Business, Liquidity, and Information Cycles

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Abstract

Stock markets play a dual role: they provide information about firms' fundamentals, which improves resource allocations, and they provide liquidity. We propose a setting in which these two roles interact: if stocks are used more intensively for liquidity, then prices reveal less information about fundamentals. We structurally estimate stock price informativeness for several countries and show that it declines when alternative liquidity sources, such as banks, are in distress. To study the real effects of this mechanism, we devise a strategy to integrate our stock-trading module into a dynamic general equilibrium model with heterogeneous firms. We calibrate the model to the US and simulate recessions with and without banking distress. In a stand-alone recession, prices become more informative, and allocation improves, mitigating output losses by 4.4%. If the recession coincides with banking distress, agents rely more on stock markets to obtain liquidity, prices become less informative, and allocation deteriorates, magnifying output losses by 22%.

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1 Introduction

Stock markets play two critical roles in market economies: allocating resources and providing liquidity. The former stems from the remarkable ability of markets to aggregate and make public information about firms' prospects that is dispersed among traders. This is usually referred to as *stock price informativeness*, guiding how investors allocate their funds across investment opportunities. The latter, commonly referred to as *market liquidity*, comes from providing a platform where traders can buy or sell stocks to satisfy their liquidity needs. The extent to which traders rely on stock markets for liquidity depends on the availability of alternative sources, such as financial intermediaries that provide liquidity by facilitating credit, commonly referred to as *funding liquidity*.

Despite a rich literature discussing the information and liquidity roles of stock markets separately, their interaction is less understood. Does the role of stock markets in providing liquidity enhance or weaken their role in providing information? How does distress in other sources of liquidity, such as the banking sector, affect price informativeness? How does the information content of stock prices vary with business cycles? How do banking crises and other credit market distress contribute to the depth of a recession?

In this paper, we make progress on three fronts. The first is *theoretical*, by building a model of stock trading where the extent to which agents use stocks to access liquidity affects the extent to which prices reflect firms' fundamentals. We then incorporate this module into a dynamic general equilibrium setting with heterogeneous firms where stock price informativeness impacts capital allocation and investment. The second front is *empirical*, by structurally estimating stock price informativeness from firm-level panel data for several countries and establishing its cyclical properties. The last front of progress is *quantitative*, by calibrating the general equilibrium model to quantify the role of price informativeness on capital allocation in recessions, with and without funding liquidity distress.

To be more precise, our theoretical contribution hinges on extending the seminal model of Grossman and Stiglitz (1980): rational traders are willing to acquire information about firms at a cost because the presence of noise traders prevents prices from perfectly revealing the information others acquire. To accommodate the two main roles of stock markets, we allow for two types of rational traders -day and night- interested in different stock properties -liquidity and fundamentals, respectively. This structure dispenses with the assumption of noise traders and creates *endogenous noise* in prices: a high price may indicate that the stock is easily traded or that the firm has strong fundamentals. The trades from one type of trader act as noise for the other. We show that, in equilibrium, (1) a linear pricing function exists where price informativeness depends on the relative weights of information about fundamentals and about liquidity contained in prices, and (2) these weights are given by how many day and night traders operate in the market, their information choices, and how aggressively they trade on their information.

We then integrate this trading module into a real business cycle model with heterogeneous firms. We provide a parsimonious link between financial and real markets by preserving a linear pricing function in a nonlinear production economy. Stocks are claims to firms' earnings, which depend on firms' idiosyncratic productivities (i.e., fundamentals). If those productivities were known, investors would allocate capital efficiently across firms. In our model, those productivities are ex ante unknown, and allocations are based on investors' best estimates derived from stock prices, which conflate fundamental information with noise generated by day traders. When funding markets malfunction, the economy relies more on stocks to access liquidity, there are more day traders, price informativeness declines, and the misallocation of resources across firms worsens.

Our model delivers a linear relationship among stock prices, firms' earnings, and stock liquidity, independent of general equilibrium considerations. This property allows us to define Price Informativeness, PI henceforth, as an analytical function of four components: the dispersion of firm productivity, the dispersion of stock price fluctuations, and their respective price loadings. This measure tells us that in a market with high PI, a firm's high stock price (relative to other firms) is a strong signal that traders have positive information about its fundamentals. Our empirical contribution consists of measuring the PI in a given country each year. We implement this structural estimation using panel data from 16 countries spanning 1984 to 2022 and show that PI exhibits cyclicality but, more importantly, declines in periods of insufficient funding liquidity, such as during the Great Recession and the COVID-19 pandemic. We structurally decompose PI fluctuations into those of its four components and show that these fluctuations are mostly explained by changes in trading activity rather than in information quality.

Finally, in our quantitative contribution, we measure the relevance of stock price informativeness on the allocation of resources, total investment, and other macro aggregates. We calibrate the parameters of the full model for the United States, assuming the economy is subject to two, possibly correlated, aggregate shocks: one affecting aggregate productivity and one affecting funding liquidity. The shock structure is meant to capture recessions with and without distress in the banking sector. We use aggregate moments and moments of the estimated pricing functions to discipline both the cost of acquiring information and the dynamics of market liquidity needs. The calibrated model successfully replicates the cyclical properties of our PI measure without explicitly targeting them.

Our PI estimate measures how much prices reveal to an outside observer what informed traders know. In the model, stock prices are the only sources of information about firms, but in reality investors use other sources, and may already know what informed traders know. We acknowledge these possibilities in our quantitative analysis, disciplining their relevance using empirical price-investment correlations across firms and time-series correlations between price informativeness and investment dispersion. We show that new stock price information for decision makers is roughly as important as the information they already know, thereby underscoring the "revelatory" importance of PI.

Using the calibration, we conduct impulse-response exercises to simulate recessions, with and without distress in funding markets. Recessions without funding market distress are *cleansing*. Increased uncertainty induces all traders to acquire more information, leading to greater price informativeness and improved resource allocation, mitigating output losses by 4.4%. In contrast, recessions with funding market distress are *sullying*. Despite all traders still acquiring more information, the heightened trading activity for liquidity purposes makes prices less informative, and resource allocation worsens, magnifying output losses by 22%. This result implies a sizable real effect of banking problems through a novel channel: weakening the information and allocative role of stock markets.

We further explore how the U.S. economy would fare in a recession with funding liquidity distress under alternative information structures. If information were exogenous, liquidity distress would reduce PI by a larger amount, with output declining by 43% more than in our benchmark with endogenous information. This result suggests that endogenous information acquisition makes stock markets to "lean against the wind" during recessions, by conveying more information about fundamentals. We also show that if the cost of information *about firms' fundamentals* were halved, PI would decline less, leading to output declines that are about 5% smaller. If, instead, the cost of information *about a stock's liquidity* were halved, PI would decline more, leading to output declines that are about 2%

larger. This result suggests transparency is nuanced: easier access to information about one source can make it harder to infer information about other sources.

Literature Review: Our paper lies at the intersection of the literature on price informativeness and the literature on input misallocation. Also on this intersection are David et al. (2016) and David and Venkateswaran (2019), perhaps the closest to our study. The former focuses on the role of informational frictions in resource allocation and measures how much each source of information contributes to productivity gaps. The latter has a larger scope and incorporates many potential frictions that can distort resource allocation in addition to informational frictions. Both studies provide static measures; hence, they are silent about cyclicality, which is our focus. Further, by formalizing how the information content in stock prices reacts to changes in aggregate conditions, we can discipline the relative weight assigned to stock prices when allocating resources over the cycle.[1]

Our work addresses seemingly conflicting results in the literature on input allocation across firms during recessions.[2] We show that those findings should be qualified by whether a recession coincides with distress in financial markets. In doing so, we provide a mechanism that accounts for Foster et al. (2016)'s finding that labor allocation worsened during the Great Recession, despite improving during previous post-80s U.S. recessions. Further, by quantitatively assessing the role of liquidity distress in misallocation, we provide a complementary channel through which financial markets affect business cycles: when banks are in distress, the informational and allocative roles of stock markets weaken. Hence, we add to the seminal literature that follows Bernanke (1983) on understanding how financial problems magnify fluctuations.

We also contribute to both the theoretical and empirical literature on price informativeness. On the theoretical front, the literature usually assumes an exogenous source of noise that prevents prices from being perfectly informative. A follow-up literature, such

[1] Goldstein (2023) provides a survey of the evidence about the relevance of stock prices in informing and affecting the decisions of managers, banks, credit rating agencies, and regulators. Also, even though their focus is not misallocation, Dow et al. (2017), Benhabib et al. (2019), and Chousakos et al. (2023) provide theoretical interactions between real and financial sectors in terms of learning and information acquisition.

[2] Alam (2020) documents a counter-cyclical dispersion of the marginal product of capital (MPK) using balance sheet data from North America and Europe. See also Oberfield (2013) and Sandleris and Wright (2014), which document an increased dispersion of MPK during the 1982 Chilean crisis and the 2001 Argentine Crisis, respectively. Flynn and Sastry (2024) and Osotimehin (2019) claim the opposite: the former argues that the US public firms' input choices become more careless and volatile, and the latter argues that within-sector allocative efficiency among French firms declines in good times.

as Stein (1987) and Vives (2014), endogenizes the information/noise ratio by assuming that two dimensions of information are condensed into a single price. Both use heterogeneity in traders' characteristics (the former on market access and the latter on private valuations) to generate imperfectly informative prices without exogenous noise.[3] We also endogenize noise in prices, but heterogeneous traders acquire common, not private, information about two dimensions of the stocks. In other words, instead of traders with access to asymmetric information, we have traders with asymmetric needs.

On the empirical front, we contribute to a recent literature that strives to measure stock price informativeness. Dávila and Parlatore (2018) use time-series regressions to measure a moving-average price informativeness *for each stock*, which requires them to make assumptions on how parameters change over time to keep the cross-sectional variation flexible. We use cross-sectional regressions to measure the price informativeness of *a representative stock over time*, which requires us to make assumptions on the extent of heterogeneity across stocks to allow parameters to change flexibly over time. Bai et al. (2016) also resort to cross-sectional regressions, but estimate a measure based on the forecasting ability of prices and focus on its long-run trends, not its cyclical properties. Our PI measures how well stock prices reflect what informed traders know at a given time, which is related to but distinct from their ability to forecast future returns. Our measure is also silent on whether such information is incorporated into decision-making, but in the quantitative analysis, we devise a method to identify its "revelatory" component.[4]

The paper proceeds as follows. Section 2 introduces a stock trading model with endogenous noise and shows how to integrate it into an otherwise standard RBC model with firm heterogeneity. Section 3 describes the data sources and the empirical strategy to compute stock price informativeness and its structural components. Then, it studies the cyclical properties of the estimated series and their relation with measures of funding liquidity distress. Section 4 calibrates the model to the United States. Section 5 uses the calibrated model to assess the quantitative relevance of liquidity distress, information costs, and additional sources of information for real variables through their effects on PI. Section 6 concludes. All proofs are contained in Appendix A.

[3]See also Rahi (2021) and Banerjee et al. (2026) for theoretical exercises that expand on Vives (2014).

[4]Our estimation strategy distinguishes "forecasting" and "revelatory" price informativeness, as defined in Bond et al. (2012). While the former concept captures how well prices predict future earnings, and affect what Dow and Gorton (1997) call "stock market efficiency," the latter captures how well prices inform decision makers and real variables, being relevant for what they call "economic efficiency."

2 Model

In this section, we build a stock trading model and incorporate it into a real business cycle model with firm heterogeneity. A firm's stock price provides information about two dimensions: the firm's profitability and the stock's liquidity, which are valued differently by different types of traders. A single price contains information about both elements; the trading activity of one type of trader masks the information from the other. Since real investors use a firm's stock price as a signal of profitability, allocative efficiency depends on the composition of traders and their information-acquisition choices. To keep the notation simple, we suppress time subscripts unless necessary.

2.1 Environment

Preferences Time is discrete. In a given period, the economy is populated by a measure one of identical *infinitely lived* households and a measure one of traders who live for just one period. The representative household has constant-relative-risk-aversion (CRRA) preferences where the utility from consuming W is given by $u(W) = \frac{W^{1-\eta}-1}{1-\eta}$, with inter-temporal elasticity of substitution $1/\eta$. Traders have constant-absolute-risk-aversion (CARA) preferences where the utility from consuming W is given by $\nu(W) = -e^{-aW}$, with risk aversion $a > 0$.[5]

Technology There is a measure one of firms (indexed by i) with profit function:

$$\Pi_i = z_{in}(\bar{K}_i + K_i) - \xi K_i^2/2\bar{K}_i - r_i K_i \tag{1}$$

where z_{in} is the productivity of firm i's capital. $\bar{K}_i$ is installed capital, and K_i is capital rented at a price r_i. While $\bar{K}_i$ cannot be changed or reallocated, K_i is chosen every period. This profit function is derived from a production function with capital and a quadratic adjustment cost, which introduces curvature. The output price is normalized to one.

[5]We can allow *long-lived* traders. With CARA utility functions, their portfolio choice problem would not be affected by wealth, and the solution would be identical. We could also allow households to be traders. Our modeling choice, however, allows us to cleanly separate the process by which information about firms enters prices from the process by which that information is used to make allocation choices in an otherwise standard RBC setting with heterogeneous firms.

Assets and Endowments There are three types of assets in the economy: capital, stocks, and foreign bonds. Households save in *capital* through a mutual fund. The mutual fund allocates capital by renting it to firms through price-discriminating, take-it-or-leave-it offers $\{K_i, r_i(z_{in})\}$ to each firm i. In words, the mutual fund rents K_i to firm i charging a rate $r_i(z_{in})$ that is conditional on the realized ex-post productivity, extracting all surplus in each state.[6] The mutual fund is a decision-making aggregator owned by households, which is meant to capture households' allocation of their savings across different firms. Hence, the mutual fund's total return r is fully distributed to households. Traders can invest in *foreign bonds* with exogenous return r^F and in firms' shares, i.e., *stocks*. Each share entitles the holder to 1 unit of installed capital at the associated firm, so the firm's outstanding share amount, i, equals $\bar{K}_i$.[7]

This market structure provides a clear split of the firm surplus: the surplus from $\bar{K}_i$ goes to traders, while the surplus from K_i goes to households through the mutual fund. This split guarantees that the profitability of holding a firm's stock depends only on z_{in}, not on the capital K_i allocated to the firm.

Funding Liquidity and Market Liquidity Traders are born at the beginning of the period, endowed with $\tilde{b}$ foreign bonds. They can buy stocks at birth (from previous traders about to die) and sell stocks at the end of the period (to newborns), but need to consume in the middle of the period. They have two ways to finance such consumption. They can obtain a loan from a bank (*funding liquidity*) or sell the stocks in advance (*market liquidity*).[8]

We assume a fraction γ of traders do not have access to funding liquidity. They are forced to sell their stocks "during the day" at a liquidity discount z_{id}, which is stock-specific. We call these traders relying on market liquidity, 'day traders'. In contrast, the

[6]Note that while K_i cannot be conditioned on z_{in}, the interest rate can be. The conditional interest rate implies that (i) while capital needs to be assigned before z_{in} is observed, the exact payment is determined later to extract all the ex-post surplus, and (ii) there is no default.

[7]The foreign bonds prevent the interest rates determined in general equilibrium from feeding back into prices. Relaxing this assumption would require estimating our proposed price informativeness measure in a general equilibrium setting, thereby breaking the clean separation between informativeness and allocations. As we discuss later, however, the interest rate affects only the intercept of the pricing function and is irrelevant for the price's signaling ability and for our purposes.

[8]This assumption of infinite marginal utility to consume intra-period is meant to capture stressful situations in which the marginal utility of obtaining funds intra-period (e.g., margin calls or covering impending debts due to payment failures) is sufficiently high. The relevance of stocks for liquidity, not only for financial institutions but also for high-income households after income shocks, was recently documented by Adams (2026). Even though we focus on banks as the main providers of funding liquidity, bond markets also play this role, underscoring the importance of market liquidity during bond market disruptions.

rest of the traders can obtain a loan at no cost (just a normalization) and hold stocks until selling "at the end of the day," so we call them 'night traders'. Everybody observes γ, and each trader knows its type at birth. Changes in γ are then meant to capture changes in *funding liquidity*: an increase in γ reflects distress in banks and/or the bond market. Changes in the liquidity discount z_{id} are meant to capture changes in a given stock's *market liquidity*, defined as the losses a day trader faces from selling the stock in the middle of the period (a liquidity discount). In what follows, we model z_{id} as exogenous, but in Appendix C, we endogenize it as the fee a day trader has to pay a dealer to compensate for the risk involved in buying the stock, holding it, and selling it later at a different price.

Information A firm's stock is characterized by two dimensions in each period, the firm's profitability z_{in} and the stock's liquidity discount z_{id}.

The firm's profitability has three components: an aggregate productivity shock (Z), a random term that can be learned (θ_{in}), and a random term that cannot be learned ($\tilde{\varepsilon}_{in}$). The learnable component θ_{in} is drawn from a prior distribution $\mathcal{N}(\bar{\theta}_{in}, \sigma^2_{\theta_{in}})$, while the unlearnable component $\tilde{\varepsilon}_{in}$ follows an AR(1) process: $\tilde{\varepsilon}_{in} = \rho\tilde{\varepsilon}^-_{in} + \varepsilon_{in}$ with $\varepsilon_{in} \sim \mathcal{N}(0, \sigma^2_{\varepsilon_{in}})$, where $\tilde{\varepsilon}^-_{in}$ is public information and $\sigma^2_{\varepsilon_{in}}$ is a measure of fundamental uncertainty. The stock's liquidity discount (z_{id}) has two components: a random term that can be learned (θ_{id}) and a random term that cannot be learned (ε_{id}). The first is drawn from $\mathcal{N}(\bar{\theta}_{id}, \sigma^2_{\theta_{id}})$ and the second from $\mathcal{N}(0, \sigma^2_{\varepsilon_{id}})$.[9]

To summarize, the firm's profitability and the stock's liquidity discount are

$$\begin{aligned} z_{in} =& Z + \theta_{in} + \tilde{\varepsilon}_{in}, \\ & where \quad \theta_{in} \sim \mathcal{N}(\bar{\theta}_{in}, \sigma^2_{\theta_{in}}), \qquad \tilde{\varepsilon}_{in} = \rho\tilde{\varepsilon}^-_{in} + \varepsilon_{in}, \quad \& \quad \varepsilon_{in} \sim \mathcal{N}(0, \sigma^2_{\varepsilon_{in}}), \\ z_{id} =& \theta_{id} + \varepsilon_{id}, \\ & where \quad \theta_{id} \sim \mathcal{N}(\bar{\theta}_{id}, \sigma^2_{\theta_{id}}) \quad \& \quad \varepsilon_{id} \sim \mathcal{N}(0, \sigma^2_{\varepsilon_{id}}), \end{aligned} \tag{2}$$

where $\theta_{id}, \theta_{in}, \varepsilon_{id}$, and ε_{in} are independently distributed across firms and over time. We allow $\sigma^2_{\theta_{in}}$, $\sigma^2_{\theta_{id}}$, $\sigma^2_{\varepsilon_{in}}$, and $\sigma^2_{\varepsilon_{id}}$ to be functions of aggregate productivity Z, but not of γ. This way, we guarantee that liquidity distress would not affect economic outcomes if it were not for changes in the information content of prices.

[9]The liquidity discount z_{id} could additionally depend on γ. As long as it affects all the firms additively, in the same way that Z affects z_{in}, our analysis remains unchanged. Also, it is straightforward to allow persistence in ϵ_{id}, as we assume for ϵ_{in}, but empirically its role is negligible (see Appendix D.2).

Traders can perfectly learn *both* θ_{id} and θ_{in} by paying a cost.[10] The fraction of $l \in \{d, n\}$ traders who choose to be informed about stock i is denoted with λ_{il}. The information cost may be different for night traders $c_n(\lambda_{in})$ and for day traders $c_d(\lambda_{id})$, and potentially depend on the fraction of informed. The unlearnable components $\varepsilon = \{\varepsilon_{id}, \varepsilon_{in}\}_{i=0}^{1}$ can be freely observed only after their realization. Finally, the mutual fund doesn't have access to this information technology and, like uninformed traders, infers z_{in} solely from observing stock market prices. We will relax this last assumption when calibrating the model, allowing the mutual fund to obtain independent signals about θ_{in} and ε_{in}.

The aggregate productivity Z and the fraction of day traders γ define a state $s = \{Z, \gamma\}$, which is public information, and follow an exogenous Markov process with joint transition probability $q_{s,s'}$.

Timing Each period starts with the realization of γ, Z and $\theta = \{\theta_{in}, \theta_{id}\}_{i=0}^{1}$. Then:

1. Day and night traders simultaneously choose whether to acquire information and how many stocks to buy from each firm.

2. Households make saving decisions and invest in the mutual fund, which allocates capital across firms after observing all stock prices.

3. $\varepsilon = \{\varepsilon_{in}, \varepsilon_{id}\}_{i=0}^{1}$ is realized, with both θ and ε becoming public information.

4. Day traders sell all their stocks at a discount z_{id}, consume, and die.

5. Production occurs, firms pay the mutual fund, and the fund pays households.

6. Night traders sell their stocks, consume, and die.

[10] That traders learn about both signals is without loss of generality, as in equilibrium the trader could combine one signal with the price to infer the other signal perfectly.

2.2 Traders' Problems and Stock Market Clearing

Portfolio Choices. A trader of type $l \in \{d, n\}$ chooses a portfolio of foreign bonds and stocks from each firm:

$$\begin{aligned}&\max_{B_l,\{X_{il}\}_{i\in[0,1]}} E\Big[-exp\Big[-a[(1+r^F)B_l + \int_i X_{il}\big(z_{in} - \mathbb{I}_{\{l=d\}}z_{id} + p_i' - p_i\big)di]\Big]\Big] \\ &s.t.\ B_l + \int_i p_i X_{il} di = \tilde{b}.\end{aligned} \tag{3}$$

where $\mathbb{I}_{\{l=d\}}$ is the indicator function for a day trader, while B_l and $\{X_{il}\}_{i\in[0,1]}$ denote the demands for foreign bonds and stocks. This is a standard portfolio-rebalancing problem between safe assets (foreign bonds at a risk-free rate of r^F) and risky assets (stocks).

Given the distributional assumptions and the information structure (a standard CARA-Normal setting), the stock demand functions are

$$\begin{aligned}X_{in}^{I*} &= \frac{E[z_{in} + p_i'|\theta] - (1+r^F)p_i}{aVar[z_{in} + p_i'|\theta]}, \qquad X_{id}^{I*} = \frac{E[z_{in} - z_{id} + p_i'|\theta] - (1+r^F)p_i}{aVar[z_{in} - z_{id} + p_i'|\theta]}, \\ X_{in}^{U*} &= \frac{E[z_{in} + p_i'|p] - (1+r^F)p_i}{aVar[z_{in} + p_i'|p]}, \qquad X_{id}^{U*} = \frac{E[z_{in} - z_{id} + p_i'|p] - (1+r^F)p_i}{aVar[z_{in} - z_{id} + p_i'|p]},\end{aligned} \tag{4}$$

where $X_{in}^{I*}, X_{id}^{I*}, X_{in}^{U*}, and X_{id}^{U*}$ represent the stock i's demand by night and day traders that are informed (I) and uninformed (U), respectively. While the informed condition expectations and variances on θ, the uninformed do it on p. The difference between the demand of day and night traders is that day traders' payoffs depend on both z_{in} and z_{id}.

Information Acquisition Choices. Denoting the information acquisition choice of trader j about firm i as $I_{ji} \in \{0, 1\}$, the end-of-period wealth of trader j of type $l \in \{d, n\}$ is

$$\begin{aligned}W_{lj}(\mathbf{I}_j) =&(1+r^F)\left(W_{0j} - \int_i I_{ji}c_l(\lambda_{il})di\right) + \\ &\int_i \left(z_{in} - \mathbb{I}_{\{l=d\}}z_{id} + p' - (1+r^F)p_i\right)\left(I_{ji}X_{il}^{I*} + (1-I_{ji})X_{il}^{U*}\right)di,\end{aligned} \tag{5}$$

where $\mathbf{I}_j$ is the vector of information choices of agent j for all stocks. Let $\mathbf{I}_j^0$ be an arbitrary information acquisition vector where the element I_{ji}^0 for a specific stock i is zero and $\mathbf{I}_j^1$ be an identical vector, except that I_{ji}^1 is one. The trader would choose $\mathbf{I}_j^1$ over $\mathbf{I}_j^0$, i.e., fixing information about all stocks, a trader j acquires information about stock i, if and only if $E\left[\nu\left(W_{lj}(\mathbf{I}_j^1)\right) \mid \mathbf{p}\right] \leq E\left[\nu\left(W_{lj}(\mathbf{I}_j^0)\right) \mid \mathbf{p}\right]$ where $\mathbf{p}$ is the vector of stock prices. In words, the trader would like to acquire information if it reduces the expected variance of her end-of-period wealth, net of the information cost. Formally,

Lemma 1. *Let $\mathbf{I}_j^0$ be an arbitrary information acquisition vector where $I_{ji}^0 = 0$ for a specific stock i and $\mathbf{I}_j^1$ be an identical vector, except that $I_{ji}^1 = 1$. Defining λ as the set of λ_{il} for all firms and traders of type $l \in \{d, n\}$, a trader j of type l would acquire information about firm i conditional on others' information choices λ if and only if,*

$$\frac{E\left[\nu\left(W_{lj}(\mathbf{I}_j^1)\right) \mid \mathbf{p}\right]}{E\left[\nu\left(W_{lj}(\mathbf{I}_j^0)\right) \mid \mathbf{p}\right]} = e^{ac_l(\lambda_{il})}\sqrt{\frac{Var[z_{in} - \mathbb{I}_{\{l=d\}}z_{id} + p_i'|\theta_i]}{Var[z_{in} - \mathbb{I}_{\{l=d\}}z_{id} + p_i'|p_i]}} \equiv \psi^{il}(\lambda) \leq 1, \tag{6}$$

Equation (6) shows the ratio of the expected variance of end-of-period wealth between acquiring information about stock i or not, all else equal. While the first term captures the cost of acquiring information about firm i and is greater than one, the second term captures the benefit of reducing variance by observing θ_i rather than just p_i and is less than one. Since traders want to reduce the variance of payoffs, they would acquire information if and only if this ratio, defined as $\psi^{il}(\lambda)$, is less than one. The combination of CARA-Normal properties, independent returns across stocks, and independent information-acquisition costs guarantees that whether to acquire information about one stock is independent of whether to acquire information about another.

Corollary 1 shows equilibrium conditions for λ_{il},

Corollary 1. *When $\sigma_{\theta_d}^2 > \sigma_{\theta_n}^2$, $\psi^{il}(\lambda)$ is monotone in λ_{il} for $l \in \{d, n\}$. Therefore,*
(i) If $\psi^{il}(\lambda) < 1 \ \forall \lambda_{il} \in [0, 1]$, all l traders become informed about stock i, i.e. $\lambda_{il}^* = 1$.
(ii) If $\psi^{il}(\lambda) > 1 \ \forall \lambda_{il} \in [0, 1]$, no l traders become informed about stock i, i.e. $\lambda_{il}^* = 0$.
(iii) Otherwise, λ_{il}^* is given by $\psi^{il}(\lambda_{il}^*) = 1$.

Stock Market Clearing Market clearing for the shares of firm i's installed capital is

$$\gamma\left[\lambda_{id}X_{id}^I + (1 - \lambda_{id})X_{id}^U\right] + (1 - \gamma)\left[\lambda_{in}X_{in}^I + (1 - \lambda_{in})X_{in}^U\right] = \bar{K}_i \tag{7}$$

2.3 Real Sector Problems and Capital Market Clearing

Representative Household's Problem. Its recursive formulation is

$$\begin{aligned} H(s,K,k) = \max_{k'} \quad & u\left(k(1+r(s,K)-\delta)-k'\right)+\beta\sum_{s'}q_{ss'}H(s',K',k') \\ s.t. \quad & K' = G(K) \end{aligned} \tag{8}$$

where $s=\{Z,\gamma\}$ denotes the aggregate state, $H(.)$ the value function, β the discount factor, δ the depreciation rate, k the individual capital holdings and K the aggregate capital holdings. $G(.)$ represents household expectations over the future path of aggregate capital. Importantly, households decide on savings in capital given the interest rate r that mutual funds pay, which depends on how well the mutual fund allocates capital.

Mutual Fund's Capital Allocation Across Firms We model the mutual fund as an aggregator that collects households' savings, allocates capital to maximize total surplus, and distributes the surplus back to households with perfect diversification. Since we assume the mutual fund can extract all ex post surplus from the rented capital and pass it to households, it allocates K_i to firm i to maximize firm i's expected profits conditional on observed prices. Given the cost of funding r and adjustment costs, the capital allocated to firm i is given by

$$K_i = \max\left\{\bar{K}_i\left(\frac{E[z_{in}|\mathbf{p}]-r}{\xi}\right),0\right\} \quad \forall i, \tag{9}$$

and implemented by a take-it-or-leave-it offer with a contract $\{K_i, r_i(z_{in})\}$ that satisfies

$$z_{in}K_i - r_i(z_{in})K_i - \xi K_i^2/2\bar{K}_i = 0 \quad \forall i, z_{in} > 0. \tag{10}$$

Hence, the mutual fund captures all ex-post surplus from the rented capital, while traders capture the ex-post surplus from the installed capital. The mutual fund distributes all surplus to households, such that

$$\int_i r_i K_i = rK.$$

where K is the total capital supplied by households.

In an environment where θ_{in} is observable, the fund would choose K_i based on $E[z_{in}|\theta_{in}]$. Hence, 'misallocation' would be due to ε_{in}, which is inevitable. In our setting, however, the mutual fund can only rely on stock prices to infer θ_{in}, hence using $E\left[z_{in}|\mathbf{p}\right]$ to make decisions. Given idiosyncratic shocks are i.i.d., the only price that contains information about $\theta_i n$ is p_i. For the choice of K_i, θ_{id} is irrelevant, yet a high stock price could stem from a high θ_{in} or a low θ_{id}. In summary, the presence of day traders prevents prices from perfectly revealing θ_{in} to the mutual fund and worsens capital allocation.

Capital Market Clearing Non-installed capital market clears,

$$\int_i K_i = K. \tag{11}$$

2.4 Equilibrium

Definition $H, r, k', G, \{K_i, r_i, X^I_{id}, X^U_{id}, X^I_{in}, X^U_{in}, \lambda_{id}, \lambda_{in}, \phi_{i0}, \phi_{i\varepsilon}, \phi_{id}, \phi_{in}, p_i\}_{i\in(0,1)}$ constitute a Linear Rational Expectations Equilibrium (LREE) such that

1. $X^I_{id}, X^U_{id}, X^I_{in}$, and X^U_{in} solve traders' portfolio choices (3), characterized in (4).
2. $\lambda_{id}, \lambda_{in}$ solve traders' information acquisition problems, characterized by Lemma 1.
3. The stock price of firm i is a linear function of θ_{id} and θ_{in}, i.e., $p_i = \phi_{i0} + \phi_{i\varepsilon}\tilde{\varepsilon}^-_{in} + \phi_{id}\theta_{id} + \phi_{in}\theta_{in}$, where $\phi_{i0}, \phi_{i\varepsilon}, \phi_{id}$, and ϕ_{in} solve stock market clearing (7).
4. k' and H solve the representative consumer's problem in (8).
5. K_i, r_i solve the mutual fund's problem in (9) and (10).
6. r clears non-installed capital market (11).
7. G is consistent with k'.

Notice we restrict attention to LREE. Linear pricing is needed to preserve Gaussian conjugates so the agents' Bayesian updating remains analytical. If the price is nonlinear, this update must be performed via numerical integration, rendering the model a large black box. In this case, we would not be able to characterize demand, derive a price equation, or estimate a structural measure of price informativeness. Before presenting these results, we highlight next the assumptions that make them possible. Unfortunately, we cannot directly test these assumptions, as relaxing them makes the model intractable.

2.4.1 Assumptions Relevant for a LREE

Besides the standard *CARA-Normal* assumptions, we resort to additional structures to preserve linear pricing. One set of assumptions relates to the distribution of capital surplus in the economy. First, production is *additive in fixed $\bar{K}$ (tradable) and adjustable K (investments).* Second, *firms rent K, which does not accumulate within a firm*. Third, the *mutual fund extracts all surplus* from renting K to firms and passes it to households. These assumptions break the potential feedback loop from capital markets to stock markets: if firms retained surplus from their investments, this surplus would go to traders. Then, traders recognize that higher prices attract greater investment, which in turn increases demand and raises prices further. As the allocated capital is nonlinear in productivity, the price becomes a nonlinear function of the fundamentals.[11] Albagli et al. (2023) theoretically shows that such feedback can be strong when investors have incentives to manipulate stock prices. Although in our setup the mutual fund is the sole determinant of investment, in reality, many decision-makers (managers, the board, banks, etc.) share this role. Hence, coordinating stock price manipulation is likely more difficult.

Second, we assume *persistent differences across firms' productivity are given by the non-learnable component, $\tilde{\varepsilon}_{in}$*, which follows an AR1, process. This assumption renders the resale price unlearnable, preserving the current price linearity. Farboodi and Veldkamp (2020) show that persistency to the learnable component, θ_{in}, also preserves price linearity but when traders are homogeneous. In our empirical analysis, however, we indirectly relax this assumption by residualizing prices using previous earnings as a proxy for $\bar{\theta}_{in}$.[12]

2.5 Price Informativeness

Pricing Function. We show next that, conditional on the fraction of informed traders, there exists a unique linear pricing function (Proposition 1). Then we characterize the

[11] Subrahmanyam and Titman (1999) make similar assumptions and interpret them as a world with derivative assets providing claims on a firm's cash flows rather than on all of its assets. Since traders can back out the capital allocated to a firm, the amount of information revealed does not depend on whether the claim is on cash flows or all assets.

[12] Albeit implicitly, we also assume that *firms do not use prices to incentivize managers*, a possibility explored in Banerjee et al. (2026). We show in Appendix D.1 that in a stylized extension where (i) the firm's productivity is linear in managerial effort and (ii) managerial compensation is linear in prices, incentive provision is orthogonal to the other roles prices serve, and our linear pricing function can also be preserved.

linear rational expectations equilibrium that arises when information is endogenous.

Proposition 1. *Given a fraction of informed traders, (λ_{in} and λ_{id}), there exists a unique linear market price for the stock of firm i that adopts the form $p_i = \phi_{i0} + \phi_{i\varepsilon}\tilde{\varepsilon}_{in}^{-} + \phi_{id}\theta_{id} + \phi_{in}\theta_{in}$, where $\phi_{in} > 0$, $\phi_{id} < 0$, and*

$$\frac{|\phi_{in}|}{|\phi_{id}|} = 1 + \frac{(1-\gamma)\lambda_{in}(\sigma^2_{\varepsilon_{id}} + Var(z_{in} + p'_{in}))}{\gamma\lambda_{id}Var(z_{in} + p'_{in})}. \tag{12}$$

The ratio $\frac{|\phi_{in}|}{|\phi_{id}|}$ in equation (12) captures the impact of θ_{in} on the price relative to θ_{id}, hence how much can be learned about the *learnable component* of firms' fundamentals θ_{in} from observing p_i. Although endogenous information acquisition is relevant for quantitatively disciplining the extent of price informativeness, it is not critical qualitatively for the mechanism. Note that even if all traders are informed (i.e., $\lambda_{in} = \lambda_{id} = 1$), price informativeness depends on the fraction of day-traders, γ. In the extremes, as the fraction of day traders approaches 0, the ratio would approach infinity, and prices would perfectly reveal what traders know about fundamentals. In contrast, as the fraction of day traders approaches 1, the ratio approaches 1, and prices would have the same loadings on fundamentals and liquidity, given that day traders care about both. Corollary 2 provides in words comparative statics about the information about θ_{in} contained in p_i.

Corollary 2. *Ceteris paribus, price becomes less sensitive (i.e., informative) about θ_{in} when*
(i) a larger fraction of traders are day traders,
(ii) a larger fraction of day traders are informed compared to night traders,
(iii) the liquidity discount has a smaller residual variance upon information than productivity.

Conditional on the fraction of day and night traders that are informed, linear pricing is unique because our setting does not exhibit *complementarities in trading*: informed traders do not learn from prices; hence, they do not condition their trading strategies on the information prices convey. The characterization of the LREE, however, is completed by endogenizing the fraction of traders who are informed, given information-acquisition choices in Lemma 1. These choices are made both by night and day traders and depend on the cost of information for each group. An information cost function that is increasing in the fraction of traders who are informed rules out *complementarities in information acquisition within a trader type*.[13] *Complementarities in information acquisition* across *trader types*,

[13]Increasing information costs is a property, for instance, of an upward-sloping supply curve for infor-

however, are a more fundamental feature: if more day traders acquire information (high λ_{id}), prices are less informative about fundamentals, magnifying the incentives for night traders to acquire information (high λ_{in}). Whether this complementarity translates into multiplicity in LREE depends on the curvature of information costs. Given our assumptions on information costs and across our various calibrations, we did not detect multiple equilibria. Lastly, any LREE becomes interior, i.e., $\lambda_{il} \in (0,1)$, when $\lim_{\lambda_{il}\to 0} c_l(\lambda_{il}) = 0$ and $\lim_{\lambda_{il}\to 1} c_l(\lambda_{il}) = \bar{C}$ where $\bar{C}$ is large enough.[14]

Price Informativeness (PI) Measure. We now define an intuitive measure of price informativeness that can be structurally estimated from the data for many countries. To do this, we introduce a simplification that we maintain throughout what follows.

Assumption 1. *The parameters $\bar{K}_i, \bar{\theta}_{in}, \bar{\theta}_{id}, \sigma^2_{\varepsilon_{in}}, \sigma^2_{\varepsilon_{id}}, \sigma^2_{\theta_{in}}$, and $\sigma^2_{\theta_{id}}$ are firm invariant.*

Assumption 1 guarantees that equilibrium fractions of informed investors λ_{in}, λ_{id} and pricing function parameters ϕ_{i0}, $\phi_{i\varepsilon}$, ϕ_{in}, ϕ_{id} are also firm invariant. This assumption implies that the only sources of heterogeneity across firms are θ_{in}, θ_{id}, ε_{in}, and ε_{id}. In other words, firms independently draw z_{in} and z_{id} from identical distributions, allowing us to exploit the cross-sectional variation in prices to estimate price informativeness.

We define Price Informativeness (PI) as the reduction in the uncertainty about a firm's productivity conditional on observing the price, normalized by the reduction in the uncertainty conditional on observing the learnable component after acquiring it at a cost. In the same spirit as Goldstein et al. (2014), this measure does not capture how much stock prices inform about future earnings, but instead how much they inform about what informed traders know.

mation or by heterogeneous information acquisition costs across traders, with the traders with the lowest cost acquiring the information first.

[14] This is in contrast to other models that replace noise trading with asymmetric information about multiple dimensions, such as Manzano and Vives (2011). In those models, informed traders are ex ante homogeneous and have private signals. When prices are more informative, they rely more on their private signals to trade, making prices even more informative; hence, when a trader relies heavily on private information, others do as well. This gives rise to complementarities in trading and possibly, equilibrium multiplicity. Complementarities in information acquisition can also arise in settings with ex-ante homogeneous traders with private signals (Ganguli and Yang, 2009) and when agents can learn about other agents' beliefs (Banerjee et al., 2018). These additional sources of complementarities are absent in our setting.

Definition The Price Informativeness (PI) measure for firm i is defined as

$$PI_i = \frac{Var[z_{in}] - Var[z_{in}|p_i]}{Var[z_{in}] - Var[z_{in}|\theta_{in}]},$$

where $Var[z_{in}]$ denotes the unconditional variance of z_{in}.

An advantage of this measure is that it lies between 0 and 1. A PI measure close to 0 would indicate that the uncertainty reduction from observing the price is negligible compared to the reduction from acquiring information. A PI measure close to 1 would suggest that observing the price is almost as useful as acquiring information and observing θ_{in}.

Corollary 3. *Under Assumption 1, PI is firm invariant, and equals*

$$PI = \frac{1}{1 + \frac{\sigma^2_{\theta_d}}{\sigma^2_{\theta_n}} \left(\frac{\phi_d}{\phi_n}\right)^2}. \tag{13}$$

Hence, under Assumption 1, the PI measure can be summarized by two parameters ($\sigma^2_{\theta_n}$ and $\sigma^2_{\theta_d}$) that captures the quality of information about the two components and two equilibrium objects (ϕ_n and ϕ_d) that capture the price impact of such information. Our empirical strategy estimates these four objects using a cross-section of firms in a given country to calculate PI annually.

3 Measuring Price Informativeness

This section provides a structural estimate of Price Informativeness (PI) for 16 countries, each for an average of 21 years, and examines its cyclical properties.

3.1 Empirical Strategy to Measure Price informativeness

Our PI measure can be directly obtained from estimating the four components in equation (13): the variances of the learnable part of stock profitability and stock liquidity ($\sigma^2_{\theta_n}$ and $\sigma^2_{\theta_d}$), and their price loadings (ϕ_n and ϕ_d). We can measure PI without solving for the full equilibrium, because pricing depends only on the behavior of short-lived traders and is independent of investment choices by long-lived households, and without specifying the traders' information acquisition technology. The challenge is to identify series for the signals θ_n and θ_d and to estimate the price loadings ϕ_n and ϕ_d from running a *cross-firm stock pricing regression for each country-year pair*.

In taking the model to the data, we have to consider that observed prices are a composite of our theoretical prices (in which the demand for stocks only takes into account firms' fundamentals and stocks' liquidity properties) and other variables not included in our model (such as speculation motives, shocks to the supply of a firm's stocks, etc). Formally, a firm i's observed prices in a given year are given by

$$p_i^s = p_i + \nu_i$$

where p_i is our theoretical construct and ν_i are additional factors we do not include in our model. Hence, we run the following cross-firm pricing regression per country-year.

$$p_i^s = \phi_0 + \phi_\varepsilon \varepsilon_{in}^- + \phi_d \theta_{id} + \phi_n \theta_{in} + \nu_i \tag{14}$$

The identification of the price loadings on the signals of profitability (ϕ_n) and liquidity (ϕ_d) per country-year is based on a cross-sectional comparison. ϕ_n is pinned down by the extent to which firms with high prices have higher profitability signals. Similarly, ϕ_d is pinned down by the extent to which firms with high prices have smaller liquidity discounts. To measure p_i^s, we use Worldscope from Thomson/Refinitiv for data on stock prices.[15] Consistent coverage began around 1985 in the US and, by 2000, in most economies in our sample.

To run these regressions, we need the *signals* of profitability and liquidity observed by informed investors, θ_{id} and θ_{in}. A common practice in the literature is to use realized values, i.e., z_{id} and z_{in}, as proxies for θ_{id} and θ_{in}. However, according to our model, regressing the price p_i^s on the realized values would lead to biased estimates of the price loadings because the measurement error would be correlated with the realized earnings,

[15]Worldscope is a leading source of cross-country financials of publicly traded companies. It provides data from 98,000 companies in more than 120 countries, which amounts to 99% of the global market capitalization in 2021. Worldscope uses a standardized template for financial information that corrects for measurable differences in accounting practices across companies and markets. The entries are subject to automated tests that verify accounting identities, detect outliers, and assess correlations for accuracy. See Reuters' Worldscope Definitions for details on standardization practices, accuracy tests, coverage, and sample selection criteria.

as formally shown in Appendix B.1. Given this drawback, we need to rely on proposing a yearly estimator of the signals about profitability (that we denote as $\widehat{\theta}_{in}$) and about liquidity (that we denote as $\widehat{\theta}_{id}$).

Signals about Profitability, $\widehat{\theta}_{in}$: From equation (2) we know informed traders form expectations about each firm's profitability as follows,

$$E[z_{in}|\theta_{in}] = Z + \theta_{in} + \rho\tilde{\varepsilon}_{in}^{-}$$

We can measure $E[z_{in}|\theta_{in}]$ by the median one-step-ahead analyst forecast for z_{in} of company i, which we denote as F_i. To do this, we use the Institutional Brokers Estimate System (I/B/E/S) from Refinitiv for daily data on analyst forecasts of earnings-per-share.[16] We access Worldscope and I/B/E/S through Wharton Research Data Services (WRDS), which provides a unique ticker for each company to link the two datasets. In the Appendix, we discuss the steps we took to make firms and countries comparable.[17]

We compute Z by the cross-sectional average of F_i. To decompose θ_{in} from $\rho\tilde{\varepsilon}_{in}^{-}$, we first construct the time series of forecast errors $\varepsilon_{in} = z_{in} - F_i$ for firm i and compute its variance $\sigma^2_{\varepsilon_n}$. Then, we obtain ρ from the autocovariance of the deviation of F_i from its cross-sectional average $E[F_i]$, since

$$\begin{aligned} Cov(F_{it} - E[F_{it}], F_{i,t+1} - E[F_{i,t+1}]) =& Cov(\theta_{int} + \rho\tilde{\varepsilon}_{in,t-1}, \theta_{in,t+1} + \rho(\rho\tilde{\varepsilon}_{in,t-1} + \tilde{\varepsilon}_{int})) \\ =& Cov(\rho\tilde{\varepsilon}_{in,t-1}, \rho^2\tilde{\varepsilon}_{in,t-1}) = \frac{\rho^3\sigma^2_{\varepsilon_n}}{1-\rho^2}. \end{aligned} \tag{15}$$

where F_{it} is the earnings forecast for firm i in period t. Having ρ, we can finally approximate $\tilde{\varepsilon}_{in}$ iterating (2) with lagged values of ε_{in}.[18] Finally, from the approximated series $\widehat{\tilde{\varepsilon}}_{in}$

[16] I/B/E/S collects forecasts about 22,000 active companies in 90 countries from over 18,000 analysts. Each observation is an analyst's forecast announcement regarding a company's balance sheet item for a particular horizon. Forecasts are available for various payoff-relevant items, but Earnings-Per-Share (EPS) has the widest coverage. We use forecasts announced within a 30-day window around the date the stock price is documented.

[17] We also use the daily exchange rates provided by I/B/E/S to standardize the currency within a market across firms, time, and variables. See Appendix B.2 on the timing assumptions that lead to our measurements (in Appendix D.3, we show the robustness of our timing assumptions). See Appendix B.3.1 for details on how we assign companies to countries, Appendix B.3.2 for sample restrictions, Appendix B.3.3 for how we adjust data to make firms comparable, Appendix B.3.4 for adjustments that allow to compare firms across countries, and Appendix B.3.5 for how we deal with M&As and stock splits.

[18] We first estimate ρ for markets that have at least 20 companies with past year's data. For the remaining markets, we use the country average if available and, if not, the overall average. For computing $\tilde{\varepsilon}_{in}$, we

we can obtain our estimate for θ_{in} as

$$\widehat{\theta}_{in} = F_i - Z - \rho\widehat{\bar{\tilde{\varepsilon}}}_{in}.$$

By taking the cross-sectional variance of $\widehat{\theta}_{in}$ in a given year, we can readily estimate one of the components of PI, $\widehat{\sigma^2_{\theta_n}}$.

Signals about Liquidity, $\widehat{\theta}_{id}$***:*** Ideally, one would use signals about the discount a trader expects to face when selling stocks, which include the compensation to dealers for price volatility, search frictions, inventory costs, etc. Unfortunately, there are no forecasts of such objects; however, the discount would be proportional to the short-run volatility of the stock price in a model where dealers are risk-averse profit maximizers with heterogeneous beliefs. We formalize this link in Appendix C: a stock with high price volatility implies the dealer's risk of holding the stock is high, charging a high fee for potentially buying it high and selling it low. Based on this microfoundation, we use the prior six months of realized price volatility as an estimator for the signal about price volatility.[19]

$$\widehat{\theta}_{id} = Vol_{t,t-5}(p_i),$$

where t is monthly. By taking the cross-sectional variance of $\widehat{\theta}_{id}$, we can estimate another component of PI, $\widehat{\sigma^2_{\theta_d}}$.

Having obtained the time series of signals about profitability and liquidity ($\widehat{\theta}_{in}$ and $\widehat{\theta}_{id}$),[20] we proceed to estimate their price loadings for each country-year pair, ϕ_n and ϕ_d. We first remove as much heterogeneity across firms as possible by residualizing the normalized stock prices to i) homogenize $\bar{K}_i$ and $\bar{\theta}_{in}$ and ii) eliminate dependencies in the distributions of θ and ε across companies (see Appendix B.3.3 for details). Then, we esti-

determine the lag order for each company-date pair based on the availability of past data on ε_{in}, with a maximum of three lags. We initialize the $AR(1)$ process as 0.

[19]To estimate the stock price volatility, we use the measure proposed by Garman and Klass (1980), which only requires the opening (O), closing (C), highest (H), and lowest (L) prices during the period. In particular, we look at the stock prices over the previous six months to compute

$$\tilde{\sigma}^2_{it} = 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2$$

for each ticker i at date t. If the resulting volatility measure exceeds the stock price, we equate it to the stock price, imposing an intuitive limited-liability rule on stock ownership. We normalize this measure with the stock price. In Appendix D.4, we provide statistics on the cross-sectional distribution of the range volatility estimates and how they evolve for the median firm.

[20]Table 12 in Appendix F show summary statistics for the US, Japan, and the UK in 2015 as examples.

mate the pricing regression (14) using the residualized stock prices for each country-year pair, $\widehat{\theta}_{in}$ and $\widehat{\theta}_{id}$ as our measures of θ_{in} and θ_{id}, and $\tilde{\varepsilon}_i^-$ for firm i estimated using forecast errors obtained when constructing $\widehat{\theta}_{in}$. We treat υ_i as a measurement error that is orthogonal to the regressors.

Under Assumption 1, the OLS estimators $\widehat{\phi}_d$ and $\widehat{\phi}_n$ are unbiased estimates of ϕ_d and ϕ_n for all country-year pairs. The estimates validate the model's predictions. The model suggests $\phi_n > 0$ and $\phi_d < 0$, although the estimation does not impose this restriction. The former is satisfied in all but one pair, while the latter is satisfied in 70% of the pairs. Furthermore, equation (12) predicts $\frac{|\phi_n|}{|\phi_d|} > 1$, which is true for 97% of the pairs.

Once we have obtained the four estimates for $\widehat{\sigma^2_{\theta_n}}$, $\widehat{\sigma^2_{\theta_d}}$, $\widehat{\phi}_n$ and $\widehat{\phi}_d$, we compute PI from equation (13) for 344 country-years pairs (see Table 13 in Appendix F for a list of countries and Table 14 for a summary of the 344 pricing regressions). Next, we discuss the PI estimation results.

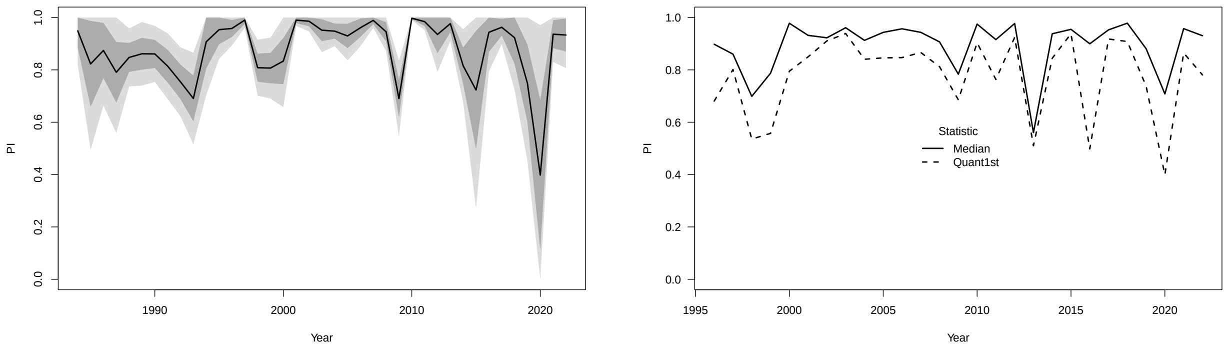
3.2 Price Informativeness Over Time and Across Countries.

As an illustration of the results, Figure 1a presents the PI series for the US, with 1- and 2-standard-deviation bootstrap confidence bands.[21] This series is cyclical: it has a time series correlation of 0.51 with aggregate stock returns and 0.45 with GDP growth rate. The largest declines in our 40-year sample are during the COVID-19 episode, the 2008-09 Great Financial Crisis (GFC), and the late 1980s and early 1990s that surrounded the long-lived Savings and Loan (S&L) crisis.[22] Although we focus on the *cyclical patterns* of the PI measure, its *levels* merit precision of interpretation. PI approaching 1 during booms may suggest, for instance, that prices almost perfectly reveal firms' productivities. This seemingly extreme result, however, is just a by-product of our stylized structure, which has only two pricing factors. Modeling additional pricing factors (beyond productivity and liquidity) naturally lowers PI levels because several other dimensions are likely conflated

[21] In Appendix F we show the time series components behind this series: forecast error variance ($\sigma^2_{\varepsilon_n}$ and $\sigma^2_{\varepsilon_d}$ in Figure 14) and signal averages ($\bar{\theta_n}$ and $\bar{\theta_d}$ in Figure 15). We provide the time-series plots of estimated $\sigma^2_{\theta n}$, $\sigma^2_{\theta d}$, ϕ_n and ϕ_d in Figure 13 of Appendix F.

[22] The cyclical patterns observed in Figure 1a are robust to allowing for persistence in the unlearnable part of liquidity ε_{id}, residualizing the prices with volatilities in the further past, a back-of-the-envelope bias correction for heterogeneity in θ_{in}, and controlling for ε_{in} directly to account for private information that is not captured by analyst forecasts. See Appendix D.2 for details.

with a firm's productivity.



(a) PI Estimates for the US

(b) Cross-Country Statistics for PI Estimate

Figure 1: The PI Estimates. Notes: In the right-hand side panel, we restrict attention to countries for which PI is estimated for at least 20 years between 1994 and 2022 to get a partially balanced sample. The countries are Germany, the United Kingdom, France, Japan, Taiwan, Canada, Sweden, and the US.

Figure 1b presents moments from the yearly distribution of PI estimates across eight countries with observations between 1995 and 2021. The median and the 1st quartile experienced declines around the Great Recession and the COVID-19 pandemic, similar to the US. Other major declines were observed in PI in *i)* most European economies around the 'Taper Tantrum' and the European sovereign debt crisis in 2013 and *ii)* UK and France around the Brexit decision in 2016.[23]

An advantage of our structural estimation of PI is that we can identify the drivers behind these large PI declines by following each of its four components individually. A clean decomposition can be obtained by considering the log of a monotonic transformation of PI from equation (13):[24]

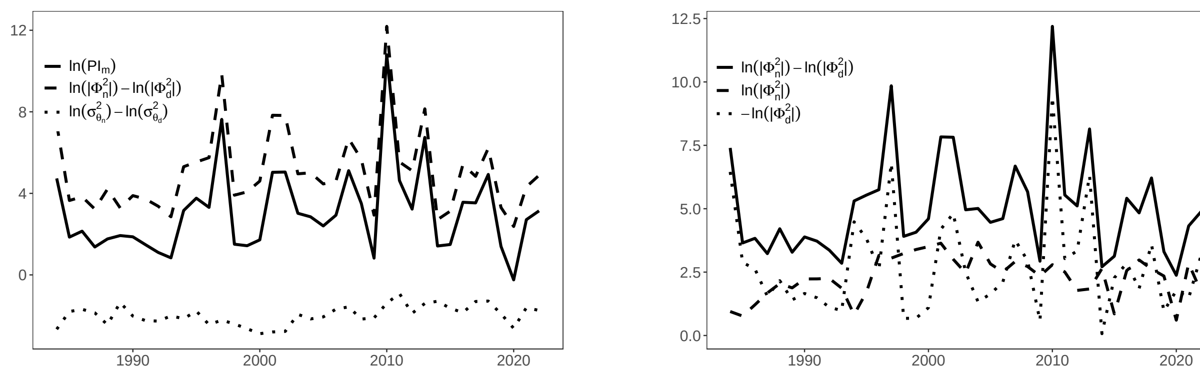
$$ln\left(\frac{PI}{1-PI}\right) = ln(\phi_n^2) + ln(\sigma_{\theta_n}^2) - ln(\phi_d^2) - ln(\sigma_{\theta_d}^2). \tag{16}$$

Figure 2a presents this PI transformation for the US (in the solid black line) together with two components: price loadings and variances. The variances (the dotted line) are im-

[23] Average PI levels do not differ much across countries, even in a larger set of countries (See Table 14 in Appendix F.), with no clear relationship between the country's (or its stock market's) development and the estimated level of PI. This pattern is not at odds with our theory: PI is not about the absolute number of stock market participants or the total amount spent on information acquisition; it is about the relative attention paid to firms' fundamentals versus stock liquidity.

[24] We thank Liyan Yang for suggesting this intuitive decomposition.

portant for the level of PI but play a relatively small role in its fluctuations relative to price loadings (the dashed line). Figure 2b further decomposes price loadings. While fluctuations in the loading of earnings (dashed line) contribute significantly, the lion's share of PI fluctuations comes from changes in the loading of liquidity (dotted line). An alternative to understand the role of each component on PI's fluctuations is: 'How much would the time series variance of the PI measure decline if the component x is kept fixed at its median value?' The variance would decline by 5%, 20%, and 72% with $\sigma^2_{\theta_d}$, ϕ_n, and ϕ_d at their median vales, respectively. If $\sigma^2_{\theta_n}$ instead was kept at its median value, the PI variance would increase by 24%. This is just a statistical decomposition as ϕ_n and ϕ_d are themselves functions of $\sigma^2_{\theta_n}$ and $\sigma^2_{\theta d}$. In the next section, we will make it structural.



(a) Decomposing PI_m

(b) Decomposing the Price Loadings

Figure 2: Contribution of the Components of PI

We now test whether the cyclicality of PI (*information cycles*) relates to usual measures of *business cycles* and *liquidity cycles*. We run the following regression:

$$PI_m = \beta_0 + \beta_1 Cycle_m + CountryFE_m + \epsilon_m, \tag{17}$$

where m denotes a market, i.e., a country-year pair. To measure business cycles ($Cycle_m$), we use two proxies: aggregate earnings and GDP growth.[25] To focus on cyclicality, we add country fixed-effects to account for PI's country-specific factors. Columns 1 to 4 in Table 1 present the results. There is a positive correlation between both measures of economic activity and the estimated PI series. The correlation becomes larger and more pre-

[25]We use growth rate of GDP measures from the World Bank. Taiwan's GDP growth measure is provided by its National Statistics Bureau. We apply linear detrending. See Table 15 in Appendix F for summary statistics of economic conditions in this panel of countries.

cisely estimated once each country-year observation is weighted by the number of stocks used to estimate PI in that country-year pair (columns 3 and 4). In other words, *stock markets reveal more information about firms when the economy is stronger.*

Table 1: The Cyclicality of the Price Informativeness Measures

	PI					
	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth Rate	0.47		2.55***			
	(0.48)		(0.38)			
Avg Earnings		3.58***		7.71***		
		(1.27)		(0.97)		
Banking Stock Perf.					0.28	0.66**
					(0.47)	(0.30)
Range	'84-'22	'84-'22	'84-'22	'84-'22	'84-'22	'84-'22
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	No	Yes	Yes	No	Yes
Observations	344	344	344	344	319	319

Notes: In (3), (4), and (6), each country-year observation is weighted with the number of stocks used in the estimation of the PI measure. *p<0.1; **p<0.05; ***p<0.01

To measure liquidity cycles, we use the ratio of the median normalized stock price of publicly listed banks to that of publicly listed non-financial firms, which we call 'Banking Stock Performance.' This measure captures how well the banking sector is performing relative to the rest of the economy, which likely affects the availability of credit (a proxy for $1 - \gamma$ in the model). Columns 5 and 6 in Table 1 present the results. Consistent with our model, stock prices become more informative about firms' fundamentals when stock markets have a lesser role in liquidity provision. In other words, *stock markets reveal more information about firms when banks are healthier.*

4 Model Calibration

We have measured PI for different countries and documented its cyclical nature. Here, we examine the impact of its fluctuations on real variables, arising from agents using $E[\theta_{in}|p_i]$ rather than θ_{in} to allocate capital. The expression for the output loss due to misallocation is a complicated object, but monotonic in the Bayesian risk associated with using $E[\theta_{in}|p_i]$ as an estimator for θ_{in}. Hence, to compute this loss, we proceed to calibrate the full model to the United States.[26]

Our model focused on prices as the single source of information for capital allocation, but in reality, decision makers rely on additional sources, which likely mitigates the importance of PI on real outcomes. To discipline the ultimate role of PI we extend our model. Instead of assuming the mutual fund makes decisions solely based on observing the theoretical prices p_i we assume it observes the same prices as the econometrician, p_i^s, an independent signal about the learnable component of firm i's fundamentals $\theta_{in}^s \sim N(\theta_{in}, \sigma^2_{\theta^s_{in}})$ and an independent signal about the non-learnable component to traders $\varepsilon_{in}^s \sim N(\varepsilon_{in}, \sigma^2_{\varepsilon^s_{in}})$. In short, the mutual fund makes decisions based on $E[z_{in}|p_i^s, \theta_{in}^s, \varepsilon_{in}^s]$ instead of $E[z_{in}|p_i]$.

These additions acknowledge that decision-makers recognize that prices contain additional noise and that they may possess information that is independent of, and distinct from, that of traders. In other words, while our empirical estimate captures how much prices inform decision makers about what informed traders know, our calibration captures the extent to which that information is new to decision makers and is then incorporated into allocations: we capture here 'revelatory price informativeness'.

4.1 Calibration Strategy

In the previous section, we have estimated the time series of the means ($\bar{\theta}_n, \bar{\theta}_d$) and the variances ($\sigma^2_{\theta_n}, \sigma^2_{\theta_d}, \sigma^2_{\varepsilon_n}$, and $\sigma^2_{\varepsilon_d}$). In this section, we finalize the model's parameterization. We start by externally calibrating $\{\bar{k}, \xi, \eta, a, \delta, \rho, r^F\}$. Given the lack of feedback from capital allocation to stock markets in our model, we can conduct the internal calibrations se-

[26]As a benchmark, in Appendix E, we show the analytical link between PI and misallocation losses under a quadratic loss function, which is not the loss function that arises in our setting.

quentially. In a first stage, we internally calibrate parameters involved in the operation of stock markets, the latent series of γ_t and the information cost parameters $\{\nu_d, \nu_d, \psi_n, \psi_d\}$. In the second stage, we internally calibrate the parameters related to capital allocation $\{\beta, \sigma_{p_i^s}, \sigma_{\theta_{in}^s}, \sigma_{\varepsilon_{in}^s}\}$ to discipline the extent to which prices affect the real sector.

4.1.1 Externally Calibrated Parameters

For households, we set the intertemporal elasticity of substitution $1/\eta$ equal to 0.5 consistent with Gruber (2013). For traders, following Farboodi and Veldkamp (2020), we set the absolute risk aversion parameter a equal to 0.05. We set the depreciation rate δ equal to 0.06 (see Bai et al. (2022)), the risk-free interest rate available to the traders r^F equal to 0.02, and the autocorrelation of the unlearnable part of profitability, ρ, to 0.[27] Lastly, because we directly estimated productivity from earnings data, we have some flexibility in setting the scale of the economy. So, we normalize the adjustment cost $\bar{k}/\xi$ to achieve an average capital level of 1.

4.1.2 Internally Calibrated Parameters of Stock Markets

Series of Liquidity Needs, γ_t: Equation (12) links γ_t to the ratio of pricing coefficients $\frac{|\phi_{in}|}{|\phi_{id}|}$, the ratio of residual payoff variances $\sigma^2_{\varepsilon_{id}}/Var(z_{in} + p'_{in})$ and the ratio of informed traders λ_n/λ_d. While the ratio of pricing coefficients and $\sigma^2_{\varepsilon_{id}}$ were estimated in Section 3 to compute PI measures, estimating $Var(z_{in} + p'_{in})$ involves capturing the uncertainty about future prices, which we approximate by estimating a first-order auto-regressive process for the estimated pricing coefficient vector $\hat{\Phi}$:

$$\hat{\Phi}_t = B_0 + B_1 \hat{\Phi}_{t-1} + W_t, \tag{18}$$

where $\hat{\Phi}_t = [\hat{\phi}_0 \; \hat{\phi}_\varepsilon \; \hat{\phi}_n \; \hat{\phi}_d]$, B_1 is a 4×4 diagonal matrix that controls the persistence, B_0 is a 4×1 vector that stores the constant terms, and W_t is a 4×1 error term where

[27] Even though we computed PI estimating $\rho > 0$, here we assume $\rho = 0$. Otherwise, the unlearnable component of productivity $\tilde{\varepsilon}_i$ never reaches an ergodic distribution under aggregate shocks, and its distribution becomes an additional state variable. We will use the calibration of θ^s_{in} to account for the missing ρ quantitatively. Still, for aggregate outcomes, the identity of the firms with high productivity in each period is irrelevant, turning ρ irrelevant in assessing the allocative implications of PI.

$W_t \sim MVN(0, Q)$ and Q is the associated variance-covariance matrix. Once estimated, (18) provides a simple formula for $Var(z_{in} + p'_{in})$.

After recovering $Var(z_{in} + p'_{in})$, we use Lemma 1 to obtain λ_n/λ_d. In an interior equilibrium, the information acquisition conditions boil down to the following equations for night and day traders:

$$e^{ac_n(\lambda_n)} \operatorname{Var}(\varepsilon_{in} + p'_i) = \operatorname{Var}(\varepsilon_{in} + p'_i) + \frac{\sigma^2_{\theta_n}}{1 + \frac{\sigma^2_{\theta_n}}{\sigma^2_{\theta_d}} \left(\frac{\phi_n}{\phi_d}\right)^2}, \tag{19}$$

$$e^{ac_d(\lambda_d)} \left(\sigma^2_{\varepsilon_d} + \operatorname{Var}(\varepsilon_{in} + p'_i)\right) = \left(\sigma^2_{\varepsilon_d} + \operatorname{Var}(\varepsilon_{in} + p'_i)\right) + \frac{\sigma^2_{\theta_n}}{1 + \frac{\sigma^2_{\theta_n}}{\sigma^2_{\theta_d}} \left(\frac{\phi_n}{\phi_d}\right)^2} + \frac{\sigma^2_{\theta_d}}{1 + \frac{\sigma^2_{\theta_d}}{\sigma^2_{\theta_n}} \left(\frac{\phi_d}{\phi_n}\right)^2}. \tag{20}$$

These two equations pin down λ_n and λ_d *for given* cost functions $c_n(.)$ and $c_d(.)$.

Information Cost Functions We parametrize the information cost function as follows:

$$c_j(\lambda_j) = \nu_j \left(\frac{1}{1 - \lambda_j}\right)^{\psi_j} - \nu_j \tag{21}$$

for $j \in \{d, n\}$, which satisfies $c_j(0) = 0$ and $\lim_{x \to 1} c_j(x) = \infty$, and according to Corollary 1 guarantees an equilibrium with $\lambda_j \in [0, 1)$.

For each set of parameters, $\{\nu_d, \nu_n, \psi_d, \psi_n\}$ there is a mapping between the loadings (ϕ_n and ϕ_d) and the fraction of informed traders (λ_n and λ_d) through equations (19) and (20). We choose these four parameters to match four moments implied by the estimated pricing function: (1) the level of information acquisition by night and day traders, (2) the increase in information acquisition in recessions, and (3) the level of PI. The level of the cost of acquiring information depends on ν_d and ν_n, while its curvature is determined by ψ_d and ψ_n. The average levels of λ_n and λ_d are hence directly informative about ν_d and ν_n. The change in information-acquisition activities, on the other hand, reveals the curvatures. Finally, the average level of PI informs how day traders respond to information acquisition by night traders: a low ψ_d (ψ_n) makes it easier for a day (night) trader to scale his information acquisition, tilting the prices to reflect more of θ_d (θ_n).

Discretizing the Aggregate States In order to estimate the aggregate state ($s_t = \{Z_t, \gamma_t\}$) dynamics, we first remove a linear trend from the productivity series Z_t (measured by the logarithm of earnings per share) and the liquidity needs series γ_t (recovered as described above). Then, we estimate a vector-auto-regression (VAR) and discretize it with a 4-state Markov chain (2 levels for each state) following Gospodinov and Lkhagvasuren (2014). We then assign each year as a high or low Z given the estimated Z grid and compute the average levels of $\sigma^2_{\theta_n}$, $\sigma^2_{\theta_d}$, $\sigma^2_{\varepsilon_n}$, and $\sigma^2_{\varepsilon_d}$ in those years. These averages correspond to variances in normal times and recessions.

Estimation Algorithm for the Stock Market To be more precise about the calibration procedure, we start with a guess $\{\nu^0_d, \nu^0_n, \psi^0_d, \psi^0_n\}$ and take the next steps:

1. Start iteration k with $\{\nu^k_d, \nu^k_n, \psi^k_d, \psi^k_n\}$. Use (19) and (20) with estimated series for pricing coefficients and parameters to infer $\lambda^k_{d,data}$ and $\lambda^k_{n,data}$ series.

2. Invert (12) to infer γ series.

3. Follow the discretization procedure discussed above to estimate a VAR for $\{Z, \gamma\}$ and discretize it into a Markov Chain. Compute the values for $\sigma^2_{\theta_n}$, $\sigma^2_{\theta_d}$, $\sigma^2_{\varepsilon_n}$, and $\sigma^2_{\varepsilon_d}$ associated with each Z level.

4. Compute the stock market equilibrium and the implied model moments M^k_{model}, displayed in Table 3.

5. Compare M^k_{model} with M^k_{data}. If the discrepancy is below the threshold, stop. If not, go back to step 1 with new $\{\nu^{k+1}_d, \nu^{k+1}_n, \psi^{k+1}_d, \psi^{k+1}_n\}$.

4.1.3 Internally Calibrated Parameters of the Real Sector

Now, we internally calibrate parameters involved in capital accumulation and allocation: β, $\sigma^2_{p^s_i}$, $\sigma^2_{\varepsilon^s_{in}}$, and $\sigma^2_{\theta^s_{in}}$. We estimate the discount factor to generate a 2% risk-free interest rate.[28] The last three parameters are not in the benchmark model, but are quantitatively relevant in disciplining how much decision makers react to prices and their information content. We discipline $\sigma^2_{p^s_i}$ directly with the R-squared of the price regression from equation (14), which indicates what portion of the variation in observed prices can be explained by θ_{in} and θ_{id}, and hence the residual contained in observed prices p^s_i.

[28]This interest rate is not the return households receive from capital (r) since the realized return accrues all the surplus to the households. Instead, we evaluate the counterfactual interest rate in the model that would clear markets in a competitive setting.

We jointly discipline the quality of mutual fund own signals, $\sigma^2_{\varepsilon^s_{in}}$ and $\sigma^2_{\theta^s_{in}}$ using the cross-sectional price-investment correlation ($cor(p^s_i, k_i)$), and the time-series correlation between PI and investment dispersion ($cor(PI, std(k_i))$. First, $cor(p^s_i, k_i)$ increases with both variances: the mutual fund pays more attention to prices when making a decision when their own signals are less informative. Second, $cor(PI, std(k_i))$ also increases with both variances: when the mutual fund pays more attention to prices, PI fluctuations have a smaller impact on capital allocation measured by the cross-sectional dispersion of investment. Even though both effects go in the same direction, the elasticity of the latter with respect to $\sigma^2_{\theta^s_{in}}$ is much larger because the mutual fund's own signal about θ_n is correlated with prices, providing a single crossing condition for identification.[29] Intuitively, both signals put limits on the extent of learning from the prices. As the precision of θ^s_{in} increases, prices become a sideshow, and fluctuations in PI are irrelevant for capital allocation. As the precision of ε^s_{in} increases, the investment decision assigns a smaller weight to stock prices, since part of the investment choices is based on the realization of ε^s_{in}.

While our benchmark suggests a tight link between prices and adjustable capital, this relation has been empirically challenged. David et al. (2016), for instance, documented a weak cross-sectional correlation between capital expenditures (CAPEX) and stock prices, arguing that learning from prices must be limited. As shown in Figure 16 in Appendix F, our data suggests a similar weak correlation (in more recent years, this correlation is even negative).[30] It has been noted, however, that CAPEX primarily captures expenses on fixed long-term assets (such as buildings and structures) that tend to be sluggish and multifaceted. This concern is further supported by the observed weak correlation between CAPEX and other variables that are presumably tightly connected to a firm's investment ability and decisions, such as previous earnings, earnings forecasts, and future earnings.

When alternative measures of investment, or proxies for the capacity to attract investment funds, are used, the relationship with prices becomes intermediate: not absent, as with CAPEX, nor perfect, as in our benchmark. To be more precise, we consider three alternative measures of investment: 1) *asset changes*, computed as the year-to-year change in total assets,[31] 2) *working capital*, and 3) *number of employees*. We also consider two indi-

[29]Our identification relies on $\sigma^2_{\varepsilon^s_{in}}$ and $\sigma^2_{\theta^s_{in}}$ being constant over time. It is impossible to rule out a source of information that independently provides the same information and fluctuates similarly to stock prices, yet doesn't react to counterfactual policies that affect stock markets.

[30]In the exercises described in this section, we transform all variables to per-unit-of-asset values to allow comparability across firms, similar to our empirical exercise in Section 3. See Appendix B.3.3 for details.

[31]Unlike CAPEX, which measures cash outflows for long-term assets, asset change measures the net

cators of how easily a firm can access funds: 1) *corporate bonds yields* and 2) *corporate bonds ratings*. Figure 17 in Appendix F shows that, for the U.S. in 2015, while CAPEX has a weak negative correlation with stock prices, the other measures tell a different story. Firms with higher stock prices tend to have larger changes in assets, higher working capital and employee levels, pay lower rates on their bonds, and have better-rated bonds. Tables 16 and 17 in Appendix F also support a tight connection: prices predict higher measures of productive capacity (including a higher CAPEX) once previous earnings, country, and time fixed effects are controlled, with and without firm fixed effects.

We consider *working capital* to be closest to the perfectly adjustable capital in our model. Working capital does not necessarily capture all productive capital, but it is a reactive proxy for short-term funds and operational flexibility that enables firms to exploit opportunities. In what follows, we use working capital as our measure of k_i.

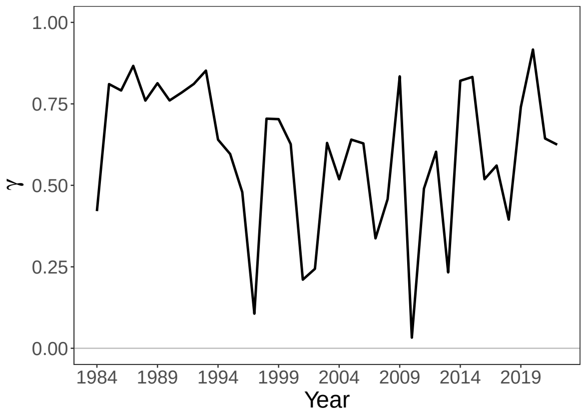
4.2 Calibration Results

The first panel of Figure 3 shows the estimated liquidity series for the U.S., suggesting elevated reliance on stock markets for liquidity purposes (high γ) around the Great Recession and the COVID-19 pandemic and a persistent period of high reliance surrounding the period of S&L crisis, from 1985 to 1995.

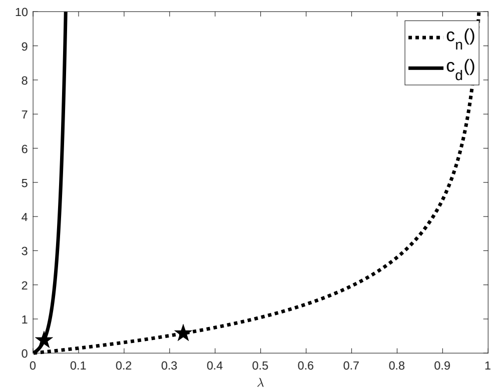
The second panel of Figure 3 shows the calibrated shape of information cost functions for day and night traders. The cost of learning for day traders is much higher and steeper than that for night traders. This result is disciplined by two observations: (*i*) the uncertainty conditional on learning about stock liquidity ($\sigma^2_{\varepsilon_d}$) is much higher than the corresponding uncertainty in fundamental payoffs ($\sigma^2_{\varepsilon_n}$), and (*ii*) the price uncertainty ($Var(\varepsilon_{in} + p'_i)$) is much larger than the dispersion of signals ($\sigma^2_{\theta_n}$ and $\sigma^2_{\theta_d}$). From (19) and (20), this is consistent with night traders' lower information costs. If information costs functions were the same, day traders would obtain more information than night traders, given the additional uncertainty they face, with a ratio (12) counterfactually low.

Table 2 summarizes the four aggregate states resulting from discretizing the (Z, γ) series and the years our method assigns to each aggregate state. We also show the signal

change in a firm's productive capacity while taking into account both current assets and mergers and acquisitions. Indeed, Cooper et al. (2008) argues that asset growth is a better predictor of future stock returns.



(a) Estimated γ Series



(b) Estimated Cost Functions

Figure 3: γ Series and Information Acquisition Costs
Notes: Panel (a) presents the estimated γ series. Panel (b) shows estimated information acquisition cost functions. Solid and dashed lines represent $c_d(\cdot)$ and $c_n(\cdot)$, respectively. Stars indicate the median λ and associated costs in the stochastic steady state.

and forecast-error standard deviations for each state. Z fluctuates between 0.049 and 0.061 (consistent with median earnings per share fluctuations) while γ fluctuates between 0.35 and 0.79. We interpret the values of γ as indicating that roughly two-thirds of traders focus exclusively on stocks' long-run earnings when banks operate well, whereas most focus on short-run price fluctuations when funding liquidity dries up.

Table 2: Estimated Aggregate State Levels

s	Z	γ	σ_{θ_n}	σ_{θ_d}	σ_{ε_n}	σ_{ε_d}	Years
1	0.049	0.35	0.059	0.17	0.036	0.14	'95-'97, '01, '02, '13, '16
2	0.049	0.79	0.059	0.17	0.036	0.14	'89, '90, '91-'94, '98-'00, '03, '09, '15, '17, '19-'21
3	0.061	0.35	0.059	0.14	0.038	0.12	'84,'04,'07,'08,'10,'11,'18
4	0.061	0.79	0.059	0.14	0.038	0.12	'85-'88,'05,'06,'12, '14, '22

Notes: The last column shows the years with Z and γ estimates closest to the values associated with each aggregate state. The values of $\sigma^2_{\theta_n}$, $\sigma^2_{\theta_d}$, $\sigma^2_{\varepsilon_n}$, and $\sigma^2_{\varepsilon_d}$ are estimated by taking the averages over the years associated with the Z values.

Table 3 summarizes all calibrated parameters, both externally and internally. We set PI corresponding to the aggregate state $\{\overline{Z}, \underline{\gamma}\}$, i.e., $\underline{PI}$, as a benchmark.

Finally, in Table 4 we validate our calibration and show it is consistent with PI fluctuations, which we do not explicitly target. *Ceteris paribus*, PI declines when the economy transitions to a state with higher market liquidity needs and increases when the economy transitions to a state with lower aggregate productivity. If both productivity declines and

Table 3: Externally and Internally Calibrated Parameters

Parameter	Value	Moment	Parameter	Value	Moment	Model	Target
$\bar{k}/\xi$	825	Normalized	ν_n	4.58	λ_d	0.06	0.02
η	2	External	ν_d	0.11	λ_n	0.26	0.33
a	0.05	External	ψ_n	0.3	$\underline{PI}$	0.87	0.87
δ	0.06	External	ψ_d	60	$\Delta\lambda$	0.23	0.22
r^F	0.02	External	β	0.98	Real Interest Rate	0.02	0.02
			$\sigma_{p_i^s}$ for $\underline{\gamma}$	4.9	R-squared for $\underline{\gamma}$	0.44	0.44
			$\sigma_{p_i^s}$ for $\overline{\gamma}$	2.5	R-squared for $\overline{\gamma}$	0.44	0.44
			$\sigma_{\varepsilon_{in}^s}$	0.02	$cor(p_i, k_i)$	0.39	0.37
			$\sigma_{\theta_{in}^s}$	0.11	$cor(PI, std(k_i))$	0.22	0.22

Notes: λ_d and λ_n are computed as the average values in the ergodic distribution of aggregate states. The data counterpart is computed as the median value in the inferred series. $\underline{PI}$ is the PI level averaged over low Z states in the ergodic distribution. Its data counterpart is computed as the average PI level in designated low Z years. The $\Delta\lambda$ is computed as the percentage change in aggregate (day and night) fraction of informed traders in an IRF exercise where the economy moves from a long sequence of high Z low γ states to a state of low Z high γ. Its data counterpart is the percentage difference in employment in the NAICS 52394 (Portfolio management and investment advice) industry during recessions and booms (CES Survey, BLS).

banking gets into distress, the first effect prevails, and PI declines. These changes are consistent with the PI's cyclical properties when productivity and liquidity are correlated.

Table 4: Untargeted PI Moments

Moment	Model	Untargeted
$\Delta PI_{\overline{z}\underline{\gamma}\to\underline{z}\underline{\gamma}}$	0.02	0.01
$\Delta PI_{\overline{z}\underline{\gamma}\to\overline{z}\overline{\gamma}}$	-0.16	-0.10
$\Delta PI_{\overline{z}\underline{\gamma}\to\underline{z}\overline{\gamma}}$	-0.10	-0.17

Notes: The ΔPI terms are computed as percentage changes in PI measures in an IRF exercise where the economy moves from a long sequence of high Z low γ states. Their data counterpart is computed as the percentage differences in average PI levels across years with different aggregate state designations.

5 Quantitative Relevance of Stock Price Informativeness

This section uses the calibrated model to assess the quantitative relevance of stock price informativeness on economic activity. The first exercise estimates an impulse response function for a recessionary shock, with and without financial-market distress. The goal is to assess whether financial distress amplifies or dampens the impact of a recessionary shock by altering the informativeness of stock prices. The second exercise compares the aggregate effects of recessions with financial distress in alternative economies, one with lower information costs and another in which traders receive information exogenously. While the first economy is useful for evaluating transparency policies, the second quantifies the role of endogenous information acquisition in the economic response to changing trader composition. Lastly, in a third exercise, we quantify the importance of alternative sources of information through economies with various combinations of prices, signals on the learnable component of productivity (θ_n^s), and signals on the unlearnable component of productivity (ε_n^s).

5.1 Allocation Effects of Productivity and Liquidity Shocks

We simulate our economy for high Z and low γ (state 3 in Table 2). We then introduce a one-period recession: a decline in Z (a transition to state 1 in Table 2). This *single shock* captures standard productivity recessions, without clear liquidity problems. We then compare this scenario to one-period recession *with* financial distress: a decline in Z *and* an increase in γ (a transition to state 2 in Table 2). This *dual shock* captures the major downturns of the US economy during our estimation period: the Great Recession in 2009 and the COVID-19 recession in 2020. Figure 4 presents the implications of these two different aggregate shocks: the dotted line is the first case, and the solid line is the second.

In the case of a single shock to productivity (dotted lines), the increase in uncertainty σ_{θ_d} that accompanies a recession induces day traders to produce more information, but the increase in σ_{ε_d} makes them trade less aggressively on their information. This combination generates less 'noise' in markets and makes stock prices more informative about fundamentals. The increase in PI improves capital allocation, partially compensating for the negative productivity shock, which, alone, without a change in PI, would have generated an output loss 4.4% larger.

What if the recession is accompanied by financial distress? With dual shocks to productivity and liquidity needs (solid lines), the participation of more day traders obscures firms' fundamentals. As a response to more uncertain fundamentals, the benefits of acquiring information also increase for night traders. Despite overall increased information acquisition (higher $\lambda = \gamma\lambda_d + (1-\gamma)\lambda_n$), PI ultimately declines, inducing a decline in

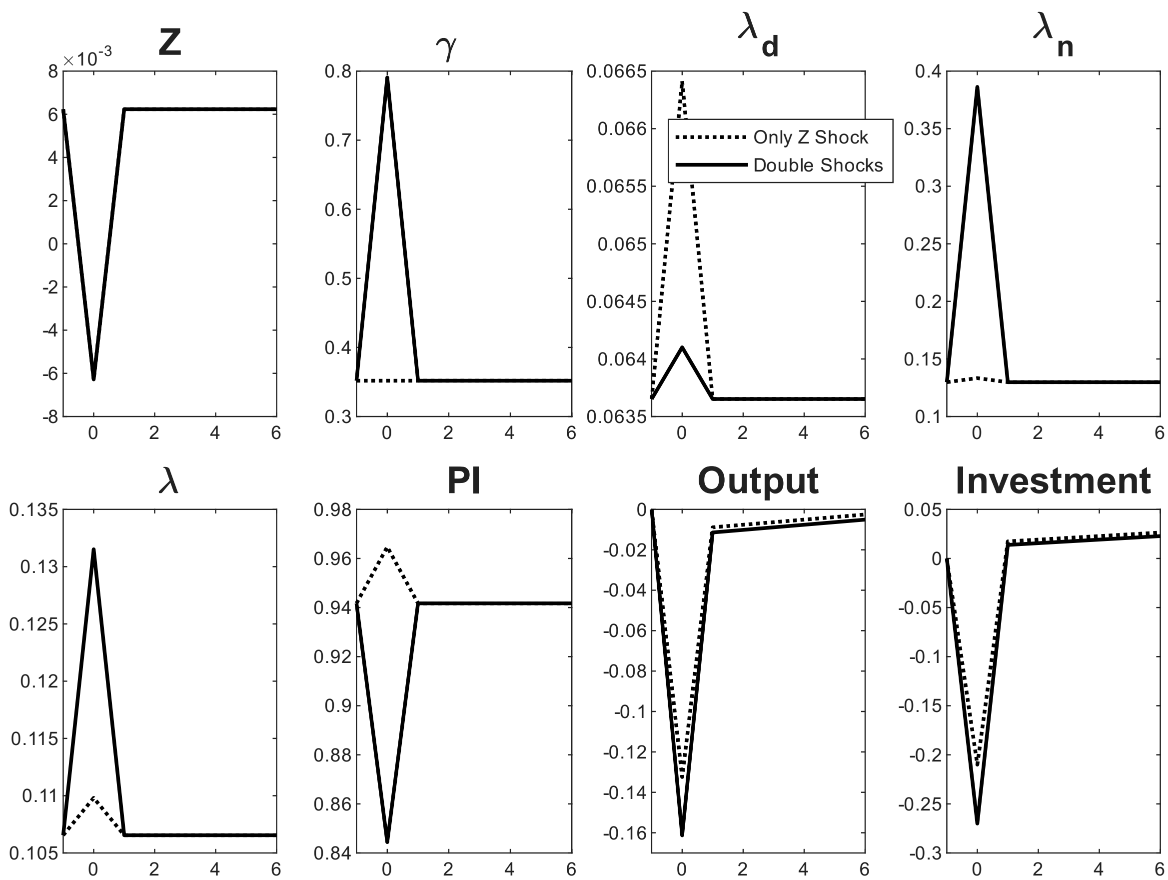


Figure 4: Impulse Response Functions. Notes: The first two panels provide the shocks that hit the economy under the benchmark and the counterfactual recession scenarios. λ denotes the aggregate fraction of traders that acquire information. Output and investment values represent the percentage changes from the pre-shock values.

output and gross investment that is 22% larger than without financial distress.[32]

5.1.1 Testable Implications

Our calibrated model generates a relation between shocks, PI, and allocations that we can empirically test across countries. First, our calibration shows that PI rises with productivity shocks and falls with financial distress, and reacts more to standard financial distress

[32]In Figure 18 of Appendix F, we compare a banking crisis with and without a drop in Z. While in both cases PI declines, this is more pronounced when there is no recession, leading to a pure misallocation decline in output (despite no reduction in Z) that is 11% of a standard recession.

than to standard productivity shocks. To test these predictions, we estimate:

$$PI_{ct} = \beta_0 + \beta_1 Z_{ct} + \beta_2 y_{ct} + F_c + F_t + \epsilon_{ct}, \tag{22}$$

where PI_{ct} is our PI measure for country c in year t, Z_{ct} represents the business cycle measured by GDP growth and y_{ct} represents the funding liquidity cycle. For y_{ct}, we use the 'Banking Stock Performance' variable, which we presented in Table 1, and several other proxies, such as binary measures of banking panics and banking equity crises (constructed by Baron et al. (2021)), and continuous measures, such as capital-asset ratios of the banking sector, loan spreads of the banks (lending rate minus treasury bill rate), and the ratio of non-performing loans to total gross loans. In low-liquidity environments, such as the Great Recession, the capital asset ratio is expected to be low, while the loan spreads and non-performing ratios are expected to be high. Finally, F_c and F_t are country- and year-fixed effects, respectively.

Table 5 presents the results. Consistent with our calibration, lower liquidity from the banking and financial sectors is associated with lower PI across all specifications. A one standard deviation increase in the capital-to-asset ratio of the banking system, for example, is associated with a 0.2 increase (0.83 standard deviations) in PI. That is, when banks are better armed to provide credit, stock prices become more informative. However, once conditioned on the level of economy-wide liquidity, lower aggregate productivity is associated with higher PI, but this association is not statistically significant.[33]

Second, misallocation from a drop in PI takes a particular form in our model: lower PI induces firms' fundamentals to look more alike, reducing investment dispersion, all else equal. We test this implication by comparing the dispersion of capital expenditures in a particular country-year pair against the level of PI in Table 6. Regardless of how country-year pairs are weighted, a higher PI is associated with greater dispersion in capital expenditures, even after controlling for the business cycle.

Our result of a recession without financial distress is reminiscent of 'cleansing recessions,' but for different reasons. In that literature, recessions reduce the cost of reallocating resources to more productive activities. In our case, recessions increase stock market

[33]Most estimates are robust to using aggregate earnings as the measure of economic activity (see Table 18 in Appendix F) or to weighting observations with the number of stocks used in the PI estimation (see Table 19 in Appendix F).

Table 5: Price Informativeness and Economic Conditions

	PI					
	Banking Stock Perf.	Bank Capital to Assets	Bank Loan Spreads (-)	Non-performing Loans (-)	Banking Panic (-)	Banking Equity Crisis (-)
	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth	-0.99	-0.64	-0.36	-1.29	-1.32	-1.35
	(0.85)	(1.20)	(1.39)	(1.47)	(0.99)	(0.99)
Liq. Measure	0.49	0.09^{**}	0.02^{***}	0.03^{***}	0.13^{*}	0.01
	(0.56)	(0.04)	(0.01)	(0.01)	(0.07)	(0.07)
Range	'84-'22	'05-'22	'84-'22	'05-'22	'84-'16	'84-'16
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	319	180	185	185	244	244

Notes: In each regression, the dependent variable is the PI. Column labels refer to the liquidity measure used in each regression. Both country and year fixed effects are included. The standard errors are clustered at the country level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

informativeness and improve resource allocation. Our work, however, highlights that 'cleansing recessions' can turn into 'sullying recessions' when accompanied by heightened liquidity concerns. Recessions accompanied by weakness in the banking sector are periods of lower PI and worse resource allocation. In prior literature, tighter borrowing constraints, time-varying risk premia, counter-cyclical adverse selection in the market for used capital, and managers' incentives to hide reallocation needs during recessions have been proposed as potential mechanisms for counter-cyclical misallocation.[34] Ours is a novel mechanism that can generate higher or lower misallocation depending on whether a recession coincides with distress in the financial sector.

Third, according to our model, information acquisition increases during downturns, whether or not funding liquidity distress is present. This is consistent with the findings of Loh and Stulz (2018) and Jiang et al. (2015). The former documents that financial analysts produce longer, more frequent reports, and that these reports have a larger price impact in bad times. The latter documents that management earnings forecasts become more frequent during recessions. Our model rationalizes these patterns as endogenous responses to less informative stock prices: *there may be less information available for decision-making*

[34]See Ordonez (2013), Khan and Thomas (2013), Fajgelbaum et al. (2017) and Straub and Ulbricht (2023) for tighter financial constraints, David et al. (2022) for time-varying risk premia, Fuchs et al. (2016) for adverse selection, and Eisfeldt and Rampini (2008) for managerial incentives.

Table 6: PI and Capital Allocation

	Dispersion of Investment			
	(1)	(2)	(3)	(4)
PI	0.004**	0.004**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
GDP Growth		0.036**		0.060*
		(0.018)		(0.031)
Range	'84-'22	'84-'22	'84-'22	'84-'22
FE	Yes	Yes	Yes	Yes
Weights	No	No	Yes	Yes
Obs	344	344	344	344

Notes: In each regression, the dependent variable is the standard deviation of normalized capital expenditures. Both country and year fixed effects are included. In columns (3) and (4), each country-year observation is weighted with the number of stocks used to estimate the PI measure. The standard errors are clustered at the country level for the unweighted regressions. *p<0.1; **p<0.05; ***p<0.01.

despite more information being generated overall.

5.2 Alternative Information Structures

In the previous exercise, we analyzed the quantitative response of PI to productivity and liquidity shocks, as well as their aggregate consequences. Here, we compare these reactions with those of alternative economies. The first column of Table 7a shows the changes in total information acquisition (λ), PI, output, and investment when the economy suffers the *dual shock* on productivity and liquidity needs. These changes are expressed as percentages relative to the benchmark aggregate state given by high Z and low γ. In this baseline economy, for instance, a dual shock that reduces Z and increases γ reduces PI by 10% and output by 16%. These numbers replicate the magnitudes of the changes depicted by the solid lines of Figure 4.

One alternative economy assumes that a fraction of traders receive signals exogenously, captured in the second column of Table 7a, where λ always equals the amount in the boom periods of the benchmark economy. This economy would suffer a 62% reduction in PI (six times larger than the benchmark with endogenous information), leading to a severe misallocation that reduces output by 23% and investment by 36%. This result highlights the quantitative relevance of endogenous information acquisition. In the econ-

Table 7: Counterfactual Estimates

Moments	Baseline	Fixed λ	low ν_n	low ν_d
$\Delta\lambda_{\overline{z}\underline{\gamma}\to\underline{z}\overline{\gamma}}$	0.234	0.000	0.195	0.227
$\Delta PI_{\overline{z}\underline{\gamma}\to\underline{z}\overline{\gamma}}$	-0.103	-0.624	-0.067	-0.121
$\Delta Y_{\overline{z}\underline{\gamma}\to\underline{z}\overline{\gamma}}$	-0.161	-0.230	-0.153	-0.164
$\Delta Inv_{\overline{z}\underline{\gamma}\to\underline{z}\overline{\gamma}}$	-0.270	-0.362	-0.241	-0.271

(a) Impulse Response Functions

Moments	Baseline	Fixed λ	low ν_n	low ν_d
Y	0.110	0.099	0.113	0.109
C	0.050	0.044	0.051	0.050
Inv	0.060	0.055	0.061	0.060
PI	0.865	0.607	0.913	0.847
λ_n	0.254	0.130	0.328	0.272
λ_d	0.064	0.082	0.065	0.074

(b) Stochastic Steady State Averages

Notes: In the top panel, each number denotes the percentage change at the moment when the economy moves from a long sequence of $\overline{z}\gamma$ states to a $\underline{z}\overline{\gamma}$ state. For the fixed γ scenario, this is equivalent to moving to $\underline{z}\overline{\gamma}$. R denotes the gross interest rate that would clear the market in a competitive economy.

omy, agents respond to lower information content in stock markets by acquiring more information, partially offsetting the reduction. Information acquisition provides a stabilizing force against recessions with financial distress.

Another alternative economy we consider is one with lower information costs. Since two types of traders acquire different information in our setting, we consider two situations, shown in the last two columns of Table 7a. If night traders can acquire information at half the cost (third column), they would trade more aggressively; PI would decline only 6.7% instead of 10%, leading output to decline 15.3% instead of 16.1%. In contrast, if day traders could acquire information at half the cost (last column), they would also trade more aggressively, PI would decline by 12.1% rather than 10%, and output would decline by 16.4%. Note that in our setting, more information acquisition does not mean better information; it just means more traders of a particular type become informed and trade more aggressively on that information, thereby affecting which signal is "more represented" in prices. Therefore, additional information made available to traders can create negative externalities by suppressing other information, as in Banerjee et al. (2018).

An economy with lower information costs for night traders, ν_n, could represent, for instance, improvements in the Securities and Exchange Commission disclosure regulations, with more information requirements to be filed with each prospectus, more frequent filings, or firm-specific statistics publications. In contrast, lower information cost for day traders, ν_d, could reflect regulations that disclose information about market transactions, such as recent changes to stress tests, the use of Central Counterparties (CCPs), disclosures about trading positions, or the use of discount windows. Our analysis shows that regulations that facilitate access to firms' profitability information make the economy more resilient to recessions and financial shocks. In contrast, those that facilitate information about stock markets' operations do the opposite.

While Table 7a shows how alternative economies fare when facing both productivity and liquidity shocks *on impact*, Table 7b shows their differences along their stochastic steady state. For instance, economies with lower information costs exhibit greater overall information acquisition by all traders. However, if information about fundamentals is cheaper, the economy displays higher capital, consumption, and output in a stochastic steady state, whereas the opposite occurs if information about assets' liquidity is cheaper.

Our exercise naturally abstracts from many channels through which transparency regulations affect markets, hence, should not be taken as direct policy advice. Yet, it helps bring forward potential spillovers from such policies and quantify them.

5.3 Relative Importance of Different Information Sources

The structural nature of our analysis allows us to decompose the importance of learning from the three main information sources in our model: stock prices, private signals on the learnable component of productivity θ^s_n, and private signals about the non-learnable (to traders) component of productivity ε^s_n. This also allows us to interpret our estimates for $\sigma_{\theta^s_{in}}$ and $\sigma_{\varepsilon^s_{in}}$. Table 8 presents the output levels across various states of the economy for alternative combinations of these three sources. Importantly, we keep the aggregate capital stock constant across scenarios to isolate losses due to static misallocation.

Two messages stand out. First, relative to the 0.11 benchmark (Table 8, first column),

Table 8: Output Under Alternative Information Sources

	Baseline	θ_n^s, ε_n^s	p^s, ε_n^s	p^s, θ_n^s	ε_n^s	θ_n^s	p^s
low Z low γ	0.104	0.089	0.100	0.085	0.077	0.065	0.080
low Z high γ	0.101	0.089	0.096	0.080	0.077	0.065	0.074
high Z low γ	0.119	0.105	0.115	0.097	0.093	0.078	0.091
high Z high γ	0.117	0.105	0.111	0.094	0.093	0.078	0.087
Stochastic Average	0.110	0.097	0.106	0.089	0.085	0.072	0.083

Notes: The first four rows refer to the various aggregate states of the economy, while the last row computes the long-run average output with the stationary distribution. All output figures are computed at the same capital level.

the largest output drop is 19% without ε_n^s (to 0.089), followed by 12% without stock prices (to 0.097) and 4% without θ_n^s (to 0.106). Note that ε_n^s is the only signal about one of the two components of productivity, hence losing it is quite costly in terms of allocations. Second, both p^s and θ_n^s are important on their own, with prices conveying a bit more information. Observing prices on top of ε_n^s leads to an increase of output of 25% (from 0.085 to 0.106), while observing private signals about θ_n on top of ε_n^s leads to an increase of output of 14% (from 0.085 to 0.097). In other words, *stock prices exhibit an economically significant "revelatory price efficiency," above and beyond other sources of information.*

6 Conclusions

Stock markets contribute to the economy in two distinct ways. One is conveying, through prices, useful information about the best use of resources. The other is allowing agents to access liquidity quickly by trading stocks. Here, we have explored how changes in the relevance of the latter affect the performance of the former. When banks (or bond markets) fall short of providing credit, agents rely more on stock markets to access liquidity, eroding the role of stocks in revealing information. To connect the two roles of stock markets, we have provided a model of price formation with endogenous information acquisition and integrated it with a real business cycle model with heterogeneous firms.

Additionally, we provide a novel measure of stock price informativeness that captures the extent to which prices reveal information about firms held by market participants.

We implement our measure across many countries and periods, enabling us to document their fluctuations and relate them to recessions and banking crises. Since our measure is structural, we can also decompose the sources behind those fluctuations. We show that the informative role of stock markets weakens particularly during periods of distress in funding liquidity. Further, this decline seems mostly related to heightened trading activity unrelated to firms' fundamentals, not to less information acquisition or worse information quality.

These findings highlight a novel link between the functioning of credit markets and stock markets. Even though these markets provide similar services, such as liquidity and information, some argue that banks are more efficient at supplying liquidity and at revealing information about firms (see discussion in Gorton and Ordonez (2023)). We have argued here that when banks are in distress, stock markets step in to supply liquidity at the expense of their role in revealing information and guiding resource allocation. We assess this link quantitatively by calibrating the full model to the United States. We show that stock markets mitigate the output losses from recessions by 4.4%, but if those recessions are accompanied by financial distress, stock markets go from "friend to foe," magnifying output losses by 22%.

Our approach entails certain limitations that we hope will spark further research. First, our modeling framework assumes the absence of feedback effects from the real economy to financial markets (prices affect investment choices, but investment choices do not affect prices). Adding this two-way feedback would imply losing the tractability provided by linear pricing, but would give rise to potential magnification forces. Second, our counterfactual analysis only centers on how the information environment affects stock price informativeness, abstracting from other potential channels through which information affects production, as in Plantin and Tirole (2018). A more comprehensive study that assesses the overall costs and benefits of information provision would provide a more robust evaluation of the desirability and regulation of information.

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A Proofs

Proof of Lemma 1. The proof extends to this environment the corresponding proof in Grossman and Stiglitz (1980). Since end-of-period wealth is additive across stocks (in terms of payoffs and information acquisition costs), proving the result for a single-asset is sufficient. First, notice that the end-of-period wealth for informed and uninformed agents can be written as

$$\begin{aligned} W_{I,j}^{n,i} =& r\left(W_{oj} - c\left(\lambda_n^i\right)\right) + [(z_{in} + p_i') - (1+r^F)p_i]X_{iI}^n \\ W_{U,j}^{n,i} =& rW_{oj} + [(z_{in} + p_i') - (1+r^F)p_i]X_{iU}^n \end{aligned} \tag{23}$$

The expected value of being informed for a night trader j can be written as

$$E[\nu(W_{I,j}^{n,i}) \mid p] = E[e^{-aW_{I,j}^{n,i}} \mid p_i] = -exp\left(-aE\left[E[W_{I,j}^{n,i} \mid \theta] - \frac{a}{2}\operatorname{Var}\left[W_{I,j}^{n,i} \mid \theta\right] \Big| p_i\right]\right) \tag{24}$$

Combining Equations (4) and (23), we can write

$$E[W_{I,j}^{n,i} \mid \theta] = r\left(W_{oj} - c\left(\lambda_n^i\right)\right) + \frac{[Z + \tilde{\theta}_{in} + E[p_i'] - (1+r^F)p_i]^2}{a\operatorname{Var}(z_{in} + p_i' \mid \theta)} \tag{25}$$

$$\operatorname{Var}[W_{I,j}^{n,i} \mid \theta] = \frac{[Z + \tilde{\theta}_{in} + E[p_i'] - (1+r^F)p_i]^2}{a^2\operatorname{Var}(z_{in} + p_i' \mid \theta)}. \tag{26}$$

Since W_{0j} and p_i are not random given θ. Thus, we can rewrite Equation (24) as

$$\begin{aligned} E[\nu(W_{I,j}^{n,i}) \mid p] =& - exp\left[-ar(W_{oj} - c(\lambda_n^i)) - \frac{[Z + \tilde{\theta}_{in} + E[p_i'] - (1+r^F)p_i]^2}{2\operatorname{Var}(z_{in} + p_i' \mid \theta)}\right] \\ =& - exp\left[-ar(W_{oj} - c(\lambda_n^i))\right] \times \\ & E\left[exp\left(\frac{-1}{2\operatorname{Var}(z_{in} + p_i' \mid \theta)}\left[Z + \tilde{\theta}_{in} + E[p_i'] - (1+r^F)p_i\right]^2\right) \mid p_i\right] \end{aligned} \tag{27}$$

Now define

$$h_{in} := \operatorname{Var}[\tilde{\theta}_{in} \mid p]$$

$$g_{in} := \frac{Z + \tilde{\theta}_{in} + E[p_i'] - (1+r^F)p_i}{\sqrt{h_{in}}}$$

so, $E[\nu(W_{I,j}^{n,i}) \mid p]$ can be rewritten as

$$E[\nu(W_{I,j}^{n,i}) \mid p] = e^{ac^n(X_{in})}\nu(rW_{oj})E_s\left[exp\left(\frac{-h_{in}}{\operatorname{Var}(z_{in} + p_i' \mid \theta)}g_{in}^2\right) \mid p_i\right] \tag{28}$$

Since p_i is a linear function of θ, conditional on p_i, $\tilde{\theta}_{in}$ is normally distributed. Therefore, g_{in}^2 is distributed with Chi-squared. Hence, moment generating function of g_{in}^2 has the form:[35]

$$E[e^{-t(g_{in})^2}|p] = \frac{1}{\sqrt{1+2t}} exp\left(\frac{-t(E[g_{in} \mid p])^2}{1+2t}\right). \tag{29}$$

Now we can rewrite,

$$\begin{aligned} E[\nu(W_{I,j}^{n,i}) \mid p] =& \frac{1}{\sqrt{1+\frac{h_{in}}{\mathrm{Var}(z_{in}+p_i'|\theta)}}} exp\left(\frac{-h_{in}E[g_{in} \mid p]^2}{2\left(\mathrm{Var}(z_{in}+p_i' \mid \theta)+h_{in}\right)}\right) \\ =& \frac{1}{\sqrt{1+\frac{h_{in}}{\mathrm{Var}(z_{in}+p_i'|\theta)}}} exp\left(\frac{-\left(Z+E[\tilde{\theta}_{in} \mid p_i]+E[p_i']-(1+r^F)p_i\right)^2}{2\left(\mathrm{Var}(z_{in}+p_i' \mid \theta)+h_{in}\right)}\right) \end{aligned} \tag{30}$$

Furthermore, notice that

$$\frac{\mathrm{Var}\left(z_{in}+p_i' \mid \theta\right)}{\mathrm{Var}\left(z_{in}+p_i' \mid p\right)} = \frac{\mathrm{Var}\left(z_{in}+p_i' \mid \theta\right)}{\mathrm{Var}\left(z_{in}+p_i' \mid \theta\right)+h_{in}} = \frac{1}{1+\frac{h_{in}}{\mathrm{Var}\left(z_{in}+p_i'|\theta\right)}} \tag{31}$$

Hence, we can rewrite it as

$$\begin{aligned} E\left[\exp\left(\frac{-h_{in}}{\mathrm{Var}\left(z_{in}+p_i' \mid \theta\right)}g_{in}^2\right)\middle| p\right] =& \sqrt{\frac{\mathrm{Var}\left(z_{in}+p_i' \mid \theta\right)}{\mathrm{Var}\left(z_{in}+p_i' \mid p_i\right)}}\times \\ & \exp\left(\frac{-\left(Z+E\left[\tilde{\theta}_{in} \mid p_i\right]+E\left[p_i'\right]-(1+r^F)p_i\right)^2}{2\left(\mathrm{Var}\left(z_{in}+p_i' \mid \theta\right)+\mathrm{Var}\left[\theta_{in} \mid p_i\right]\right)}\right) \end{aligned} \tag{32}$$

Then,

$$\begin{aligned} E\left[\nu(W_I^{n,i}j) \mid p\right] =& e^{ac(\lambda_{in})}\nu(rW_{oj})\sqrt{\frac{\mathrm{Var}\left(z_{in}+p_i' \mid \theta\right)}{\mathrm{Var}\left(z_{in}+p_i' \mid p_i\right)}}\times \\ & \exp\left(\frac{-\left(Z+E\left[\tilde{\theta}_{in} \mid p_i\right]+E\left[p_i'\right]-(1+r^F)p_i\right)^2}{2\left(\mathrm{Var}\left(z_{in}+p_i' \mid \theta\right)+\mathrm{Var}\left[\theta_{in} \mid p_i\right]\right)}\right) \end{aligned} \tag{33}$$

[35]For this to work, we need $\mathrm{Var}(z_{in}+p_i' \mid \theta)$ to be deterministic given p_i, i.e., $\mathrm{Var}[\mathrm{Var}(z_{in}+p_i' \mid \theta) \mid p_i] = 0$. $\mathrm{Var}(z_{in}+p_i' \mid \theta) = \mathrm{Var}(\varepsilon_{in}+p_i')$ is not a function of θ or a function of p_i.

Following similar steps for the value of being uninformed yields

$$E\left[\nu\left(W_{u,j}^{n,i}\right) \mid p\right] = \nu\left(rW_{o_j}\right)\exp\left(\frac{-\left(Z + E\left[\tilde{\theta}_{in} \mid p_i\right] + E\left[p_i'\right] - (1+r^F)p_i\right)^2}{2\left(\mathrm{Var}\left(z_{in} + p_i' \mid \theta\right) + \mathrm{Var}\left[\theta_{in} \mid p_i\right]\right)}\right) \tag{34}$$

Therefore,

$$\frac{E\left[\nu\left(W_{I,j}^{n,i}\right) \mid p\right]}{E\left[\nu\left(W_{u,j}^{n,i}\right) \mid p\right]} = e^{ac(\lambda_{in})}\sqrt{\frac{\mathrm{Var}\left(z_{in} + p_i' \mid \theta\right)}{\mathrm{Var}\left(z_{in} + p_i' \mid \theta\right) + \mathrm{Var}\left(\theta_{in} \mid p_i\right)}}$$

□

Proof of Proposition 1. Conjecture a linear price function for each aggregate state s:

$$p_i^s = \phi_{i0}^s + \phi_{in}^s\theta_{in} + \phi_{id}^s\theta_{id} + \phi_{i\varepsilon}^s\tilde{\varepsilon}_{in}^- \tag{35}$$

Then, the signals uninformed traders will use from observing the price can be drawn from $(p_i^s - \phi_{i0}^s - \phi_{i\varepsilon}^s\tilde{\varepsilon}_{in}^- - \phi_{id}^s\theta_{id})/\phi_{in}$ and $(p_i^s - \phi_{i0}^s - \phi_{i\varepsilon}^s\tilde{\varepsilon}_{in}^- - \phi_{in}^s\theta_{in})/\phi_{id}$ for θ_{in} and θ_{id}, respectively. Since the prior distributions are Gaussian and the signal is a linear function of a Gaussian random variable, the posterior distribution for z_{in} is also Gaussian with mean and variance:

$$E_s\left[z_{in} \mid p_i\right] = Z + \frac{\frac{\bar{\theta}_{in}}{\sigma_{\theta_{in}}^2} + \frac{1}{\sigma_{\theta_{id}}^2}\left(\frac{\phi_{in}^s}{\phi_{id}^s}\right)^2\left(\frac{p_i - \phi_{i0}^s - \phi_{id}^s\bar{\theta}_{id} - \phi_{i\varepsilon}^s\tilde{\varepsilon}_{in}^-}{\phi_{in}^s}\right)}{\frac{1}{\sigma_{\theta_{in}}^2} + \frac{1}{\sigma_{\theta_{id}}^2}\left(\frac{\phi_{in}^s}{\phi_{id}^s}\right)^2} + \rho\tilde{\varepsilon}_{in}^- \tag{36}$$

$$\mathrm{Var}_s\left[z_{in} \mid p_i\right] = \left(\frac{1}{\sigma_{\theta_{in}}^2} + \frac{1}{\sigma_{\theta_{id}}^2}\left(\frac{\phi_{in}^s}{\phi_{id}^s}\right)^2\right)^{-1} + \sigma_{\varepsilon_{in}}^2 \tag{37}$$

Using these, we can write down the expectation and the variance for the total payoff from holding one share of the firm i:

$$E_s\left[z_{in} + p_i' \mid p_i\right] = E_s\left[z_{in} \mid p_i\right] + \sum_{s'} q_{ss'}[\phi_{io}^{s'} + \phi_{in}^{s'}\bar{\theta}_{in} + \phi_{id}^{s'}\bar{\theta}_{id} + \phi_{i\varepsilon}^{s'}\rho\tilde{\varepsilon}_{in}^-] \tag{38}$$

$$
\begin{aligned}
\operatorname{Var}_s\left[z_{in}+p_i' \mid p_i\right] &= \operatorname{Var}_s\left(\theta_{in} \mid p_i\right)+\operatorname{Var}_s\left(\varepsilon_{in}+p_i'\right) \\
&= \left(\frac{1}{\sigma_{\theta_{in}}^2}+\frac{1}{\sigma_{\theta_{id}}^2}\left(\frac{\phi_{in}^s}{\phi_{id}^s}\right)^2\right)^{-1} \\
&\quad + \operatorname{Var}_s\left(\phi_{0i}^{s'}+\phi_{di}^{s'}\theta_{di}+\phi_{ni}^{s\prime}\theta_{ni}+\left(1+\phi_{\varepsilon i}^{s'}\rho^2\right)\varepsilon_{in}+\phi_{\varepsilon i}^{s'}\rho\tilde{\varepsilon}_{in}^{-}\right)
\end{aligned} \tag{39}
$$

and then, market-clearing is,

$$
\begin{aligned}
&(1-\gamma)\lambda_{in}^s\left[\frac{Z+\tilde{\theta}_{in}+E_s\left[p_i'\right]-(1+r^F)p_i}{a\operatorname{Var}_s\left(\varepsilon_{in}+p_i'\right)}\right]+\gamma\lambda_{id}^s\left[\frac{Z+\tilde{\theta}_{in}-\theta_{id}+E_s[p_i']-(1+r^F)p_i}{a\left(\sigma_{\varepsilon_{id}}^2+\operatorname{Var}_s\left(\varepsilon_{in}+p_i'\right)\right)}\right]+ \\
&(1-\gamma)\left(1-\lambda_{in}^s\right)\left[\frac{E_s\left[z_{in}\mid p_i\right]+E_s\left[p_i'\right]-(1+r^F)p_i}{a\left(\operatorname{Var}_s\left(\varepsilon_{in}+p_i'\right)+\operatorname{Var}_s\left(\theta_{in}\mid p_i\right)\right)}\right]+ \\
&\gamma\left(1-\lambda_{id}^s\right)\left[\frac{E_s\left[z_{in}-z_{id}\mid p_i\right]+E_s\left[p_i'\right]-(1+r^F)p_i}{a\left(\operatorname{Var}_s\left(\varepsilon_{in}+p_i'\right)+\operatorname{Var}_s\left(\theta_{in}-\theta_{id}\mid p_i\right)\right)}\right]=\overline{K_i}
\end{aligned} \tag{40}
$$

We suppress the aggregate state s in the rest of the proof to declutter the notation. First, denote

$$
\begin{aligned}
\chi_1 &= \frac{\gamma\lambda_{id}}{a\left(\sigma_{\varepsilon_{id}}^2+\operatorname{Var}\left(\varepsilon_{in}+p_i'\right)\right)} & \chi_3 &= \frac{\gamma\left(1-\lambda_{id}\right)}{a\left(\sigma_{\varepsilon_{id}}^2+\operatorname{Var}\left(\varepsilon_{in}+p_i'\right)+\operatorname{Var}\left(\theta_{in}-\theta_{id}\mid p_i\right)\right)} \\
\chi_2 &= \frac{(1-\gamma)\lambda_{in}}{a\operatorname{Var}\left(\varepsilon_{in}+p_i'\right)}, & \chi_4 &= \frac{(1-\gamma)\left(1-\lambda_{in}\right)}{a\left(\operatorname{Var}\left(\varepsilon_{in}+p_i'\right)+\operatorname{Var}\left(\theta_{in}\mid p_i\right)\right)}
\end{aligned} \tag{41}
$$

and $\chi=(\chi_1+\chi_2+\chi_3+\chi_4)$. One can rearrange the terms to get

$$
\begin{aligned}
&(\chi_1+\chi_2)\left(\theta_{in}+\rho\tilde{\varepsilon}_{in}^{-}\right)-\chi_1\theta_{id}+\chi\left(Z+\sum_{s'}\left[\phi_{i0}^{s'}+\phi_{in}^{s'}\bar{\theta}_n+\phi_{id}^{s'}\bar{\theta}_d+\phi_{i\varepsilon}^{s'}\rho\tilde{\varepsilon}_{in}^{-}\right]q_{ss'}\right) \\
&+(\chi_3+\chi_4)\left(\rho\tilde{\varepsilon}_{in}^{-}+\frac{\frac{\bar{\theta}_{in}}{\sigma_{\theta_{in}}^2}+\frac{1}{\sigma_{\theta_{id}}^2}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2\left(\frac{p_i-\phi_{i0}-\phi_{id}\bar{\theta}_{id}-\phi_{i\varepsilon}\tilde{\varepsilon}_{in}^{-}}{\phi_{in}}\right)}{\frac{1}{\sigma_{\theta_{in}}^2}+\frac{1}{\sigma_{\theta id}^2}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2}\right) \\
&-\chi_3\frac{\frac{\bar{\theta}_{id}}{\sigma_{\theta_{id}}^2}+\frac{1}{\sigma_{\theta_{in}}}\left(\frac{\phi_{id}}{\phi_{in}}\right)^2\left(\frac{p_i-\phi_{i0}-\phi_{in}\bar{\theta}_{in}-\phi_{i\varepsilon}\tilde{\varepsilon}_{in}^{-}}{\phi_{id}}\right)}{\frac{1}{\sigma_{\theta_{id}}^2}+\frac{1}{\sigma_{\theta_{in}}^2}\left(\frac{\phi_{id}}{\phi_{in}}\right)^2}-\chi(1+r^F)p_i=\bar{K}_i
\end{aligned} \tag{42}
$$

Next, we rearrange terms to leave p_i alone:

$$\underbrace{\left[(1+r^F)\chi + \chi_3 \frac{\left(\frac{\phi_{id}}{\phi_{in}}\right)^2 \frac{1}{\sigma^2_{\theta_{in}}} \operatorname{Var}\left[\theta_{id} \mid p_i\right]}{\phi_{id}} - (\chi_3+\chi_4) \frac{\left(\frac{\phi_{in}}{\phi_{id}}\right)^2 \frac{1}{\sigma_{\theta_{id}}} \operatorname{Var}\left[\theta_{in} \mid p_i\right]}{\phi_{in}}\right]}_{\tilde{\phi}} p_i =$$

$$\underbrace{(\chi_1+\chi_2)}_{\tilde{\phi}^s_{in}}\theta_{in} \underbrace{-\chi_1}_{\tilde{\phi}^s_{id}}\theta_{id}$$

$$+\left[\rho\chi\left(1+\sum_s q_{ss'}\phi^{s'}_{i\varepsilon}\right) - (\chi_3+\chi_4)\left(\frac{\operatorname{Var}\left[\theta_{in} \mid p_i\right]}{\sigma^2_{\theta id}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2 \frac{\phi_{i\varepsilon}}{\phi_{in}}\right) + \chi_3 \frac{\operatorname{Var}\left[\theta_{id} \mid p_i\right]}{\sigma^2_{\theta in}}\left(\frac{\phi_{id}}{\phi_{in}}\right)^2 \frac{\phi_{i\varepsilon}}{\phi_{id}}\right]\tilde{\varepsilon}^-_{in} +$$

$$\chi\left(Z + \sum_{s'}\left[\phi^{s'}_{i0} + \phi^{s'}_{in}\bar{\theta}_{in} + \phi^{s'}_{id}\bar{\theta}_{id}\right] q_{ss'}\right) +$$

$$+\chi_3 \operatorname{Var}\left[\theta_{id} \mid p_i\right]\left[\frac{\phi_{0i}+\phi_{ni}\bar{\theta}_{in}}{\phi_{di}}\left(\frac{\phi_{id}}{\phi_{in}}\right)^2 \frac{1}{\sigma^2_{\theta_{in}}} - \frac{\bar{\theta}_{id}}{\sigma^2_{\theta_{id}}}\right] - \bar{K}_i$$

$$-(\chi_3+\chi_4)\operatorname{Var}\left[\theta_{in} \mid p_i\right]\left[\frac{\phi^s_{0i}+\phi^s_{id}\bar{\theta}_{id}}{\phi_{in}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2 \frac{1}{\sigma^2_{\theta_{id}}} - \frac{\bar{\theta}_{in}}{\sigma^2_{\theta_{in}}}\right] \tag{43}$$

The price p_i that clears the market for given $\lambda_{id}^{,}\lambda_{in}^{\in}[0,1]$ is unique because the demand for each stock i is strictly monotonic and unbounded below and above for $p_i \in R^+$ while the supply for stock i is a finite constant.

Notice that, in (43), p_i becomes a linear function of θ_{in}, θ_{id}, and $\tilde{\varepsilon}^-_{in}$ where $\phi^s_{in} = \frac{\tilde{\phi}^s_{in}}{\tilde{\phi}}$ and $\phi^s_{id} = \frac{\tilde{\phi}^s_{id}}{\tilde{\phi}}$. Furthermore, the expression given in the proposition follows immediately.

$$\frac{|\phi^s_{in}|}{|\phi^s_{id}|} = \frac{|\chi_1+\chi_2|}{|-\chi_1|} = 1 + \frac{(1-\gamma)\lambda_{in}(\sigma^2_{\varepsilon_{id}} + Var(z_{in}+p'_{in}))}{\gamma\lambda_{id}Var(z_{in}+p'_{in})}. \tag{44}$$

□

B Implementation of the Empirical Strategy

To implement our empirical strategy to measure PI, and to take the data closer to the model, we need to take care of potential biases of using different measures and to adjust the data in ways we describe here. First, we prove that using the realizations for z_{in} and z_{id} biases the estimators of the pricing loadings, hence justifying the need to resort to proxies of their learnable counterparts to run the regressions. Second, we describe our methodology for mapping the model's timeline with the data. Third, we discuss several adjustments to the data to make it consistent with the model.

B.1 Biases of Using realization of z_{in} and z_{id} on Pricing Regressions.

Proposition 2. *Let $\rho = 0$.*[36] *An OLS regression of the price (p_i) on realized values (z_{id} and z_{in}) would give biased estimates of ϕ:*

1. $E[\hat{\phi}_0^B] = \phi_0 + \frac{\bar{\theta}_n \sigma^2_{\varepsilon n} \phi_n}{\sigma^2_{\varepsilon n} + \sigma^2_{\theta_n}} + \frac{\bar{\theta}_d \sigma^2_{\varepsilon_d} \phi_d}{\sigma^2_{\varepsilon_d} + \sigma^2_{\theta_d}}$
2. $E[\hat{\phi}_n^B] = \phi_n \left(1 - \frac{\sigma^2_{\varepsilon n}}{\sigma^2_{\varepsilon n} + \sigma^2_{\theta_n}}\right)$
3. $E[\hat{\phi}_d^B] = \phi_d \left(1 - \frac{\sigma^2_{\varepsilon_d}}{\sigma^2_{\varepsilon_d} + \sigma^2_{\theta_d}}\right)$

The bias becomes larger as the residual uncertainty after acquiring information ($\sigma^2_{\varepsilon_n}, \sigma^2_{\varepsilon_d}$) increases.

Proof. The pricing function under $\rho = 0$ becomes

$$\begin{aligned} P_i =& \Phi_o + \Phi_n \theta_{in} + \Phi_d \theta_{id} \\ =& \Phi_o + \Phi_n z_{in} + \Phi_d z_{id} - \Phi_n \varepsilon_{in} - \Phi_d \varepsilon_{id}. \end{aligned}$$

Hence, when the price is regressed on θ_{in} and θ_{id}, the error term becomes $\nu_i = -\Phi_n \varepsilon_{in} - \Phi_d \varepsilon_{id}$, which is correlated with z_{in}. Let $\tilde{Z}_i$=[1 $\quad z_{in} \quad z_{id}$] ,$\tilde{\Phi} = [\Phi_o \quad \Phi_n \quad \Phi_d]$. Then

$$\hat{\Phi}_{OLS} = \tilde{\Phi} - \Phi_n \left(\frac{1}{n} \sum \tilde{Z}_i \tilde{Z}_i'\right)^{-1} \left(\frac{1}{n} \sum \tilde{Z}_i \varepsilon_{in}\right) - \Phi_d \left(\frac{1}{n} \sum \tilde{Z}_i \tilde{Z}_i{}'\right)^{-1} \left(\frac{1}{n} \sum \tilde{Z}_i \varepsilon_{id}\right).$$

[36] The argument generalizes to $\rho > 0$, with more tedious algebra. Dávila and Parlatore (2018) discuss a similar bias in a different setting.

First, because θ_{in}, θ_{id}, and ε_{in} are independent, the second term on the right-hand side can be decomposed as:

$$\left(\frac{1}{n}\sum \tilde{Z}_i\tilde{Z}_i'\right)^{-1}\left(\frac{1}{n}\sum \tilde{Z}_i\varepsilon_{in}\right) = \left(\frac{1}{n}\sum \tilde{Z}_i Z_i'\right)^{-1}\left(\frac{1}{n}\sum[\varepsilon_{in} \quad \theta_{in}\varepsilon_{in}+\varepsilon_{in}^2 \quad \theta_{id}\varepsilon_{in}+\varepsilon_{id}\varepsilon_{in}]\right)$$

$$\xrightarrow{\text{p}} \underbrace{\begin{bmatrix} 1 & \overline{Z_n} & \overline{Z_d} \\ \overline{Z_n} & \overline{Z_n Z_n} & \overline{Z_n Z_d} \\ \overline{Z_d} & \overline{Z_n Z_d} & \overline{Z_d Z_d} \end{bmatrix}^{-1}}_{\mathbf{Z}^{-1}} \begin{bmatrix} 0 \\ \sigma_{\varepsilon_n}^2 \\ 0 \end{bmatrix},$$

where $\xrightarrow{\text{p}}$ denotes convergence in probability and $\overline{X_n}$ denotes $E[X_i]$. We can further write

$$Z^{-1} = \frac{1}{\det(z)}\begin{bmatrix} \sigma_{\varepsilon_n}^2+\sigma_{\theta_n}^2+\overline{\theta}_n^2(\sigma_{\varepsilon_d}^2+\sigma_{\theta_d}^2+\overline{\theta}_d^2)-\overline{\theta}_n^2\overline{\theta}_d^2 & -(\sigma_{\varepsilon_d}^2+\sigma_{\theta_d}^2)\overline{\theta}_n^2 & -\theta_d(\sigma_{\varepsilon_n}^2+\sigma_{\theta_n}^2) \\ -(\sigma_{\varepsilon_d}^2+\sigma_{\theta_d}^2)\overline{\theta}_n & \sigma_{\varepsilon_d}^2+\sigma_{\theta_d}^2 & 0 \\ -\theta_d(\sigma_{\varepsilon_n}^2+\sigma_{\theta_n}^2) & 0 & \sigma_{\theta_n}^2+\sigma_{\varepsilon_n}^2 \end{bmatrix}.$$

Then, we can characterize the term as

$$\left(\frac{1}{n}\sum \tilde{Z}_i\tilde{Z}_i'\right)^{-1}\left(\frac{1}{n}\sum \tilde{Z}_i\varepsilon_{in}\right) = Z^{-1}\begin{bmatrix} 0 \\ \sigma_{\varepsilon_n}^2 \\ 0 \end{bmatrix} = \frac{1}{det(Z)}\begin{bmatrix} \sigma_{\varepsilon_n}^2(\sigma_{\varepsilon_d}^2+\sigma_{\theta_d}^2)\overline{\theta}_n \\ \sigma_{\varepsilon_n}^2(\sigma_{\varepsilon_d}^2+\sigma_{\theta_d}^2) \\ 0 \end{bmatrix},$$

where

$$\begin{aligned} det(z) =& 1\left((\sigma_{\varepsilon_n}^2+\sigma_{\theta_n}^2+\overline{\theta}_n^2)(\sigma_{\varepsilon_d}^2+\sigma_{\theta_d}^2+\overline{\theta}_d^2)-\overline{\theta}_n^2\overline{\theta}_d^2\right)-\overline{\theta}_n\left(\overline{\theta_n}(\sigma_{\varepsilon_d}^2+\sigma_{\theta_d}^2+\overline{\theta}_d^2)-\overline{\theta_d\theta_n\theta_d}\right) \\ &+\overline{\theta_d}\left(\overline{\theta_n\theta_n\theta_d}-\overline{\theta}_d(\sigma_{\varepsilon_n}^2+\sigma_{\theta_n}^2+\overline{\theta}_n^2)\right) \\ =&\sigma_{\varepsilon_n}^2\sigma_{\varepsilon_d}^2+\sigma_{\varepsilon_n}^2\sigma_{\theta_d}^2+\sigma_{\varepsilon_n}^2\overline{\theta}_d^2+\sigma_{\varepsilon_d}^2\sigma_{\theta_n}^2+\sigma_{\varepsilon_d}^2\overline{\theta}_n^2+\sigma_{\theta_n}^2\sigma_{\theta_d}^2+\sigma^2\theta_d\overline{\theta}_d^2+\sigma^2{}_{\theta_d}\overline{\theta}_n^2 \\ &-\sigma_{\varepsilon_d}^2\sigma_{\varepsilon_n}^2-\sigma_{\theta_d}^2\overline{\theta}_n^2-\overline{\theta}_d^2\overline{\theta}_n^2+\overline{\theta}_n^2\overline{\theta}_d^2+\overline{\theta}_d^2\overline{\theta}_n^2-\sigma_{\varepsilon n}^2\overline{\theta}_d^2-\sigma_{\theta_n}^2\overline{\theta}_d^2-\overline{\theta}_n^2\overline{\theta}_d^2 \\ =&\sigma_{\varepsilon_n}^2\sigma_{\varepsilon_d}^2+\sigma_{\varepsilon_n}^2\sigma_{\theta_d}^2+\sigma_{\varepsilon_d}^2\sigma_{\theta_n}^2+\sigma_{\theta_n}^2\sigma_{\theta_d}^2. \end{aligned}$$

Following similar steps would yield:

$$\left(\frac{1}{n}\sum \tilde{Z}_i\tilde{Z}_i'\right)^{-1}\left(\frac{1}{n}\sum \tilde{Z}_i\varepsilon_{id}\right) = \frac{1}{det(Z)}\begin{bmatrix}\sigma^2_{\varepsilon_d}(\sigma^2_{\varepsilon_n}+\sigma^2_{\theta_n})\overline{\theta}_d \\ \\ 0 \\ \\ \sigma^2_{\varepsilon_d}(\sigma^2_{\varepsilon_n}+\sigma^2_{\theta_n})\end{bmatrix}.$$

Therefore,

$$\hat{\Phi}_{OLS} = \widetilde{\Phi} \;-\; \frac{1}{(\sigma^2_{\varepsilon_n}+\sigma^2_{\theta_n})(\sigma^2_{\varepsilon_d}+\sigma^2_{\theta_d})}\begin{bmatrix}-\sigma^2_{\varepsilon_n}(\sigma^2_{\varepsilon_d}+\sigma^2_{\theta_d})\overline{\theta}_n\Phi_n - \sigma^2_{\varepsilon_d}(\sigma^2_{\varepsilon_n}+\sigma^2_{\theta_n})\overline{\theta}_d\Phi_d \\ \\ \sigma^2_{\varepsilon_n}(\sigma^2_{\varepsilon_d}+\sigma^2_{\theta_d})\Phi_n \\ \\ \sigma^2_{\varepsilon_d}(\sigma^2_{\varepsilon_n}+\sigma^2_{\theta_n})\Phi_d\end{bmatrix}$$

$$= \begin{bmatrix}\Phi_o + \frac{\overline{\theta}_n\sigma^2_{\varepsilon_n}\Phi_n}{\sigma^2_{\varepsilon_n}+\sigma^2_{\theta_n}} + \frac{\overline{\theta}_d\sigma^2_{\varepsilon_d}\Phi_d}{\sigma^2_{\varepsilon_d}+\sigma^2_{\theta_d}} \\ \\ \Phi_n(1-\frac{\sigma^2_{\varepsilon_n}}{\sigma^2_{\varepsilon_n}+\sigma^2_{\theta_n}}) \\ \\ \Phi_d(1-\frac{\sigma^2_{\varepsilon_d}}{\sigma^2_{\varepsilon_d}+\sigma^2_{\theta_d}})\end{bmatrix}.$$

□

B.2 Data Timing

Our data sources are of varying frequencies, and the accounting years (AY) differ across firms, which introduces several timing challenges. First, while the data on stock prices is monthly, data on company fundamentals is yearly. Second, flow variables, such as earnings, refer to flows during the AY, while stock variables, such as total assets, refer to values at the end of the AY.[37] Third, the earnings-per-share (eps) forecast announcements are available daily, despite by construction, the relevant target dates are yearly.

To tackle these challenges, we consider the stock price for each stock i six months before the respective firm's AY ends. Call this date D_{it} where t refers to the associated year. For each stock-year pair it, we use the stock price at D_{it} to represent the model object p_i. Next, we map the median of the analysts' forecasts that are announced within a 15-day band around D_{it} for the current year eps to $Z + \theta_{in} + \rho\tilde{\varepsilon}^-_{in}$. The realized value for

[37]Furthermore, the accounting year generally differs across firms, and fundamentals are publicly announced a couple of months after the last day of the accounting year.

the same eps is then mapped to $Z + \theta_{in} + \rho\tilde{\varepsilon}_{in}^{-} + \varepsilon_{it}$.[38]

Figure 5 provides an example for a firm i whose previous AY ended in December 1995. Then, p_i is measured in June 1996. For θ_{in}, we use the forecasts announced around June 1996 for the earnings during the AY that ends in December 1996 (eps_i^f). The latest announcement for earnings (eps_i^a) on December 1995 represents what's publicly known when p_i is determined. For θ_{id}, we look at the realized range volatility between December 1995 and June 1996 ($Range_i$). The realized range volatility between June 1996 and December 1996 provides z_{id}.

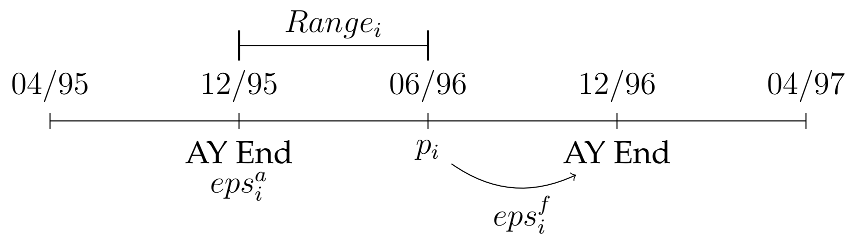


Figure 5: A Timing Example

This choice has implications for the interpretation of coefficients. Since most companies end their accounting year on December 31st, the yearly estimates generally refer to stock prices and forecasts around June of the corresponding year. Hence, the effects of a major event before June, e.g., Bernanke's 'Taper Tantrum' in May 2013, are expected to be seen in the estimates for 2013. On the other hand, the effects of a major event after June, e.g., the collapse of Lehman Brothers in September 2008, are expected to be reflected in the 2009 estimates.[39]

B.3 From Data to Model

B.3.1 Market Assignment

There are multiple ways of defining the relevant market for a given economy. While both I/B/E/S and Worldscope assign each company to a country, the assignments are inconsistent. Worldscope, before 2013, assigned companies based on "... country of major

[38] If the stock prices were sampled at the same date for all firms, the traders' information set would differ firm by firm. Instead, we sample prices at different points in time to make sure that *i)* prices are equally spaced within the respective firm's AY and *ii)* the previous year's fundamentals are already announced, i.e., the stock prices reflect traders' knowledge of $\tilde{\varepsilon}_{in}^{-}$. If no earnings forecasts are available six months prior, we use five and seven months prior, in that order.

[39] We drop Australia from our sample because the fiscal year for the majority of companies ends in July, leading to the price being evaluated around January 1st and indeterminacy regarding which year's real activity the price would be associated with.

Table 9: Discrepancy Between the Original and the Exchange-Based Country Assignments

#	IBES Assign.	Stock Exch. Assign.	#	WS Assign.	Stock Exch. Assign.
0.13	Brazil	United States	0.07	China	Hong Kong
0.12	Netherlands	United States	0.03	Netherlands	United Kingdom
0.09	China	Hong Kong	0.03	Finland	United States
0.08	Switzerland	United States	0.03	Netherlands	United States
0.06	Finland	United States	0.02	Netherlands	Poland
0.05	United Kingdom	United States	0.02	Switzerland	Germany
0.05	Hong Kong	United States	0.02	Netherlands	Germany
0.04	France	United States	0.01	China	United States
0.04	Germany	United States	0.01	Finland	United Kingdom
0.03	Netherlands	United Kingdom	0.01	Finland	Sweden

Notes: The table shows ten pairs of countries with the highest fraction of discrepancy between the original and the stock exchange-led assignments in our final sample. Each number represents the fraction of the companies with the original assignment (I/B/E/S or WS) reassigned to another country based on where they trade.

operations revenue of the company and if not determined by operations then country of headquarters", while after 2013, the assignment was based on the primary listing of the company. On the other hand, I/B/E/S assigns companies based on "country of domicile". The assigned country does not always match between the two datasets. To overcome these inconsistencies, we reassign each company to a country based on the location of the stock exchange where its shares are traded.

First, we remove all stocks that have multiple nation or industry assignments in Worldscope. Second, we remove stocks that are cross-listed across multiple exchanges.[40] Third, we link stock exchanges to countries using the bridge provided by Worldscope and aggregate the exchanges within a single country. If the stock exchange information is missing, listed as 'others,' or the stock is traded over the counter, we assign the stock to a market based on the Worldscope nation assignment.

We prefer grouping companies by stock exchange because stock prices are primarily determined by traders in that country and their liquidity needs. Hence, measuring PI requires grouping companies by who owns and trades their shares. Regardless, in most cases, the disconnect between the exchange country and the home country is minimal. Table 9 provides the fraction of companies that are reassigned based on their stock exchange and the country assigned to them by I/B/E/S or Worldscope.

[40] I/B/E/S and Worldscope sometimes use different identifiers for the same company's stock on different exchanges. For example, we've noticed an instance where "SUEZ" and "SUEZ LYONNAISE DES EAUX" refer to the same company but trade on different markets and have different I/B/E/S tickers ("SZE" and "@LYE"). While Worldscope retains data for both, I/B/E/S only selects and collects the forecast for "@LYE." Unfortunately, it is not possible to systematically deal with these instances.

B.3.2 Sample Restrictions

First, to guarantee an unambiguous match between the relevant monthly stock prices and the yearly fundamentals for each firm, we remove observations for which *i)* firms are in the finance/insurance sectors or ever cross-listed in multiple stock exchanges, *ii)* the listed accounting year-end dates are inconsistent (more than 12 months ahead) with the date of the stock price, or *iii)* the financial statements are announced earlier than the end of the reported accounting year or after more than six months. Second, to exclude firms that promise short-run losses with the possibility of abnormally high earnings in the long run, we remove observations for which the company's earnings forecast indicates losses exceeding 10% of its total asset value.[41] Third, to run the Fama-French analysis to homogenize firms as much as possible, we need monthly stock prices available six months before and after, and we require the associated market to have more than 30 stocks that constitute a balanced panel with at least 12 months of stock price data available in the past 24 months. Finally, we winsorize the adjusted earnings forecasts, earnings, and stock prices at the 5% level to address stock anomalies and potential data inaccuracies. We restrict attention to countries with 10 or more years of PI estimates for the panel data analyses.

B.3.3 Data Adjustments

We make two adjustments before estimating the pricing functions. First, in the model, the stock-level shocks ($\theta_{in}, \theta_{id}, \varepsilon_{in}, \varepsilon_{id}$) are assumed to be independently distributed across firms. While providing tractability, this assumption rules out any correlation across stocks beyond the one driven by the aggregate shock. Additionally, to ensure Φ does not vary across stocks, we assume the expected earnings ($\bar{\theta}_{in}$) and installed capital $\bar{K}_i$ do not vary across firms within a market. To accommodate departures from these assumptions in the data, we perform a factor analysis to residualize stock prices from common factors, past earnings, and total assets.

The factor analysis involves running the following regression for each stock i in market m (a country-year pair) at date t,

$$R_{it} = \alpha_i + \beta_{1i} MR_{mt} + \beta_{2i} SMB_{mt} + \beta_{3i} HML_{mt} + \epsilon_{it} \tag{45}$$

using monthly observations from $t - 23$ to t where $R_{it} = (p_{it} - p_{it-1})/p_{it-1}$. We construct the three Fama-French factors for each market-date pair using a balanced panel of stock prices over the past 24 months. The market return (MR) is constructed from the month-

[41] These observations are predominantly pharmaceutical companies that run consistent losses for several years. The correlation between earnings and stock price forecasts is negative for these firms, while it is close to 1 for the rest of the sample.

to-month change in aggregate market cap. The small-minus-big (SMB) is the difference in the aggregate returns of the top and bottom 30% stocks in terms of market cap. The high-minus-low (HML) is the difference in the aggregate returns of the top and bottom 30% stocks in terms of book-to-market ratio. We then use the estimates for β_{1i}, β_{2i}, and β_{3i}, which represent the factor loadings (the 'betas') for firm i, to residualize the prices by regressing them on second-order polynomials of the estimated betas, latest eps announcement (representing $\bar{\theta}_{in}$), and total assets (representing $\bar{K}_i$).

Second, in the model, we assume each stock provides ownership of one unit of installed capital in the firm. In the data, however, the meaning of a single share, hence the stock price and earnings-per-share (eps), differ across firms. To make these variables comparable across firms and consistent with our model, we transform the factor-adjusted stock prices, eps, and eps forecasts to per-unit-of-asset values. We do this by multiplying the original value by the number of outstanding shares of the firm during a year and dividing it by the value of the Total Assets reported at the end of that year.

Table 10 shows summary statistics for the series we used in this Section to estimate pricing functions for the US in 2015.

Table 10: Summary Statistics for the US in 2015, Pricing Function

variable	mean	sd	min	median	max
ALPHA	0.00	0.03	-0.09	0.00	0.73
BMarketReturn	1.07	0.99	-18.14	1.00	6.70
BSMB	0.10	0.36	-1.68	0.08	5.37
BHML	-0.07	1.55	-46.56	-0.18	7.18
p	1.52	1.26	0.30	1.12	6.21
$\bar{K}_i$ ($1000)	11,674	34,216	20	2,115	552,257
$\bar{\theta}_n$	0.05	0.06	-0.57	0.05	0.15

Notes: The p and $\bar{\theta}_n$ figures are per unit of asset values constructed by multiplying original figures by the number of outstanding shares and dividing them by the value of their total assets. Total assets ($\bar{K}_i$) are given in thousands of US dollars.

B.3.4 Exchange Rate Adjustments

The previous discussion refers to adjusting data in a given market. To allow for cross-sectional and time-series comparability, we need to standardize the exchange rates for each market. I/B/E/S and Worldscope provide the currency used in each entry, while I/B/E/S further provides daily exchange rates throughout its sample coverage. First, we determine the dominant currency for each market using the most commonly used currency across its stocks in Worldscope. Second, we convert all values in a market (prices, actuals, forecasts, etc.) to the dominant currency using the exchange rate for the closest available date. Third, for countries that have adopted the Euro as their exchange rate, we convert all numbers to the country's original currency using the exchange rate at the time of adoption. We validate our steps by comparing a random sample of our adjusted series with other sources that already present the data in the destination exchange rate.

B.3.5 Mergers and Acquisition

Mergers and acquisitions (M&A) and stock splits create challenges for time-series compatibility of data by changing what the company consists of from one year to the other. Both I/B/E/S and Worldscope describe how they handle M&As and stock splits in their respective guidebooks. We went through the raw data for ten well-known cases,[42] and all ten were consistent with the explanations:

1. The acquiring company retains its I/B/E/S ticker and entity name, continuing to report stock data under these identifiers. The data recording for the acquired company is discontinued.
2. In the case of a merger, the newly formed entity continues using the I/B/E/S ticker of one of the original companies and adopts a new entity name. The I/B/E/S ticker of the other company ceases to record data.
3. For stock splits, both I/B/E/S and Worldscope databases adjust their records to reflect the new stock size, ensuring consistency across reported values.

[42]These are Pfizer's acquisition of Warner-Lamber in 2000, Vodafone's acquisition of Mannesmann in 2000, Exxon and Mobil merger in 1999, Glaxo Wellcome and SmithKline Beecham merger in 2000, Gaz de France and Suez merger in 2008, Dow Chemical and DuPont merger in 2009 and the following division into spinoffs in 2019, Heinz and Kraft merger in 2015, United Technologies and Raytheon merger in 2019, Apple's stock split in 2020, and Tesla's stock split in 2022. See Footnote 40 for a distinct issue we noticed during this exercise.

C Microfoundations for Liquidity Discount

In this section, we microfound the additive liquidity discount paid by day traders, z_{id}, as a fee that is proportional to the previously observed stock price volatility (our empirical measure of θ_{id}). We augment the baseline model in Section 2 by introducing new agents and restructuring the timing assumptions to accommodate our empirical approach. We focus the description of the new environment on how this extension adds to the baseline model.

C.1 Environment

Dealers We introduce a new class of agents: dealers. Similar to traders, dealers have deep pockets and CARA preferences $u^b(W) = -e^{-a_d W}$. Unlike traders, they are born in the afternoon and live for two periods.

Market Structure A dealer who was born in the afternoon of period $t-1$ can intermediate twice: i) buy stocks in the evening of $t-1$ and sell them to new traders in the morning of t, and ii) buy stocks in the afternoon of t and sell them to new traders in the morning of $t+1$. Similarly, day traders in period t would like to access cash twice during the day: in the afternoon and in the evening of t. Consequently, each day trader arranges to meet two different cohorts of dealers: the cohort born in $t-1$ (which we refer to as the cohort AF in t) and the cohort born in t (which we refer to as the cohort EV in t). We assume each day trader divides their sales equally between the afternoon and the evening for simplicity. Figure 6 demonstrates the dealer's lifespan across two periods. Prices are determined competitively in these meetings.

Information The decentralized markets open after z_{in} is realized. Therefore, the only remaining uncertainty concerns p'_i, and dealers have diffuse priors for it. Afternoon dealer j receives a signal $F_{ij}^{AF} \sim N(p'_i, \sigma^2_{F_i^{AF}})$, leading to posterior distribution $N(F_{ij}^{AF}, \sigma^2_{F_i^{AF}})$ for p'_i. Evening dealer j receives a signal $F_{ij}^{EV} \sim N(p'_i, \sigma^2_{F_i^{EV}})$, leading to posterior distribution $N(F_{ij}^{EV}, \sigma^2_{F_i^{EV}})$ for p'_i. Both $\sigma^2_{F_i^{AF}}$ and $\sigma^2_{F_i^{EV}}$ are random variables. Therefore, day traders not only care about the distribution of p'_i, but also about the distribution of the dealers' signals. In the morning of period t (when day traders buy stocks in the centralized market)$\sigma^2_{F_i^{EV}}$ is unlearnable; it is only revealed at the decentralized markets in the evening. In contrast, $\sigma^2_{F_i^{AF}}$ can be learned from observing, at a cost, decentralized markets of the evening of $t-1$. Traders' priors on signal variances are $\sigma^2_{F_i^{AF}} \sim N(\theta_{AF}, \sigma^2_{AF})$ and $\sigma^2_{F_i^{EV}} \sim N(\theta_{EV}, \sigma^2_{EV})$, respectively.

Discussion of the Structure The additional trading rounds help in two ways. First, they help distinguish the *centralized* market in the benchmark setting of the main text, which operates each morning, from the *decentralized* markets where day traders unload their stocks early. Second, they help rationalize our empirical strategy in Section 3, using past price volatility as a signal of the liquidity discount a day trader will pay when selling stocks.

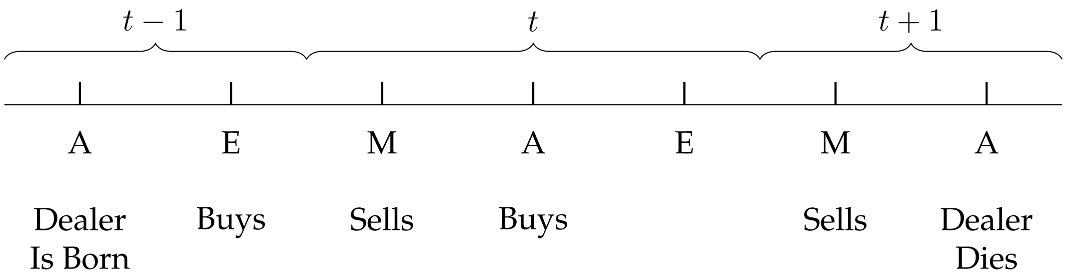


Figure 6: Timing for the Dealers

C.2 Dealers' Pricing

Now we solve for the discount that dealers charge to day traders when facing uncertainty about p_i'. We start with the price charged by an evening dealer j, p_{ij}^{EV}, which satisfies the market-clearing condition:

$$\frac{E_j^{EV}[p_i'] - p_{ij}^{EV}}{a_d Var_j^{EV}[p_i']} = 1. \tag{46}$$

Given the signal structure for the evening dealers, $p_{ij}^{EV} = F_{ij}^{EV} - a_d \sigma^2_{F_i^{EV}}$, where $F_{ij}^{EV} = p_i' + \sigma_{F_i^{EV}} s_{ij}$ (with $s_{ij} \sim iidN(0,1)$) is the idiosyncratic signal of an evening dealer j. Note that the realized variance of prices determined by a continuum of evening dealers will equal to $\sigma^2_{F_i^{EV}}$. Similarly, the price charged by an afternoon dealer j, p_{ij}^{AF} satisfies the market-clearing condition:

$$\frac{E_j^{AF}[p_i'] - p_{ij}^{AF}}{a_d Var_j^{AF}[p_i']} = 1. \tag{47}$$

Lemma 2. *An informed day trader's ex-ante distribution of offload revenue can be represented as*

$$N\left(E[p_i'] - \frac{a_d\left(\theta_{EV} + \sigma^2_{F_i^{AF}}\right)}{2}, V[p_i'] + \frac{\theta_{EV} + a_d^2\sigma^2_{EV} + \sigma^2_{F_i^{AF}}}{2}\right),$$

while an uninformed day trader's ex-ante distribution of offload revenue can be represented as

$$N\left(E[p_i'] - \frac{a_d\left(\theta_{EV} + \theta_{AF}\right)}{2}, V[p_i'] + \frac{\theta_{EV} + \theta_{AF} + a_d^2\left(\sigma^2_{EV} + \sigma^2_{AF}\right)}{2}\right),$$

where $E[p_i']$ and $V[p_i']$ are from the traders' prior on the next period's centralized market price.

Proof. The price of an evening meeting is $p_{ij}^{EV} = p_i' + \sigma_{F_i^{EV}} s_{ij} - a_d \sigma^2_{F_i^{EV}}$. Its expectation is

$$E[p_{ij}^{EV}] = E[p_i'] - a_d \theta_{EV}$$

and variance

$$V[p_{ij}^{EV}] = V[p_i'] + V(\sigma_{F_i^{EV}} s_{ij}) + V(a_d \sigma^2_{F_i^{EV}}) - 2Cov(\sigma_{F_i^{EV}} s_{ij}, a_d \sigma^2_{F_i^{EV}}). \tag{48}$$

We can write

$$\begin{aligned} V[\sigma_{F_i^{EV}} s_{ij}] =& V(\sigma_{F_i^{EV}})V(s_{ij}) + V(\sigma_{F_i^{EV}})E^2(s_{ij}) + E^2(\sigma_{F_i^{EV}})V(s_{ij}) \\ =& V(\sigma_{F_i^{EV}}) + E(\sigma^2_{F_i^{EV}}) - V(\sigma_{F_i^{EV}}) = \theta_{EV}, \end{aligned} \tag{49}$$

and

$$Cov(\sigma_{F_i^{EV}} s_{ij}, a_d \sigma^2_{F_i^{EV}}) = a_d \left(E(\sigma^3_{F_i^{EV}} s_{ij}) - E(\sigma_{F_i^{EV}} s_{ij}) E(\sigma^2_{F_i^{EV}}) \right) = 0. \tag{50}$$

Thus, the ex-ante distribution of the evening offload price for the day traders is $p_{ij}^{EV} \sim N(E[p_i'] - a_d \theta_{EV}, V[p_i'] + \theta_{EV} + a_d^2 \sigma^2_{EV})$. Similarly, the price of an afternoon meeting is $p_{ij}^{AF} = p_i' + \sigma_{F_i^{AF}} s_{ij} - a_d \sigma^2_{F_i^{AF}}$, and we can construct the ex-ante distribution of the afternoon offload prices following the same steps, which becomes $p_{ij}^{AF} \sim N(E[p_i'] - a_d \theta_{AF}, V[p_i'] + \theta_{AF} + a_d^2 \sigma^2_{AF})$. If the day trader becomes informed about the signal variance of the afternoon traders, then $\sigma^2_{AF} = 0$ and $\theta_{AF} = \sigma_{F_i^{AF}}$, so the ex-ante distribution for the informed day trader is $p_{ij}^{AF} \sim N(E[p_i'] - a_d \sigma^2_{F_i^{AF}}, V[p_i'] + \sigma^2_{F_i^{AF}})$.

Since the traders offload their holdings to afternoon and evening dealers equally, the distribution of their payoff would be as given in the lemma. □

Proposition 3. *There is a mapping between the model with microfounded liquidity discount (new model) and the model presented in Section 2 (baseline model) with the following adjustments:*

1. ϵ_{in} *does not show persistence, i.e.,* $\rho = 0$*, and*
2. *the liquidity premium has a component that is trader specific, i.e., it equals* $\theta_{id} + \epsilon_{id} + \hat{\epsilon}_{ijd}$*, where* $\hat{\epsilon}_{ijd} \sim N(0, \sigma^2_{\hat{\epsilon}_{id}})$.

In this mapping,

1. $\theta_{id} = \frac{a_d}{2} \left(\sigma^2_{F_i^{AF}} + \theta_{EV} \right)$, $\quad \bar{\theta}_{id} = \frac{a_d}{2} \left(\theta_{AF} + \theta_{EV} \right)$, $\quad \sigma^2_{\theta_{id}} = \frac{1}{4} a_d^2 \sigma^2_{AF}$,

2. $\epsilon_{id} = \frac{1}{2}a_d\left(\sigma^2_{F_i^{EV}} - \theta_{EV}\right)$, $\sigma^2_{\epsilon_{id}} = \frac{1}{4}a_d^2\sigma^2_{EV}$,

3. $\hat{\epsilon}_{ijd} = \frac{1}{2}\left(2p_i' - F_{ij}^{AF} - F_{ij}^{EV}\right)$, $\sigma^2_{\hat{\epsilon}_{id}} = \frac{1}{4}\left(\sigma^2_{F_i^{AF}} + \theta_{EV}\right)$.

Proof. Let $R_{ij}^{AF} = F_{ij}^{AF} - p_i'$ and $R_{ij}^{EV} = F_{ij}^{EV} - p_i'$.

In the baseline model, the informed day trader's expected payoff is $\theta_{in} + E[p_i'] - \theta_{id}$. In the new model, it is $\theta_{in} + E[p_i'] - \frac{a_d}{2}\left(\sigma^2_{F_i^{AF}} + \theta_{EV}\right)$. Thus, these are the same when

$$\theta_{id} = \frac{a_d}{2}\left(\sigma^2_{F_i^{AF}} + \theta_{EV}\right).$$

In the baseline model, the day trader's realized payoff is $z_{in} + p_i' - z_{id}$, where $z_{id} = \theta_{id} + \epsilon_{id} + \hat{\epsilon}_{ijd}$. In the new model, it is $z_{in} + \frac{1}{2}\left(F_{ij}^{AF} + F_{ij}^{EV} - a_d\sigma^2_{F_i^{AF}} - a_d\sigma^2_{F_i^{EV}}\right)$. Then, these are the same when

$$p_i' - \theta_{id} - \epsilon_{id} - \hat{\epsilon}_{ijd} = \frac{1}{2}\left(F_{ij}^{AF} + F_{ij}^{EV} - a_d\sigma^2_{F_i^{AF}} - a_d\sigma^2_{F_i^{EV}}\right),$$

which can be decomposed as

$$p_i' - \hat{\epsilon}_{ijd} = \frac{1}{2}\left(F_{ij}^{AF} + F_{ij}^{EV}\right) \implies \hat{\epsilon}_{ijd} = \frac{1}{2}\left(2p_i' - F_{ij}^{AF} - F_{ij}^{EV}\right),$$

and

$$\theta_{id} + \epsilon_{id} = \frac{1}{2}\left(a_d\sigma^2_{F_i^{AF}} + a_d\sigma^2_{F_i^{EV}}\right) \implies \epsilon_{id} = \frac{a_d}{2}\left(\sigma^2_{F_i^{EV}} - \theta_{EV}\right).$$

In the baseline model, the informed day trader's payoff variance is $\sigma^2_{\epsilon_{id}} + \sigma^2_{\hat{\epsilon}_{id}} + V(p_i' + \sigma^2_{\epsilon_{in}})$. In the new model it is $\frac{1}{4}\left(\sigma^2_{F_i^{AF}} + \theta_{EV} + a_d^2\sigma^2_{EV}\right) + V(p_i' + \sigma^2_{\epsilon_{in}})$. Also, note that $E[\epsilon_{id}] = E[\hat{\epsilon}_{ijd}] = 0$, consistent with the baseline model. Then, it would follow that

$$\sigma^2_{\epsilon_{id}} = \frac{1}{4}a_d^2\sigma^2_{EV}, \qquad \sigma^2_{\hat{\epsilon}_{id}} = \frac{1}{4}\left(\sigma^2_{F_i^{AF}} + \theta_{EV}\right).$$

Lastly, in the baseline model, $\theta_{id} \sim N(\bar{\theta}_{id}, \sigma^2_{\theta_{id}})$, thus,

$$\bar{\theta}_{id} = \frac{a_d}{2}\left(\theta_{AF} + \theta_{EV}\right), \quad \sigma^2_{\theta_{id}} = \frac{1}{4}a_d^2\sigma^2_{AF}.$$

□

Proposition 3 shows that the baseline model in Section 2 can be microfounded through dealers who facilitate day traders in obtaining funds but charge them for the risk they face until they can unload their purchases. In addition to demonstrating how the additive liquidity discount arises naturally in our CARA-normal setting, the microfoundation also provides a foundation for our use of past price volatility as a signal for future liquidity discount. Note that the realized variance of evening prices would equal $\sigma^2_{F_i^{EV}}$. Thus, in this microfoundation, the overlapping structure allows the use of the price variance at time $t-1$ as the signal θ_{id} at time t.

D Robustness Checks

D.1 Incentive Provision through Prices

In this section, we introduce an incentive problem in the spirit of Dow and Gorton (1997) and Banerjee et al. (2026). In particular, there is a manager in each firm whose effort, z_{in}, influences firm productivity. The manager's effort is observable but not contractible; thus, compensation must be a function of the market price. The stock price, therefore, serves an additional purpose: providing appropriate incentives for managers.

Incentive provisions can take many forms, most of which would disrupt the linear pricing function, which is critical for our methodology (see Section 2.4.1). Here, we show that the role of prices in incentive provision, a la Banerjee et al. (2026), would be orthogonal to their role in conveying information when modeled in a way to preserve linearity.

Suppose each firm in our model has a manager who can exert effort to influence $z_{in}(e_i)$. Let this relation be **linear** of the form, $z_{in} = Z + \theta_{in} + \tilde{\varepsilon}_{in}^{-} + e_i$. Following Banerjee et al. (2026), assume that this effort is (1) observable but not verifiable, and (2) the firm rewards it with a contract linear in the stock price: $A + Bp_i$. We maintain the assumptions in the baseline model where the parameters $\bar{K}_i, \bar{\theta}_{in}, \bar{\theta}_{id}, \sigma^2_{\varepsilon_{in}}, \sigma^2_{\varepsilon_{id}}, \sigma^2_{\theta in}$, and $\sigma^2_{\theta id}$ are firm invariant. Then, the contract will be the same across firms.

A manager with mean-variance preferences, information set $\mathcal{I}_m$ (which may or may not include θ_{in} and θ_{id}), and effort cost function $c(e_i)$ will solve:

$$max_{e_i} E[A + Bp_i(e_i)|\mathcal{I}_m] - \Xi Var[A + Bp_i(e_i)|\mathcal{I}_m] - c(e_i).$$

We next guess and verify that the optimal effort e_i^* is not a function of θ_{in}, θ_{id}, and $\tilde{\varepsilon}_{in}^{-}$. In this case, we can write prices as a linear function of efforts, i.e., $p_i(e) = \tilde{p}_i + De$ for some D coefficient that is a function of the parameters. Under this guess, the manager's problem simplifies to:

$$max_e BDe - c(e).$$

and the solution to this problem is indeed independent of θ_{in}, θ_{id}, and $\tilde{\varepsilon}_{in}^{-}$, as guessed.

This solution implies that when efforts affect productivity linearly, and contracts are linear in stock prices, the optimal level of effort is such that $c'(e_i^*) = BD$. The left-hand side is the marginal cost of effort. The right-hand side is the marginal benefit of effort, which is the marginal impact of effort on prices, D, multiplied by the marginal impact of prices on compensation, B.

Why is this result relevant? Because, if e_i^* is not a function of θ_{in}, θ_{id}, and $\tilde{\varepsilon}_{in}^{-}$, then e_i^* behaves isomorphically to Z in the pricing equation and would be absorbed in the ϕ_0 term in our empirical estimation. Hence, neither the measurement of PI nor the quantitative analysis is affected by the presence of incentive provision. The specifics of the optimal effort choice and the contract would not matter. To reiterate, this non-relevance result is based on very specific assumptions: that efforts affect productivity linearly and that incentive contracts are linear in prices. Relaxing either of these assumptions would lead to nonlinear pricing functions.

D.2 PI Estimates under Alternative Model Assumptions

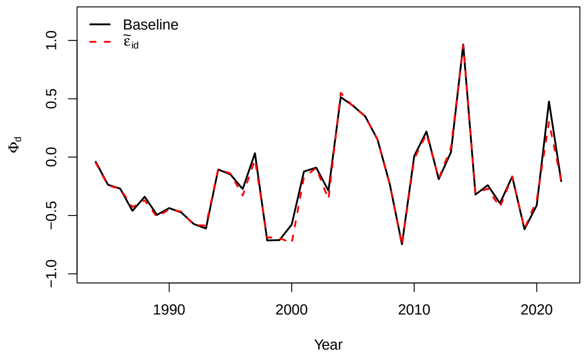
In this section, we evaluate the robustness of the estimated PI series to three deviations from our modeling assumptions. First, we allow for persistence in ε_{id}. Second, we allow for cross-firm heterogeneity in θ_{id}. Third, we allow some market participants to have private information about ε_{in}.

Persistence in Volatility: In the baseline model, we allow persistence in the unlearnable part of the fundamentals via $\tilde{\varepsilon}_n^{-}$. This helps us maintain earnings persistence while keeping pricing linear. It is possible that a similar persistence exists in the volatilities. Then, this persistent part would be a pricing factor and, if correlated with θ_{id}, could lead to omitted-variable bias. In this exercise, we ask how the PI series would change as a result of allowing for persistence through $\tilde{\varepsilon}_d^{-}$. We calculate it the same way we do for $\tilde{\varepsilon}_n^{-}$, using the persistence in the forecast errors. Figure 7 shows the PI series when we account for volatility persistence. The correction leads to very small changes in the estimates of ϕ_d and PI.

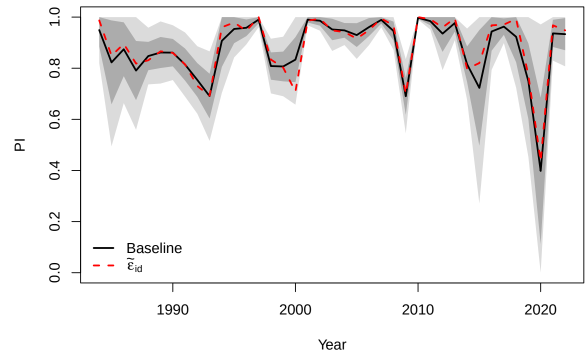
Heterogeneity in $\bar{\theta}_{id}$: Assumption 1 states : "the parameters $\bar{K}_i, \bar{\theta}_{in}, \bar{\theta}_{id}, \sigma^2_{\varepsilon_{in}}, \sigma^2_{\varepsilon_{id}}, \sigma^2_{\theta in}$, and $\sigma^2_{\theta id}$ are firm invariant." While we explicitly residualize the price for empirical counterparts for $\bar{K}_i$ and $\bar{\theta}_{in}$, there is no empirical counterpart for the objects $\bar{\theta}_{id}, \sigma^2_{\varepsilon_{in}}, \sigma^2_{\varepsilon_{id}}, \sigma^2_{\theta in}$, and $\sigma^2_{\theta id}$. In particular, heterogeneity in $\bar{\theta}_{id}$ would yield heterogeneous ϕ_{i0}, which would be captured by the residual and lead to omitted-variable bias.[43] This bias (when small enough) would pull the ϕ_d estimate away from 0, exaggerating the effect of θ_{id} on the price. Next, we perform two exercises to investigate the magnitude of such bias.

First, we do a theoretical bias correction under simplifying assumptions. Under the

[43]Firm-level heterogeneity in these parameters can potentially affect the entire pricing function. The effect of parameter heterogeneity on ϕ_d and ϕ_n is more difficult to interpret, since the estimated slopes would just be a weighted average of the true slopes. Having said that, a numerical sensitivity analysis we run with our stock trading model around the calibrated parameters indicates small changes in equilibrium for ϕ_d and ϕ_n.



(a) U.S. Φ_d



(b) U.S. PI

Figure 7: Persistent volatility and baseline estimates for the U.S.
Notes: The alternative series are constructed by introducing persistence in volatility through $\tilde{\varepsilon}_{id}$ in the same way we introduce $\tilde{\varepsilon}_{in}$.

remaining assumptions of our model, the bias will equal

$$\text{Bias}(\hat{\phi}_d) = \phi_{\bar{\theta}_{id}} \frac{\text{Cov}(\bar{\theta}_{id}, \theta_{id})}{\text{Var}(\theta_{id})}.$$

where

$$\text{Cov}(\bar{\theta}_{id}, \theta_{id}) = \text{Var}(\bar{\theta}_{id}).$$

A numerical exercise with our calibrated parameters suggests a $\phi_{\bar{\theta}_{id}}$ value around -23.5.[44] We do a back-of-the-envelope calculation where we assume $\bar{\theta}_{id}$ has a Gaussian distribution with a standard deviation equaling $0.1 * \mu_{\theta_d}$.[45] Given the rest of the estimated parameters, we can construct a bias-corrected PI measure for the U.S.

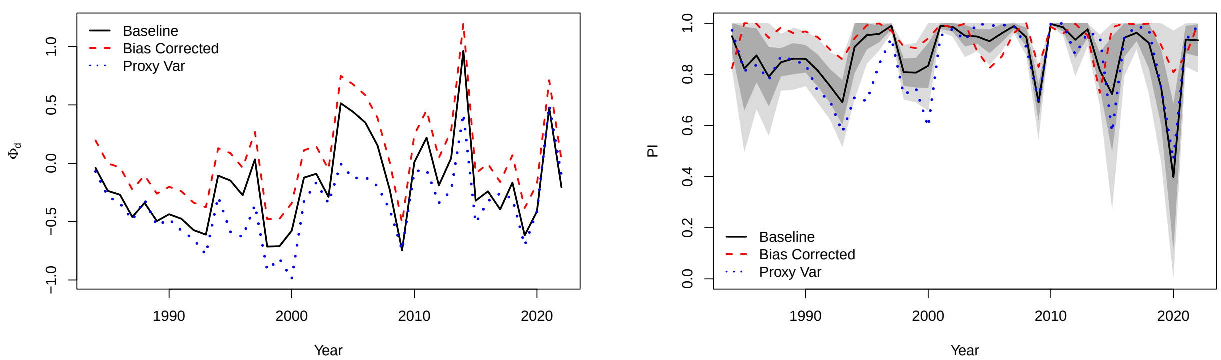
Figure 8 shows the PI series with this back-of-the-envelope bias-correction in the dashed line. The correction leads to generally smaller fluctuations in PI as expected. There is no significant change in the important events, and the bias-corrected estimates are generally within the confidence bands of the baseline PI estimates.

[44] This corresponds to a comparative static where we vary the value of $\bar{\theta}_d$, recompute the equilibrium, and observe the equilibrium value of ϕ_0. The relationship is exactly linear, providing a slope measure.

[45] The choice of the standard deviation has to be arbitrary without some external knowledge of the distribution of this unobserved component. As the supposed standard deviation increases, bias-correction becomes more aggressive, and a larger fraction of ϕ_d estimates becomes positive, inconsistent with our theory and with the asset pricing literature's findings. Therefore, we believe our choice is a reasonable benchmark.

Second, we use a proxy for each stock's persistent volatility component: volatility lags from earlier periods. In particular, we residualize prices with the realized volatility in the six months prior to the period where we measure θ_d.[46]

The resulting PI series is shown in the dotted line of Figure 8. It is broadly within the confidence bands of the original series. This series shows larger fluctuations in PI than the theoretical bias correction exercise. This might indicate mean-reversion in stock volatility and a possible underestimation of the PI's cyclicality.



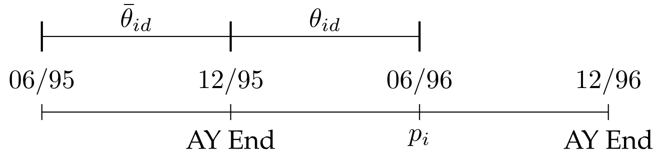
(a) U.S. Φ_d (b) U.S. PI

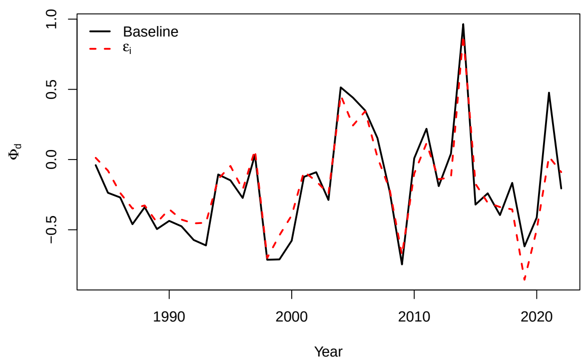
Figure 8: Bias-corrected and baseline estimates for the U.S.

Notes: The dotted lines are constructed by residualizing for the realized volatilities 6 to 12 months before the price is measured, as a proxy for heterogeneous $\bar{\theta}_{id}$. The dashed lines are constructed by a theoretical bias correction exercise for heterogeneous $\bar{\theta}_{id}$, where we assume $\bar{\theta}_{id}$ has a Gaussian distribution with a standard deviation equaling $0.1 * \mu_{\theta_d}$ and construct $\phi_{\bar{\theta}_{id}}$ numerically using our calibrated model.

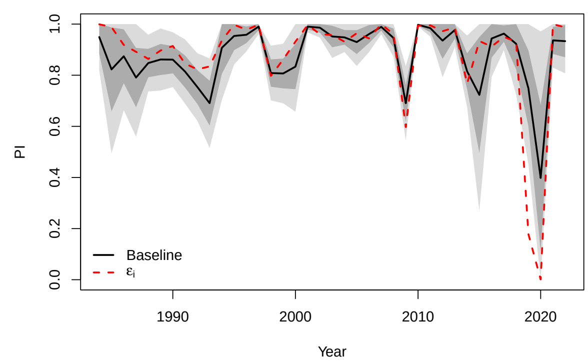
Private Information about Unlearnable Component: It is possible that real decision makers have private information that regular traders do not have, and reveal it partly if participating in stock markets. Then, ε_{in} would appear as a pricing factor, and if correlated with θ_{in}, lead to an omitted variable bias. We can include ε_{in} directly in our pricing regression and see whether the estimated PI series changes significantly. The resulting PI series is shown in the dotted line of Figure 9. It is again broadly within the confidence bands of the original series, indicating a limited role of such insider trading in the pricing regressions.

[46] In the specification we present here, we use the period 12 to 6 months prior to the price measurement. Using earlier lags or averaging the lagged values yields very similar results. To keep the samples identical, we replace missing values for lagged variables with country-year averages.





(a) U.S. Φ_d



(b) U.S. PI

Figure 9: Insider-trading and baseline estimates for the U.S.
Notes: The dashed lines are constructed by explicitly controlling for analyst forecast errors ε_{in} in pricing regressions.

D.3 Monthly Variation in Forecasts

In the baseline analysis, we focus on earnings forecasts issued six months prior to the fiscal year-end. This ensures that six months have passed since the end of the prior fiscal year; hence, most firms have already made their associated earnings announcements. Therefore, the prices at that point already carry the information from the previous year's earnings.

If forecasts change substantially month to month, our results would be sensitive to the timing assumptions we make; we show that the month-to-month variation in earnings forecasts is relatively small. We focus on forecasts from companies in the US and Japan and set the monthly forecast for a stock as the median forecast 15 days of the beginning of the month. We restrict attention to firms whose fiscal years end in the usual months -January in the US and March in Japan- and to forecasts made 4 to 8 months before the fiscal year-end. We only include firms whose forecasts are announced in all months.

Figure 10 shows the monthly variation in forecasts for the median stock. In the US, the monthly standard deviation of the median stock is almost always below 6% of the mean, whereas it's mostly below 10% in Japan.

Figure 11 plots the normalized forecast error, i.e., the absolute forecast error divided by the realized value, for the median stock. In both the US and Japan, forecast error declines as the forecast date approaches the fiscal year's end, with few exceptions. However, the improvement for the median stock mostly stays small.

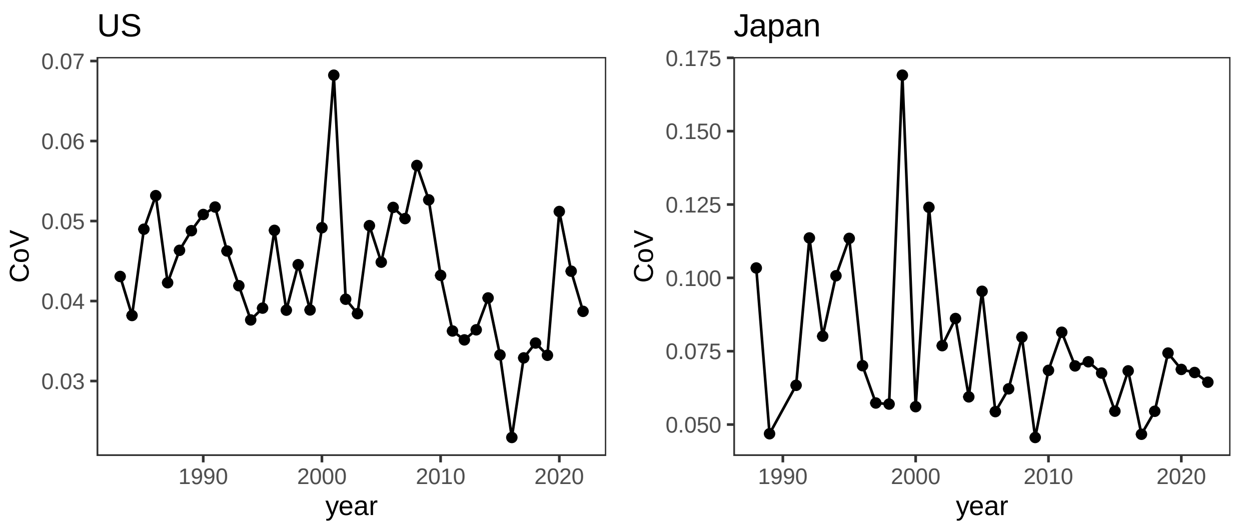


Figure 10: Month-to-Month Coefficient of Variation of Earnings-per-Share Forecasts for the Median Firm

D.4 Range Volatility Measures

In this section, we provide summary statistics on the range volatility measure we use. Figure 12 depicts the median firm's normalized range volatility measures for Japan and the US. We restrict attention to years where there are at least 40 stocks with monthly price data that allows the estimation of range volatility. Both measures are relatively stable, with high volatility episodes in 2001, 2008, and 2020.

The experience of the median firm is representative of the majority of the firms in both stock markets. Table 11 provides the cross-sectional summary statistics for Japan and the US in 2018. The interquartile range is similar to the time series variation for the median firm.

Table 11: The Summary Statistics for the Normalized Range Volatilities in 2018

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
US	0.05	0.12	0.17	0.21	0.24	1
Japan	0.03	0.13	0.18	0.22	0.25	1

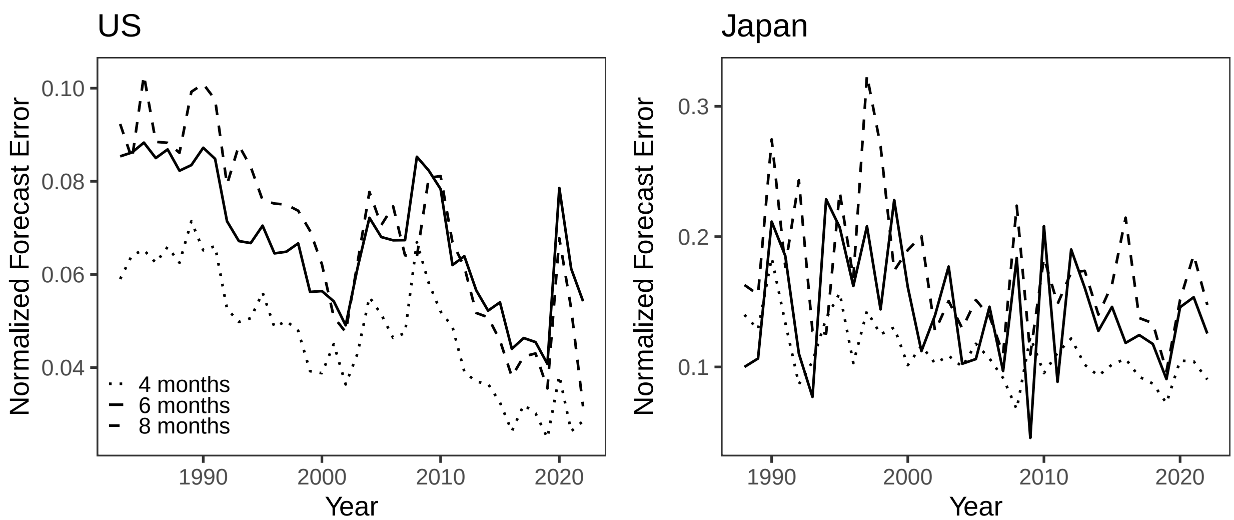


Figure 11: Forecast Error for Earnings-per-Share Forecasts for the Median Firm
Notes: The dotted, solid, and dashed lines represent the normalized errors for forecasts made 8, 6, and 4 months before the fiscal year-end date for the median stock, respectively.

E The Relationship Between PI and Misallocation Losses

Misallocation follows from the mutual fund having to use $E[\theta_{in}|p_i]$ instead of θ_{in} in allocating capital. The expression for the output loss due to misallocation is complicated, but it is monotonic in the Bayesian risk associated with using $E[\theta_{in}|p_i]$ as an estimator for θ_{in}.

Here we derive the analytical relation between PI and misallocation losses under a quadratic loss function, where the frequentist risk would equal the summation of a squared bias ($E[E[\theta_{in}|p_i] - \theta_{in}]^2$) and a variance ($\mathrm{Var}[E[\theta_{in}|p_i] - \theta_{in}]$) term. In Proposition 4, we derive (i) the ex-ante and interim (conditional on p_i) risk measures for the mutual fund's estimator and (ii) the ex-post estimation error.

Proposition 4. *Under Assumption 1 and the squared loss function, the mutual fund's estimator is unbiased, and the ex-ante and interim (conditional on p_i) risk involved with the inference equals*

$$R(\theta_{in}, E[\theta_{in}|p_i]) = \frac{1}{\frac{1}{\sigma^2_{\theta_n}} + \frac{1}{\sigma^2_{\theta_d}}\left(\frac{\phi_n}{\phi_d}\right)^2}.$$

The estimation error for firm i is given by

$$E[\theta_{in}|p_i] - \theta_{in} = \frac{\frac{(\bar{\theta}_n - \theta_{in})}{\sigma^2_{\theta_n}} + \frac{\phi_n}{\phi_d}\frac{(\theta_{id} - \bar{\theta}_d)}{\sigma^2_{\theta_d}}}{\frac{1}{\sigma^2_{\theta_n}} + \frac{1}{\sigma^2_{\theta_d}}\left(\frac{\phi_n}{\phi_d}\right)^2}$$

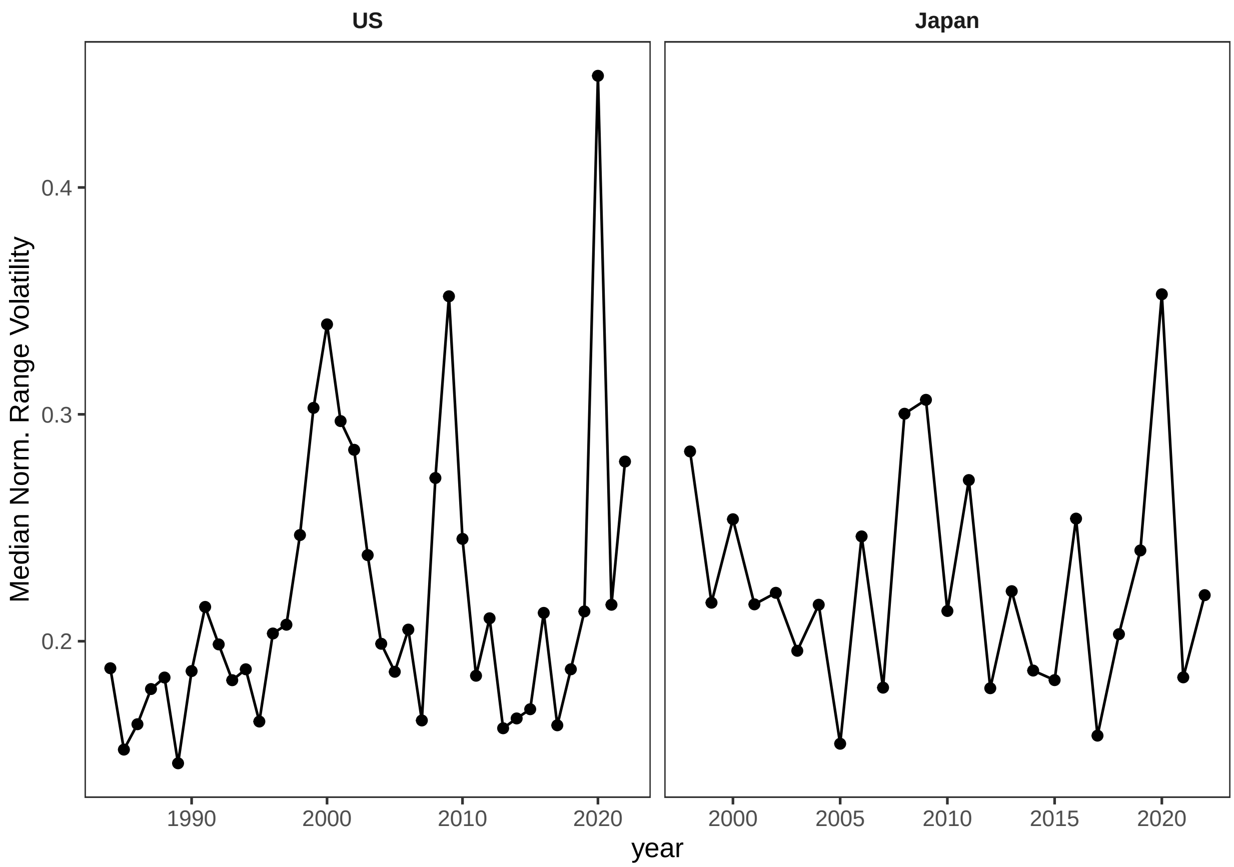


Figure 12: Normalized Range Volatilities for the Median Firm

Proof. The ex-ante bias associated with the hedge fund's estimator can be written as:

$$
\begin{aligned}
|E\left[E[\theta_{in} \mid p_i] - \theta_{in}\right]| &= \left| \frac{\frac{\bar{\theta}_{in}}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2 \left(\frac{p_i - \phi_{i0} - \phi_{id}\bar{\theta}_{id} - \phi_{i\varepsilon}\overline{\tilde{\varepsilon}_{in}}}{\phi_{in}}\right)}{\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2} - \bar{\theta}_{in} \right| \\
&= \left| \frac{\frac{\bar{\theta}_{in}}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2 \left(\frac{\phi_{i0} + \phi_{id}\bar{\theta}_{id} + \phi_{in}\bar{\theta}_{in} + \phi_{i\varepsilon}\overline{\tilde{\varepsilon}_{in}} - \phi_{i0} - \phi_{id}\bar{\theta}_{id} - \phi_{i\varepsilon}\overline{\tilde{\varepsilon}_{in}}}{\phi_{in}}\right)}{\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2} - \bar{\theta}_{in} \right| \\
&= \left| \frac{\frac{\bar{\theta}_{in}}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2 \bar{\theta}_{in}}{\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2} - \bar{\theta}_{in} \right| = 0.
\end{aligned}
$$

The variance associated with the estimator can be written as:

$$\begin{aligned}\text{Var}\left[E[\theta_{in} \mid p_i] - \theta_{in}\right] &= \text{Var}\left[\frac{\frac{\bar{\theta}_{in}}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2\left(\frac{\phi_{id}(\theta_{id}-\bar{\theta}_{id})+\phi_{in}\theta_{in}}{\phi_{in}}\right)}{\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2} - \theta_{in}\right] \\ &= \frac{\text{Var}\left[\frac{\bar{\theta}_{in}}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2\left(\frac{\phi_{id}\theta_{id}}{\phi_{in}}\right) - \frac{\theta_{in}}{\sigma^2_{\theta_{in}}}\right]}{\left(\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2\right)^2} \\ &= \frac{\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2}{\left(\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2\right)^2} = \frac{1}{\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2}.\end{aligned}$$

Lastly, under the mean-squared error loss function,

$$R\left(\theta_{in}, E[\theta_{in}|p_i]\right) = \left|E\left[E[\theta_{in} \mid p_i] - \theta_{in}\right]\right|^2 + \text{Var}\left[E[\theta_{in} \mid p_i] - \theta_{in}\right].$$

Hence

$$R\left(\theta_{in}, E[\theta_{in}|p_i]\right) = 0 + \frac{1}{\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2}. \tag{51}$$

□

As shown in Proposition 4, the frequentist risk is independent of θ_{in}, hence equal to the Bayesian risk.[47] Corollary 4 summarizes what Proposition 4 implies about the characteristics of firms that get under and over-invested.

Corollary 4. *Under Assumption 1 and the squared loss function,*

1. *capital is under-allocated to productive (high θ_{in}) firms and over-allocated to unproductive firms,*
2. *the likelihood of allocating capital to an inefficient firm increases as the signal about its stock's liquidity is more encouraging than expected, and*
3. *the likelihood of not allocating capital to an efficient firm increases as the signal about its stock's liquidity is more discouraging than expected.*

[47]The Bayesian risk is defined as $\int R\left(\theta_{in}, E[\theta_{in}|p_i]\right) dF(\theta_{in})$.

In other words, stocks may be priced higher due to higher long-term value or lower fluctuations in short-term resale value. Thus, compared to the benchmark, firms with lower (higher) than expected θ_{id} shocks are allocated more (less) capital. This prediction is consistent with the evidence provided by Amihud and Levi (2023), that an exogenous decline in a firm's stock liquidity lowers the firm's investment.

F Additional Figures and Tables

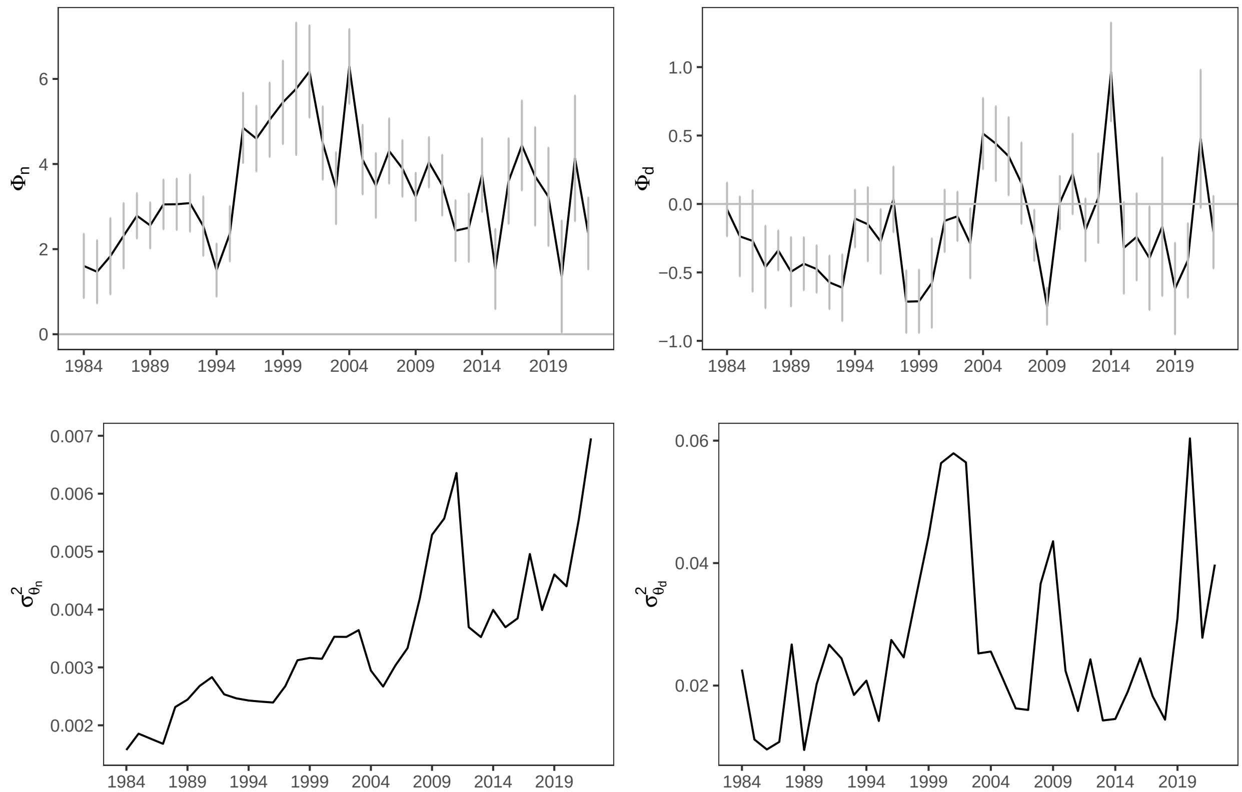


Figure 13: Estimated Price Informativeness Components for the US

Table 12: Summary Statistics for Random Variables

(a) US Estimates

var	mean	sd	min	median	max
θ_n	0.06	0.06	-0.23	0.06	0.99
θ_d	0.21	0.14	0.05	0.17	1.00
ε_n	-0.01	0.04	-0.82	0.00	0.12
ε_d	0.02	0.10	-0.65	0.03	0.84
$\tilde{\varepsilon}$	-0.01	0.05	-0.90	0.00	0.27

(b) Japan Estimates

var	mean	sd	min	median	max
θ_n	0.05	0.04	-0.03	0.04	0.17
θ_d	0.22	0.16	0.03	0.18	1.00
ε_n	0.00	0.02	-0.16	0.00	0.06
ε_d	0.04	0.12	-0.59	0.03	0.51
$\tilde{\varepsilon}$	0.00	0.02	-0.13	0.00	0.05

(c) UK Estimates

var	mean	sd	min	median	max
θ_n	0.08	0.06	-0.22	0.07	0.31
θ_d	0.20	0.12	0.04	0.17	0.91
ε_n	0.00	0.04	-0.33	0.00	0.28
ε_d	-0.01	0.08	-0.51	0.00	0.34
$\tilde{\varepsilon}$	-0.01	0.04	-0.33	0.00	0.25

Notes: The figures are per unit of asset values constructed by multiplying original figures with the number of outstanding shares and dividing them by the value of their total assets.

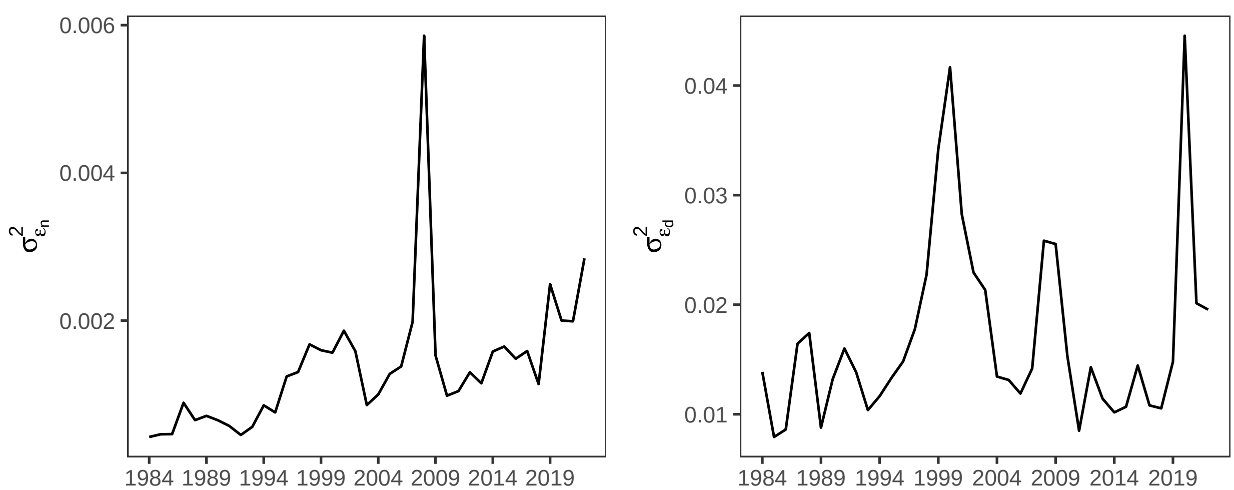


Figure 14: Forecast Error Variance Estimates in the US for a Balanced Panel

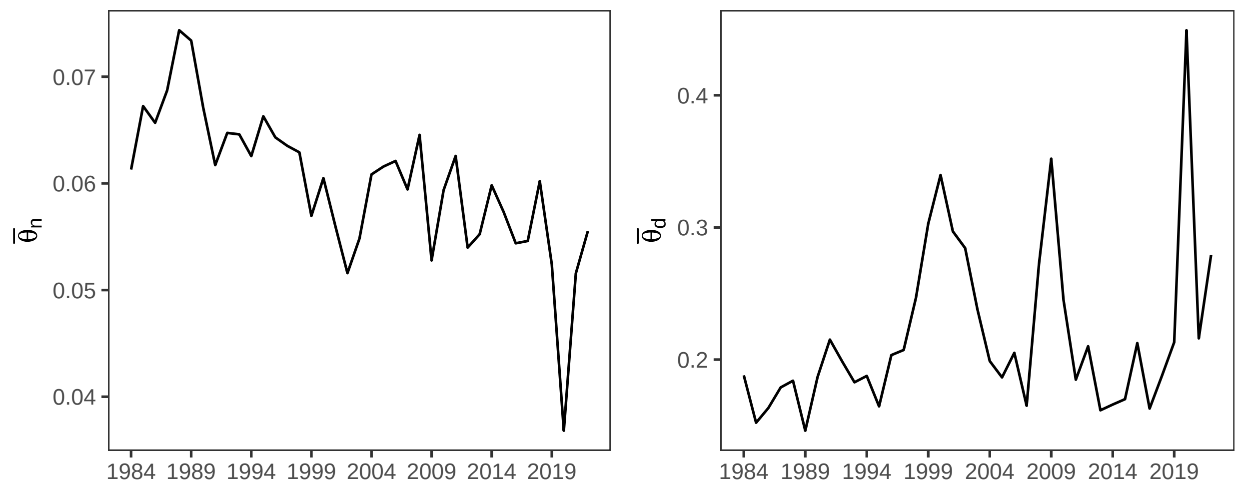


Figure 15: Median Earnings and Volatility Signals in the US for a Balanced Panel

Table 13: List of Countries and the Data Coverage

CountryName	IBESCode	YearRange	CountryName	IBESCode	YearRange
Germany	ED	2000 - 2022	Japan	FJ	1998 - 2022
France	EF	2000 - 2022	South Korea	FK	1994 - 2022
Italy	EI	2004 - 2021	Malaysia	FM	1997 - 2022
Switzerland	ES	2001 - 2022	Thailand	FT	2004 - 2022
United Kingdom	EX	1992 - 2022	Brazil	LB	2009 - 2022
Taiwan	FA	1999 - 2022	Canada	NC	1991 - 2022
China	FC	2006 - 2022	Sweden	SS	1999 - 2022
Hong Kong	FH	2004 - 2022	United States	US	1984 - 2022

Table 14: Summary Statistics for Pricing Regressions

Country	Avg ϕ_n	Avg ϕ_d	Avg PI	Avg R^2	Year Range
Brazil	2.898	-0.483	0.764	0.567	'09–'22
Canada	2.417	-0.150	0.720	0.345	'91–'22
China	4.672	-0.540	0.797	0.570	'06–'22
France	3.639	-0.185	0.839	0.550	'00–'22
Germany	3.831	-0.125	0.816	0.504	'00–'22
Hong Kong	2.336	-0.399	0.726	0.600	'04–'22
Italy	4.230	-0.019	0.843	0.652	'04–'21
Japan	4.626	-0.134	0.883	0.542	'98–'22
Malaysia	2.700	-0.328	0.827	0.703	'97–'22
South Korea	2.419	-0.202	0.835	0.520	'94–'22
Sweden	4.286	-0.345	0.841	0.578	'99–'22
Switzerland	4.111	0.174	0.861	0.622	'01–'22
Taiwan	2.866	0.059	0.947	0.668	'99–'22
Thailand	2.801	0.010	0.842	0.597	'04–'22
United Kingdom	2.260	-0.448	0.689	0.548	'92–'22
United States	3.433	-0.187	0.893	0.448	'84–'22

Notes: The first three columns present time-averages of ϕ_n and ϕ_d estimates, and R^2 estimates (adjusted for the initial price) from pricing regression in Equation 14. The fourth column is the time-average of PI measures, and the last column is the year range used for each country.

Table 15: Economic Conditions in the Panel of Countries

Statistic	N	Mean	St. Dev.	Min	Max
Bank Capital to Assets	180	6.865	1.954	4.109	10.565
Bank Loan Spreads	185	4.039	6.645	-0.032	39.216
Non-performing Loans	185	2.471	2.509	-0.090	16.911
Banking Panic	244	0.041	0.199	0	1
Banking Equity Crisis	244	0.037	0.189	0	1
PI	344	0.818	0.232	0.012	1.000
Avg Earnings	344	0.052	0.016	0.016	0.098
GDP Growth Rate	344	0.026	0.031	-0.102	0.120
Banking Stock Performance	319	0.103	0.049	0.015	0.294

Notes: The average earnings denote the weighted average of the normalized earnings. The liquidity crisis indicators, Banking Panic, and Banking Equity Crisis are from Baron et al. (2021). The continuous liquidity measures, Bank Capital to Asset, Bank Loan Spreads, and Non-performing Loans are from the World Bank. The authors estimate the PI measure.

Table 16: Stock Price - Input Allocation Relation

	CAPEX	Asset Change	Working Capital	Employees	Median Bond YTM	Median Bond Rtg
	(1)	(2)	(3)	(4)	(5)	(6)
Price	0.00^{***}	0.02^{***}	0.06^{***}	0.10^{***}	-0.20^{***}	-0.30^{***}
	(0.00)	(0.00)	(0.00)	(0.03)	(0.04)	(0.11)
Earnings(t-1)	0.02^{***}	0.18^{***}	0.08^{***}	5.41^{***}	-8.80^{***}	-30.04^{***}
	(0.00)	(0.01)	(0.02)	(0.47)	(0.68)	(1.91)
Range	'84-'22	'85-'22	'84-'22	'84-'22	'02-'22	'02-'22
Country&Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,458	101,130	115,970	88,322	9,654	8,626

Notes: First four columns have all countries, the last two only have US data. See Figure 16 for details on the variables. Notes: *p<0.1; **p<0.05; ***p<0.01

Table 17: Stock Price - Input Allocation Relation, Firm Fixed Effects

	CAPEX	Asset Change	Working Capital	Employees	Median Bond YTM	Median Bond Rtg
	(1)	(2)	(3)	(4)	(5)	(6)
Price	0.01^{***}	0.03^{***}	0.02^{***}	0.06^{***}	-0.06^{**}	-0.20^{***}
	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.06)
Earnings(t-1)	0.06^{***}	0.18^{***}	0.15^{***}	-0.03	-3.19^{***}	-12.46^{***}
	(0.00)	(0.02)	(0.01)	(0.24)	(0.38)	(1.04)
Range	'84-'22	'85-'22	'84-'22	'84-'22	'02-'22	'02-'22
Country&Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,458	101,130	115,970	88,322	9,654	8,626

Notes: The first four columns have all countries, the last two only have US data. See Figure 16 for details on the variables. Notes: *p<0.1; **p<0.05; ***p<0.01

Table 18: Price Informativeness and Economic Conditions, Alternative Measure

	PI					
	Banking Stock Perf.	Bank Capital to Assets	Bank Loan Spreads (-)	Non-performing Loans (-)	Banking Panic (-)	Banking Equity Crisis (-)
	(1)	(2)	(3)	(4)	(5)	(6)
Agg. Earnings	0.66	1.95	-0.32	2.22^{*}	-0.63	-0.50
	(1.39)	(1.31)	(2.32)	(1.32)	(1.93)	(1.87)
Liq. Measure	0.38	0.08^{**}	0.02^{***}	0.03^{***}	0.13^{*}	0.01
	(0.52)	(0.04)	(0.01)	(0.00)	(0.07)	(0.07)
Range	1984-2022	2005-2022	1984-2022	2005-2022	1984-2016	1984-2016
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	319	180	185	185	244	244

Notes: In each regression, the dependent variable is PI. Column labels refer to the liquidity measure used in each regression. The standard errors are clustered at the country level. *p<0.1; **p<0.05; ***p<0.01

Table 19: Price Informativeness and Economic Conditions, Weighted Least Squares

	PI					
	Banking Stock Perf.	Bank Capital to Assets	Bank Loan Spreads (-)	Non-performing Loans (-)	Banking Panic (-)	Banking Equity Crisis (-)
	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth	-2.52^{***}	-3.53^{***}	-2.65^{**}	-4.31^{***}	-2.16^{***}	-2.14^{***}
	(0.70)	(1.07)	(1.23)	(1.11)	(0.76)	(0.76)
Liq. Measure	1.55^{***}	0.21^{***}	-0.04^{**}	0.07^{***}	0.05	0.05
	(0.44)	(0.04)	(0.02)	(0.02)	(0.04)	(0.04)
Range	1984-2022	2005-2022	1984-2022	2005-2022	1984-2016	1984-2016
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	319	180	185	185	244	244

Notes: In each regression, the dependent variable is PI. Column labels refer to the liquidity measure used in each regression. Each country-year observation is weighted with the number of stocks used to estimate the PI measure. *p<0.1; **p<0.05; ***p<0.01

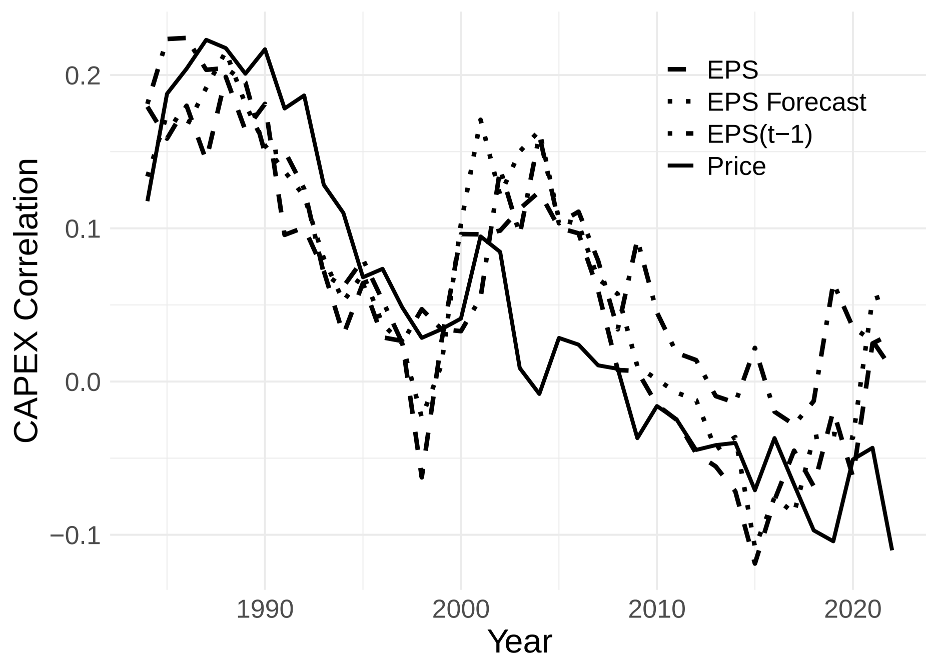


Figure 16: CAPEX vs Price and Earnings in the U.S.
Notes: All variables are normalized by total assets. EPS(t-1) refers to the previous announcement of earnings, while EPS refers to the announcement to come.

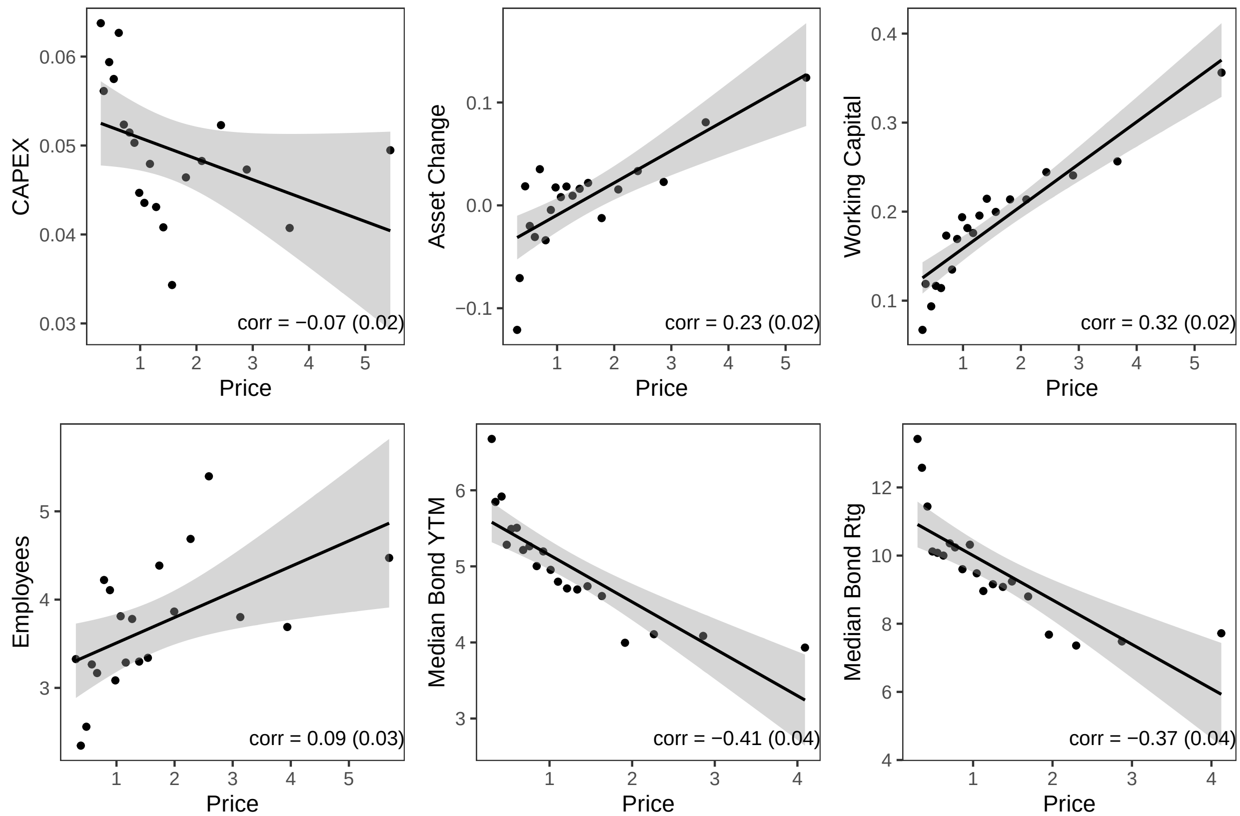


Figure 17: Binscatter Plot of Price Correlations with Measures of Input Allocation, U.S. 2015

Notes: The bands are for a 95% significance level. CAPEX, Asset Change, and Working Capital are normalized by total assets. Employees refer to the number of employees per 1M$ of total assets for scaling. A lower bond rating indicates a better-rated bond. We use monthly bond returns from WRDS, constructed from FINRA's TRACE (Trade Reporting and Compliance Engine) datasets. Link between bonds and issuers is done using each bond's CUSIP. We restrict attention to senior-level bonds with at least 6 months to maturity. Using the maturity date, coupons, and the price, we construct a yield-to-maturity for each bond. Lastly, for each firm-month, we calculate the median yield-to-maturity across all the bonds the firm had outstanding at that time. Similar results using the mean, minimum, or maximum yield-to-maturity

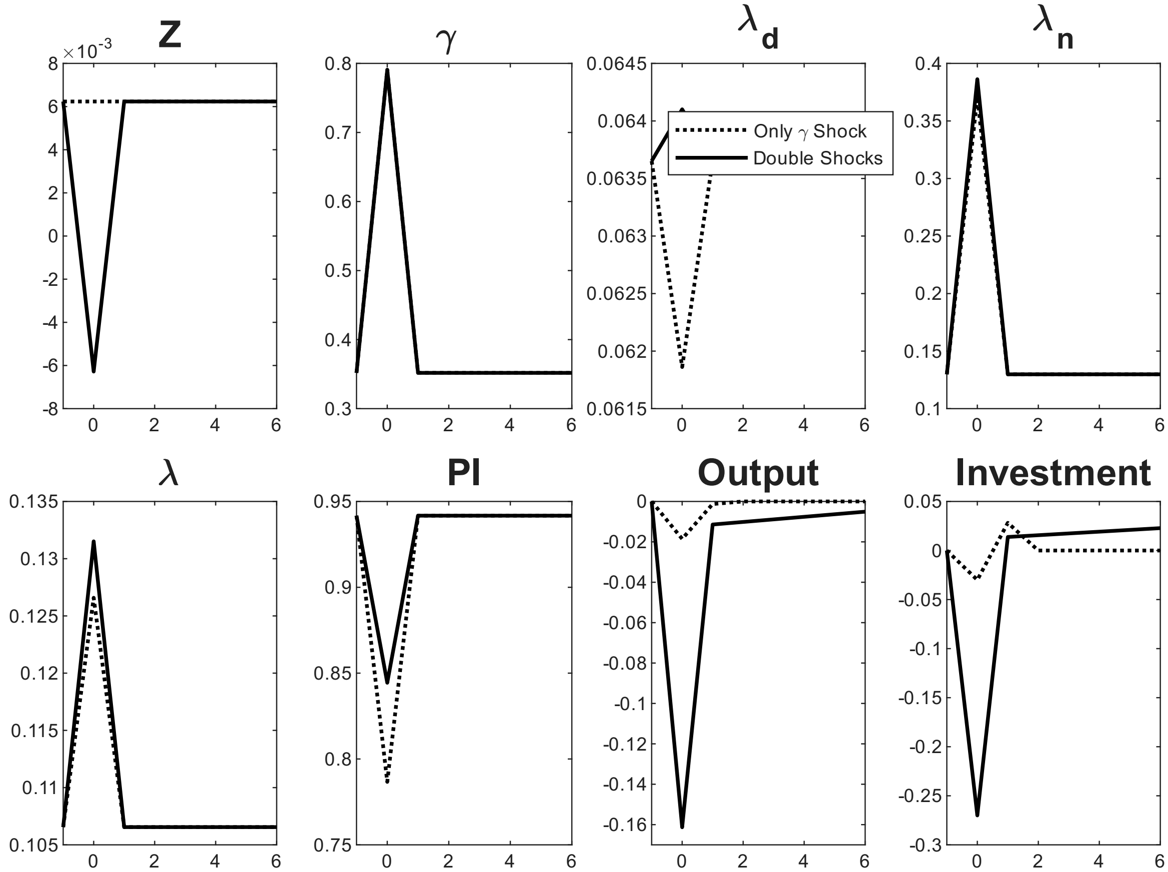


Figure 18: Additional Impulse Response Functions
Notes: The first two panels provide the shocks that hit the economy under the benchmark and the counterfactual recession scenarios. λ denotes the aggregate fraction of traders that acquire information. Output and investment values represent the percentage changes from the pre-shock values.