Business, Liquidity, and Information Cycles

Gorkem Bostanci* Guillermo Ordoñez†

August 12, 2025

Abstract

Stock markets play a dual role: they provide information about firms' fundamentals, which improves resource allocations, and they provide liquidity to traders. 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 effect of this mechanism, we devise a strategy to integrate our trading module into a dynamic general equilibrium model with heterogeneous firms. We calibrate the model to the US and show that in recessions, prices become more informative and allocation improves, mitigating output losses by 4.4%, but only if banks function normally. Otherwise, traders rely more on stock markets to obtain liquidity, prices become less informative, and allocation deteriorates, magnifying output losses by 22%.

Acknowledgments: We thank Robert Barro and three anonymous referees for excellent comments and suggestions. We also Isaac Baley, Markus Brunnermeier, Joel David, Eduardo Davila, Jason DeBacker, Itay Goldstein, Alexander Guembel, Christian Hellwig, Priit Jeenas, Patrick Kehoe, Ben Lester, Victoria Liu, Alessandro Peri, Lukas Schmid, Laura Veldkamp, Venky Venkateswaran, Jaume Ventura, Liyan Yang, and seminar participants at ASU, CEMFI, Columbia, CREi, CUHK, Guelph, HEC Paris, HKU, HKUST, Leeds School, McMaster, Padova, Penn, Princeton, SFU, SaMMF, Toronto, Toulouse, UBC, UC3M, UCSB, UC Boulder, U of Victoria, Western and various conferences for useful discussions. Jan Rosa and Harvey Chan provided excellent research assistance. The usual waiver of responsibility applies.

*University of British Columbia, Email: gorkem.bostanci@ubc.ca
†University of Pennsylvania and NBER, Email: ordonez@econ.upenn.edu

1 Introduction

Stock markets play two critical roles in market economies: allocating resources and providing liquidity. The former comes from the remarkable ability of markets to aggregate information about firms' prospects that is dispersed among traders and to make it public. 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. How much traders rely on stock markets to obtain liquidity depends on the functioning 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 and information acquisition where both the information and the noise about firms' fundamentals contained in asset prices are partly determined by how much agents use stocks to access liquidity. 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 insight of Grossman and Stiglitz (1980): rational traders are willing to acquire information about firms at a cost because the participation of noise traders prevents prices from perfectly revealing information that others acquire. To accommodate the two main roles of stock markets, we instead allow for two types of rational traders -day and night- inter-

ested in different asset properties -liquidity and fundamentals, respectively. This structure dispenses with assuming noise traders and creates *endogenous noise* in prices: a high price may indicate that the stock has a stable price and can be 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 is given by the relative weights of information on asset's payoffs and liquidity, 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 do this by providing a link between financial and real markets where the linear pricing function is preserved in a non-linear production economy, such that the model remains tractable. Stocks are claims to firms' earnings, which depend on firms' idiosyncratic productivities (i.e., firms' fundamentals). If those productivities were known, investors would allocate capital across firms efficiently. In our model, those productivities are ex-ante unknown, and allocations are based on the investors' best guesses based on stock prices, which are noisy given the participation of day traders. When funding markets malfunction, traders rely more on stocks to access liquidity, price informativeness declines, and the misallocation of resources across firms worsens.

Our model delivers a linear relationship between stock prices, firms' earnings, and stocks' liquidity, which is 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 having a high stock price (relative to other firms) is a strong sign that traders have positive information about its profitability. Our empirical contribution consists of measuring the PI in a given country each year. We implement this structural estimation with panel data from 17 countries, ranging from 1984 to 2022, and show that PI exhibits cyclicality, but more importantly, it declines in periods of insufficient funding liquidity, such as the Great Recession and COVID-19 pandemic episodes. We structurally decompose the fluctuations in PI into the fluctuations of its four components, and show that these periods are mostly explained by a change in trading activity, and not by a change in information quality.

Finally, in our quantitative contribution, we measure the relevance of stock price infor-

mativeness on the allocation of resources, total investment, and other macro aggregates. We calibrate the parameters of the full model to the United States, assuming the economy is subject to two, possibly correlated, aggregate shocks: one on aggregate productivity and one on 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 jointly discipline the cost of acquiring information and the dynamics of market liquidity needs. The calibrated model successfully replicates the cyclical properties of the estimated PI measure without explicitly targeting them. Despite assuming in the model that decision makers only learn about firms' fundamentals from stock prices, realistically, there are other sources of information that investors use to allocate resources across firms. We add them in this quantitative analysis and discipline them using empirical price-investment correlation across firms and time series correlation of price informativeness and investment dispersion.

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, price informativeness and resource allocation improve, and output losses are mitigated 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 indicates a sizable real effect of banking problems through a novel channel: weakening the information and allocative role of stock markets.

We also explore quantitatively how the economy would fare when facing a recession with funding liquidity distress under alternative information structures. If information were exogenous, funding liquidity distress would reduce stock price informativeness more drastically, leading to worse allocations and investment drops, with output declining 43% more than our benchmark with endogenous information. If the cost of information *about firms' fundamentals* were half as large, price informativeness would decline less, leading to output declines that are about 5% smaller. If, instead, the cost of information *about a stock's liquidity* were half as large, price informativeness would decline more, leading to output declines that are about 2% larger. These results suggest that regulations facilitating information about firms' profitability make the economy more resilient. Those facilitating information about stock markets' operations do the opposite.

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]

We contribute more generally to the seemingly conflicting results obtained by the literature that analyzes input allocation across firms in 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 can account for Foster et al. (2016)'s finding that labor allocation worsens during the Great Recession, despite improving during previous post-80s US recessions. Further, by quantitatively assessing the role of liquidity distress on misallocation, we provide a complementary channel to how financial markets affect business cycles: when banks are in distress, the informational and allocative role of stock markets weakens. 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 as Stein (1987) and Vives (2014), endogenizes the information/noise ratio by assuming two dimensions of information condensed at a single price. Both use heterogeneity in traders' characteristics (the former on market access and the latter on private valuations)

[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.

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 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, with a focus on distinguishing between "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," Dávila and Parlatore (2018) use time-series regressions to measure revelatory price informativeness *for each stock in average*, which requires them to make assumptions on how parameters change over time to keep the cross-sectional variation flexible. We also estimate revelatory price informativeness, but 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 instead estimate forecasting price efficiency and focus on its long-run trends, not its cyclical properties. Consistent with our results, they claim their measure also captures revelatory price efficiency because of the observed correlations with decisions and real variables.

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 on real variables through their impact on price informativeness. Section 6 concludes. All proofs are contained in Appendix A.

[3]See also Rahi (2021) and Banerjee et al. (2021) for theoretical exercises that expand on Vives (2014). Related work by Manzano and Vives (2011), Ganguli and Yang (2009) and Breon-Drish (2015) explores equilibrium uniqueness in these contexts when there is learning both from prices and from private signals.

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 long-term profitability and the stock's short-term liquidity, which are valued differently by different types of traders. Since a single price contains information about two elements, the trading activity of one type of trader masks the information from the other type. Since the real sector decides whether to invest in a given firm using its stock price as a signal of the firm's long-term profitability, the degree of input misallocation in the economy depends on different trading needs and information production in stock markets. To keep the notation simple, we suppress time subscripts unless necessary.

2.1 Environment

Preferences Time is indexed by $t = 0, 1, 2, ...$ 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 $a > 0$.

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 obtained from a production function on capital and a perfectly elastic output price normalized to one. The second term, a quadratic adjustment cost, introduces curvature to the production function.

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

rents capital to firms making a take-it-or-leave-it, price-discriminating, offer $\{K_i, r_i(z_{in})\}$ 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.[4] 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 total return r of the mutual fund is fully distributed to households. Traders can invest in *foreign bonds* supplied at exogenous return r^F and firms' shares, i.e., *stocks*. Each share gives ownership of 1 unit of installed capital at the associated firm, making the outstanding share amount of firm i equal to $\bar{K}_i$. All traders are born endowed with $\tilde{b}$ foreign bonds.

This market structure guarantees that the firm 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 only depends on z_{in} and not the capital K_i allocated to the firm. As in Subrahmanyam and Titman (1999), this set of assumptions is critical to have linear pricing in equilibrium.

Funding Liquidity and Market Liquidity Traders born at the beginning of the period. They can buy stocks at birth (from previous traders about to die) and sell stocks at the end of the period (to newborns). We assume, however, they 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*).

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 firm-specific. We call these traders relying on market liquidity, 'day traders'. In contrast, the 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 comes from distress in banks and funding markets. 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 an asset 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

[4]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.

for the risk involved in buying the stock, holding it, and selling it later at a different price.

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

The profitability of the firm has three components: the 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.[5] The liquidity discount of the stock (z_{id}) consists of two parts: a random term that can be learned (θ_{id}) and a random term that cannot be learned (ε_{id}). The first component is drawn from $\mathcal{N}(\bar{\theta}_{id}, \sigma^2_{\theta_{id}})$ and the second from a prior distribution $\mathcal{N}(0, \sigma^2_{\varepsilon_{id}})$.[6]

To summarize the distributions of the profitability and liquidity of a firm,

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

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.

The fraction of $l \in \{d, n\}$ traders who choose to be informed about stock i is denoted with λ_{il}. Being informed implies for night traders paying $c(\lambda_{in})$ and for day traders paying $c(\lambda_{id})$ to learn *both* θ_{id} and θ_{in} perfectly, where $c(\cdot)$ is increasing.[7] The nonlearnable

[5] We capture persistent differences in idiosyncratic returns across stocks through $\tilde{\varepsilon}_{in}$, the component that cannot be learned. Farboodi and Veldkamp (2020), on the other hand, uses the learnable component to capture such dynamics. Unlike their setting, the future pricing function in our setting is stochastic. If persistence were in the learnable component, the pricing function would become nonlinear.

[6] 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.

[7] We impose the same cost function for day and traders here for simplicity and relax it when calibrating the model. The increasing cost function rules out equilibrium multiplicity that may arise from complementarities in information acquisition. It can be motivated, for instance, by an upward-sloping supply curve

components $\varepsilon = \{\varepsilon_{id}, \varepsilon_{in}\}_{i=0}^{1}$ are learned for free, but only after their realization. Finally, the mutual fund doesn't have access to this information technology, and similar to uninformed traders, it infers z_{in} purely from observing stock market prices. We will relax this last assumption when calibrating the model, allowing the mutual fund to obtain independent signals about both 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 a Markov process with joint transition probability $q_{s,s'}$.

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

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 to a dealer at a discount z_{id}, consume, and die.
5. Production occurs, firms pay the mutual fund, and the fund pays households.
6. Night traders and dealers sell their stocks to newborn traders, consume, and die.

2.2 Traders' Problems and Stock Market Clearing

Traders choose whether to acquire information and how much to demand of each stock, conditional on information or lack thereof, which determines their expectations and uncertainty about each firm's valuation and each stock's liquidity properties.

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

Portfolio Choices. A trader chooses how many of their endowed foreign bonds to keep, and how many stocks to buy from each firm,

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

where $\mathbb{I}_{\{l=d\}}$ is the indicator function for a day trader, B_l and $\{X_{il}\}_{i\in[0,1]}$ denote the demands for foreign bonds and stocks by each type of trader $l\in\{d,n\}$. This is a standard portfolio rebalancing problem between safe assets (the foreign bond agents are endowed with and that pays 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 by informed and uninformed, day and night, traders are,

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

where $X_{in}^{I*}, X_{id}^{I*}, X_{in}^{U*}, and X_{id}^{U*}$ represent the asset demand by night and day traders that are informed (I) and uninformed (U), respectively. Notice that the difference between the demand of informed and uninformed is that informed condition expectations and variances on θ and uninformed 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

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

where $\mathbf{I}_j$ is the vector of information choices for all stocks. Let $\mathbf{I}_j^0$ be an arbitrary

information acquisition vector where the element I^0_{ji} for a specific stock i is zero and $\mathbf{I}^1_j$ be an identical vector, except that I^1_{ji} is one. The trader would choose $\mathbf{I}^1_j$ over $\mathbf{I}^0_j$, i.e., fixing information about all stocks, a trader j acquires information about stock i, if and only if $E\left[V\left(W_{nj}(\mathbf{I}^1_j)\right) \mid p\right] \leq E\left[V\left(W_{nj}(\mathbf{I}^0_j)\right) \mid p\right]$ where 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 $\mathbf{I}^0_j$ be an arbitrary information acquisition vector where $I^0_{ji} = 0$ for a specific stock i and $\mathbf{I}^1_j$ be an identical vector, except that $I^1_{ji} = 1$. Defining λ as the set of λ_{il} for all firms and traders of type $l \in \{d, n\}$, a trader l would acquire information about firm i conditional on others' information choices λ if and only if,*

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

Lemma 1 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 captures the benefits in terms of reducing the variance by observing θ_i instead of just observing p_i, and is less than one. Since traders want to reduce the variance of payoffs, they would acquire information if this ratio $\psi^{il}(\lambda)$ is less than one, and not acquiring if it is greater 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 from acquiring information about another.

Corollary 1 shows equilibrium conditions for λ_{il}, for $l \in \{d, n\}$.

Corollary 1. *$\psi^{il}(\lambda)$ 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

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

2.3 Real Sector Problems and Capital Market Clearing

Representative Household's Problem. Its recursive formulation is

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

where $s = \{Z, \gamma\}$ denotes the aggregate state, $H(.)$ is the value function, β is the discount factor, δ is the depreciation rate, k is the individual capital holdings and K is the aggregate capital holdings. $G(.)$ represents the household expectations over the future path of the aggregate capital, which includes capital depreciation. 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 saving orders from households, allocates capital in the best possible way to extract as much surplus as possible to distribute to households with no risk given perfect diversification. Since we assume the mutual fund can extract all the 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 optimal allocation choice is given by

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

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

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

Hence, the mutual fund obtains all the ex-post surplus from the rented capital, while the ex-post surplus from the installed capital is obtained by traders. Firms make zero profits ex-ante and ex-post. 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 the stock price p_i to infer θ_{in}, hence using $E[z_{in}|p_i]$ to make decisions. 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 existence of day traders prevents prices from perfectly revealing θ_{in} to the mutual fund, and worsens the allocation of capital.

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 choices, characterized in Corollary 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 (11).
7. G is consistent with k'.

2.5 Price Informativeness

Pricing Function. Proposition 1 shows the existence of a linear rational expectations equilibrium.

Proposition 1. *There exists a 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 $\frac{|\phi_{in}|}{|\phi_{id}|}$ captures the impact of θ_{in} on the price relative to θ_{id}. Therefore, Proposition 1 provides a simple equation that describes how much can be learned about firms' fundamentals θ_{in} from observing p_i. Corollary 2 provides in words the comparative statics of the impact of θ_{in} on 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) day payoff has a smaller residual variance after information acquisition than night payoff.

Corollary 3 provides sufficient conditions for the LREE being interior.

Corollary 3. *Let $\lim_{\lambda_{il}\to 0} c(\lambda_{il}) = 0$ and $\lim_{\lambda_{il}\to 1} c(\lambda_{il}) = \bar{C}$ where $\bar{C}$ is large enough. Then, any LREE is interior, i.e., $\lambda_{il} \in (0, 1)$.*

Price Informativeness Measure. We now define an intuitive measure of price informativeness that we can structurally measure in the data for many countries. To do this, we need to introduce a simplification that we maintain in 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 are ex-ante identical in size and primitive distributions: they independently draw z_{in} and z_{id} from the same distributions. This assumption allows us to use the cross-sectional variation of prices in estimating 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 similar spirit of Goldstein et al. (2014), this measure does not capture how muc stock prices tell us about future earnings, but instead how much they tell us about what we could have learned by getting informed at a cost.

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}.

Under Assumption 1 PI is firm invariant and we can write it explicitly as follows.

Corollary 4. *Under Assumption 1, the PI measure 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 next consists of estimating these four objects using the cross-section of firms in a given country to calculate PI yearly.

3 Measuring Price Informativeness

This section structurally measures Price Informativeness (PI) yearly for 17 countries and studies 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 having to solve for the full equilibrium because pricing just depends on the behavior of short-lived traders and is independent of investment choices by long-lived households. 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 the realized prices that are observed in the market are a composite of our theoretical prices (in which traders demand stocks only considering firms' fundamentals and stocks' liquidity properties) and other variables that are included in observed prices but not taken into account when traders form their demand (such as speculation motives, shocks to firms after traders submit their demand, 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 that determine prices but are not included 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 comes from a cross-section comparison. ϕ_n captures the extent to which firms with high prices have higher profitability signals. Similarly, ϕ_d captures 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.[8] Consistent coverage starts around 1985 for the US and by 2000 for most economies.

[8]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 check accounting identities, outliers, and correlations for accuracy. See Reuters' Worldscope Definitions for details on standardization practices, accuracy tests, coverage, and sample selection criteria.

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, 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, $\widehat{\theta}_{in}$***:*** We exploit the formation of informed traders' expectations about each firm's profitability from equation (2),

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

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.[9] 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 details on the steps we took to make firms and countries comparable.[10]

Measuring Z by the cross-sectional average of F_i, we need to decompose θ_{in} from $\rho\tilde{\varepsilon}_{in}^{-}$. For this decomposition, 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

[9] 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.

[10] We use forecasts announced within a 15-day window around the date the stock price is documented. 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.1 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.

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}.[11] Finally, from the approximated series $\widehat{\tilde{\varepsilon}}_{in}$ we can obtain our estimate for θ_{in} as

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

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

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 object; 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.[12]

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

[11] 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 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.

[12] 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.2, we provide statistics on the cross-sectional distribution of the range volatility estimates and how they evolve for the median firm.

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

Having obtained the time series of signals about profitability and liquidity ($\widehat{\theta}_{id}$ and $\widehat{\theta}_{in}$),[13] 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 estimate 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 $\sigma^2_{\widehat{\theta}_n}$, $\sigma^2_{\widehat{\theta}_d}$, $\widehat{\phi}_n$ and $\widehat{\phi}_d$, we compute PI from equation (13) for 344 country-years pairs (see Table 13 in Appendix F for details and a summary of the 344 pricing regressions). Next, we discuss PI's cyclical properties.

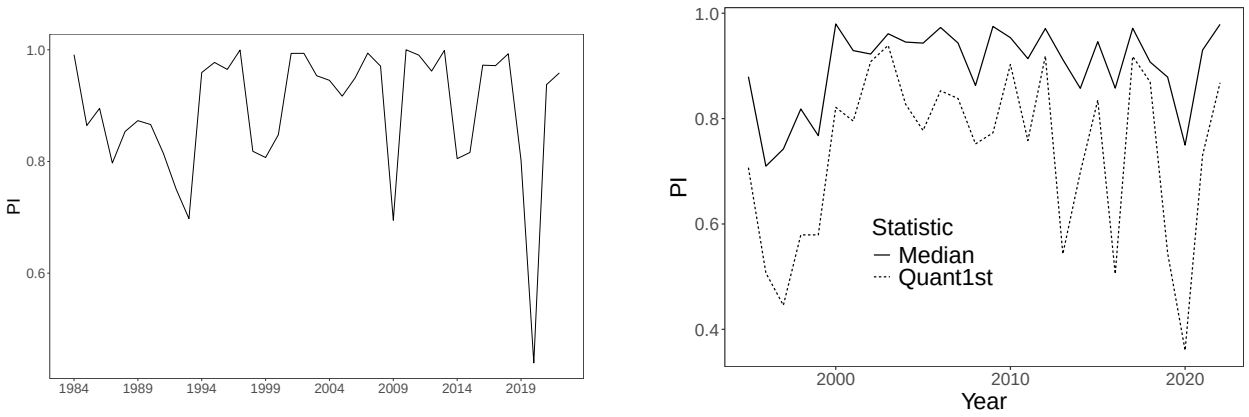
3.2 Price Informativeness Over Time and Across Countries.

As an illustration of results, Figure 1a presents the PI series for the US.[14] 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.

An advantage of our structural estimation of PI is that we can identify the drivers

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

[14] 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 12), signal averages ($\bar{\theta}_n$ and $\bar{\theta}_d$ in Figure 13), and variances ($\sigma^2_{\theta_n}$ and $\sigma^2_{\theta_d}$ in Figure 14).



(a) PI Estimates for the US

(b) Cross-Country Statistics for PI Estimate

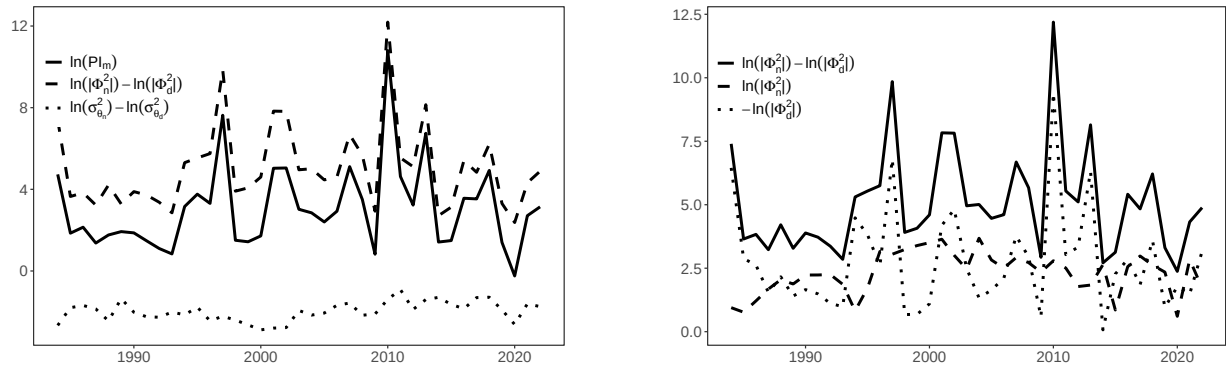
Figure 1: The PI Estimates. Notes: We restrict attention to countries for which PI is estimated for at least 20 years between 1994 and 2022 to get a partially balanced sample. The countries are Australia, Germany, the United Kingdom, France, Japan, Taiwan, Canada, Sweden, and the US.

behind these large PI declines by following individually each of its four components. A clean decomposition can be obtained by considering the log of a monotonic transformation of PI from equation (13):[15]

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

Figure 2a presents this measure (in the solid black line) together with two components: price loadings and variances. The variances (the dotted line) are important 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 the fluctuations in the loading of earnings (dashed line) contribute a significant amount, the lion's share of PI fluctuations comes from changes in the loading of liquidity (the 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 $\sigma_{\theta_d}^2$, ϕ_n, and ϕ_d at their median vales, respectively. If $\sigma_{\theta_n}^2$ 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 $\sigma_{\theta_n}^2$ and $\sigma_{\theta d}^2$. In the next section we will make it structural.

[15]We thank Liyan Yang for suggesting this intuitive decomposition. We provide the time-series plots of estimated $\sigma_{\theta n}^2$, $\sigma_{\theta d}^2$, ϕ_n and ϕ_d in Figure 11 of Appendix F.



(a) Decomposing PI_m

(b) Decomposing the Price Loadings

Figure 2: Contribution of the Components of PI

Figure 1b presents moments from the yearly distribution of PI estimates across nine 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)* Korea around the Asian Financial Crisis in 1997, *ii)* most European economies around the 'Taper Tantrum' and the European sovereign debt crisis in 2013, and *iii)* UK and France around the Brexit decision in 2016.

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.[16] 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 precisely 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.*

[16] 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.

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 doing 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 confirmed its cyclicality. Here we discipline the impact of its fluctuations on real variables, through misallocation that follows from agents using $E[\theta_{in}|p_i]$ instead of θ_{in} when allocating capital. The expression for the output loss due to misallocation is complicated but monotonic in the Bayesian risk associ-

ated with using $E[\theta_{in}|p_i]$ as an estimator for θ_{in}. As a benchmark, in Appendix E, we show the analytical link between PI and misallocation losses under a quadratic loss function. Since this is not the loss function that arises in our setting, we proceed to calibrate the full model to the United States to measure the impact of PI fluctuations on allocations.

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 $\theta_{in}^s \sim N(\theta_{in}, \sigma^2_{\theta_{in}^s})$ and an independent signal about the non-learnable component to traders $\varepsilon_{in}^s \sim N(\epsilon_{in}, \sigma^2_{\varepsilon_{in}^s})$. 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 concede that decision makers recognize prices contain additional noise, and that they may have independent and unique information relative to traders.

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 sequentially. 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. Additionally, we set the depreciation

rate δ equal to 0.06,[17] 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.[18] Lastly, because we directly estimated the level of productivity from earnings data, we have a degree of freedom to set 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 $W_t \sim MVN(0,Q)$ 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:

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

[17] Consistent with recent measures for public firms by Bai et al. (2022) using both BEA and Compustat.

[18] 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.

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

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:

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

for $j\in\{d,n\}$, which satisfies $c_j(0)=0$ and $\lim_{x\to 1}c_j(x)=\infty$, and according to Corollary 3 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 pricing parameters (ϕ_n and ϕ_d) and the fraction of informed agents (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, tell us about the curvatures. Finally, the average level of PI informs on 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 pro-

cedure, we start with a guess $\{\nu_d^0, \nu_n^0, \psi_d^0, \psi_n^0\}$ and take the next steps:

1. Start iteration k with $\{\nu_d^k, \nu_n^k, \psi_d^k, \psi_n^k\}$. Use (19) and (20) with estimated series for pricing coefficients and parameters to infer $\lambda_{d,data}^k$ and $\lambda_{n,data}^k$ 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 $\sigma_{\theta_n}^2$, $\sigma_{\theta_d}^2$, $\sigma_{\varepsilon_n}^2$, and $\sigma_{\varepsilon_d}^2$ associated with each Z level.

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

5. Compare M_{model}^k with M_{data}^k. If the discrepancy is below the threshold, stop. If not, go back to step 1 with new $\{\nu_d^{k+1}, \nu_n^{k+1}, \psi_d^{k+1}, \psi_n^{k+1}\}$.

4.1.3 Internally Calibrated Parameters of the Real Sector

Now, we internally calibrate parameters involved in capital accumulation and allocation: β, $\sigma_{p_i^s}^2$, $\sigma_{\varepsilon_{in}^s}^2$, and $\sigma_{\theta_{in}^s}^2$. We estimate the discount factor to generate a 2% risk-free interest rate.[19] 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 $\sigma_{p_i^s}^2$ 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_i^s.

We jointly discipline the quality of mutual fund own signals, $\sigma_{\varepsilon_{in}^s}^2$ and $\sigma_{\theta_{in}^s}^2$ using the cross-sectional price-investment correlation ($cor(p_i^s, k_i)$), and the time-series correlation between PI and investment dispersion ($cor(PI, std(k_i))$. First, $cor(p_i^s, k_i)$ increases with both variances: the mutual fund pays more attention to prices when making 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

[19] 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.

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.[20] Intuitively, both signals put limits to 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, as a part of investment choices is based on the realization of ε^s_{in}.

While our benchmark generates a very tight relation between prices and adjustable capital, this relation has been challenged empirically. 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. In Figure 15 in Appendix F, we find a similar weak correlation (in more recent years, this correlation is even negative). 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 consideration is consistent with the observed weak correlation between CAPEX and other variables that would presumably would also be tightly connected to a firm's investment ability and decisions, such as previous earnings, earnings forecasts, and future earnings.

Using alternative measures of investments, or proxies for the capacity to attract funds for investments, the relation with prices is, however, intermediate: not absent as with CAPEX, nor perfect as in our benchmark. To be more precise we consider three alternative measures of investments: 1) *asset changes*, computed as the year-to-year change in total assets,[21] 2) *working capital*, and 3) *number of employees*. We also consider two measures that capture how easily a firm can access funds when needed: 1) *corporate bonds yields* and 2) *corporate bonds ratings*. Figure 16 in Appendix F shows, for the U.S. in 2015, that 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 employees, pay lower rates on their bonds, and their bonds are better rated. Tables 16 and 17 in Appendix F also support a tight connection: prices

[20] 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.

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

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. Since *working capital* is the one closest to our model's adjustable capital, in what follows, we use it as our proxy for k_i.

4.2 Calibration Results

The calibrated liquidity series γ for the United States and the underlying cost functions (the internally calibrated parameters of stock markets) are depicted in Figures 3 and 4, respectively. The first panel of Figure 3 shows the estimated liquidity series for the U.S., suggesting elevated transitory reliance on stock markets for liquidity purposes (high γ) around the Great Recession and the COVID-19 pandemics and a persistent period of high reliance surrounding the period of S&L crisis, from 1985 to 1995. These results are consistent with the periods of a sizeable decline in PI. The second panel of Figure 3 shows the estimated series of market liquidity needs for the median of developed economies using the estimated information costs for the US. Naturally, these series are less volatile than for a single country but display similar patterns of increase during periods of global stress, like the COVID-19 pandemic or the European Sovereign Debt crisis.

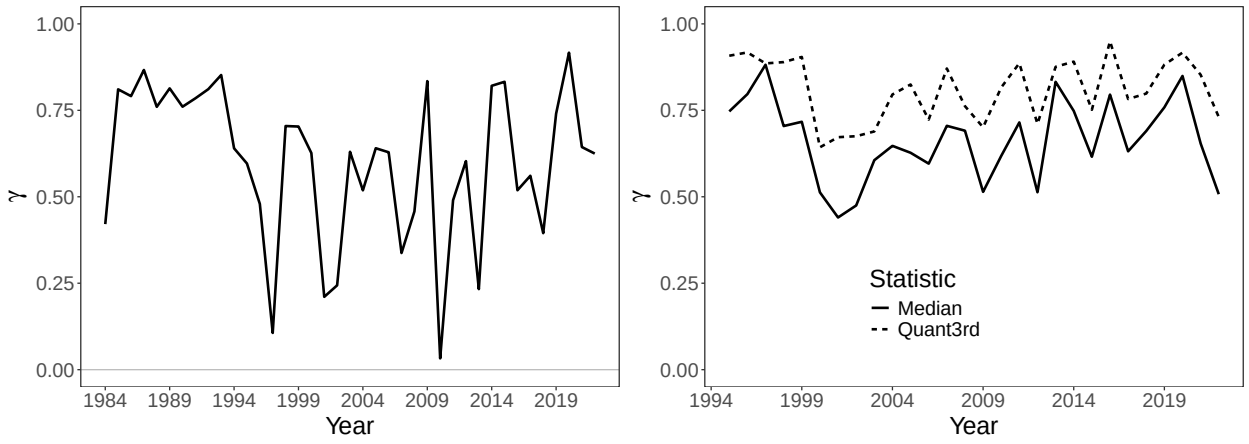


Figure 3: γ Series Implied by the Estimated Cost Function Notes: The left panel presents the estimated γ series for the United States, while the right panel presents the cross-sectional moments from a panel of countries using the cost function estimate from the US. To get a partially balanced sample, we restrict attention to countries where a PI is estimated for at least 20 years between 1994 and 2022. The countries are Australia, Germany, United Kingdom, France, Japan, Taiwan, Canada, Sweden, and the US.

Figure 4 displays the shape of the estimated 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 ($\sigma^2_{\epsilon_d}$) is much higher than the corresponding uncertainty in fundamental payoffs ($\sigma^2_{\epsilon_n}$), and (*ii*) the price uncertainty ($Var(\epsilon_{in} + p'_i)$) is much larger than the dispersion of signals ($\sigma^2_{\theta_n}$ and $\sigma^2_{\theta_d}$). As a result, (19) and (20) indicate that night traders must be paying a higher cost of information. Under symmetric cost functions, day traders would be willing to obtain more information than night traders, given the additional uncertainty they face, and price informativeness would be counterfactually too low.

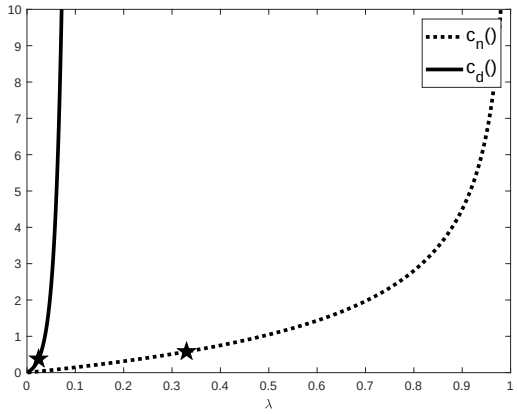


Figure 4: Estimated Information Acquisition Cost Functions. Notes: The solid and the dashed lines represent $c_n()$ and $c_d()$, respectively. The stars refer to the median λ and associated costs in the stochastic steady state.

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 standard deviations of signals and forecast errors in each state. Z fluctuates between 0.049 and 0.061 (consistent with median earnings per share fluctuations) while γ fluctuates between 0.37 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, while most consider stocks' short-run price fluctuations when funding liquidity dries up.

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

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.

transitions to a state with lower aggregate productivity. If both productivity declines and banking gets in distress, the first effect prevails, and PI declines.

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
			$\sigma_{\varepsilon^s_{in}}$	0.02	$cor(p_i, k_i)$	0.39	0.37
			$\sigma_{\theta^s_{in}}$	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).

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 distress in financial markets. This comparison aims to assess how financial distress amplifies or dampens the impact of a recessionary shock through changes in stock price informativeness. 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 shows the quantitative importance of modeling information as a choice. Lastly, in a third exercise, we quantify the importance of alternative sources of information through economies that can access 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 5 presents the implications of these two different aggregate shocks: the dotted line is the first case and the solid line is the second case.

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 higher 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 the allocation of capital, partially compensating for the negative productivity shock, which alone, without a change in PI, would have generated an output loss that is 4.4% larger.

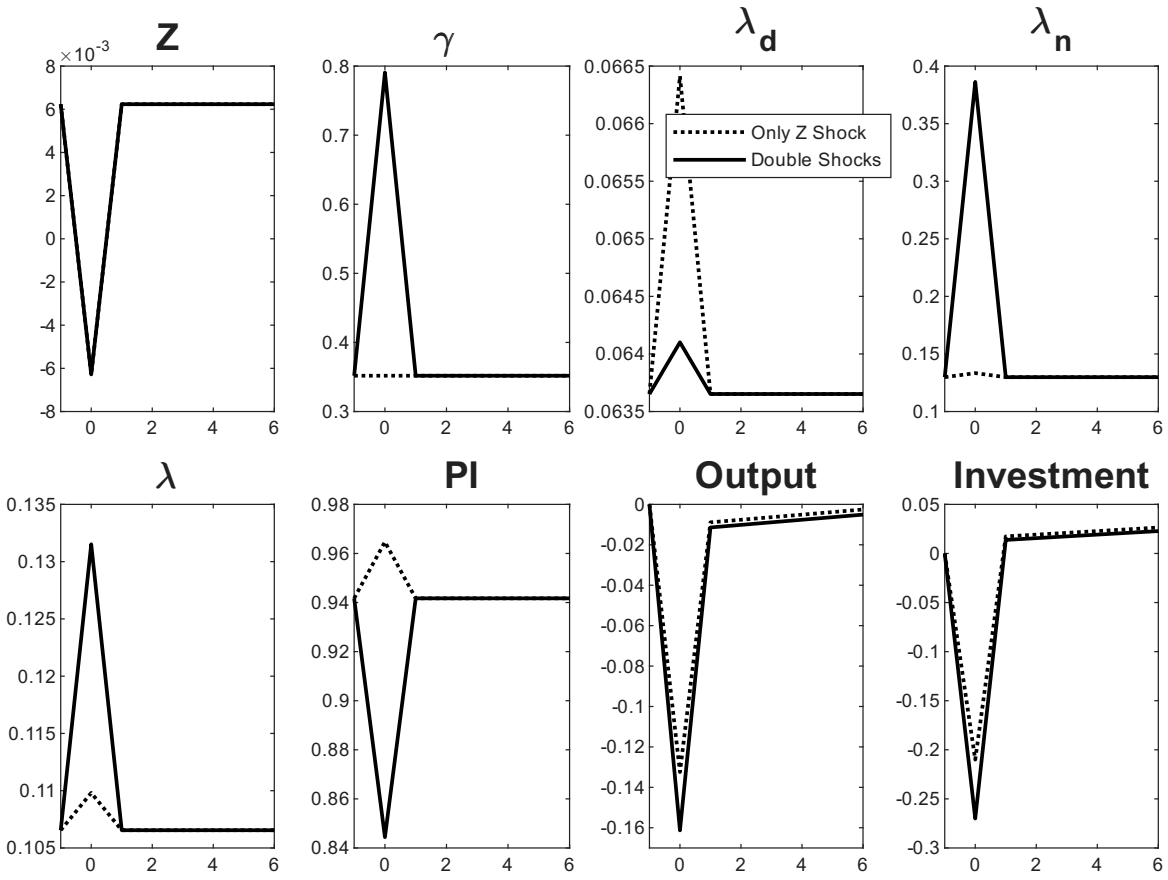


Figure 5: Impulse Response Functions. Notes: The first two panels provide the shocks that hit the economy under the benchmark and the counterfactual recession scenarios. λ denotes the aggregate fraction of traders that acquire information. Output and investment values represent the percentage changes from the pre-shock values.

What if the recession is accompanied by financial distress? With a dual shock to productivity and liquidity needs (solid lines), the participation of more day traders conceals firms' fundamentals. As a response to more uncertain fundamentals, the benefits of acquiring information also increase for night traders. Despite more information acquisition overall, PI ultimately declines. The decline in output and gross investment induced by lower PI would be 22% larger relative to the case without financial distress.[22]

[22]In Figure 17 of Appendix F, we compare a banking crisis with and without a drop in Z. While in both cases PI declines, this is more marked when there is no recession, generating a pure misallocation decline in output (despite no reduction in Z) that is 11% of a standard recession.

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 goes up with productivity shocks, goes down with financial distress, and reacts more to a standard financial distress than to a standard productivity shock. To study the sensitivity of PI to productivity and financial distress, 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.

Table 5 presents the results. Consistent with our calibration, less liquidity provided by banking and financial sectors is associated with less 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 high PI, which is not statistically significant.[23]

Second, misallocation from a drop in PI takes a particular shape in our model: less PI induces firms' fundamentals to look more alike, reducing the dispersion of investment, 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

[23]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).

different country-year pairs are weighted, higher PI is correlated to a higher dispersion in capital expenditures, even after controlling for the impact of the cycle.

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

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 informativeness and allow for better resource allocation. Our work, however, highlights that 'cleansing recessions' can turn into 'sullying recessions' when accompanied by heightened liquidity concerns. Recessions accompanied by a weakness in the banking sector become periods of lower PI and worse allocation of resources. 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.[24] 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 with or without funding liquidity distress. This is consistent with the findings of Loh and

[24]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.

Stulz (2018) and Jiang et al. (2015). The former documents that financial analysts produce longer and more frequent reports, and their 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 despite more information generation overall*.

5.2 Alternative Information Structures

In the previous exercise, we analyzed the quantitative response of PI to productivity and liquidity shocks and its 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 ($\lambda = \gamma\lambda_d + (1-\gamma)\lambda_n$), 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 5.

One alternative economy assumes that a fraction of traders receive signals exoge-

nously, 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 economy, agents react to lower information content in stock markets by acquiring more information and partially offsetting such reduction. Information acquisition provides a stabilizing force against funding liquidity 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 can acquire information at half the cost (last column), they would also trade more aggressively, PI would decline by 12.1% instead of 10%, leading output to decline 16.4%. Note that in our setting, more information acquisition does not mean better information, just that more traders of a particular type become informed and trade more aggressively upon such information, affecting which signal is "more represented" in prices.

An economy with lower information costs for night traders, ν_n, corresponds, for instance, to 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, corresponds to regulations that disclose information about market transactions, such as recent changes that disclose 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 information about firms' profitability make the economy more resilient to recessions with financial shocks. In contrast, those that facilitate information about 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 how the aggregates from these alternative economies would differ in their stochastic steady state. For instance, economies with lower information costs would display more information acquisition by all traders overall. However, if information about fundamentals is cheaper, the economy displays higher

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 $\overline{z}\underline{\gamma}$ 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.

levels of capital, consumption, and output in a stochastic steady state, with the opposite happening if information about markets' operations and assets' liquidity is cheaper.

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, signals on the learnable component of productivity θ_n^s, and signals about the non-learnable (to traders) component of productivity ε_n^s. This also allows us to interpret our estimates for $\sigma_{\theta_{in}^s}$ and $\sigma_{\varepsilon_{in}^s}$. Table 8 provides the output levels in various states of the economy under alternative combinations of these three sources. Importantly, we keep the level of capital stock the same in each scenario, to focus on the 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 additional sources of information.

6 Conclusions

Stock markets contribute to the economy in two distinct ways. One is conveying through prices 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 fall short in providing credit, agents rely more on stocks to access liquidity, deteriorating their information revelation role. To connect the two roles of stock markets, we have provided a model of price formation with endogenous information acquisition about a firm's fundamentals, and integrated it with a general equilibrium real business cycles model with heterogeneous firms.

We provide a novel measure of stock price informativeness that captures the ability

of prices to reveal available information, which is useful for making investment decisions, and not their forecasting ability, which mechanically goes down before unexpected events. Since our measure is structural, we can measure changes in price informativeness for many countries and periods and 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 to be mostly related to a heightened trading for reasons not related to firms' fundamentals, not because of less information acquisition or worse information quality.

We assess the quantitative effect of a reduction in price informativeness on real outcomes by calibrating the full model to the United States. We show that changes in stock markets mitigate the output losses from negative productivity shocks by 4.4%, but if those recessions are accompanied by financial distress, changes in stock markets go from "friend to foe," magnifying output losses by 22%. Our counterfactuals further suggest that facilitating access to information about firms' fundamentals would lead to higher levels of output and consumption with reduced fluctuations, while facilitating access to liquidity-relevant information, such as trading volumes or dealers' details, does the opposite.

Our study highlights a novel link between the functioning of credit markets and stock markets. Even though these markets provide similar services, like liquidity and information, some argue banks are more efficient in supplying liquidity and stocks in revealing information (see discussion in Gorton and Ordonez (2023)). We have argued here that when banks are in distress, stocks supply liquidity at the expense of their role in revealing information and guiding resource allocations.

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 more comprehensive evaluations about the desirability and regulation of information.

References

Alam, M Jahangir (2020), "Capital misallocation: Cyclicality and sources," *Journal of Economic Dynamics and Control*, 112, 103831.

Amihud, Yakov and Shai Levi (2023), "The effect of stock liquidity on the firm's investment and production," *The Review of Financial Studies*, 36, 1094–1147.

Bai, Hang, Erica Li, Chen Xue, and Lu Zhang (2022), "Asymmetric Investment Rates," NBER Working Paper 29957.

Bai, Jennie, Thomas Philippon, and Alexi Savov (2016), "Have financial markets become more informative?" *Journal of Financial Economics*, 122, 625–654.

Banerjee, Snehal, Jesse Davis, and Naveen Gondhi (2021), "Incentivizing effort and informing investment: the dual role of stock prices," Working Paper, SSRN.

Baron, Matthew, Emil Verner, and Wei Xiong (2021), "Banking crises without panics," *The Quarterly Journal of Economics*, 136, 51–113.

Benhabib, Jess, Xuewen Liu, and Pengfei Wang (2019), "Financial markets, the real economy, and self-fulfilling uncertainties," *The Journal of Finance*, 74, 1503–1557.

Bernanke, Ben (1983), "Non-monetary Effects of the Financial Crisis in the Propagation of the Great Depression," *American Economic Review*, 73, 257–276.

Bond, Philip, Alex Edmans, and Itay Goldstein (2012), "The real effects of financial markets," *Annu. Rev. Financ. Econ.*, 4, 339–360.

Breon-Drish, Bradyn (2015), "On existence and uniqueness of equilibrium in a class of noisy rational expectations models," *The Review of Economic Studies*, 82, 868–921.

Chousakos, Kyriakos, Gary Gorton, and Guillermo Ordonez (2023), "Information Dynamics and Macro Fluctuations," *AEJ: Macroeconomics*, 15, 372–400.

Cooper, Michael J, Huseyin Gulen, and Michael J Schill (2008), "Asset growth and the cross-section of stock returns," *the Journal of Finance*, 63, 1609–1651.

David, Joel M, Hugo A Hopenhayn, and Venky Venkateswaran (2016), "Information, misallocation, and aggregate productivity," *The Quarterly Journal of Economics*, 131, 943–1005.

David, Joel M, Lukas Schmid, and David Zeke (2022), "Risk-adjusted capital allocation and misallocation," *Journal of Financial Economics*, 145, 684–705.

David, Joel M and Venky Venkateswaran (2019), "The sources of capital misallocation," *American Economic Review*, 109, 2531–67.

Dávila, Eduardo and Cecilia Parlatore (2018), "Identifying price informativeness," Working Paper, National Bureau of Economic Research.

Dow, James, Itay Goldstein, and Alexander Guembel (2017), "Incentives for information production in markets where prices affect real investment," *Journal of the European Economic Association*, 15, 877–909.

Dow, James and Gary Gorton (1997), "Stock market efficiency and economic efficiency: is there a connection?" *The Journal of Finance*, 52, 1087–1129.

Eisfeldt, Andrea L. and Adriano A. Rampini (2008), "Managerial incentives, capital reallocation, and the business cycle," *Journal of Financial Economics*, 87, 177 – 199.

Fajgelbaum, Pablo D, Edouard Schaal, and Mathieu Taschereau-Dumouchel (2017), "Uncertainty traps," *The Quarterly Journal of Economics*, 132, 1641–1692.

Farboodi, Maryam and Laura Veldkamp (2020), "Long-run growth of financial data technology," *American Economic Review*, 110, 2485–2523.

Flynn, Joel and Karthik Sastry (2024), "Attention Cycles," Working Paper, Princeton University.

Foster, Lucia, Cheryl Grim, and John Haltiwanger (2016), "Reallocation in the great recession: cleansing or not?" *Journal of Labor Economics*, 34, S293–S331.

Fuchs, William, Brett Green, and Dimitris Papanikolaou (2016), "Adverse selection, slow-moving capital, and misallocation," *Journal of Financial Economics*, 120, 286 – 308.

Ganguli, Jayant Vivek and Liyan Yang (2009), "Complementarities, multiplicity, and supply information," *Journal of the European Economic Association*, 7, 90–115.

Garman, Mark B and Michael J Klass (1980), "On the estimation of security price volatilities from historical data," *Journal of business*, 67–78.

Goldstein, Itay (2023), "Information in financial markets and its real effects," *Review of Finance*, 27, 1–32.

Goldstein, Itay, Yan Li, and Liyan Yang (2014), "Speculation and hedging in segmented markets," *The Review of Financial Studies*, 27, 881–922.

Gorton, Gary and Guillermo Ordonez (2023), *Macroeconomics and Financial Crises*, Princeton University Press, Princeton.

Gospodinov, Nikolay and Damba Lkhagvasuren (2014), "A moment-matching method for approximating vector autoregressive processes by finite-state Markov chains," *Journal of Applied Econometrics*, 29, 843–859.

Grossman, Sanford J and Joseph E Stiglitz (1980), "On the impossibility of informationally efficient markets," *The American Economic Review*, 70, 393–408.

Gruber, Jonathan (2013), "A tax-based estimate of the elasticity of intertemporal substitution," *The Quarterly Journal of Finance*, 3, 1350001.

Jiang, Haiyan, Ahsan Habib, and Rong Gong (2015), "Business cycle and management earnings forecasts," *Abacus*, 51, 279–310.

Khan, Aubhik and Julia K Thomas (2013), "Credit shocks and aggregate fluctuations in an economy with production heterogeneity," *Journal of Political Economy*, 121, 1055–1107.

Loh, Roger K and René M Stulz (2018), "Is Sell-Side Research More Valuable in Bad Times?" *The Journal of Finance*, 73, 959–1013.

Manzano, Carolina and Xavier Vives (2011), "Public and private learning from prices, strategic substitutability and complementarity, and equilibrium multiplicity," *Journal of Mathematical Economics*, 47, 346–369.

Oberfield, Ezra (2013), "Productivity and misallocation during a crisis: Evidence from the Chilean crisis of 1982," *Review of Economic Dynamics*, 16, 100 – 119.

Ordonez, Guillermo (2013), "The asymmetric effects of financial frictions," *Journal of Political Economy*, 121, 844–895.

Osotimehin, Sophie (2019), "Aggregate productivity and the allocation of resources over the business cycle," *Review of Economic Dynamics*, 32, 180–205.

Plantin, Guillaume and Jean Tirole (2018), "Marking to market versus taking to market," *American Economic Review*, 108, 2246–2276.

Rahi, Rohit (2021), "Information acquisition with heterogeneous valuations," *Journal of Economic Theory*, 191, 105155.

Sandleris, Guido and Mark L. J. Wright (2014), "The Costs of Financial Crises: Resource Misallocation, Productivity, and Welfare in the 2001 Argentine Crisis," *The Scandinavian Journal of Economics*, 116, 87–127.

Stein, Jeremy C (1987), "Informational externalities and welfare-reducing speculation," *Journal of Political Economy*, 95, 1123–1145.

Straub, Ludwig and Robert Ulbricht (2023), "Endogenous Uncertainty and Credit Crunches," *Review of Economic Studies*, page rdad110.

Subrahmanyam, Avanidhar and Sheridan Titman (1999), "The going-public decision and the development of financial markets," *The Journal of Finance*, 54, 1045–1082.

Vives, Xavier (2014), "On the possibility of informationally efficient markets," *Journal of the European Economic Association*, 12, 1200–1239.

A Proofs

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

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

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

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

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

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

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

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

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

Now define

$$\begin{aligned} h_{in} &:= \operatorname{Var}[\tilde{\theta}_{in} \mid p] \\ g_{in} &:= \frac{Z + \tilde{\theta}_{in} + E[p_i'] - (1 + r^I)p_i}{\sqrt{h_{in}}} \end{aligned}$$

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

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

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:[25]

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

Now we can rewrite,

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

Furthermore, notice that

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

Hence, we can rewrite it as

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

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

Then,

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

Following similar steps for the value of being uninformed yields

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

Therefore,

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

□

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:

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

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

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

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

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

and then, market-clearing is,

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

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

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

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

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

Next, we rearrange terms to leave p_i alone:

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

$$
\begin{aligned}
&\underbrace{(\chi_1+\chi_2)}_{\tilde{\phi}^s_{in}}\theta_{in}-\underbrace{\chi_1}_{\tilde{\phi}^s_{id}}\theta_{id}+\left[\rho\chi\left(1+\sum_s q_{ss'}\phi_{i\varepsilon}^{s'}\right)-(\chi_3+\chi_4)\left(\frac{\mathrm{Var}\left[\theta_{in}\mid p_i\right]}{\sigma^2_{\theta id}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2\frac{\phi_{i\varepsilon}}{\phi_{in}}\right)\right.\\
&\left.+\chi_3\frac{\mathrm{Var}\left[\theta_{id}\mid p_i\right]}{\sigma^2_{\theta in}}\left(\frac{\phi_{id}}{\phi_{in}}\right)^2\frac{\phi_{i\varepsilon}}{\phi_{id}}\right]\tilde{\varepsilon}_{in}^{-}+\chi\left(Z+\sum_{s'}\left[\phi_{i0}^{s'}+\phi_{in}^{s'}\bar{\theta}_{in}+\phi_{id}^{s'}\bar{\theta}_{id}\right]q_{ss'}\right)+\\
&+\chi_3\,\mathrm{Var}\left[\theta_{id}\mid p_i\right]\left[\frac{\phi_{0i}+\phi_{ni}\bar{\theta}_{in}}{\phi_{di}}\left(\frac{\phi_{id}}{\phi_{in}}\right)^2\frac{1}{\sigma^2_{\theta_{in}}}-\frac{\bar{\theta}_{id}}{\sigma^2_{\theta_{id}}}\right]-\bar{K}_i\\
&-(\chi_3+\chi_4)\,\mathrm{Var}\left[\theta_{in}\mid p_i\right]\left[\frac{\phi^s_{0i}+\phi^s_{id}\bar{\theta}_{id}}{\phi_{in}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2\frac{1}{\sigma^2_{\theta_{id}}}-\frac{\bar{\theta}_{in}}{\sigma^2_{\theta_{in}}}\right]
\end{aligned}
\tag{43}
$$

In (43), $\phi^s_{in}=\frac{\tilde{\phi}^s_{in}}{\tilde{\phi}}$ and $\phi^s_{id}=\frac{\tilde{\phi}^s_{id}}{\tilde{\phi}}$. Hence, the expression in the Proposition follows. □

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 $\rho = 0$.*[26] *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 z_{in} z_{id}] ,$\tilde{\Phi} = [\Phi_o \quad \Phi_n \quad \Phi_d]$. Then

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

[26] 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:

$$\left(\frac{1}{n}\sum \tilde{Z}_i\tilde{Z}_i'\right)^{-1}\left(\frac{1}{n}\sum \tilde{Z}_i\varepsilon_{in}\right) = \left(\frac{1}{n}\sum \tilde{Z}_i Z_i'\right)^{-1}\left(\frac{1}{n}\sum [\varepsilon_{in} \quad \theta_{in}\varepsilon_{in}+\varepsilon_{in}^2 \quad \theta_{id}\varepsilon_{in}+\varepsilon_{id}\varepsilon_{in}]\right)$$
$$\xrightarrow{\text{p}} \underbrace{\begin{bmatrix} 1 & \overline{Z_n} & \overline{Z_d} \\ \overline{Z_n} & \overline{Z_n Z_n} & \overline{Z_n Z_d} \\ \overline{Z_d} & \overline{Z_n Z_d} & \overline{Z_d Z_d} \end{bmatrix}^{-1}}_{\mathbf{Z}^{-1}} \begin{bmatrix} 0 \\ \sigma^2_{\varepsilon_n} \\ 0 \end{bmatrix},$$

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

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

Then, we can characterize the term as

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

where

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

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,

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

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

□

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.[27] 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

[27] 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 $Z + \theta_{in} + \rho\tilde{\varepsilon}_{in}^{-} + \varepsilon_{it}$.[28]

Figure 6 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}.

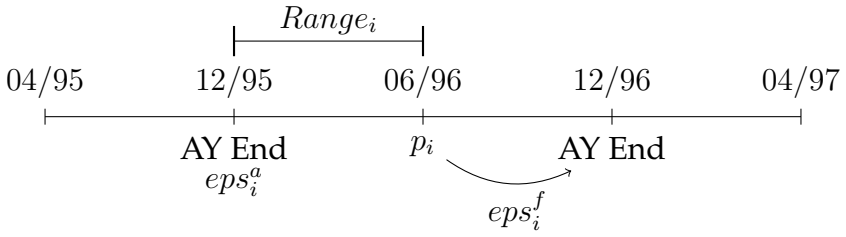


Figure 6: A Timing Example

This choice has implications for the interpretation of coefficients. Since the end of the accounting year is December 31st for most companies, the yearly estimates will generally refer to the 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 seen in the estimates for 2009.[29]

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, this assignment is inconsistent. Worldscope, before 2013, assigned companies based on "... country of major

[28] 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.

[29] 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 in which the company's 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 in multiple exchanges.[30] 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 based on the stock exchange because the stock prices are determined primarily by that country's traders and their liquidity needs. Hence, measuring PI necessitates grouping companies based on who owns and trades their shares. Regardless, in most cases, the exchange-country disconnect 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.

[30] I/B/E/S and Worldscope sometimes use different identifiers for the stocks of the same company in 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 a possibility of abnormally high earnings in the long run, we remove observations where the company's earnings forecast indicates losses larger than 10% of the total value of its assets.[31] 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 a 5% level to deal with stock anomalies and potential inaccuracies in data.

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,

$$R_{it} = \alpha_i + \beta_{1i} MR_{mt} + \beta_{2i} SMB_{mt} + \beta_{3i} HML_{mt} + \epsilon_{it} \tag{44}$$

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 based on a balanced panel of stock prices from the past 24 months. The market return (MR) is constructed by looking at the month-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

[31] 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.

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 with 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 date of the closest available

exchange rate. 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,[32] 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.

[32] 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 30 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 $u^b(W) = -e^{-a_b W}$. 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 of period t would like to access cash twice during the day: the afternoon and 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 7 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 is regarding p'_i, and dealers have diffuse priors on 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 to use past price volatility as a signal about the liquidity discount a day trader will pay when selling stocks.

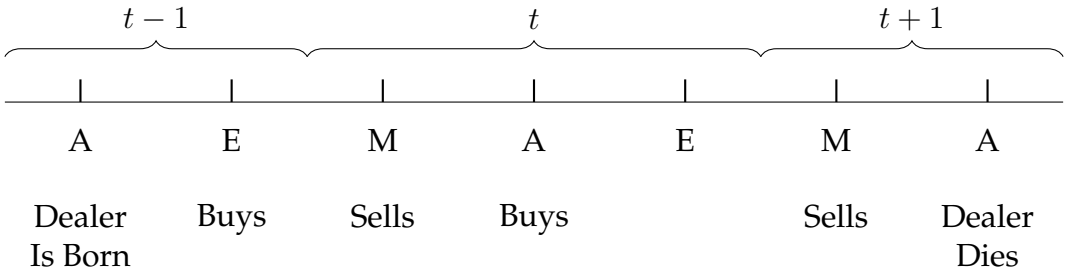


Figure 7: Timing for the Dealers

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:

$$\frac{E_j^{EV}[p_i'] - p_{ij}^{EV}}{a_b Var_j^{EV}[p_i']} = 1. \tag{45}$$

Given the signal structure for the evening dealers, $p_{ij}^{EV} = F_{ij}^{EV} - a_b \sigma^2_{F_i^{EV}}$, 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:

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

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

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

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

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

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 $p_{ij}^{EV} = p_i' + \sigma_{F_i^{EV}} s_{ij} - a_b \sigma^2_{F_i^{EV}}$. Its expectation is

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

and variance

$$V[p_{ij}^{EV}] = V[p_i'] + V(\sigma_{F_i^{EV}} s_{ij}) + V(a_b \sigma^2_{F_i^{EV}}) - 2Cov(\sigma_{F_i^{EV}} s_{ij}, a_b \sigma^2_{F_i^{EV}}). \tag{47}$$

We can write

$$\begin{aligned} V[\sigma_{F_i^{EV}} s_{ij}] =& V(\sigma_{F_i^{EV}}) V(s_{ij}) + V(\sigma_{F_i^{EV}}) E^2(s_{ij}) + E^2(\sigma_{F_i^{EV}}) V(s_{ij}) \\ =& V(\sigma_{F_i^{EV}}) + E(\sigma^2_{F_i^{EV}}) - V(\sigma_{F_i^{EV}}) = \theta_{EV}, \end{aligned} \tag{48}$$

and

$$Cov(\sigma_{F_i^{EV}} s_{ij}, a_b \sigma^2_{F_i^{EV}}) = a_b \left(E(\sigma^3_{F_i^{EV}} s_{ij}) - E(\sigma_{F_i^{EV}} s_{ij}) E(\sigma^2_{F_i^{EV}}) \right) = 0. \tag{49}$$

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

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

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

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

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 $\theta_{in} + E[p'_i] - \frac{a_b}{2} \left(\sigma^2_{F_i^{AF}} + \theta_{EV} \right)$. Thus, these are the same when

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

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 $z_{in} + \frac{1}{2} \left(F_{ij}^{AF} + F_{ij}^{EV} - a_b \sigma^2_{F_i^{AF}} - a_b \sigma^2_{F_i^{EV}} \right)$. Then, these are the same when

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

which can be decomposed as

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

and

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

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 $\frac{1}{4} \left(\sigma^2_{F_i^{AF}} + \theta_{EV} + a_b^2 \sigma^2_{EV} \right) + V(p'_i + \sigma^2_{\epsilon_{in}})$. Also, note that $E[\epsilon_{id}] = E[\hat{\epsilon}_{ijd}] = 0$, consistent with the baseline model. Then, it would follow that

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

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

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

□

Proposition 3 shows that the baseline model in Section 2 can be microfounded through dealers who facilitate day traders to obtain 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 Monthly Variation in Forecasts

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

If the forecasts change substantially month-to-month, then our results would be sensitive to the timing assumptions made. Here, we show that the month-to-month variation in earnings forecasts is relatively small. We focus on the forecasts of companies in the US and Japan and set the monthly forecast for a stock as the median forecast made within 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.

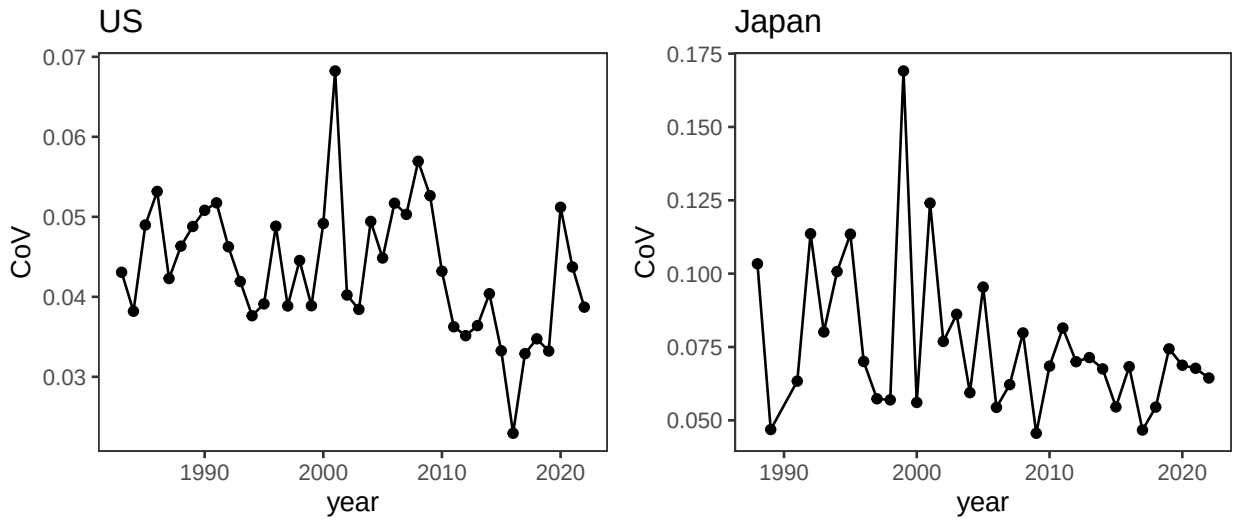


Figure 8: Month-to-Month Coefficient of Variation of Earnings-per-Share Forecasts for the Median Firm

Figure 8 shows the monthly variation in forecasts for the median stock. In the US, the monthly standard deviation for the median stock is almost always below 6% of the mean, while it's mostly below 10% for Japan.

Figure 9 plots the normalized forecast error, i.e., the absolute forecast error divided by the realized value, for the median stock. For both the US and Japan, the forecast error

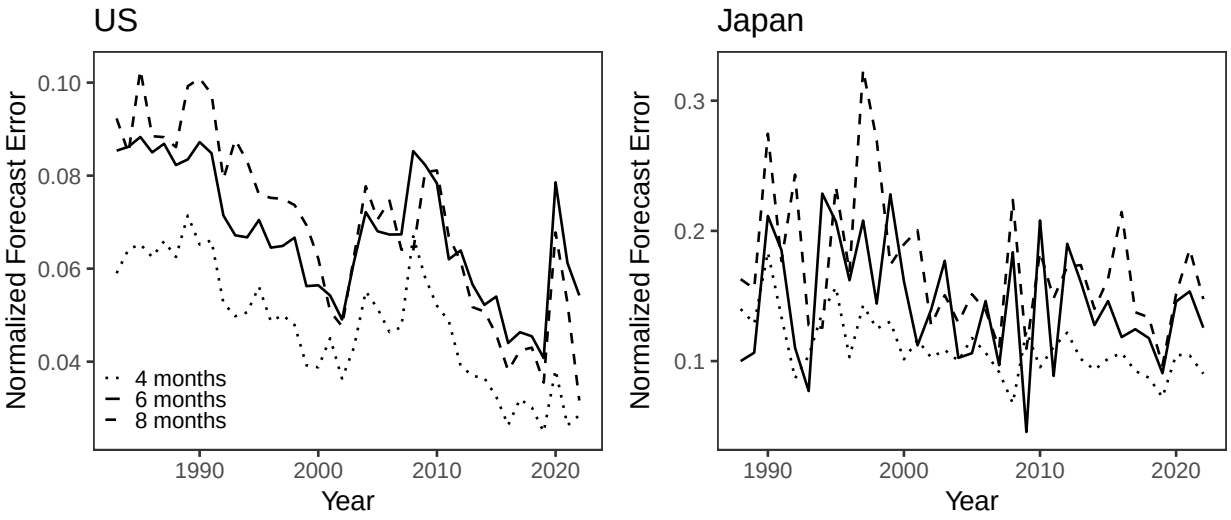


Figure 9: Forecast Error for Earnings-per-Share Forecasts for the Median Firm
Notes: The dotted, solid, and dashed lines represent the normalized errors for forecasts made 8, 6, and 4 months before the fiscal year-end date for the median stock, respectively.

declines as the forecast date becomes closer to the fiscal year's end, with few exceptions. However, the improvement for the median stock mostly stays small.

D.2 Range Volatility Measures

In this section, we provide summary statistics on the range volatility measure we use. Figure 10 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 in 2018 for Japan and the US. 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

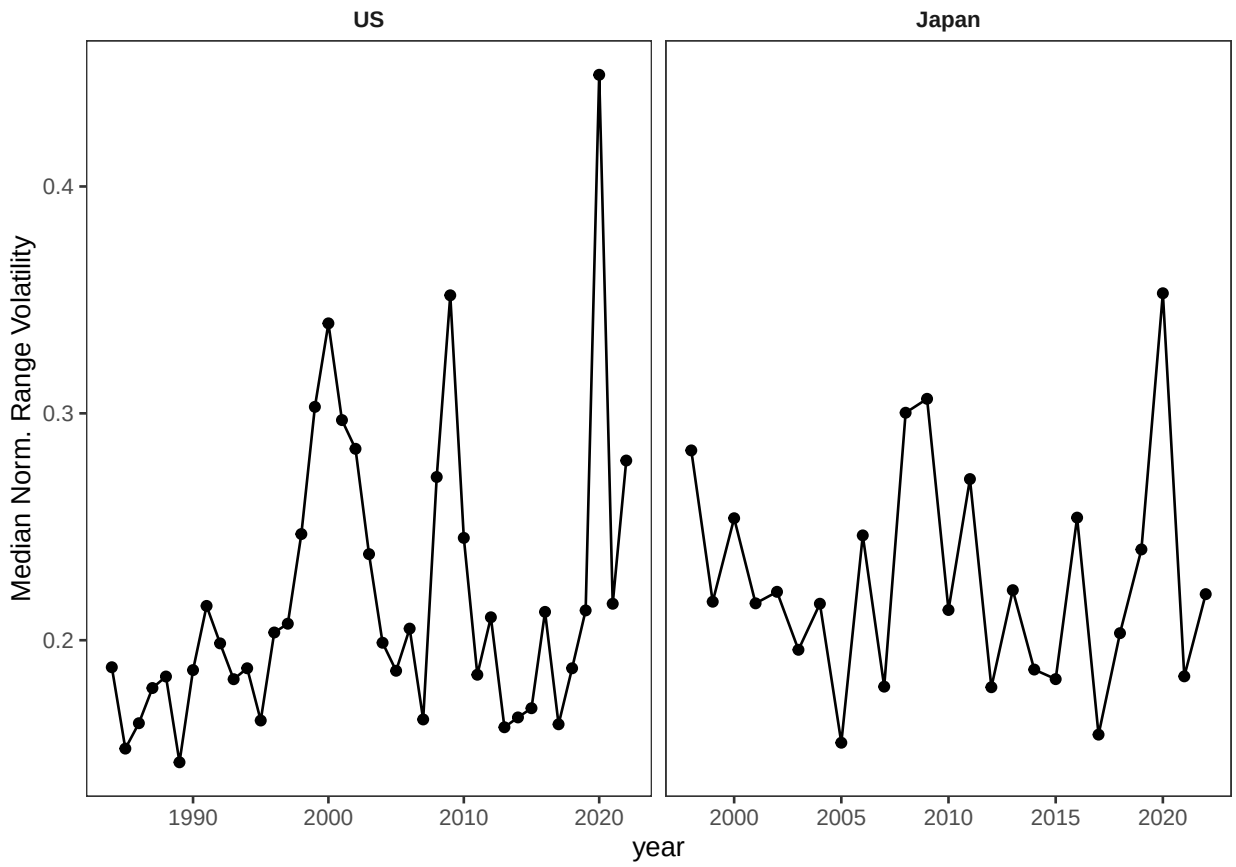


Figure 10: Normalized Range Volatilities for the Median Firm

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 ($\text{Var}[E[\theta_{in}|p_i] - \theta_{in}]$) 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

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

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

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

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

$$R\left(\theta_{in}, E[\theta_{in}|p_i]\right) = 0 + \frac{1}{\frac{1}{\sigma^2_{\theta_{in}}} + \frac{1}{\sigma^2_{\theta_{id}}}\left(\frac{\phi_{in}}{\phi_{id}}\right)^2}. \tag{50}$$

□

As shown in Proposition 4, the frequentist risk is independent of θ_{in}, hence equal to the Bayesian risk.[33] Corollary 5 summarizes what Proposition 4 implies about the characteristics of firms that get under and over-invested.

Corollary 5. *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.*

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

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

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

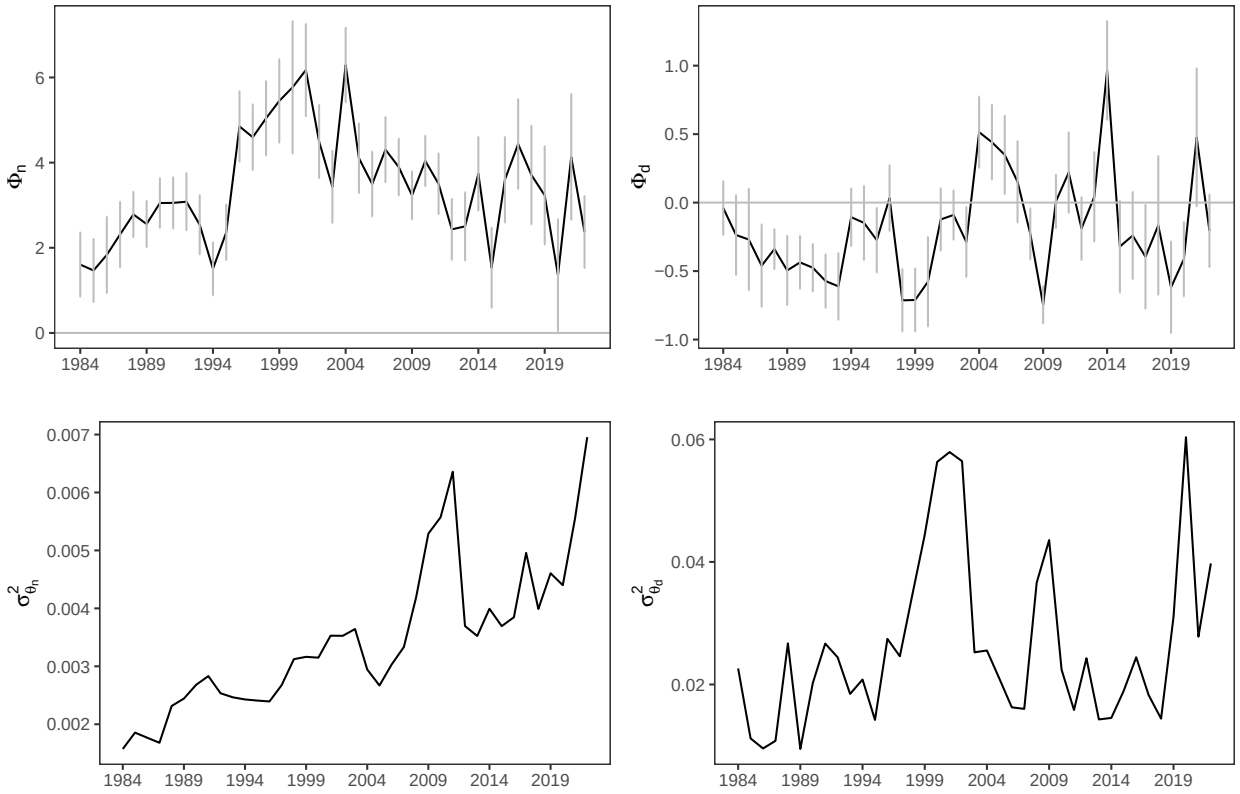


Figure 11: Estimated Price Informativeness Components for the US

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.

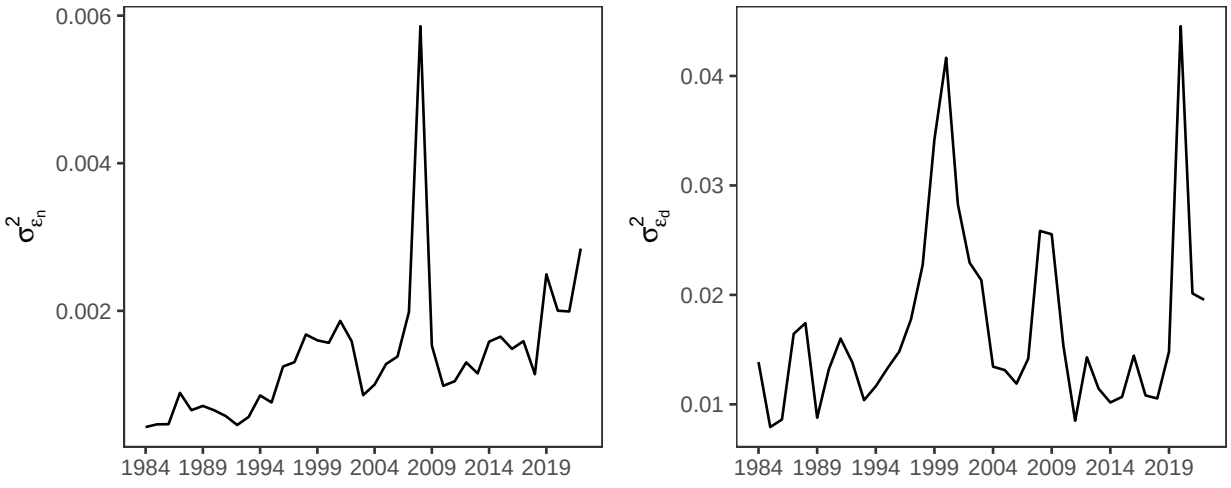


Figure 12: Forecast Error Variance Estimates in the US for a Balanced Panel

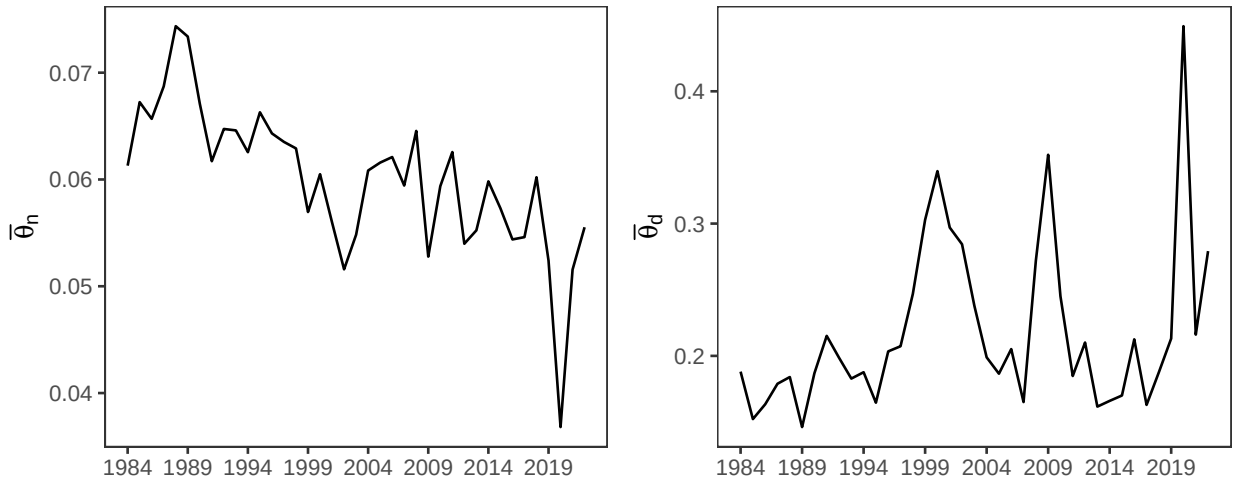


Figure 13: Median Earnings and Volatility Signals in the US for a Balanced Panel

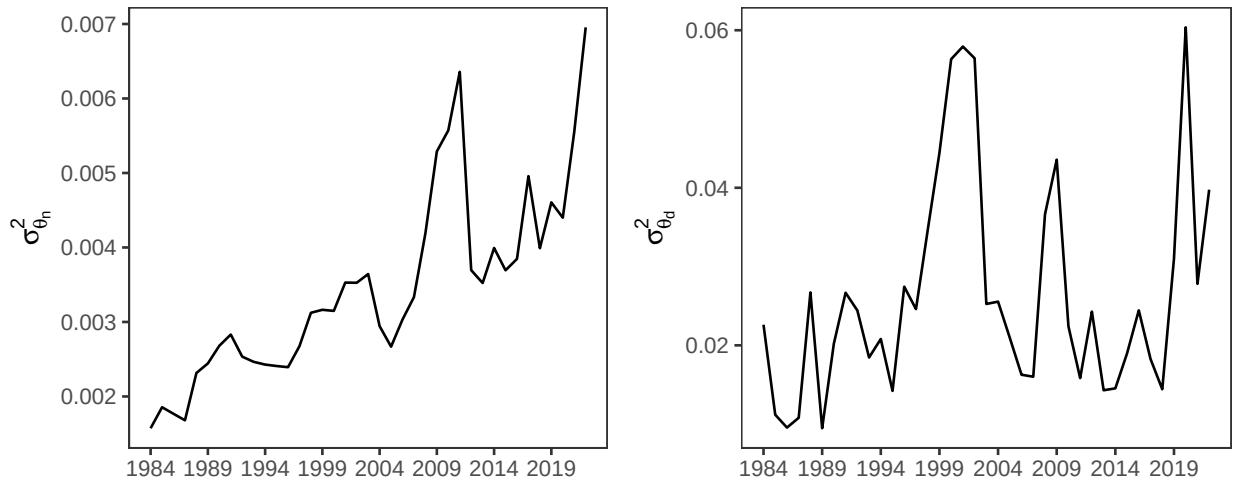


Figure 14: Variances of the Earnings and Volatility Signals in the US for a Balanced Panel

Table 13: List of Countries and the Data Coverage

CountryName	IBESCode	YearRange	CountryName	IBESCode	YearRange
Germany	ED	2000 - 2022	South Korea	FK	1994 - 2022
France	EF	2000 - 2022	Malaysia	FM	1997 - 2022
Italy	EI	2004 - 2021	Thailand	FT	2004 - 2022
Switzerland	ES	2001 - 2022	Brazil	LB	2009 - 2022
United Kingdom	EX	1992 - 2022	Canada	NC	1991 - 2022
Taiwan	FA	1999 - 2022	Finland	SF	2008 - 2022
China	FC	2006 - 2022	Sweden	SS	1999 - 2022
Hong Kong	FH	2004 - 2022	United States	US	1984 - 2022
Japan	FJ	1998 - 2022			

Table 14: Summary Statistics for Pricing Regressions

Country	Avg ϕ_n	Avg ϕ_d	Avg R^2	Avg PI	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 15 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 15 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

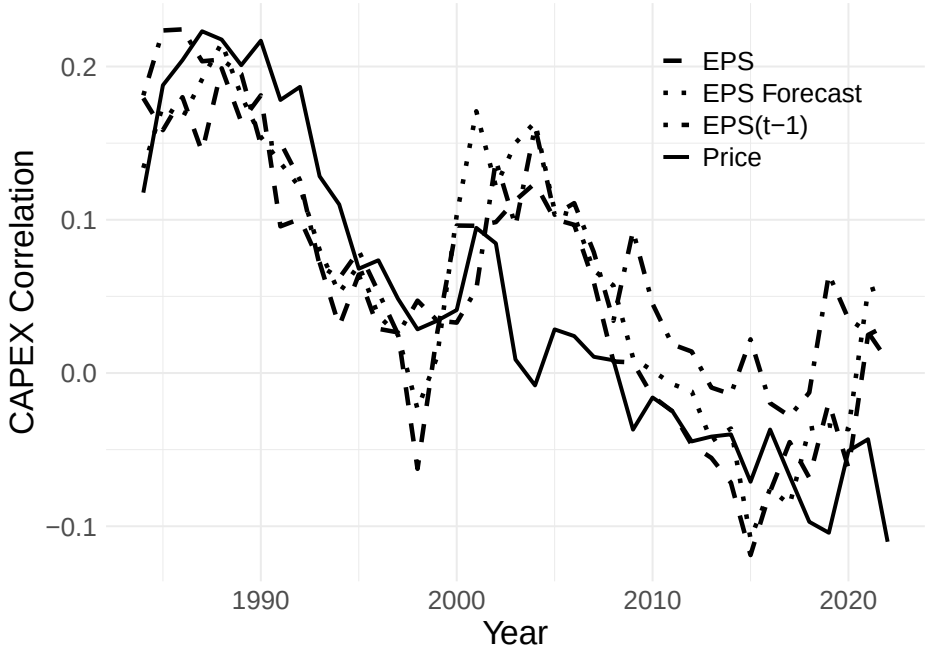


Figure 15: CAPEX vs Price and Earnings in the U.S.
Notes: All variables are normalized by total assets. EPS(t-1) refers to the previous announcement of earnings, while EPS refers to the announcement to come.

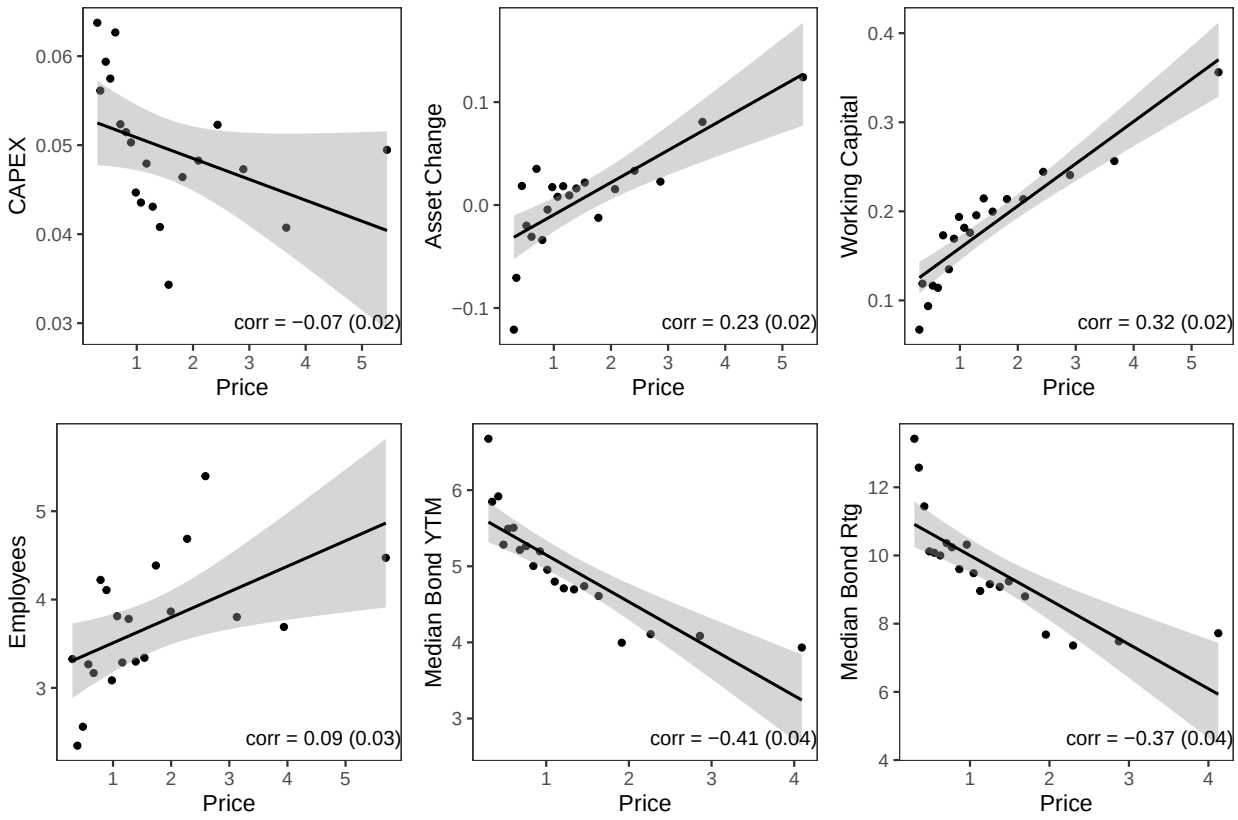


Figure 16: Binscatter Plot of Price Correlations with Measures of Input Allocation, U.S. 2015

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 smaller bond rating refers to 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 and observations that are at least 6 months before 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 the maximum yield-to-maturity

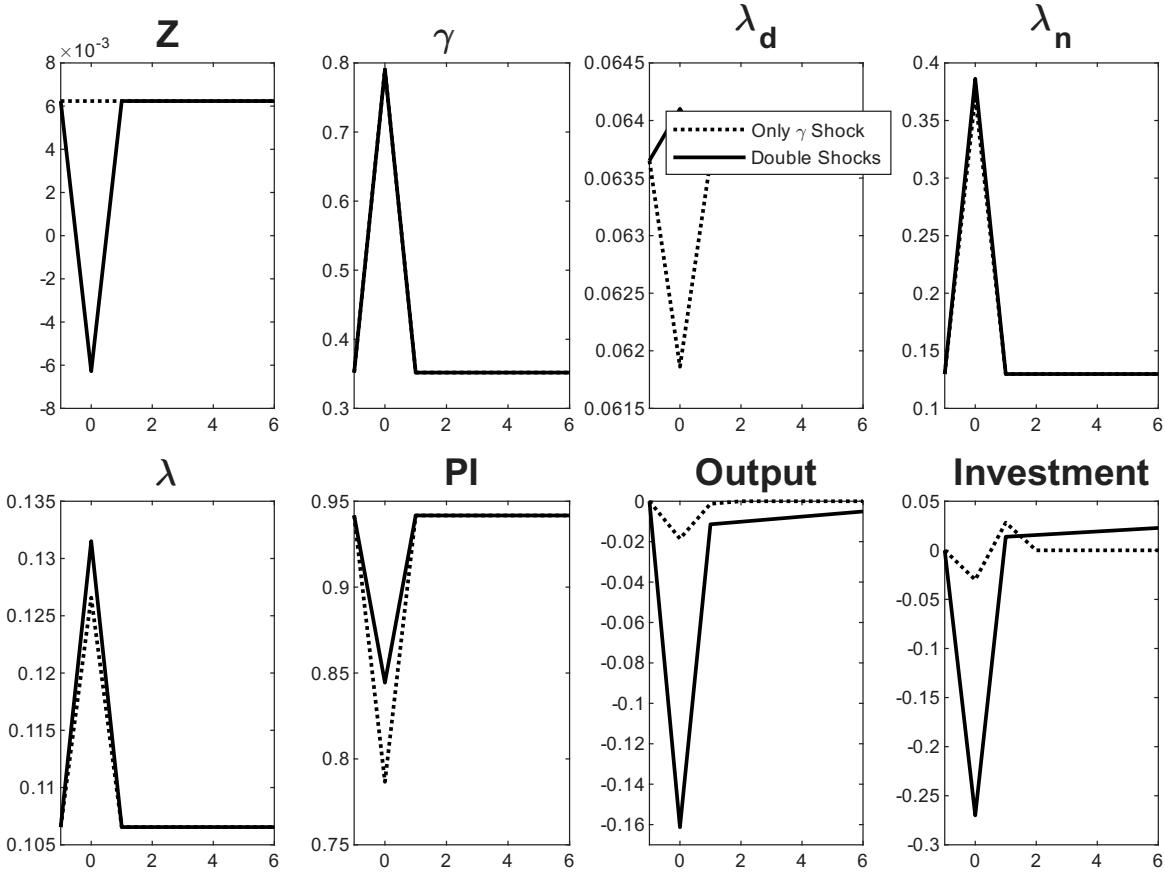


Figure 17: Additional Impulse Response Functions

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.