this result is associated with the relatively large persistence of this variable as indicated in Table 2. However, for horizons beyond one year the driving source of variation in mq becomes predictability of growth in marginal profits, with the respective slopes being significant (at the 5% level) at all horizons. In fact, at intermediate and long horizons ($K > 7$) it turns out that the slopes associated with Δm become larger than one in magnitude. This indicates that the predictability of future marginal profits accounts for more than 100% of the variation in current mq . The reason for such pattern is that the investment return slopes have the wrong sign (negative) at all forecasting horizons (although these estimates are not statistically significant).

The results for the equal-weighted market index, presented in Figure 5, are similar to the results for the value-weighted index. In this case, the investment return slopes are positive at all forecasting horizons. However, the magnitudes of these estimates are relatively small (below 10% in most cases) and these estimates are not significant (at the 5% level) at any forecasting horizon. Consequently, the coefficients corresponding to Δm are above 90% (in magnitude) at long horizons. These estimates are statistically significant (at the 5% level) at most horizons with the exception of short horizons ($K < 4$). As in the case with value-weighted investment returns the predictability of future mq is the dominant source of variation in current mq in the near future ($K < 3$), but this effect decays to zero at a fast pace.

We compute the variance decomposition for mq by using the alternative data on the investment return and its components. The alternative data arises from GMM estimation with portfolios deciles formed on Tobin's Q , as explained in Section 3. The variance de-

compositions for the value- and equal weighted indexes are presented in Figures 6 and 7, respectively. In both cases, the patterns are quite similar to the benchmark variance decompositions discussed above. At $K = 20$, the estimates for the coefficients associated with r and Δm are -0.20 and -1.17 , respectively in the case of the value-weighted index. In what concerns the equal-weighted index the return and profits growth slopes are -0.01 and -0.98 , respectively, at the 20-year horizon.

Overall, the results from this section clearly indicate that the major source of variation in the profits-to-q ratio is predictability of future marginal profits growth. On the other hand, predictability of future investment returns does not explain any variation in the profitability ratio.

6 VAR implied predictability

In this section, we estimate an alternative variance decomposition for the profits-to-Q ratio based on a first-order VAR.

6.1 Methodology

Following Cochrane (2008), we specify the following first-order restricted VAR,

$$r_{t+1} = a_r + b_r m q_t + \varepsilon_{t+1}^r, \quad (25)$$

$$\Delta m_{t+1} = a_m + b_m m q_t + \varepsilon_{t+1}^m, \quad (26)$$

$$m q_{t+1} = a_{mq} + \phi m q_t + \varepsilon_{t+1}^{mq}, \quad (27)$$

where the ε s represent error terms. This VAR system is estimated by OLS (equation-by-equation) with Newey and West (1987) t -statistics (computed with one lag).

By combining the VAR above with the present-value relation in Eq. (30), we obtain the

following variance decomposition for mq at each horizon K :

$$\begin{aligned}
1 &= b_r^K - b_m^K + b_{mq}^K, \\
b_r^K &\equiv \frac{b_r(1 - \rho^K \phi^K)}{1 - \rho\phi}, \\
b_m^K &\equiv \frac{b_m(1 - \rho^K \phi^K)}{1 - \rho\phi}, \\
b_{mq}^K &\equiv \rho^K \phi^K.
\end{aligned} \tag{28}$$

In this variance decomposition, the predictive slopes at each forecasting horizon K are obtained from the one-period VAR slopes instead of being directly estimated from long-horizon regressions as in the previous section.¹¹ If the first-order VAR does not fully capture the dynamics of the data generating process for r , mq , and Δm , it follows that the variance decomposition will be a poor approximation of the true decomposition for the profitability ratio. The t -statistics associated with the predictive coefficients are computed from the t -statistics for the VAR slopes by using the Delta method.¹²

We can also compute the variance decomposition for an infinite horizon ($K \rightarrow \infty$):

$$\begin{aligned}
1 &= b_r^{lr} - b_m^{lr}, \\
b_r^{lr} &\equiv \frac{b_r}{1 - \rho\phi}, \\
b_m^{lr} &\equiv \frac{b_m}{1 - \rho\phi}.
\end{aligned} \tag{29}$$

In this decomposition, all the variation in the current profits-to-Q ratio is associated with either return or profit growth predictability. The t -statistics for the long-run coefficients, b_r^{lr}, b_m^{lr} , are based on the standard errors of the one-period VAR slopes by using the Delta method. Following [Cochrane \(2008\)](#), we compute t -statistics for two null hypotheses: the

¹¹Cochrane (2008, 2011) specify a similar decomposition for the dividend yield.

¹²Details are available upon request.

first null assumes that there is only marginal profits growth predictability,

$$H_0 : b_r^{lr} = 0, b_m^{lr} = -1,$$

while the second null hypothesis assumes that there is only return predictability:

$$H_0 : b_r^{lr} = 1, b_m^{lr} = 0.$$

6.2 Results

The VAR-based decomposition for the value-weighted index are shown in Table 4 (Panel A) and Figure 8. The results are relatively similar to those corresponding to the decomposition based on direct regressions. As in the benchmark case, the investment return coefficients are negative at all horizons (and not statistically significant) in virtue of the negative one-month VAR return slope (-0.06). Consequently, the coefficients associated with marginal profits are higher than one in magnitude at most horizons ($K > 5$), and these estimates are statistically significant (at the 5% level) in most cases. At short horizons ($K < 3$), the dominant source is predictability of future mq , yet, this effect dies out at longer horizons. At very long horizons, the results in Table 4 indicate that the return and profits coefficients are -0.26 and -1.24 , respectively. However, we clearly reject the null that $b_r^{lr} = 1, b_m^{lr} = 0$ (t -ratios above 2.50 in magnitude), while clearly cannot reject the null that $b_r^{lr} = 0, b_m^{lr} = -1$.

The results for the equal-weighted index are presented in Table 4 (Panel B) and Figure 9. As in the decomposition based on long-horizon regressions the investment return slopes are positive, but the magnitudes are close to zero and there is no statistical significance at any horizon. This implies that, apart from the near horizons, the coefficients associated with Δm are close to -0.90 . The main difference relative to the VAR-based variance decomposition associated with the value-weighted index relies on the fact that the cash flow coefficients are not significant at the 5% level, but there is significance at the 10% level. The lower

significance stems from the one-month slope for Δm being not significant (t-ratio of -1.48), thus, there is higher estimation uncertainty in the case of the equal-weighted index. At very long horizons, the slopes corresponding to return and growth in marginal profits are 0.05 and -0.94 , respectively. We clearly cannot reject the null that $b_m^{lr} = -1$, but reject (at the 10% level) the null that $b_m^{lr} = 0$ (t-ratio of -1.87).

Overall, the results of of the VAR-based variance decomposition for mq are consistent with the benchmark variance decomposition estimated in the previous section. What drives variation in the profits-to-Q ratio is predictability of future cash flows with predictability of future investment returns playing a very marginal role. On the other hand, predictability of future mq is only relevant at short horizons.

7 A variance decomposition for q

In this section, we look at the predictive ability of Tobin's Q rather than the profits-to-Q ratio. This enables to isolate the forecasting power of Q from the effect of marginal profits.

The present-value dynamic relation for the log Q (q) at each forecasting horizon K is given by

$$q_t = const. - \sum_{j=1}^K \rho^{j-1} r_{t+j} + \sum_{j=1}^K \rho^{j-1} (1 - \rho) m_{t+j} + \rho^K q_{t+K}. \quad (30)$$

There are three major differences relative to the present-value relation associated with mq derived in Section 4. First, in the right hand side of the equation above we have the level (rather than the growth) of log marginal profits. Second, the signs associated with future investment returns and marginal profits flip sign in comparison to the decomposition for mq . Third, future log marginal profits are scaled by the term $1 - \rho$. This present-value relation is analogous to the present-value relation associated with the stock price derived in [Campbell, Lo, and Mackinlay \(1997\)](#), where q replaces the log stock price (p), m is analogous to the log dividend (d), and r replaces the log stock return.

We estimate weighted long-horizon regressions of future log investment returns, log

marginal profits, and the log Tobin's Q on the current log Q:

$$\sum_{j=1}^K \rho^{j-1} r_{t+j} = a_r^K + b_r^K q_t + \varepsilon_{t+K}^r, \quad (31)$$

$$\sum_{j=1}^K \rho^{j-1} (1 - \rho) m_{t+j} = a_m^K + b_m^K q_t + \varepsilon_{t+K}^m, \quad (32)$$

$$\rho^K q_{t+K} = a_q^K + b_q^K q_t + \varepsilon_{t+K}^q. \quad (33)$$

As in Section 5, by combining the present-value relation with the forecasting regressions above, we obtain an identity involving the predictability coefficients associated with q_t , at each horizon K :

$$1 = -b_r^K + b_m^K + b_q^K. \quad (34)$$

The shares associated with future investment returns and marginal profits flip sign in comparison to the decomposition associated with mq in light of the different present-value relation for q .

Figure 10 presents the variance decomposition for q when we use the value-weighted market average. We can see that both sources of predictability drive the variation in the current log Q. Indeed, at both intermediate and long forecasting horizons, the slopes associated with return and profit predictability are both around 50% in magnitude. Specifically, at $K = 20$, the return and profit slopes are -0.53 and 0.48 , respectively. The positive profit coefficients are statistically significant at all forecasting horizons. On the other hand, the negative investment return coefficients are also significant (at the 5% level) at most horizons (with a few exceptions at middle horizons). At $K = 1$, the dominant source of variation in q is its own predictability. Yet, such effect decays to zero at a very fast rate. This indicates that q is significantly less persistent than mq .

The results for the equal-weighted average presented in Figure 11 are qualitatively similar to those for the value-weighted index. There is a slightly large share of cash-flow predictability at long horizons: At $K = 20$, the return and profit slopes are -0.46 and 0.55 , respectively.

As in the value-weighted case, the profit slopes are statistically significant at all horizons. On the other hand, there is less significance for the return slopes as only at both short and long horizons those coefficients are significant at the 5% level. The larger standard errors in the variance decomposition for the equal-weighted index are consistent with the results obtained for mq in Section 5.

Overall, the results of this section indicate that the cash-flow channel plays a much more important role in driving the variation in q than in the case of mq . Nevertheless, the return channel continues to play an important role, especially in the case of the value-weighted index.

8 Conclusion

This paper explores the sources of fluctuations in marginal Q and aggregate investment. We assume a parsimonious model with standard production and adjustment cost technologies and estimate investment returns for the aggregate of firms on the Compustat database. Subsequently we estimate the share of capital and adjustment cost parameters by employing GMM estimation. We derive a present value relation to show that variations in the ratio of marginal profitability of capital to the marginal value of capital (that is, marginal Q) must reflect shocks to the growth rate of the marginal profitability of capital, or shocks to expected investment returns, or both.

We conduct predictability tests and find that the ratio of marginal profitability of capital to marginal Q can predict the growth rate of the marginal profitability of capital at horizons of up to 20 years. A high ratio of marginal profitability of capital to marginal Q implies high future growth rates of the marginal profitability of capital. On the contrary, investment returns is not predictable by the ratio. Thus, virtually the entire variation in the ratio of the marginal profitability of capital to marginal Q is driven by marginal profitability shocks. This finding suggests, that managers' investment decisions respond strongly to shocks to the

growth rate of profits, and stands in contrast to the prominent findings of the sources of fluctuations in stock prices.

Table 1: GMM estimation of structural parameters

This table reports the one-step GMM results from estimating jointly the investment Euler equation and the valuation equation moments, that is, α is the capital share and a is the adjustment cost. The standard errors corresponding to the estimated parameters are reported in parentheses. $\frac{C}{\bar{Y}}$ is the ratio in percent of the implied capital adjustment costs over sales. $|e_i^R|$ and $|e_i^Q|$ are the mean absolute Euler equation error and valuation error, respectively, χ^2 , $d.f.$, and p_{χ^2} are the statistic, the degrees of freedom, and the p -value for the χ^2 test on the null that all the errors are jointly zero. The sample is 1961–2014.

	Aggregate market		Tobin's Q deciles	
	EW	VW	EW	VW
α	0.25	0.19	0.30	0.26
[se]	[0.04]	[0.03]	[0.03]	[0.08]
a	14.57	14.57	19.28	19.27
[se]	[0.03]	[0.03]	[0.04]	[0.04]
$\frac{C}{\bar{Y}}$	10.49%	10.49%	13.89%	13.89%
$ e_i^R $			8.88%	7.63%
$ e_i^Q $			0.41	0.41
χ^2			8.87	8.90
$d.f.$			18	18
p_{χ^2}			0.96	0.96

Table 2: Descriptive statistics: VW index

This table reports descriptive statistics for the variables associated with the value-weighted index. The variables are the log investment return (r), log growth in marginal profits (Δm), and log profits-to-Q ratio (mq). The sample is 1962–2014. ϕ designates the first-order autocorrelation. The correlations between the variables are presented in Panel B.

Panel A					
	Mean	S.D.	Min.	Max.	ϕ
r	0.08	0.07	-0.11	0.25	0.15
Δm	0.00	0.10	-0.24	0.28	0.22
mq	-1.72	0.09	-1.90	-1.56	0.90
Panel B					
	r	Δm	mq		
r	1.00	0.95	0.20		
Δm		1.00	0.10		
mq			1.00		

Table 3: Descriptive statistics: EW index

This table reports descriptive statistics for the variables associated with the equal-weighted index. The variables are the log investment return (r), log growth in marginal profits (Δm), and log profits-to-Q ratio (mq). The sample is 1962–2014. ϕ designates the first-order autocorrelation. The correlations between the variables are presented in Panel B.

Panel A					
	Mean	S.D.	Min.	Max.	ϕ
r	0.11	0.07	-0.09	0.27	0.17
Δm	0.00	0.10	-0.23	0.26	0.23
mq	-1.57	0.09	-1.76	-1.41	0.92
Panel B					
	r	Δm	mq		
r	1.00	0.93	0.20		
Δm		1.00	0.05		
mq			1.00		

Table 4: VAR estimates

This table reports the VAR(1) estimation results when the predictor is the profits-to-Q ratio. The variables in the VAR are the log investment return (r), log growth in marginal profits (m), and log profits-to-Q ratio (mq). The results in Panels A and B correspond to the value- and equal-weighted investment returns, respectively. b denote the VAR slopes associated with lagged mq , while t denotes the respective Newey and West (1987) t -statistics (calculated with one lag). R^2 is the coefficient of determination for each equation in the VAR, in %. b^{lr} denote the long-run coefficients (infinite horizon). $t(b_r^{lr} = 0)$ and $t(b_r^{lr} = 1)$ denote the t -statistics associated with the null hypotheses ($b_r^{lr} = 0, b_m^{lr} = -1$) and ($b_r^{lr} = 1, b_m^{lr} = 0$), respectively. The full sample corresponds to annual data for the 1962–2014 period. Italic, underlined, and bold numbers denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	b	t	R^2	b^{lr}	$t(b_r^{lr} = 0)$	$t(b_r^{lr} = 1)$
Panel A (VW)						
r	-0.06	-0.48	0.01	-0.26	-0.53	<u>-2.57</u>
Δm	-0.31	<i>-1.71</i>	0.07	-1.24	-0.50	<u>-2.53</u>
mq	0.90	13.42	0.81			
Panel B (EW)						
r	0.01	0.10	0.00	0.05	0.10	<i>-1.92</i>
Δm	-0.24	-1.48	0.06	-0.94	0.13	<i>-1.87</i>
mq	0.92	16.39	0.85			

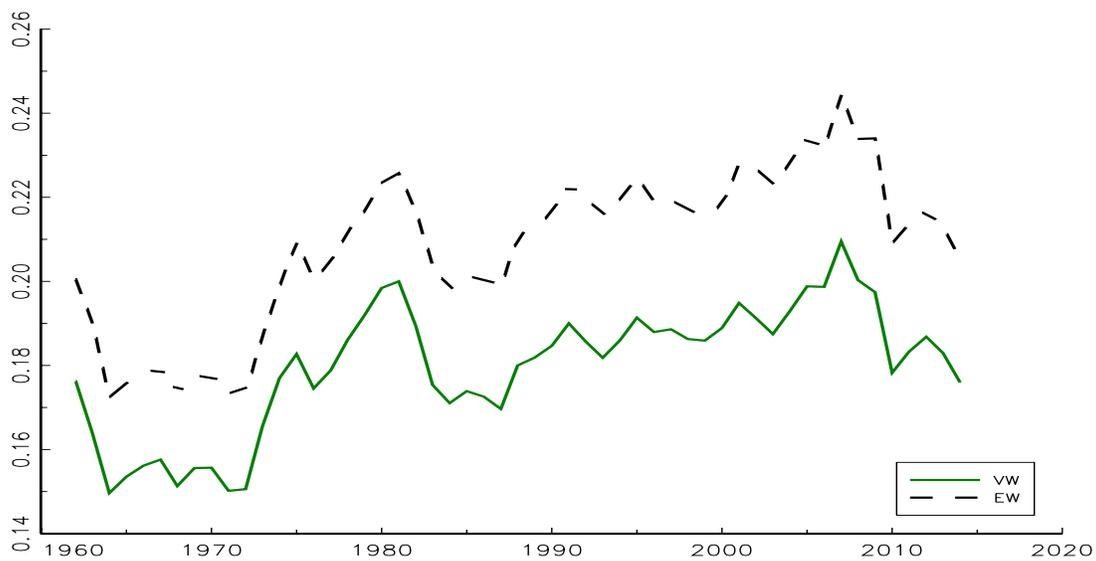


Figure 1: Marginal profits-to-Q ratio

This figure plots the time-series for the value-weighted (VW) and equal-weighted (EW) marginal profits-to-Q ratio. The sample is 1962 to 2014.

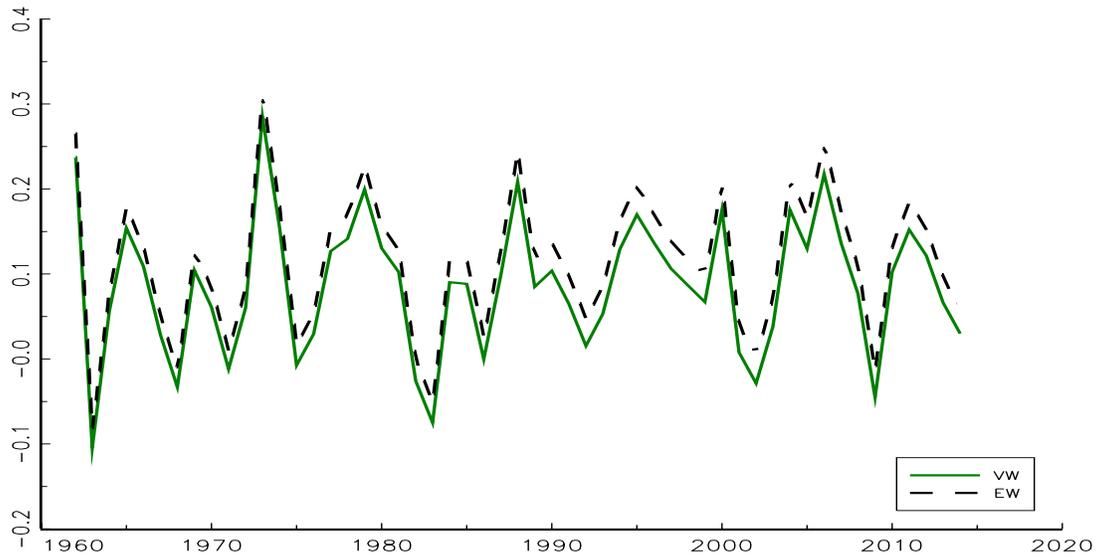


Figure 2: Investment return

This figure plots the time-series for the value-weighted (VW) and equal-weighted (EW) investment return. The sample is 1962 to 2014.

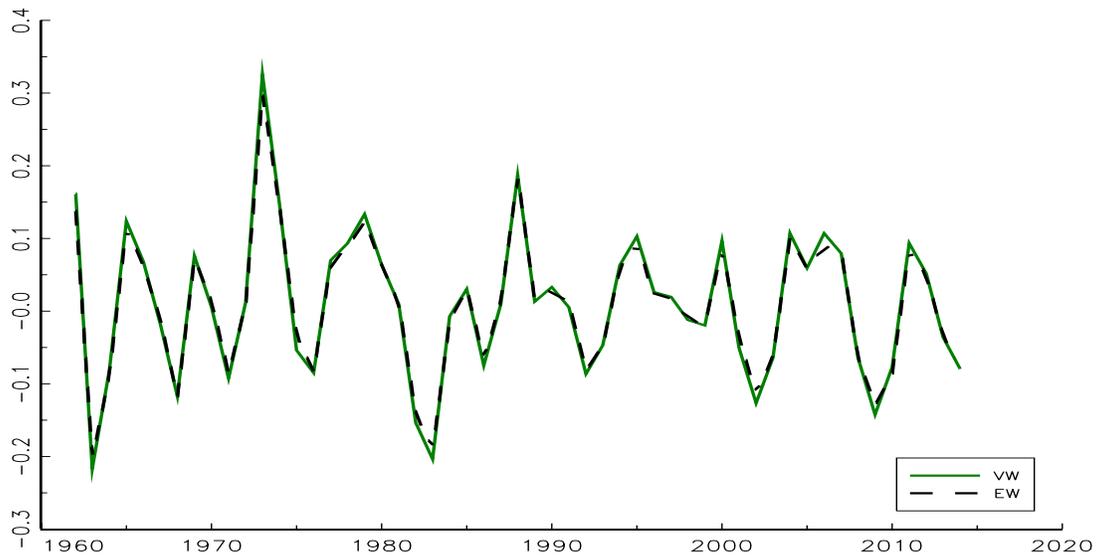
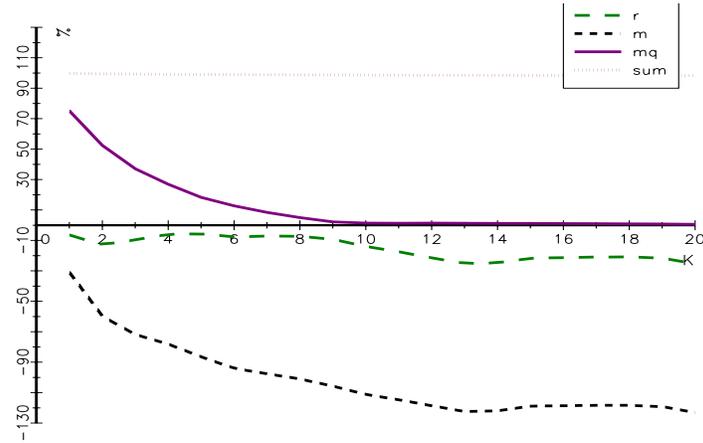
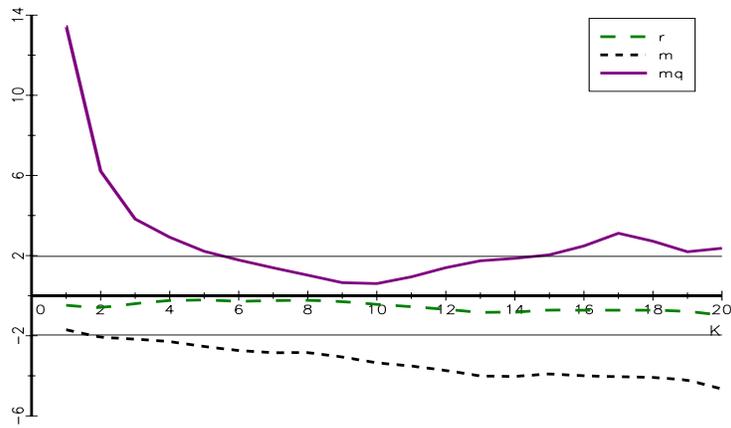


Figure 3: Growth in marginal profits

This figure plots the time-series for the value-weighted (VW) and equal-weighted (EW) growth rate in marginal profits. The sample is 1962 to 2014.



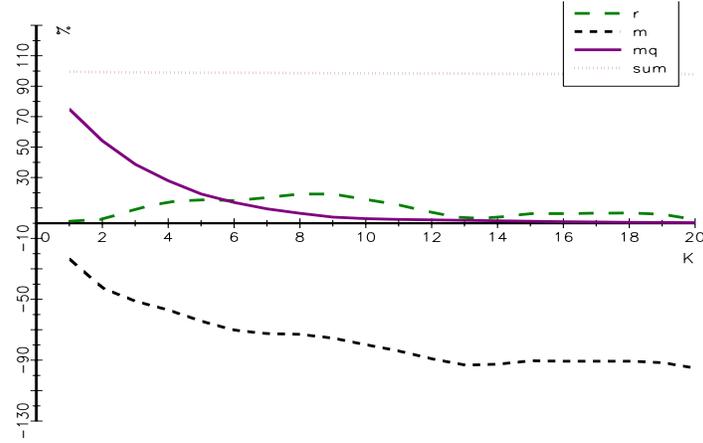
Panel A (slopes)



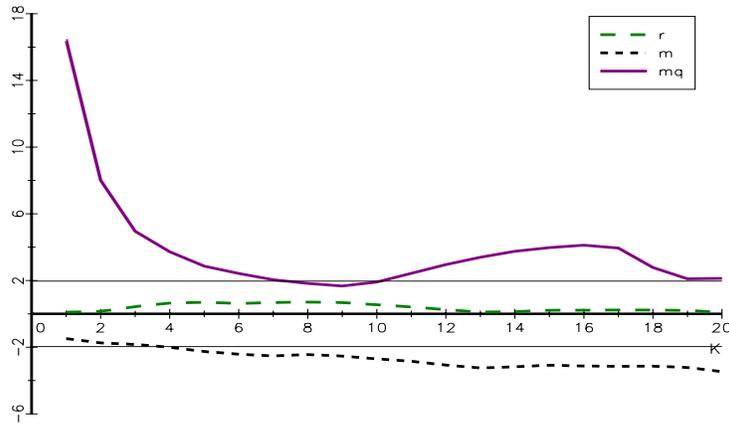
Panel B (t -stats)

Figure 4: Direct term structure of predictive slopes: VW return

This figure plots the term structure of multiple-horizon predictive coefficients, and respective t -statistics, for the case of the value-weighted investment return. The predictive slopes are obtained from weighted long-horizon regressions. The coefficients are associated with the log investment return (r), log growth in marginal profits (m), and log profits-to-Q ratio (mq). The forecasting variable is mq in all three cases. “Sum” denotes the value of the variance decomposition, in %. The long-run coefficients are measured in %, and K represents the number of years ahead. The horizontal lines represent the 5% critical values ($-1.96, 1.96$). The original sample is 1962 to 2014.



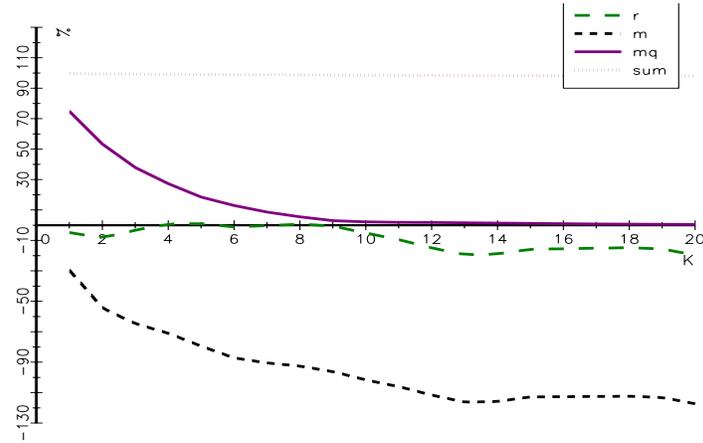
Panel A (slopes)



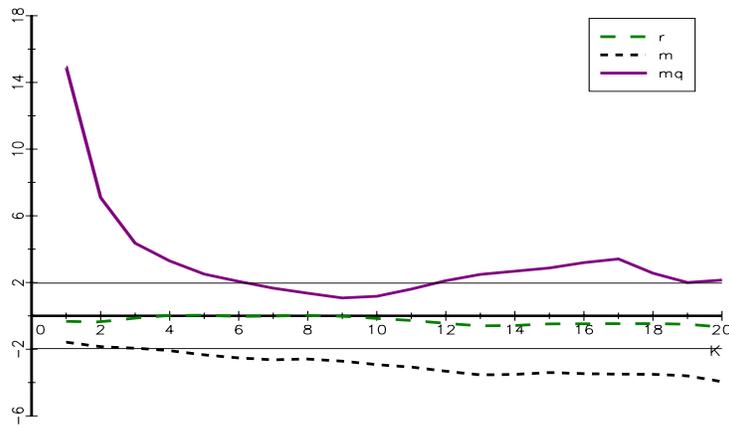
Panel B (t -stats)

Figure 5: Direct term structure of predictive slopes: EW return

This figure plots the term structure of multiple-horizon predictive coefficients, and respective t -statistics, for the case of the equal-weighted investment return. The predictive slopes are obtained from weighted long-horizon regressions. The coefficients are associated with the log investment return (r), log growth in marginal profits (m), and log profits-to-Q ratio (mq). The forecasting variable is mq in all three cases. “Sum” denotes the value of the variance decomposition, in %. The long-run coefficients are measured in %, and K represents the number of years ahead. The horizontal lines represent the 5% critical values ($-1.96, 1.96$). The original sample is 1962 to 2014.



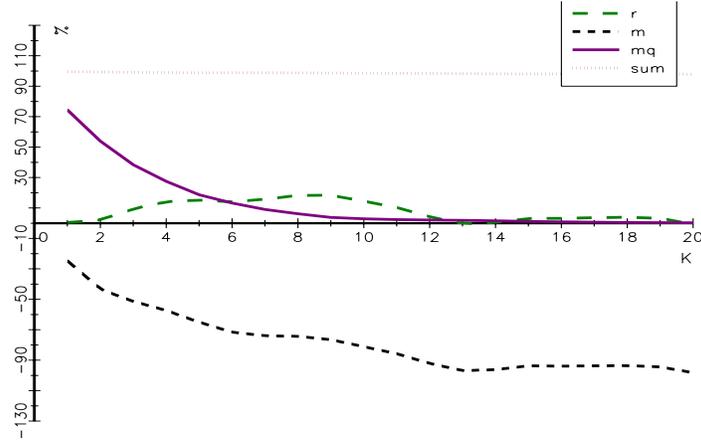
Panel A (slopes)



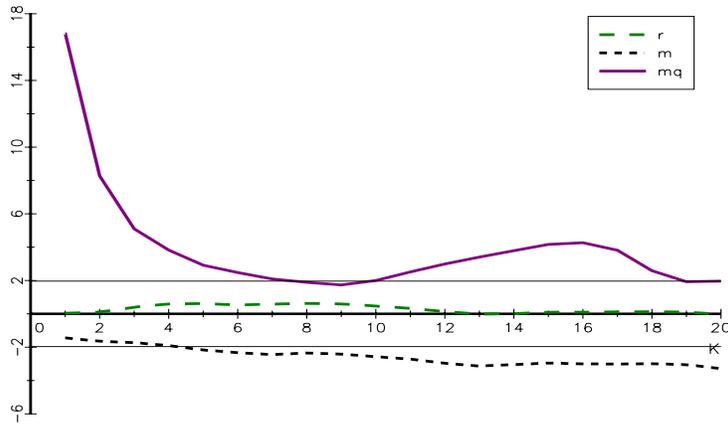
Panel B (t -stats)

Figure 6: Direct term structure of predictive slopes: alternative VW return

This figure plots the term structure of multiple-horizon predictive coefficients, and respective t -statistics, for the case of the alternative value-weighted investment return. The predictive slopes are obtained from weighted long-horizon regressions. The coefficients are associated with the log investment return (r), log growth in marginal profits (m), and log profits-to-Q ratio (mq). The forecasting variable is mq in all three cases. “Sum” denotes the value of the variance decomposition, in %. The long-run coefficients are measured in %, and K represents the number of years ahead. The horizontal lines represent the 5% critical values ($-1.96, 1.96$). The original sample is 1962 to 2014.



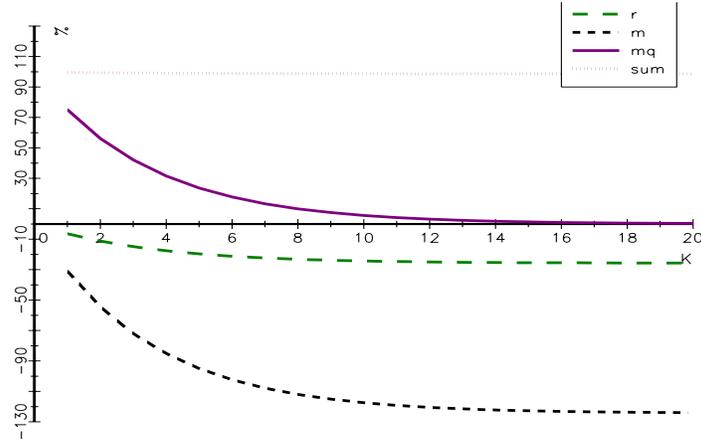
Panel A (slopes)



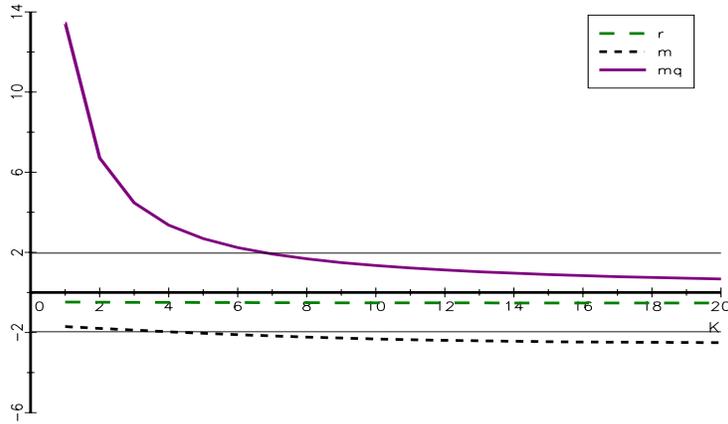
Panel B (t -stats)

Figure 7: Direct term structure of predictive slopes: alternative EW return

This figure plots the term structure of multiple-horizon predictive coefficients, and respective t -statistics, for the case of the alternative equal-weighted investment return. The predictive slopes are obtained from weighted long-horizon regressions. The coefficients are associated with the log investment return (r), log growth in marginal profits (m), and log profits-to-Q ratio (mq). The forecasting variable is mq in all three cases. “Sum” denotes the value of the variance decomposition, in %. The long-run coefficients are measured in %, and K represents the number of years ahead. The horizontal lines represent the 5% critical values ($-1.96, 1.96$). The original sample is 1962 to 2014.



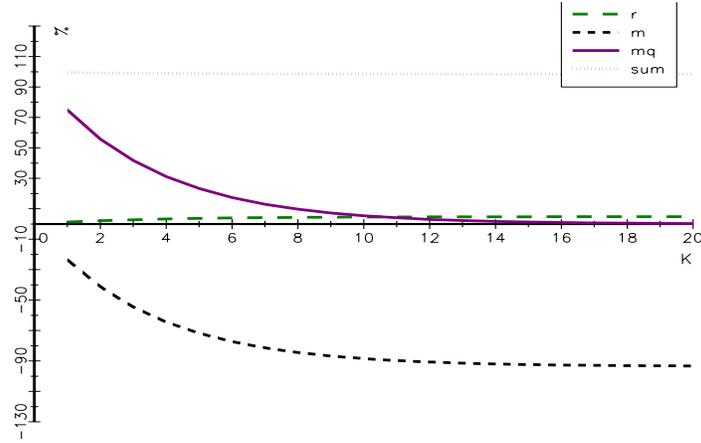
Panel A (slopes)



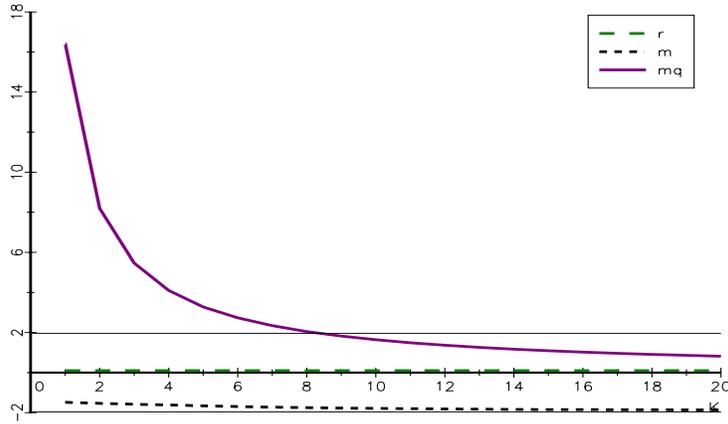
Panel B (t -stats)

Figure 8: VAR-based term structure of predictive slopes: VW return

This figure plots the term structure of multiple-horizon predictive coefficients, and respective t -statistics, for the case of the value-weighted investment return. The predictive slopes are obtained from a first-order VAR. The coefficients are associated with the log investment return (r), log growth in marginal profits (m), and log profits-to-Q ratio (mq). The forecasting variable is mq in all three cases. “Sum” denotes the value of the variance decomposition, in %. The long-run coefficients are measured in %, and K represents the number of years ahead. The horizontal lines represent the 5% critical values ($-1.96, 1.96$). The original sample is 1962 to 2014.



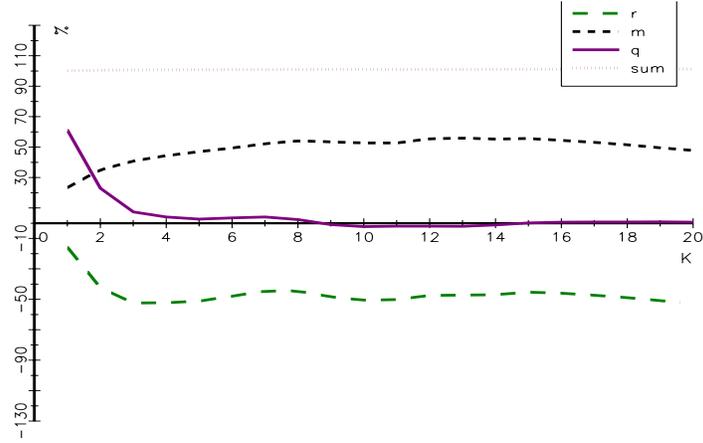
Panel A (slopes)



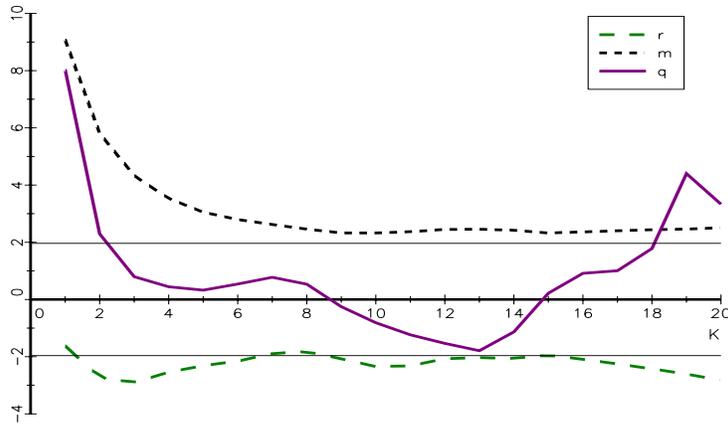
Panel B (t -stats)

Figure 9: VAR-based term structure of predictive slopes: EW return

This figure plots the term structure of multiple-horizon predictive coefficients, and respective t -statistics, for the case of the equal-weighted investment return. The predictive slopes are obtained from a first-order VAR. The coefficients are associated with the log investment return (r), log growth in marginal profits (m), and log profits-to-Q ratio (mq). The forecasting variable is mq in all three cases. “Sum” denotes the value of the variance decomposition, in %. The long-run coefficients are measured in %, and K represents the number of years ahead. The horizontal lines represent the 5% critical values ($-1.96, 1.96$). The original sample is 1962 to 2014.



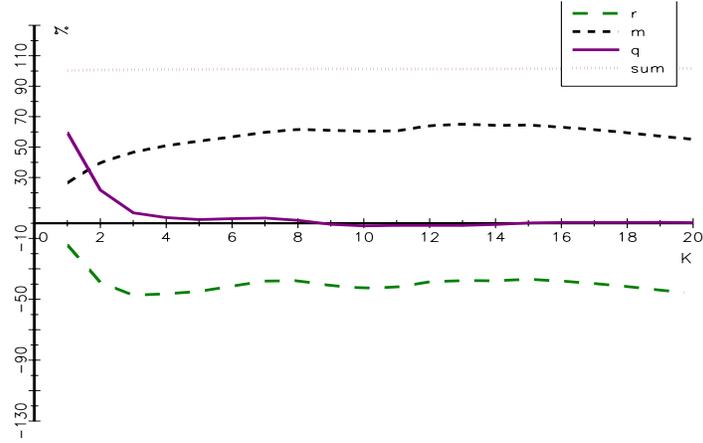
Panel A (slopes)



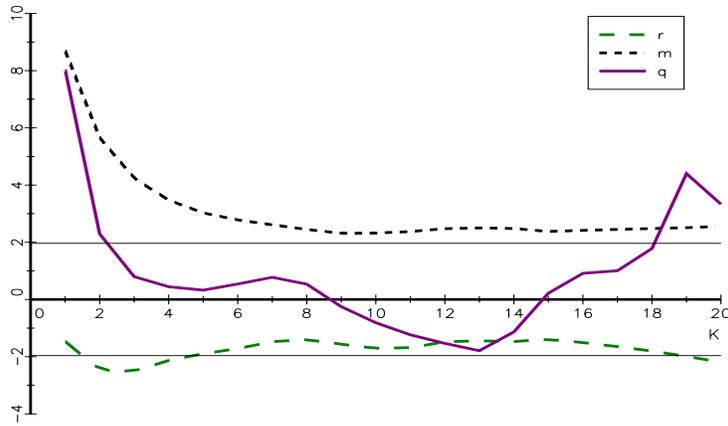
Panel B (t -stats)

Figure 10: Variance decomposition for q : VW return

This figure plots the term structure of multiple-horizon predictive coefficients, and respective t -statistics, for the case of the value-weighted investment return. The predictive slopes are obtained from weighted long-horizon regressions. The coefficients are associated with the log investment return (r), log marginal profit (m), and log marginal Q (q). The forecasting variable is q in all three cases. “Sum” denotes the value of the variance decomposition, in %. The long-run coefficients are measured in %, and K represents the number of years ahead. The horizontal lines represent the 5% critical values ($-1.96, 1.96$). The original sample is 1962 to 2014.



Panel A (slopes)



Panel B (t -stats)

Figure 11: Variance decomposition for q : EW return

This figure plots the term structure of multiple-horizon predictive coefficients, and respective t -statistics, for the case of the equal-weighted investment return. The predictive slopes are obtained from weighted long-horizon regressions. The coefficients are associated with the log investment return (r), log marginal profit (m), and log marginal Q (q). The forecasting variable is q in all three cases. “Sum” denotes the value of the variance decomposition, in %. The long-run coefficients are measured in %, and K represents the number of years ahead. The horizontal lines represent the 5% critical values ($-1.96, 1.96$). The original sample is 1962 to 2014.

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