The Learning Channel in Asset Pricing: Firm-Level Evidence

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February 27, 2025

Preliminary draft. Not intended for circulation.

Abstract

We examine how market participants learn about unobservable drivers of firm profitability and incorporate this information into asset prices. We develop a structural learning model about firms' profitability and estimate its parameters for each firm using earnings data. Our findings reveal that the expected change in profitability, over both short and long run, significantly predicts future stock returns. This predictive power remains robust after controlling for known factors, suggesting it captures unique information not fully accounted for by existing asset pricing factors. The results provide new insights into the dynamics of information processing and have important implications for understanding the relationship between expected firm fundamentals and stock return predictability.

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1. Introduction

Understanding firm profitability is a central theme in financial economics, with far-reaching implications for asset pricing, corporate finance, and the efficient allocation of capital in the economy. Profitability is a key metric for evaluating a firm's financial health, growth prospects, and ability to generate shareholder value. It is therefore crucial for investors, analysts, and policymakers to develop a deep understanding of the factors that drive firm profitability drivers and how market participants learn about and incorporate this information into their decision-making processes.

Firm profitability has consistently been shown to predict stock returns robustly, even after accounting for transaction costs (Detzel, Novy-Marx, and Velikov, 2023; Chen and Zimmermann, 2022; Hou, Xue, and Zhang, 2020). This highlights the critical role of profitability in driving asset prices. In both prominent types of factor models, Fama-French and Q-factor models, current profitability plays a key role in explaining future returns. In this paper, we demonstrate that the expected change in profitability provides unique predictive power for future returns, beyond what is captured by traditional factors such as current profitability or momentum.

We structurally estimate the extent to which agents learn from firm earnings about future profitability. Our model posits that firm profitability is driven by an unobservable factor, with agents updating their beliefs based on realized firm- and industry-level earnings. By explicitly modeling the learning process and quantifying the speed and efficiency of belief updates, we offer new insights into how information is incorporated into financial markets. This structural framework enables us to disentangle the role of learning about firm fundamentals in shaping asset prices.

A growing body of research has explored the information content of firm earnings and their impact on stock prices, emphasizing earnings as a key signal of future profitability

(Kothari, 2001; Bernard and Thomas, 1989; Brown and Niederhoffer, 1968). However, the degree to which agents learn from earnings and update their beliefs about a firm's future profitability remains an open question. Traditional asset pricing models often assume perfect information and rational expectations, but in practice, agents face information frictions and may exhibit bounded rationality when processing financial information (Daniel et al., 1998; Barberis et al., 1998). In this paper, we focus on quantifying these information frictions and examining their implications for asset prices.

Our estimation of expected firm-level profitability is unique in the sense that we only use quarterly earnings announcement data and no other signals based on stock prices. We structurally estimate the parameters governing a mean-reverting profitability process driven by an unobservable firm-level profitability factor. Industry-level profitability serves agents as an example of an informative signal relevant in the learning process. Using a Simulated Method of Moments, we match firm-level earnings data using an expanding window of observations, enabling us to estimate the in-sample speed at which firm profitability converges to its anchor points. The estimated parameters for firm- and industry-level profitability, combined with earnings surprises derived from both, are then used to predict the change in firm profitability levels.

We find that the expected change in profitability predicts stock returns even after controlling for current profitability levels. Importantly, the expected change in profitability is derived solely from realized earnings data. Sorting firms based on the expected change in profitability produces a significant monthly return spread of 0.3%, which is not explained by existing Fama-French or Q-factors. Furthermore, we decompose the expected change in profitability into long-run and short-run components and show that both are quantitatively significant for return predictability. Each component is associated with a positive and significant return spread, not spanned by existing factors.

Our study provides the first structural estimates of cross-sectional learning parameters for individual firms, measuring how learning about firm fundamentals influences future returns. We demonstrate that this learning process plays a key role in asset pricing by showing that the extracted earnings surprises uniquely predict future returns. Without learningif both short- and long-term drivers were fully observablethese earnings surprises would hold no explanatory power for future profitability or stock return patterns. However, since we find that firm- and industry-level earnings do predict future returns, our results highlight the importance of learning in asset pricing and offer new insights into how information shapes stock prices.

Our findings carry significant implications for a diverse set of stakeholders. For investors, understanding how agents learn from earnings can enhance investment strategies and uncover mispricing opportunities stemming from informational inefficiencies. For example, an investor who effectively anticipates the market's reaction to a firms earnings surprise may capitalize on subsequent price adjustments.

For corporate managers, our results underscore the importance of transparent and effective communication with the market. Consistently meeting or exceeding market expectations and clearly articulating profitability prospects can lead to higher stock prices and reduced costs of capital. Additionally, our findings highlight the potential risks of earnings management or opaque disclosure policies, which may undermine market confidence and valuation.

Policymakers and regulators can draw insights from our work on the critical role of information dissemination in fostering market efficiency and stability. Ensuring that firms provide timely, accurate, and transparent financial disclosures can reduce information asymmetries, enhance the quality of investor decision-making, and promote the efficient allocation of capitalcontributing to healthier and more stable financial markets.

Furthermore, our structural estimation framework extends beyond firm earnings to other contexts where learning and information processing are pivotal. Applications include pricing of initial public offerings, the impact of macroeconomic announcements on stock prices, and the cross-market transmission of information. By offering a rigorous method to quantify and analyze learning behavior, our research provides a foundation for future studies.

2. Expected firm profitability

Expected firm profitability is a key determinant of future returns in prominent factor models, such as the Fama-French five-factor model (FF5) and the Q-factor model. Fama and French (2006) emphasize an accounting identity indicating that, after controlling for the book-to-market ratio, firms with higher profitability are expected to generate higher returns.

We incorporate learning about an unobservable driver of firm profitability into a traditional model where firms maximize their operating profits.

Let Π_{it} represent firm i's operating profits at time t:

$$\Pi_{it} = X_{it} A_{it} \tag{1}$$

where A_{it} denotes the firm's productive assets, and X_{it} measures cash flows per unit of asset and is the main profitability variable of focus in our paper. Building on the frameworks of Liu, Whited, and Zhang (2009) and Hou, Mo, Xue, and Zhang (2021), firms optimize investment (I) and capital (A) to maximize the market value of equity:

$$V_{it} = \max_{I,A} E_t \left[\sum_{s=0}^{\infty} M_{t+s} D_{it+s} \right] \tag{2}$$

The firms cash flows, D_{it}, account for operating profits less adjustment costs and investment expenditures: $D_{it} = X_{it} A_{it} - \frac{a}{2} \left(\frac{I_{it+1}}{A_{it+1}} \right)^2 A_{it} - I_{it}$, where M_t is an exogenous stochastic discount factor. The first-order condition, under the assumption of linear homogeneity in adjustment costs, yields the following expression for investment returns:

$$r_{it+1}^{I} = \frac{X_{it+1} + (1-\delta)q_{it+1} + \frac{a}{2}\left(\frac{I_{it+1}}{A_{it+1}}\right)^2}{q_{it}}, \tag{3}$$

where q_{it} represents the marginal q, the present value of future marginal profits from an additional unit of capital. Here, q_{it} also serves as the Lagrangian multiplier for the capital accumulation equation:

$$A_{it+1} = I_{it} + (1-\delta)A_{it}.$$

Taking expectations of both sides of the investment return equation yields:

$$\mathbb{E}_t(R_{it+1}^{I}) = \frac{\mathbb{E}_t\left[X_{it+1} + (1-\delta)q_{it+1} + \frac{a}{2}\left(\frac{I_{it+1}}{A_{it+1}}\right)^2\right]}{q_{it}}, \tag{4}$$

Assuming independence, the firms expected investment return, $\mathbb{E}_t(R_{it+1}^{I})$, depends on expected firm profitability, $\mathbb{E}_t(X_{it+1})$, expected marginal q, $\mathbb{E}_t(q_{it+1})$, and expected future investment growth, $\mathbb{E}_t\left(\left(\frac{I_{it+1}}{A_{it+1}}\right)^2\right)$.

$$\mathbb{E}_t(R_{it+1}^{I}) = \frac{\mathbb{E}_t(X_{it+1}) + (1-\delta)\mathbb{E}_t(q_{it+1}) + \frac{a}{2}\mathbb{E}_t\left(\left(\frac{I_{it+1}}{A_{it+1}}\right)^2\right)}{q_{it}} \tag{5}$$

In this paper, we focus on expected future profitability, $\mathbb{E}_t(X_{it+1})$. We maintain the independence assumption, as the factors influencing future profitability are likely to affect expected marginal q, $\mathbb{E}_t(q_{it+1})$, and expected future investment growth, $\mathbb{E}_t\left(\left(\frac{I_{it+1}}{A_{it+1}}\right)^2\right)$, in the same direction or to a lesser extent due to their intrinsic relationships.

Marginal q represents the present value of future marginal profits from additional capital investment, which directly depends on expected cash flows. Therefore, improvements in profitabilitydriven by factors such as stronger demand, operational efficiency, or favorable market conditions naturally lead to an increase in expected marginal q. However, because q aggregates expectations over multiple periods and incorporates broader return dynamics, its sensitivity to specific profitability drivers is likely moderated by market smoothing mechanisms and diversification effects.

Similarly, future investment growth adjusts in response to changes in expected profitability, as firms optimize their capital stock to align with projected returns. However, this relationship is tempered by dynamic adjustment costs, financial constraints, and strategic considerations, which can dampen the immediate impact of profitability shifts on $\mathbb{E}_t\left(\left(\frac{I_{it+1}}{A_{it+1}}\right)^2\right)$. For instance, while profitability improvements stemming from macroeconomic conditions or firm-specific innovations may incentivize higher investment, adjustment frictions and capacity constraints often result in delayed or smaller-scale investment responses. Empirical studies, such as Liu et al. (2009) and Hou et al. (2021), confirm a positive correlation between profitability factors, q, and investment returns, though the magnitude of these effects diminishes as one moves from profitability to investment-related metrics.

Thus, while the factors influencing $\mathbb{E}_t(X_{it+1})$ also affect $\mathbb{E}_t(q_{it+1})$ and investment growth, their relative impact on these metrics tends to be smaller due to moderating dynamics. As a result, expected profitability remains the primary driver of changes in expected returns.

2.1 Learning about firm profitability drivers

We model the realized cash flows per unit of assets for firm i, X_{it}, as a mean-reverting process that is persistent over time.

$$dX_{it} = \lambda_i(\mu_{it} - X_{it})dt + \sigma_{iX} dW_{it}^X, \tag{6}$$

where λ_i is the speed of mean reversion, determining how quickly X_{it} adjusts towards its underlying driver μ_{it}, and σ_{Xi} is the volatility of realized cash flows. Importantly, while X_{it} is observable, the fundamental driver of cash flows, μ_{it}, is unobservable and follows its own stochastic, mean-reverting process as in Andrei, Mann, and Moyen (2019):

$$d\mu_{it} = \kappa_i(\bar{\mu}_i - \mu_{it})dt + \sigma_{\mu i} dW_{it}^{\mu}. \tag{7}$$

Here, κ_i denotes the speed at which μ_{it} reverts to its steady-state level $\bar{\mu}_i$, which is observable and represents the unconditional level of firm profitability, or the long-run profitability driver.

Agents infer and learn about the short-run driver μ_{it} from observed cash flows X_{it} and a noisy signal s_{it}:

$$s_{it} = \mu_{it} + \epsilon_{it}^{s}, \tag{8}$$

where $\epsilon_{it}^{s} \sim N(0, \sigma_{is}^2)$. Using all available information at time t, summarized in the information set $\mathcal{F}_t$, agents form their posterior beliefs about μ_{it}, denoted as $\hat{\mu}_{it} = \mathbb{E}(\mu_{it}|\mathcal{F}_t)$.

Proposition 1. *The dynamics of belief formation for $\hat{\mu}_{it}$ are given by:*

$$d\hat{\mu}_{it} = \kappa_i(\bar{\mu}_i - \hat{\mu}_{it})dt + \frac{\lambda_i \nu_{it}}{\sigma_{iX}} d\tilde{W}_{it}^{X} + \frac{\nu_{it}}{\sigma_{is}} d\tilde{W}_{it}^{s}, \tag{9}$$

where ν_{it} is the posterior uncertainty, evolving as:

$$d\nu_{it} = \left(\sigma_{\mu_i}^2 - 2\kappa_i \nu_{it} - \frac{\lambda_i^2 \nu_{it}^2}{\sigma_{ix}^2} - \frac{\nu_{it}^2}{\sigma_{is}^2} \right) dt. \tag{10}$$

The Filtering Theorem applied to derive the belief formation dynamics is discussed in Appendix A and proofs are in Appendix B.

Agents update their beliefs about μ_{it} based on surprises in realized cash flows and the signal. These surprises, denoted $d\tilde{W}_t^{Xi}$ and $d\tilde{W}_t^{is}$, are standard Brownian shocks:

$$d\tilde{W}_{it}^{X} = \frac{dX_{it} - \lambda_i(\hat{\mu}_{it} - X_{it})dt}{\sigma_{iX}}, \tag{11}$$

and

$$d\tilde{W}_{it}^{s} = \frac{ds_{it} - \hat{\mu}_{it}dt}{\sigma_{is}}. \tag{12}$$

Proposition 2. *The expected firm-level profitability at time $\tau > t$, $E_t(X_{i\tau})$, is driven by the current profitability, X_{it}, and short- and long-run profitability drivers, $\hat{\mu}_{it}$ and $\bar{\mu}_i$, respectively.*

$$E_t(X_{i\tau}) = \overbrace{a_i X_{it}}^{\text{current profitability}} + \underbrace{\overbrace{b_i \hat{\mu}_{it}}^{\text{short-run}} + \overbrace{c_i \bar{\mu}_i}^{\text{long-run}}}_{\text{expected profitability drivers}}, \tag{13}$$

where

$$a_i = e^{-\lambda_i(\tau - t)}, \tag{14}$$

$$b_i = \frac{\lambda_i}{\lambda_i - \kappa_i}\left[e^{-\kappa_i(\tau - t)} - e^{-\lambda_i(\tau - t)}\right], \tag{15}$$

and

$$c_i = 1 + \frac{\kappa_i}{\lambda_i - \kappa_i} e^{-\lambda_i(\tau - t)} - \frac{\lambda_i}{\lambda_i - \kappa_i} e^{-\kappa_i(\tau - t)}. \tag{16}$$

Proposition 2 highlights the factors influencing agents' expectations of future profitability $X_{it+\tau}$. First, current profitability X_{it} acts as the initial anchor, gradually diminishing over time at a rate determined by λ_i. Second, the expected change in profitability is influenced by two key components: mean reversion, which drives profitability toward the steady-state level $\bar{\mu}_i$, and the learning effect, which refines expectations based on updated beliefs about the unobservable driver $\hat{\mu}_{it}$. The information contained in the dynamics of X_{it}, and $\hat{\mu}_{it}$, and the steady-state level $\bar{\mu}_i$ shapes the belief formation process, enabling agents to make well-informed and forward-looking expectations about future firm profitability.

While existing literature has primarily examined the impact of current profitability on future returns, this paper emphasizes the predictive power of changes in firm profitability driven by both short- and long-run factors.

2.2 Model without learning

To isolate and quantify the impact of pure learning on asset prices, we compare a setting where firm profitability is fully observable to one where agents update their beliefs based on earnings surprises. Consider the case where the profitability factor μ_{it} is fully observable from the signal, i.e., $\mu_{it} = s_{it}$, which implies $\sigma_{is} = 0$. In this scenario, the expected profitability at time τ, $E_t(X_{i\tau})$, is determined entirely by the current profitability level X_{it}, the current profitability factor μ_{it}, and the expected mean reversion:

$$E_t(X_{i\tau}) = X_{it} + (\bar{\mu}_i - X_{it})\left[1 - e^{-\lambda_i \tau}\right] + \frac{\lambda_i(\mu_{it} - \bar{\mu}_i)}{\lambda_i - \kappa_i}\left[e^{-\kappa_i \tau} - e^{-\lambda_i \tau}\right]. \tag{17}$$

Without learning, earnings surprises have no effect on μ_{it}, and consequently, they do not influence $E_t(X_{i\tau})$, since μ_{it} is directly observable and evolves according to:

$$d\mu_{it} = \kappa_i(\bar{\mu}_i - \mu_{it})dt + \sigma_{\mu i} dW_{it}^{\mu}. \tag{18}$$

However, in a setting with learning, agents update their posterior beliefs about μ_{it} based on the realization of earnings surprises $d\tilde{W}_{it}^x$ and industry-level signals $d\tilde{W}_{it}^s$, leading to the following belief updating process:

$$d\hat{\mu}_{it} = \kappa_i(\bar{\mu}_i - \hat{\mu}_{it})dt + \frac{\lambda_i \nu_{it}}{\sigma_{ix}} d\tilde{W}_{it}^x + \frac{\nu_{it}}{\sigma_{is}} d\tilde{W}_{it}^s. \tag{19}$$

Testable Implication of the Learning Channel in Asset Pricing:

To empirically distinguish the impact of learning from the effects of mean-reverting drivers of profitability, we test whether the belief updating terms $\frac{\lambda_i \nu_{it}}{\sigma_{ix}} d\tilde{W}_{it}^x$ and $\frac{\nu_{it}}{\sigma_{is}} d\tilde{W}_{it}^s$ are priced in the cross-section of stock returns after controlling for current firm- and industry-level profitability, as well as the mean-reversion parameters λ_i and κ_i. If these shocks are priced, it would indicate that firm profitability μ_{it} is not fully observable from industry-level profitability signals, confirming that learning plays a significant role in shaping investor beliefs about firm fundamentals and, consequently, asset prices.

3. Data & Estimation

3.1 Data

We start our sample in January 1972 due to the availability of earnings announcement data and book equity in Compustat quarterly files. Return data comes from CRSP. Control variables are obtained from `openassetpricing.com` and factor data comes from Ken French and Lu Zhang's websites. Our sample ends in 2021.

Following Hou et al. (2015), we measure profitability as ROE, computed as income before extraordinary items (Compustat quarterly item IBQ) divided by 1-quarter-lagged book equity. As in Davis, Fama, and French (2000), book equity is shareholders' equity, plus balance-sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ). We use redemption value (item PSTKRQ) if available, or carrying value for the book value of preferred stock.

3.2 Proxies for the observable signal s_{it}

In our model, we assume that a firm's profitability, denoted as X_{it}, converges over time to an unobservable driver of firm profitability, μ_{it}. Agents form beliefs about μ_{it} using a noisy signal s_{it}. A suitable candidate for this informative signal should be an observable variable to which firm-level profitability naturally converges. Industry-level profitability serves as an ideal candidate for this signal, supported by extensive literature documenting the significant influence of industry-wide factors on individual firm profitability.

Empirical research has established that industry membership significantly influences firm profitability and stock returns. Hou (2007) finds that, within the same industry, big firms lead small firms. Firms in more concentrated industries earn lower returns, even after controlling for other return determinants (Hou and Robinson, 2006). Moskowitz and Grinblatt (1999) document that momentum investment strategies, which buy past winning stocks and sell past losing stocks, are significantly less profitable once we control for industry momentum. Novy-Marx (2013) explore the trend in firm profitability and its predictive power for stock returns and document how industry earnings trends influence future firm-level profitability and investment decisions. Furthermore, Hou et al. (2021) highlight that industry earnings contain predictive information about firm-level profitability, reinforcing the role of industry-wide accounting data as a signal for firm fundamentals.

These studies collectively support the assumption that industry-level profitability serves as a relevant and informative signal in shaping firm-level profitability expectations. By incorporating learning mechanisms into our model, we aim to quantify how industry-wide earnings influence firm-specific profitability beliefs and, in turn, asset prices.

Specifically, we define this observable signal to be the median industry-level ROE, estimated for each firm i at each quarter t. We use the Fama-French 30 industry classification as the primary categorization scheme.[1] This classification groups firms by their primary business activities and market characteristics, ensuring that firms within an industry share common external influences such as supply chain dynamics, regulatory environments, and technological advancements. These shared factors drive industry-level profitability trends, making industry profitability a natural anchor for firm-level profitability drivers.

Furthermore, industry profitability is time-varying, reflecting changing market conditions, competitive pressures, and shifts in industry-specific profitability drivers. For instance, industries sensitive to macroeconomic conditions, such as manufacturing or consumer goods, often exhibit profitability patterns that mirror broader economic cycles. Similarly, technology-driven industries may experience profitability shifts due to innovation or market disruptions. The dynamic nature of industry profitability ensures it remains a relevant benchmark for individual firms' profitability, capturing both systematic factors and industry-specific trends to which firms' profitability levels tend to adjust over time. By using industry profitability as the signal s_{it}, our model effectively incorporates these empirically supported relationships into the belief formation process.

3.3 Firm-level estimation

We employ a structural estimation approach to estimate the learning parameters $\theta_i = (\lambda_i, \kappa_i, \sigma_{\mu_i})$ for individual firms using earnings data only. The estimation matches the firm- and industry-level cash-flow dynamics implied by the learning model to observed data, leveraging firm-specific

[1] For robustness, we also test the Fama-French 12 industry classification and Fama French 12 and size (small versus large firms) classification. Our results remain robust to the change in classification.

information and cross-sectional variations. To avoid look-ahead bias, all model parameters are estimated for each firm on a rolling basis, with the estimation window extending every two years.

The estimation procedure aims to match three key moments between the model and the data:

1. Autocorrelation of firm-level ROE (AC(1)): Reflects the persistence in a firms profitability.

2. Autocorrelation of industry-level ROE (AC(1)): Captures industry-wide dynamics affecting profitability.

3. Covariance between firm-level and industry-level ROE: Highlights the relationship between a firms performance and its industry.

We minimize a loss function based on the weighted difference between the simulated and observed moments: $LossFunction_i = (m(\theta_i) - m')'W(m(\theta_i) - m')$, where $m(\theta_i)$ represents simulated moments, m' represents observed moments, and W is the weighting matrix.

To initialize the parameters, we use a combination of direct data estimates and Ordinary Least Squares (OLS) regressions. Firm-specific cash flow volatility (σ_{Xi}) is estimated as the standard deviation of realized ROE. Steady-state profitability ($\bar{\mu}_i$) is the in-sample long-run mean ROE. The volatility of the observed signal σ_{is} is set to the in-sample standard deviation of the industry ROE. The initial mean reversion speeds (λ_0, κ_0) are derived from AR(1) OLS regressions on firm-level and industry-level ROE, respectively. To ensure reliability, any initial estimates (λ_0, κ_0) outside the range [0, 5] are excluded. Simulations of both of μ_{it} and $\hat{\mu}_{it}$ start from its steady state.

The final parameters are refined using Simulated Method of Moments (SMM), where a rolling window approach ensures that only historical data available at time t is used to avoid look-ahead bias.

Figure 1 illustrates the histograms of estimated parameters λ_i and κ_i, confirming that the estimates are within plausible ranges.

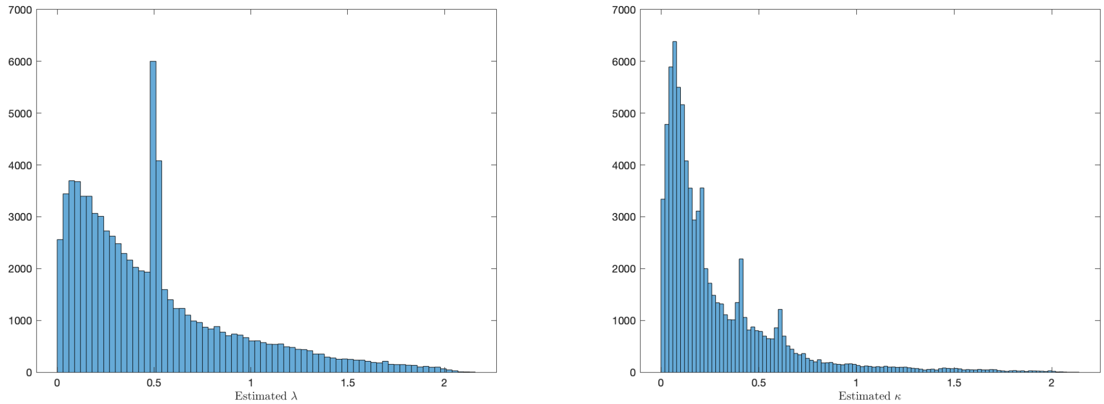

FIGURE 1: **The Cross Section of the Estimated Learning Parameters**
This figure displays the histogram of the estimated learning parameters from the structural firm-level estimation. It displays the estimates of λ_i and κ_i for individual firms that are being estimated using a rolling-window of historical realized ROE. Only data for each individual firm and the industry ROE (median level of FF12 ROE) is used to estimate these parameters.

3.4 Recovering earnings surprises and measuring current beliefs about firm profitability $\hat{\mu}_{it}$

Each quarter t, we use the most recent set of estimated parameters θ_i from the latest rolling estimation to recover firm- and industry-level earnings surprises associated with announcements at t. These parameters are carefully selected to ensure that no data beyond t is used in the estimation process, maintaining consistency with the information available at that time.

To form beliefs $\hat{\mu}_{it}$ and calculate the time series of earnings surprises, we apply Proposition 1 alongside equations (A.8) and (A.9). The initial belief $\hat{\mu}_{i0}$ is set to the steady-state level $\bar{\mu}_i$, and σ_{is} is set to the in-sample standard deviation of industry ROE. We iterate over all quarterly observations from quarter 0 to t, storing the calculated earnings surprises $d\tilde{W}_{it}^X$ and $d\tilde{W}_{it}^s$, as well as $\bar{\mu}_i$, for the final quarter t.

3.5 Expected profitability factor

We compute each firm's expected profitability using the estimated parameters λ_i and κ_i alongside the recovered $\hat{\mu}_{it}$. Applying Proposition 2 with a one-year horizon ($\tau = 1$), we estimate the next-year expected profitability, $E_t(X_{it+1})$.[2]

We use the firm-level expected profitability to construct the expected profitability factor using two-way sorts, incorporating profitability and firm size, and three-way sorts, incorporating profitability, firm size, and the investment-to-assets ratio.

Two-way sorts

Each month t, stocks are sorted into expected-change-in-ROE groups (robust, average, weak) based on 30-40-30 NYSE breakpoints. Expected change in ROE is measured using the most recent return on equity (ROE) data, as of month t. Stocks are also divided into two size groups (small, large) using the median NYSE breakpoint. These groups are rebalanced monthly.

We form six portfolios from the intersection of the two size groups and three expected-change-in-ROE groups. Each portfolios value-weighted average return is calculated for month $t+1$. The two-way expected profitability factor is the average return on robust portfolios minus the average return on weak portfolios:

$$\Delta\text{ROE}_t^{2-way} = \frac{R_{t,t+1}^{Robust,Large} + R_{t,t+1}^{Robust,Small} - R_{t,t+1}^{Weak,Large} - R_{t,t+1}^{Weak,Small}}{2}. \tag{20}$$

Three-way sorts

For three-way sorts, stocks are further grouped by the investment-to-assets ratio (I/A). At the end of each June, stocks are sorted into deciles based on their I/A ratio, calculated as the change in total assets (Compustat annual item AT) over the fiscal year ending in $t-1$, divided by total assets from the previous year. Size and profitability sorts are performed as described for the two-way sorts.

Eighteen portfolios are formed by combining the size, expected-change-in-ROE, and I/A groups. The three-way factor is the difference between the average return of robust portfolios and weak

[2]Our results are robust to different τ values, as this parameter does not vary cross-sectionally. Changing τ alters the relative weights of current profitability and other factors but does not affect the overall conclusions.

portfolios:

$$\Delta\text{ROE}_t^{3-way} = \frac{\sum_{i=1}^{3}\sum_{j=1}^{2} R_{t,t+1}^{Robust,IA_i,Size_j} - \sum_{i=1}^{3}\sum_{j=1}^{2} R_{t,t+1}^{Weak,IA_i,Size_j}}{6}. \tag{21}$$

4. Results

Understanding the dynamics of firm profitability requires analyzing both short-term fluctuations and long-term trends. The estimated parameters λ_i, κ_i, and various noise components provide valuable insights into how firms adjust, revert, and learn about their profitability over time. We report summary statistics for all variables in Table I.

One key aspect of the dynamics of firms' profitability is the speed of mean reversion (λ_i). On average, firms profitability exhibits a reversion speed of 0.4600, though this varies significantly across firms, as indicated by a standard deviation of 0.3945. Some firms show no mean reversion at all, while others revert rapidly, with a maximum value of 2.1376. Most firms, however, fall within an interquartile range of 0.1607 to 0.5928, suggesting that while profitability generally trends back toward its long-run level, the pace of adjustment differs widely.

Closely linked to this is the rate of mean reversion of unobservable driver of firm profitability (κ_i). The average mean reversion rate is 0.2129, also with a substantial degree of variation (0.2243 standard deviation). Some firms experience near-static dynamics, while others undergo rapid revisions, leading to more frequent update rates.

Firm-specific earnings shocks ($d\tilde{W}_{it}^x$) show a high degree of volatility, with a mean of -0.0564 and a standard deviation of 1.6911. The extreme values range from -27.6580 to 30.1730, highlighting the substantial variability in firm-level earnings surprises. While most firms experience relatively modest surprises, the presence of such outliers suggests that abrupt profitability shifts are not uncommon.

By contrast, industry-wide earnings shocks ($d\tilde{W}_{it}^s$) tend to be more stable. With a mean of -0.3765 and a standard deviation of 0.2375, these shocks fluctuate within a much narrower band compared to firm-level surprises. The 25th and 75th percentiles (-0.4492 and -0.2441, respectively) reinforce the idea that industry trends serve as a more gradual, predictable force shaping firm profitability.

The estimated volatility of the firm profitability driver (σ_{μ_i}) is quite low, averaging just 0.0069 with a tight standard deviation of 0.0041. This suggests that the underlying driver of profitability, while unobservable, is relatively stable over time. This estimated low volatility is due to the fact that we choose a reasonably stable source of information as a signal in our empirical section, which is based on median ROE levels within industry. Consequently, the estimated precision of agents' beliefs about profitability (ν_{it}) is also relatively small (0.0001 on average), indicating that while firms may experience profitability shocks from industry signals, the rate at which these beliefs refine over time remains rather consistent.

The belief estimate of firm profitability ($\hat{\mu}_{it}$) is centered around 0.1139, with limited dispersion (0.0263 standard deviation). Most firms cluster within a reasonable range, though extreme cases show that some firms experience drastically negative or abnormally high expected profitability. In the long run, firms appear to stabilize around an estimated average profitability level ($\bar{\mu}_i$) of 0.1302, reinforcing the idea that profitability expectations converge toward a stable industry norm.

Finally, examining expected changes in profitability provides further insight. The average change is 0.0360, with most of the variation driven by short-run adjustments (0.0309). Long-run changes, by contrast, contribute much less (0.0051), reinforcing the notion that while firms do experience fluctuations in profitability, the long-term trajectory remains relatively steady.

Taken together, these estimates provide a detailed view of firm profitability dynamics. The mean expected firm profitability is 3.6% per annum, approximately one-third of the average firm profitability (ROE) of 11.25% observed in our sample. A significant portion of this expected change in profitability comes from the short-run component, which exhibits both positive and negative fluctuations. In contrast, the estimated long-run component remains strictly positive, indicating a persistent underlying profitability trend. Firms vary in their speed of reversion to long-term profitability, their sensitivity to earnings surprises, and the efficiency with which investors update their beliefs. The considerable heterogeneity across these dimensions highlights the necessity of incorporating learning frictions and industry-wide information signals when evaluating firm profitability and its role in asset pricing.

4.1 Portfolio returns

Table II presents the average monthly value-weighted returns of portfolios, sorted according to their size and expected change in profitability levels. We find that as the expected change in profitability increases, the average returns of the corresponding portfolios rise monotonically. This effect is particularly pronounced among small firms. Small firms with the highest expected change in profitability (i.e., top 30%) generate, on average, 0.432% higher monthly returns than small firms in the bottom 30% of firms sorted on the expected change in profitability. For large firms, this differential is more modest at 0.162% per month, yet still statistically significant.

Examining the short-run and long-run components separately, we find that the return spread between high and low expected profitability portfolios is driven by both components. The return differential (RMW) for small firms is 0.388% per month when sorting based on short-run expected profitability, compared to 0.337% for the long-run component. Similarly, for large firms, the return spread due to the short-run component is 0.133%, whereas for the long-run component, it is slightly higher at 0.173%. These results suggest that short-term fluctuations in profitability expectations contribute significantly to cross-sectional return variation, particularly among small firms, where learning plays a substantial role in shaping investor expectations.

Furthermore, the statistical significance of these spreads differs across firm size groups. The return differential associated with short-run expected profitability is highly significant for small firms, with a t-statistic of 3.608, while for large firms, it is weaker and insignificant, with a t-statistic of 1.587. The long-run component exhibits a similar pattern, with the profitability effect being stronger and more significant for smaller firms (t-statistic 3.835) compared to larger firms (t-statistic 2.054). These findings highlight that small firms' stock returns are more sensitive to changes in profitability expectations, particularly in the short run, suggesting that investors may demand a higher premium for firms with greater uncertainty in profitability revisions.

Overall, the results confirm that profitability expectations are an important determinant of stock returns, with both short-term and long-term expected revisions playing a relevant role. The stronger effect observed among small firms aligns with the notion that information about future profitability is incorporated more slowly into their prices, leading to higher expected returns for firms experiencing upward profitability revisions.

4.2 Time-series spanning regressions

Tables III to V presents the results of time-series spanning regressions, testing whether the expected change in profitability earns positive abnormal returns that cannot be explained by traditional asset pricing factors. The average return spread on the two-way sorted factor ($\Delta \text{ROE}^{2-way}$) is 0.306 percent per month, while for three-way sorts, it is 0.137 percent per month. These return spreads persist even after controlling for well-established factors in the Fama-French and Q-factor models, indicating that expected changes in profitability capture unique information not fully accounted for by current profitability factors.

The alpha estimates remain statistically significant across all specifications demonstrating that firms with higher expected profitability earn positive abnormal returns. The significance levels are particularly strong in more comprehensive factor models, with t-statistics exceeding 3.0 in most cases. Notably, when including all six Fama-French factors (FF6F), the alpha remains high at 0.326 percent, with a t-statistic of 5.904, confirming the robustness of the expected change in profitability return premium.

Our key finding is that both the short-run and long-run components of expected profitability changes predict future returns. Table IV shows that the short-run component earns an alpha of 0.243 percent per month in the baseline two-way sorted model, increasing to 0.260 percent when controlling for FF6F factors. The long-run component exhibits similarly strong predictive power, with an alpha of 0.276 percent per month in the baseline model and 0.286 percent in the FF6F specification. These results suggest that both short- and long-term drivers of profitability expectations drive near-term stock returns, contributing significantly to return predictability.

The adjusted R-squared values, which measure how much of the variation in expected profitability changes is captured by existing factor models, range from 10 to 49 percent across all specifications. This indicates that although traditional factors explain some portion of expected profitability-driven returns, more than half of the variation remains unexplained, reinforcing the notion that learning about profitability dynamics introduces a distinct return premium. The inclusion of the momentum factor (MOM) in the most extensive factor models does not reduce the alpha of the expected profitability factor, nor it eliminates its significance.

Overall, these results highlight that expected changes in profitability represent a key return driver beyond current profitability levels. The persistent alpha estimates and high statistical significance across multiple model specifications confirm that profitability revisions are not fully captured by existing factor models, supporting the role of learning frictions and market inefficiencies in shaping asset prices.

4.3 Fama-MacBeth cross-sectional regressions

Table VI presents the results of Fama-MacBeth regressions, examining the relationship between firm characteristics and future one-month stock returns. The expected change in profitability is a significant predictor of returns, with a t-statistic exceeding 4, indicating strong statistical significance. Notably, the expected change in profitability remains significant even after controlling for other firm characteristics such as current profitability (ROE), accruals, size (ME), book-to-market ratio (BM), investment, and past returns. The coefficient on the expected change in profitability suggests that firms experiencing upward revisions in profitability expectations earn higher returns in the following month.

In Table VII, we extend this analysis to assess the predictive power of expected profitability changes over longer horizons. The results confirm that the expected change in profitability due to the short-run component predicts returns up to nine months into the future. Specifically, the coefficient on the expected change in profitability is large and statistically significant for returns over three-month (t-stat = 4.535), six-month (t-stat = 3.902), and nine-month horizons (t-stat = 3.551). This suggests that market participants do not immediately incorporate profitability revisions into stock prices, leading to return predictability over multiple months.

In contrast, current profitability (ROE) exhibits predictive power for returns only up to three months ahead, with its significance declining over longer horizons. For example, the t-statistic for ROE is 3.318 for three-month returns but drops to 2.575 for six-month returns and becomes insignificant at the nine-month horizon. This contrast highlights that expected changes in profitability provide additional information about future returns beyond what is captured by current profitability levels.

These findings highlight the importance of both short- and long-run profitability expectations in shaping future stock returns. The fact that expected profitability changes continue to predict returns beyond the short term suggests that investors are slow to adjust to profitability revisions, creating return opportunities for those who incorporate these insights into their investment strategies.

4.4 Testing the learning channel

In Tables VIII and IX, we examine the impact of learning on asset prices. Both surprises originating from firm and industry-level earnings announcements predict returns after controlling for current firm- and industry- levels of profitability, see Table IX.

When we further control for the firm- and industry-level profitability (our estimated learning coefficients) λ_i and κ_t, we find that the firm-level earnings surprises remain to be significantly predicting future one-month returns, see Table IX. This holds also after controlling for firm-level controls or for the current levels and long-run levels of firm profitability measures $\hat{\mu}_{it}$ and $\bar{\mu}$, respectively.

Our results indicate that learning about the unobservable drivers of firm profitability plays a relevant role in asset pricing.

5. Conclusion

Our paper provides evidence that learning about firm profitability plays a critical role in asset pricing. Our findings reveal that expected changes in profitability predict future stock returns beyond what is captured by current profitability measures, traditional asset pricing factors, or momentum. Both short- and long-run components of expected profitability revisions drive return predictability, with short-run changes exerting a stronger influence, particularly among smaller firms.

We demonstrate that market participants are slow to incorporate profitability revisions into stock prices, leading to significant return spreads. Our Fama-MacBeth regression results confirm that expected changes in profitability predict returns up to nine months ahead, whereas current profitability loses its predictive power beyond three months. Moreover, our tests of the learning mechanism show that firm- and industry-level earnings surprises remain strong return predictors, even after controlling for observed profitability levels and other firm characteristics.

These insights have direct implications for investors, portfolio managers, and policymakers. For investors, recognizing the markets underreaction to profitability revisions presents an opportunity to generate alpha by tilting portfolios toward firms with improving profitability expectations. For asset managers, incorporating learning-based signals into stock selection strategies can enhance risk-adjusted returns. For policymakers and corporate managers, the findings underscore the importance of transparent financial disclosures, as they influence the pace at which investors update their beliefs and prices adjust.

In an environment of heightened market volatility and frequent valuation swings, understanding how learning frictions shape asset prices is more relevant than ever. Our research highlights the inefficiencies in how profitability information is processed, providing a roadmap for those seeking to capitalize on mispricings in equity markets.

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Tables

	Mean	StdDev	Min	Max	25th	75th
ROE	0.1125	2.1848	-33.3330	31.5830	0.0429	0.6734
Accruals	-0.0298	0.0839	-0.4404	0.4060	-0.0688	0.0083
ME	2838	11204	0.9754	223610	58.1350	1241
BM	0.8022	0.7436	-1.5375	10.2630	0.3494	1.0337
Investment	0.9964	0.5009	0.0071	5.3760	0.6963	1.2021
ret	0.0137	0.1384	-0.7161	1.6356	-0.0562	0.0721
Mom12m	0.1608	0.5686	-0.9432	12.9790	-0.1484	0.3456
λ_i	0.4600	0.3945	0.0000	2.1376	0.1607	0.5928
κ_i	0.2129	0.2243	0.0000	2.0881	0.0708	0.2706
$d\tilde{W}_{it}^x$	-0.0564	1.6911	-27.6580	30.1730	-0.3544	0.2821
$d\tilde{W}_{it}^s$	-0.3765	0.2375	-2.1599	0.8342	-0.4492	-0.2441
σ_{μ_i}	0.0069	0.0041	0.0002	0.0232	0.0039	0.0094
ν_{it}	0.0001	0.0001	0.0000	0.0005	0.0000	0.0001
$\hat{\mu}_{it}$	0.1139	0.0263	-6.0878	0.2143	0.1011	0.1303
$\bar{\nu}_i$	0.0003	0.0006	0.0000	0.0076	0.0000	0.0003
$\bar{\mu}_i$	0.1302	0.0174	0.0712	0.1768	0.1211	0.1421
Expected change in ROE	0.0360	0.0241	-3.5039	0.1584	0.0169	0.0506
... due to the short-run component	0.0309	0.0196	-3.5182	0.1578	0.0155	0.0435
... due to the long-run component	0.0051	0.0071	0.0000	0.0870	0.0008	0.0063

TABLE I: Summary statistics.

Expected change in ROE	Small	Large
Robust (R)	1.3133	0.8165
Average	1.0733	0.6394
Weak (W)	0.8812	0.6547
RMW	0.4320	0.1618
	(3.868)	(1.943)
due to the short-run component		
Robust (R)	1.2920	0.7905
Average	1.0886	0.6515
Weak (W)	0.9040	0.6577
RMW	0.3880	0.1327
	(3.608)	(1.587)
due to the long-run component		
Robust (R)	1.2972	0.8181
Average	1.0435	0.6417
Weak (W)	0.9598	0.6454
RMW	0.3374	0.1726
	(3.835)	(2.054)

TABLE II: Two-way Portfolio sorts. FF30.

Expected Change in Profitability

Panel A	ΔROE^{2-way}	CAPM	FF2F	FF3F	FF4F	FF5F	FF6F
alpha	0.306	0.203	0.179	0.235	0.306	0.333	0.326
	(3.898)	(3.233)	(3.079)	(4.226)	(5.722)	(6.103)	(5.904)
MKTRF		0.164	0.133	0.109	0.100	0.090	0.091
		(12.175)	(10.326)	(8.638)	(8.270)	(7.032)	(7.084)
SMB			0.195	0.203	0.149	0.148	0.148
			(9.907)	(10.864)	(7.800)	(7.792)	(7.772)
HML				-0.147	-0.127	-0.092	-0.085
				-(8.049)	-(7.222)	-(3.967)	-(3.511)
RMW					-0.198	-0.206	-0.207
					-(8.035)	-(8.301)	-(8.345)
CMA						-0.086	-0.091
						-(2.311)	-(2.417)
MOM							0.011
							(.894)
Adj R2		20.106%	31.500%	38.256%	44.335%	44.747%	44.728%
Obs.		586	586	586	586	586	586

Panel B	ΔROE^{3-way}	CAPM	Q2	Q3	Q4	Q5	Q5+Mom
alpha	0.137	0.090	0.072	0.138	0.179	0.206	0.208
	(3.004)	(2.200)	(1.844)	(3.546)	(4.508)	(4.851)	(4.949)
R_MKT		0.074	0.059	0.037	0.031	0.027	0.029
		(8.415)	(6.707)	(4.093)	(3.521)	(2.882)	(3.158)
R_ME			0.094	0.095	0.079	0.075	0.066
			(7.207)	(7.545)	(6.072)	(5.692)	(4.888)
R_IA				-0.140	-0.141	-0.140	-0.136
				-(6.958)	-(7.107)	-(7.026)	-(6.865)
R_ROE					-0.061	-0.046	-0.071
					-(4.063)	-(2.685)	-(3.833)
R_EG						-0.041	-0.052
						-(1.770)	-(2.235)
MOM							0.033
							(3.358)
Adj R2		10.661%	17.828%	24.008%	25.981%	26.251%	27.535%
Obs.		586	586	586	586	586	586

TABLE III: Portfolio alphas.

Expected Change in Profitability due to the short-run component

Panel A	ΔROE^{2-way}	CAPM	FF2F	FF3F	FF4F	FF5F	FF6F
alpha	0.243	0.134	0.108	0.168	0.244	0.274	0.260
	(3.195)	(2.100)	(1.851)	(3.019)	(4.587)	(5.072)	(4.769)
MKTRF		0.173	0.140	0.114	0.104	0.092	0.096
		(12.619)	(10.759)	(9.031)	(8.696)	(7.329)	(7.523)
SMB			0.210	0.219	0.161	0.160	0.159
			(10.606)	(11.699)	(8.499)	(8.501)	(8.481)
HML				-0.156	-0.134	-0.095	-0.082
				-(8.552)	-(7.728)	-(4.131)	-(3.419)
RMW					-0.211	-0.219	-0.223
					-(8.616)	-(8.938)	-(9.069)
CMA						-0.099	-0.108
						-(2.660)	-(2.893)
MOM							0.022
							(1.738)
Adj R2		21.291%	33.909%	41.186%	47.759%	48.300%	48.479%
Obs.		586	586	586	586	586	586

Panel B	ΔROE^{3-way}	CAPM	Q2	Q3	Q4	Q5	Q5+Mom
alpha	0.121	0.075	0.058	0.123	0.165	0.188	0.191
	(2.782)	(1.847)	(1.486)	(3.199)	(4.201)	(4.478)	(4.572)
R_MKT		0.074	0.059	0.037	0.031	0.027	0.030
		(8.436)	(6.762)	(4.131)	(3.546)	(2.969)	(3.245)
R_ME			0.091	0.091	0.075	0.072	0.062
			(6.987)	(7.322)	(5.827)	(5.485)	(4.688)
R_IA				-0.140	-0.141	-0.140	-0.136
				-(7.014)	-(7.171)	-(7.096)	-(6.937)
R_ROE					-0.062	-0.049	-0.074
					-(4.181)	-(2.900)	-(4.025)
R_EG						-0.036	-0.046
						-(1.538)	-(2.001)
MOM							0.033
							(3.342)
Adj R2		10.710%	17.469%	23.771%	25.870%	26.044%	27.319%
Obs.		586	586	586	586	586	586

Table IV: Portfolio alphas.

Expected Change in Profitability due to the long-run component

Panel A	ΔROE^{2-way}	CAPM	FF2F	FF3F	FF4F	FF5F	FF6F
alpha	0.276	0.193	0.170	0.224	0.291	0.286	0.286
	(4.051)	(3.010)	(2.836)	(3.866)	(5.165)	(4.958)	(4.904)
MKTRF		0.132	0.103	0.080	0.071	0.073	0.072
		(9.605)	(7.717)	(6.064)	(5.591)	(5.393)	(5.316)
SMB			0.185	0.193	0.142	0.142	0.142
			(9.117)	(9.921)	(7.082)	(7.082)	(7.075)
HML				-0.141	-0.121	-0.128	-0.128
				-(7.392)	-(6.583)	-(5.234)	-(4.995)
RMW					-0.186	-0.184	-0.184
					-(7.178)	-(7.055)	-(7.021)
CMA						0.016	0.016
						(.399)	(.399)
MOM							0.000
							-(.034)
Adj R2		13.495%	24.159%	30.549%	36.096%	36.003%	35.893%
Obs.		586	586	586	586	586	586

Panel B	ΔROE^{3-way}	CAPM	Q2	Q3	Q4	Q5	Q5+Mom
alpha	0.112	0.078	0.061	0.087	0.138	0.172	0.175
	(3.180)	(2.461)	(2.054)	(2.900)	(4.574)	(5.396)	(5.535)
R_MKT		0.054	0.038	0.029	0.023	0.017	0.019
		(7.860)	(5.829)	(4.234)	(3.398)	(2.415)	(2.756)
R_ME			0.092	0.093	0.073	0.068	0.059
			(9.381)	(9.506)	(7.419)	(6.839)	(5.894)
R_IA				-0.057	-0.058	-0.056	-0.052
				-(3.659)	-(3.882)	-(3.756)	-(3.545)
R_ROE					-0.074	-0.055	-0.078
					-(6.565)	-(4.271)	-(5.610)
R_EG						-0.054	-0.064
						-(3.060)	-(3.639)
MOM							0.030
							(4.087)
Adj R2		9.413%	21.158%	22.798%	28.005%	29.027%	30.898%
Obs.		586	586	586	586	586	586

TABLE V: Portfolio alphas.

	$r_{t,t+1}$
Intercept	0.310
	(5.043)
ROE	10.146
	(5.858)
Expected change in ROE:	10.146
	(5.858)
Accruals	-2.092
	-(5.590)
ME	0.000
	-(2.797)
BM	0.378
	(4.564)
Investment	-0.222
	-(4.611)
ret(-1,0)	-4.272
	-(7.265)
ret(-12,-1)	0.059
	(.285)
Adj R2	3.499%
	1,338,103

TABLE VI: Fama MacBeth regressions. Future one-month return ($r_{t,t+1}$) being regressed on firm characteristics observed at time t. Newey-West adjusted t-stats. Winsorizing at 1% level.

	$r_{t,t+3}$	$r_{t,t+6}$	$r_{t,t+9}$	$r_{t,t+12}$
Intercept	1.462	3.026	3.114	-22.306
	(2.054)	(2.138)	(.907)	-(.658)
ROE	0.672	1.023	0.680	-1.234
	(3.318)	(2.575)	(.779)	-(.191)
Expected change in ROE:	29.417	50.509	61.498	9.465
	(4.535)	(3.902)	(3.551)	(.106)
Accruals	-5.767	-11.774	-26.386	-156.460
	-(4.541)	-(3.775)	-(1.898)	-(1.096)
ME	0.000	0.000	-0.001	-0.001
	-(2.696)	-(2.584)	-(2.767)	-(1.058)
BM	1.119	2.528	5.238	27.073
	(3.859)	(3.675)	(2.306)	(1.164)
Investment	-0.612	-1.155	-1.021	5.934
	-(3.937)	-(3.596)	-(.921)	(.535)
ret(-1,0)	-4.325	-3.517	-1.705	3.168
	-(4.094)	-(2.213)	-(.524)	(.105)
ret(-12,-1)	0.102	-0.726	-3.848	-24.363
	(.147)	-(.483)	-(1.551)	-(1.680)
Adj R2	3.927%	4.050%	4.043%	3.769%
Obs.	1,338,103	1,338,103	1,338,103	1,338,103

TABLE VII: Fama MacBeth regressions. Future three- to twelve-month returns are regressed on firm characteristics observed at time t. Newey-West adjusted t-stats.

Testing the Learning Channel:

	$r_{t,t+1}$	$r_{t,t+1}$	$r_{t,t+1}$	$r_{t,t+1}$	$r_{t,t+1}$	$r_{t,t+1}$
Intercept	0.710	0.875	0.316	0.503	0.036	0.166
	(2.709)	(3.206)	(1.296)	(2.026)	(.146)	(.716)
ROE	0.146	0.133	0.166	0.152	0.331	0.317
	(2.250)	(1.867)	(2.528)	(2.089)	(4.398)	(5.034)
Industry ROE	11.036	10.836	12.787	12.800	11.137	10.670
	(2.162)	(2.202)	(2.537)	(2.626)	(2.456)	(2.567)
$\nu_{it} * d\tilde{W}^x_{it}$		992.930		986.826		521.216
		(3.063)		(3.025)		(2.369)
$\nu_{it} * d\tilde{W}^s_{it}$		10576.599		8769.730		5697.347
		(2.640)		(2.110)		(1.899)
λ_i			-0.032	-0.100	0.319	0.281
			-(.265)	-(.699)	(3.482)	(3.079)
κ_i			1.858	1.802	1.329	1.299
			(6.162)	(5.193)	(6.391)	(7.361)
					-2.060	-2.041
					-(5.017)	-(5.640)
					0.000	0.000
					-(2.661)	-(2.777)
					0.377	0.371
					(4.255)	(4.586)
					-0.225	-0.221
					-(4.264)	-(4.627)
					-4.358	-4.454
					-(6.266)	-(7.436)
					0.046	0.039
					(.219)	(.190)
Adj R2	0.683%	0.966%	1.000%	1.290%	3.738%	4.036%
Obs.	1,338,103	1,338,103	1,338,103	1,338,103	1,338,103	1,338,103

TABLE VIII: Testing the learning mechanism.

	$r_{t,t+1}$	$r_{t,t+1}$
Intercept	-0.161	-0.028
	-(.479)	-(.092)
ROE	0.326	0.316
	(5.702)	(5.456)
Industry ROE	9.077	8.644
	(2.535)	(2.507)
$\hat{\mu}_{it}$	0.945	0.288
	(.637)	(.200)
$\bar{\mu}_i$	4.518	6.522
	(.566)	(.829)
$\nu_{it} * d\tilde{W}^x_{it}$		473.314
		(2.170)
$\nu_{it} * d\tilde{W}^s_{it}$		5107.744
		(1.776)
λ_i	0.332	0.285
	(3.386)	(2.863)
κ_i	1.342	1.329
	(7.565)	(7.439)
Accruals	-2.079	-2.051
	-(5.904)	-(5.935)
ME	0.000	0.000
	-(2.951)	-(2.912)
BM	0.373	0.367
	(4.758)	(4.741)
Investment	-0.222	-0.219
	-(4.834)	-(4.819)
ret(-1,0)	-4.448	-4.529
	-(7.976)	-(8.056)
ret(-12,-1)	0.028	0.023
	(.142)	(.114)
Adj R2	3.984%	4.251%
Obs.	1,338,103	1,338,103

TABLE IX: Testing the learning mechanism.

A. Appendix: Filtering Theorem

According to Theorem 12.2 from Liptser and Shiryaev (2013), in a system represented by a set of observables s_t and unobservable θ_t with the following dynamics:

$$d\theta_t = \left(a_0(t) + a_1(t)\theta_t + a_2(t)s_t\right) dt + \sum_{i=1}^{2} b_i(t) dW_i(t) \tag{A.1}$$

$$ds_t = \left(A_0(t) + A_1(t)\theta_t + A_2(t)s_t\right) dt + \sum_{i=1}^{2} B_i(t) dW_i(t), \tag{A.2}$$

the posterior beliefs about θ_t, defined as $\hat{\theta}_t$ and the posterior uncertainty ν_t evolve according to

$$d\hat{\theta}_t = \left(a_0(t) + a_1(t)\hat{\theta}_t + a_2(t)s_t\right) dt + \left[(b \circ B) + \nu_{it} A_1'(t)\right] (B \circ B)^{-1} \left[ds_t - \left(A_0(t) + A_1(t)\hat{\theta}_t + A_2(t)s_t\right) dt\right], \tag{A.3}$$

and

$$d\nu_t = \left[a_1(t)\nu_t + \nu_t a_1'(t) + (b \circ b) - \left((b \circ B) + \nu_t A_1'(t)\right) (B \circ B)^{-1} \left((b \circ B) + \nu_t A_1'(t)\right)\right] dt. \tag{A.4}$$

Out set of observables, $s_t = (X_{it}, s_{it})'$, is described by the following dynamics

$$\begin{bmatrix} dX_{it} \\ ds_{it} \end{bmatrix} = \left(\underbrace{\begin{bmatrix} 0 \\ 0 \end{bmatrix}}_{A_0} + \underbrace{\begin{bmatrix} \lambda_i \\ 1 \end{bmatrix}}_{A_1} \mu_t + \underbrace{\begin{bmatrix} -\lambda_i & 0 \\ 0 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} X_{it} & s_{it} \end{bmatrix} \right) dt + \underbrace{\begin{bmatrix} 0 \\ 0 \end{bmatrix}}_{B_1} dW_t^{\mu} + \underbrace{\begin{bmatrix} \sigma_{ix} & 0 \\ 0 & \sigma_{is} \end{bmatrix}}_{B_2} \begin{bmatrix} dW_{it}^X \\ dW_{it}^s \end{bmatrix}, \tag{A.5}$$

and the unobservable in our model is the firm profitability μ_{it}, i.e., $\theta_t = \mu_{it}$, which evolves according to

$$d\mu_{it} = \left(\underbrace{\kappa_i}_{a_0} \bar{\mu}_i \underbrace{-\kappa_i}_{a_1} \mu_{it} \right) dt + \underbrace{\sigma_{\mu}}_{b_1} dW_{it}^{\mu} + \underbrace{\begin{bmatrix} 0 & 0 \end{bmatrix}}_{b_2} \begin{bmatrix} dW_{it}^X \\ dW_{it}^s \end{bmatrix}. \tag{A.6}$$

Applying Theorem 12.2 yields the following dynamics for the posterior beliefs $\hat{\mu}_{it}$, $\hat{\mu}_{it} = E_t(\mu_{it} | \mathcal{F}_t)$

$$d\hat{\mu}_{it} = \kappa_i(\bar{\mu}_i - \hat{\mu}_{it})dt + \frac{\lambda_i \nu_{it}}{\sigma_{ix}} d\tilde{W}_{it}^x + \frac{\nu_{it}}{\sigma_{is}} d\tilde{W}_{it}^s, \tag{A.7}$$

where

$$d\tilde{W}_{it}^x = \frac{dX_{it} - \lambda_i(\hat{\mu}_{it} - X_{it})dt}{\sigma_{ix}}, \tag{A.8}$$

and

$$d\tilde{W}_{it}^s = \frac{ds_{it} - \hat{\mu}_{it} dt}{\sigma_{is}}. \tag{A.9}$$

Posterior uncertainty ν_{it}, $\nu_{it} = E_t([\mu_{it} - \hat{\mu}_{it}]^2)$ evolves according to

$$d\nu_{it} = \left(\sigma_{\mu_i}^2 - 2\kappa_i \nu_{it} - \frac{\lambda_i^2 \nu_{it}^2}{\sigma_{ix}^2} - \frac{\nu_{it}^2}{\sigma_{is}^2} \right) dt. \tag{A.10}$$

B. Appendix: Proofs

Proof of Proposition 2

Proof. Posterior beliefs $\hat{\mu}_{it}$ and posterior uncertainty ν_{it} evolve according to

$$d\hat{\mu}_{it} = \kappa_i(\bar{\mu}_i - \hat{\mu}_{it})dt + \frac{\lambda_i \nu_{it}}{\sigma_{ix}} d\tilde{W}_{it}^x + \frac{\nu_{it}}{\sigma_{is}} d\tilde{W}_{it}^s, \tag{B.1}$$

and

$$d\nu_{it} = \left(\sigma_{\mu_i}^2 - 2\kappa_i \nu_{it} - \frac{\lambda_i^2 \nu_{it}^2}{\sigma_{ix}^2} - \frac{\nu_{it}^2}{\sigma_{is}^2}\right) dt. \tag{B.2}$$

To derive the conditional expectation of future firm-level profitability at time τ, $X_{i\tau}$: $E_t(X_{i\tau})$, we first define the conditional expectation of future μ_{is}, formed at t, $\forall s > t$:

$$E_t(\mu_{is}) = \bar{\mu}_i + (\hat{\mu}_{it} - \bar{\mu}_i)e^{-\kappa_i(s-t)}. \tag{B.3}$$

Next, we define $y_t = e^{\lambda_i t} X_{it}$, with the following properties.

$$dy_t = e^{\lambda_i t}(dX_{it} + \lambda x_{it} dt) = e^{\lambda_i t}(\lambda_i \mu_{it} dt + \sigma_{ix} dW_{it}^x) \tag{B.4}$$

$$y_\tau = y_t + \lambda_i \int_t^\tau e^{\lambda_i s} \mu_{is} ds + \sigma_{ix} \int_t^\tau e^{\lambda_s s} dW_{is}^x \tag{B.5}$$

The expected value of y_τ is given by

$$E_t(y_\tau) = y_t + \lambda_i \int_t^\tau e^{\lambda_i s} E_t(\mu_{is}) ds = y_t + \lambda_i \int_t^\tau e^{\lambda_i s} \left(\bar{\mu}_i + (\hat{\mu}_{it} - \bar{\mu}_i)e^{-\kappa_i(s-t)}\right) ds$$

$$E_t(y_\tau) = y_t + \lambda_i \bar{\mu}_i \frac{1}{\lambda_i}\left[e^{\lambda_i \tau} - e^{\lambda_i t}\right] + \frac{\lambda_i(\hat{\mu}_{it} - \bar{\mu}_i)}{\lambda_i - \kappa_i}\left(e^{(\lambda_i - \kappa_i)\tau + \kappa_i t} - e^{\lambda_i t}\right), \tag{B.6}$$

which translates into

$$E_t(X_{i\tau}) = \underbrace{X_{it} e^{-\lambda_i(\tau - t)}}_{\lim_{t \to -\infty} = 0} + \bar{\mu}_i \left[1 - \underbrace{e^{-\lambda_i(\tau - t)}}_{\lim_{t \to -\infty} = 0}\right] + \frac{\lambda_i(\hat{\mu}_{it} - \bar{\mu}_i)}{\lambda_i - \kappa_i} \underbrace{\left[e^{-\kappa_i(\tau - t)} - e^{-\lambda_i(\tau - t)}\right]}_{\lim_{t \to -\infty} = 0}. \tag{B.7}$$

This expectation converges to the long-run mean $\bar{\mu}_i$. □