Market Power and Price Informativeness*

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Abstract

We study the distributional effects of asset ownership on price informativeness in a general equilibrium model featuring large investors (oligopolists) who have price impact and learn about individual asset payoffs, and competitive fringe that only learns from asset prices. We find that price informativeness is non-monotonic in the oligopolists' aggregate size, decreasing in the sector's concentration and in the size of the passive oligopolistic sector. We further decompose the size effect into a learning channel capturing investors' quality of private signals and an information pass-through channel measuring the sensitivity of investors' trades to private signals, and show that the latter channel is the primary source of variation in price informativeness.

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1 Introduction

Investing in financial assets is one of the major cornerstones of wealth accumulation. The demand side of financial markets is typically divided between institutional investors, often distinguished by their large size and the amount of information they produce[1], and retail investors, who are small and relatively less informed. The distribution of asset ownership and its impact on market stability and welfare has attracted considerable attention from market participants, policy makers, and academics. One major consideration is the effect of *large* active and passive investors on asset prices and, more broadly, on capital allocation efficiency. In this paper, we analyze theoretically the impact of the size, concentration, and active/passive ownership share of large investors on price informativeness, a measure of market efficiency that has gained significant interest among academics over the last few years (e.g., Bai, Philippon, and Savov (2016), Davila and Parlatore (2020), and Farboodi, Matray, Veldkamp, and Venkateswaran (2020)).[2]

At the heart of our analysis lies an endogenous trade-off between the information acquisition and trading decisions of investors of different sizes. On the one hand, some large active investors may decide to acquire private signals, the use of which could increase the amount of information revealed in asset prices. On the other hand, all large investors also recognize their price impact, which makes them trade less on any information they acquire *and* affects their learning choices. We show that this tradeoff can be captured by two channels that determine the behavior of price informativeness: the *information pass-through channel*, which quantifies the sensitivity of trading decisions to information, and the *learning channel*, which isolates the pure effect of the information choices on portfolios. The interaction of these two channels results in price informativeness that has a non-monotonic relationship with aggregate share of large investors and a strong negative relationship with the concentration of their ownership. We also show how these channels generate a negative general equilibrium amplification effect on price informativeness from an increase in the size of the passive investing sector through re-optimization of active learning decisions.

To explore the endogenous interaction between learning and trading, we build a new theory

[1] For example, in 2019, the institutional ownership of an average stock in the US equaled around 60%. Within the institutional sector, active investors who rely on private information hold about the same share of the market as do passive investors who do not trade for information reasons. The ownership structure is heavily skewed, with the ten largest investors holding, on average, 35% of total shares outstanding, and it varies greatly across individual assets.

[2] Our measure of price informativeness, defined as as the covariance of the price with the fundamental, normalized by the volatility of the price, has a strong economic appeal in that it can be derived as a welfare measure using Q-theory. It increases with the correlation between the price and the fundamental, and the volatility of the fundamental, as correlation is more meaningful when the unobserved variable is more volatile. Analytically, it represents the reduction in the variance of posterior beliefs when agents use price as a signal about fundamentals.

that features large investors with varying sizes. Specifically, our setting includes a mass of atomless competitive traders, called the fringe, each of whom takes prices as given, and l large *oligopolists*– investors who know that their trades move prices.[3] Each oligopolist is endowed with a capacity to collect information, which they can use to reduce uncertainty about asset payoffs. They are also able to learn from market prices. Fringe investors do not have any information capacity but they can learn from the public signal of the price. Finally, oligopolists are strategic in that they respond optimally to other investors' endogenous learning and portfolio decisions across multiple assets, defined to be heterogeneous in terms of their supply process and fundamental volatility.

We model individual learning choices using the theory of rational inattention of Sims (2003). Investors allocate their learning capacity optimally across assets, depending on the assets' characteristics and the investors' objective functions. After learning choices have been made, trading takes place via demand schedule competition. Broadly, our theory extends the work of Kyle (1989) and Vives (2011) to allow for endogenous information choices under non-symmetric allocations of information and trades. The equilibrium is a fixed point involving not only demand schedules but also learning choices across multiple assets and multiple oligopolists. Both choices are asymmetric if oligopolists differ in terms of their sizes. This generalization is non-trivial and allows us to address new questions concerning the impact of large investors' aggregate size and concentration on price informativeness as well as the role of differential information capacity when we include passive investors.

In order to gain further insights into the role of information pass-through and the learning channels in determining price informativeness, we contrast two market structures: perfect competition, where informed investors are atomless, and monopoly, with one informed large trader. We show that in the perfectly competitive case, increasing the size of the informed sector at the expense of the size of the fringe, monotonically increases price informativeness for each asset. The learning and information pass-through channels collapse to one. Intuitively, because investors have no price impact, they always fully act on their information, which then gets revealed in asset prices. With a larger mass of informed investors, more information capacity is devoted to learning about each asset's payoff. Consequently, price informativeness increases both in the aggregate and in the cross-section of individual assets.

[3] This modeling assumption stands in contrast to that in the literature with oligopolistic traders and noise traders, in which oligopolists make up 100% of the market; hence, comparative statics with respect to the sector size are trivially ruled out. Additionally, the presence of competitive fringe ensures existence of equilibrium for small number of strategic traders, in contrast to Kyle (1989).

By contrast, in the case of a monopolistic investor, we find that the aggregate price informativeness is *non-monotonic* in the size of a monopolist, first increasing—just like in the competitive limit—but eventually decreasing to zero as the size grows. The primary force responsible for this non-monotonic behavior is the information pass-through channel. On the one hand, as the price impact of his trades grows, the monopolist reduces trading sensitivity to his signals, revealing less information in prices. On the other hand, size itself increases the importance of his trades for market clearing, meaning they reveal more information in prices. Eventually, in the limit, a monopolist that makes up the whole market does not trade at all. In sum, the presence of market power can have a detrimental effect on price informativeness.

To allow for richer ownership structures, we further study the predictions of the model with oligopolistic investors. Due to complexity of the modeling framework, which involves solving for equilibrium in learning and trading strategies, we resort to numerical solutions. In the first experiment, we study the model results as a function of size of the oligopolistic sector. We find a hump-shaped response of price informativeness, a result that is qualitatively consistent with the one based on the monopolistic framework. Also similar, a decomposition of price informativeness into the learning channel and the information pass-through channel reveals that the information pass-through channel is the primary force driving price informativeness. In the second experiment, we vary the concentration of the oligopolistic sector, holding its total size fixed. We show that an increase in concentration, conditional on sector size, reduces price informativeness, the result driven by both the learning and the information pass-through channels. Intuitively, an increased concentration means polarization of sizes and a smaller information pass-through for both the oligopolist that grows in size (because of the growing price impact) and the one that diminishes in size (because of a lower economic importance). Simultaneously, since investors endogenously adjust their learning, we also observe a reduction in average price informativeness due to the learning channel, driven by the fact that the shrinking oligopolist is specializing and the growing oligopolist is diversifying learning. Overall, the two channels contribute to the total negative relationship between concentration and price informativeness.

In the third experiment, we increase the size of the passive sector at the cost of the active sector. We show that the aggregate price informativeness generally decreases, yet still exhibits a hump-shaped pattern driven by information pass-through. A more nuanced picture emerges for individual assets. As the size of the passive sector increases, the now smaller active investors focus their learning on fewer assets. Specifically, assets in large supply (with higher returns to learning) observe an increase in their price informativeness, while assets in small supply (with lower returns to learning) observe a decrease. This heterogenous cross-sectional response to a growing passive sector is observationally consistent with the pattern of cross-sectional changes in price informativeness documented in Farboodi et al. (2020).

In our final experiment, we examine the role of endogenous learning. We compare the predictions of our benchmark model with a model in which learning choices are exogenously fixed, holding the informational capacity constraint the same across models. We show that fixing information choices significantly affects the conclusions of our experiments. In the experiments that change total size or the size of passive sector, an exogenously fixed information choice determines the size of the oligopolistic sector which maximizes price informativeness. This optimum can be higher or lower than that implied by the endogenous-information benchmark model, depending on the distribution of the exogenous information. For the concentration experiment, we show that fixing information choices can actually overturn the result that price informativeness is decreasing in concentration, giving instead a hump-shaped response for certain parameter values. Intuitively, the only channel that operates in the exogenous information case is the information pass-through channel; hence, the shape of the price informativeness response crucially depends on the information endowment of the oligopolist whose information pass-through changes the most (through their size) in the experiment. We conclude that allowing for endogenous learning is essential when studying the interaction between ownership structure and information content of asset prices.

1.1 Related Literature

The literature on informed trading with market power dates back to Kyle (1985) and Grinblatt and Ross (1985) whose setups feature one strategic trader, and Kyle (1989) and Holden and Subrahmanyam (1992), who extend the model to an oligopolistic framework.[4] The effects of market size on price informativeness and efficiency have been studied in models of oligopolistic financial markets by Vives (2011), Rostek and Weretka (2012), and Vives (2014). Lambert, Ostrovsky, and Panov (2018) further extend the Kyle (1989) model to study the relation between the number of strategic traders and information content of prices in a general stochastic environment. Kyle, Ou-Yang, and Wei (2011) allow for endogenous information acquisition in a one-asset economy, but their mechanism focuses on the contracting features of delegation. Finally, Yang (2020) ex-

[4]Models in which traders condition on others' decisions also include Foster and Viswanathan (1996) and Back, Cao, and Willard (2000).

amines the role of price feedback effects in the oligopolistic market for firm disclosure and price informativeness.

Our work differs from the literature in several dimensions. The first important departure is the way in which we model size, or market power. The literature typically uses either a market maker (or market making sector) or atomistic traders. As a result, the relative 'size' or 'market power' of informed participants only gets adjusted if the total number of informed or uninformed traders changes. Our framework adjusts size and market power of individual traders by changing their assets under management, making it relevant for our motivating empirical evidence. The second important departure is that all of the papers assume either a single large trader, or a set of symmetric (in size) large traders. Our model allows for arbitrary distributions of size and market power, which allows us to characterize the impact of sector concentration. To our knowledge, our paper is the first theoretical information-driven treatment of the effects of sector concentration on price informativeness. Third, none of the papers studies the implications of the model that features both active and passive large traders in the multi-asset framework. This problem has become particularly relevant in recent years with a sudden growth of the passive sector. Finally, most (but not all) of the papers on strategic trading do not consider endogenous information acquisition, or cross-sectional effects of multiple assets, which are both angles we examine as well, linking us to another strand of the extant literature, discussed below.

Our general equilibrium model builds on the literature on endogenous information choice, in the spirit of Sims (1998, 2003). More closely related to our application are the models of costly information of Van Nieuwerburgh and Veldkamp (2009, 2010), Mondria (2010), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), and Kacperczyk, Nosal, and Stevens (2019). Ours is the first theoretical study to introduce (heterogeneous) market power into a model with endogenous information acquisition. This aspect allows us to study strategic responses of oligopolistic traders in terms of their demand and information choices. Within the theory of rational inattention, we show that the framework with large investors leads to an interior learning solution, a contrast to the previous studies with competitive agents, in which each investor learns about one asset only. Finally, and very distinctly, the competitive framework under rational inattention would imply a monotonic relation between aggregate size and price informativeness, whereas this relation becomes hump shaped when price impact is explicitly modeled.

More generally, our study can be placed in the literature on information production and asset prices. Bond, Edmans, and Goldstein (2012) survey the literature on information production in financial markets, emphasizing the differences between new information produced in markets (revelatory price efficiency: RPE) and what is already known and merely reflected in prices (forecasting price efficiency: FPE). Our focus is solely on RPE and is largely dictated by the modeling framework we use.[5] Goldstein and Yang (2015) study incentives for trading on private information and its effect on price informativeness, identifying effects similar to our measure of information pass-through in a setup with exogenous information. Relative to that paper, we additionally introduce multiple assets and market power, as well as a public price signal. In a broader institutional context, Stein (2009) develops a model of market efficiency and sophisticated (arbitrage) capital in the presence of capital constraints. Garleanu and Pedersen (2018) examine the role of search frictions in asset management for price efficiency. Breugem and Buss (2019) study the impact of benchmarking on price informativeness in a costly information acquisition competitive equilibrium model.

Our paper also connects to empirical literature on the topic. Bai, Philippon, and Savov (2016) show that price informativeness is greater for stocks with greater institutional ownership. Our model delivers such a result for a range of ownership values. However, our theoretical analysis implies that, beyond certain levels, ownership may in fact reduce price informativeness, due to excessive price impact. Our micro-founded equilibrium model allows us to study the underlying economic mechanism in depth, as well as additionally investigate the role of ownership concentration and passive ownership. Farboodi et al. (2020) examine differences in price informativeness between companies included and not included in the S&P 500 index. They show that the indexed companies exhibit larger efficiency and are the only ones to exhibit an increase in price informativeness, which they attribute to a composition effect of these companies, being older and larger. We show that the predictions of our model are consistent with these empirical findings, suggesting that they may be partially due to a rise of passive investing. Kacperczyk, Sundaresan, and Wang (2020) show that the stock ownership by active institutional investors, domestic and foreign, causally increases price informativeness of stocks in which they invest more. Finally, we add to a growing empirical literature that studies the impact of market structure in asset management on various economic outcomes. Following the diseconomies of scale argument of Chen, Hong, Huang, and Kubik (2004), Pástor, Stambaugh, and Taylor (2015) show significant diseconomies of scale at the industry level. Using a merger between BlackRock and BGI as a shock to market power, Massa, Schumacher, and

[5] Theoretical work on asset prices and real efficiency also includes Dow and Gorton (1997), Subrahmanyam and Titman (1999), Kurlat and Veldkamp (2015), and Edmans, Goldstein, and Jiang (2015).

Yan (2020) study the asset allocation responses of their competitors. Our work complements these studies by studying theoretically the effect of ownership structure on price informativeness.

The rest of the paper is organized as follows. In Section 2, we present a set of motivating facts on institutional ownership and its concentration. Section 3 and Section 4 present the theoretical framework, the equilibrium concept, and derive theoretical results for the competitive and monopolistic cases of the model. In Section 5, we derive numerical solutions for the oligopolistic setting of the model and discuss comparative statics. Section 6 concludes.

2 Motivating Facts

In this section, we present a number of facts that motivate our theoretical investigation. To position our model in the appropriate empirical context, we assume that institutional investors are a close empirical representation of investors with market power; also, at least some of them get private signals. We believe this assumption is not controversial given the extant evidence on the topic; however, we note that our model is not geared to confront all economically relevant aspects of institutional trading such as agency, optimal contracting, or managerial turnover.

First, we show that institutional investors hold a large fraction of equities in many developed economies. Second, we show that the holdings of the largest institutions, a measure of investor concentration, are significant in most markets. Finally, using US market data, we demonstrate a large and increasing role of passive institutional investors. While we present time-series trends, our focus in the model is on the static effects of market structures observed in the data.[6]

The set of facts we document are derived from global institutional stock ownership data from Factset. Factset provides comprehensive information on institutional ownership of equity from over 40 countries. These data are considered the most comprehensive in the market and cover more than 98% of total value of publicly listed companies worldwide. The data are measured at a quarterly frequency and span the period 2000–2017.

Our first variable is institutional ownership, calculated as the stock-level share of stocks held by financial institutions at the end of a given year relative to the number of shares outstanding. Since we are interested in market-level quantities, we take simple averages across all stocks in our sample. Because institutions tend to favor large companies in their portfolios we use equal

[6] A parallel microstructure literature (Boehmer and Kelley (2009)) examines empirically the relation between institutional ownership and price efficiency due to trading intensity. Efficiency there is measured using variance ratios and pricing errors. Their conclusions are akin to ours.

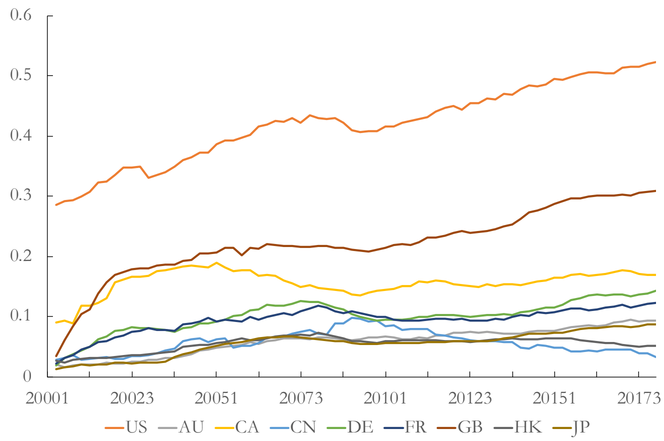

Figure 1: Institutional ownership worldwide.

weighting, rather than value weighting, as a more conservative metric of the patterns in the data. We present the data for the largest equity markets worldwide, including Australia, Canada, China, France, Germany, Hong Kong, Japan, the United Kingdom, and the United States. We present the time-series evolution of institutional size in Figure 1. The data indicate a large cross-country variation in the importance of institutional owners. Capital market-based economies, such as the UK and the US, have the highest levels of institutional ownership, with the US having an average ownership of almost 60%.[7] Bank-based economies, such as Germany, France, and Japan have lower levels of institutional holdings. However, except for China, all of these markets have witnessed a rapid increase in institutional ownership by 200% to 300% over the last 20 years. As institutional investors currently make up a significant percentage of total global asset holdings, questions of their optimal size are of increased importance.

Next, we focus on market concentration. We define concentration as the ratio of the holdings of the top-5 largest institutions to total institutional holdings for a given stock. As before, we further average the ratios across all stocks in each period. We present the time-series evolution of the country-specific quantities in Figure 2. Despite their different levels of institutional ownership, all the markets exhibit a high degree of market concentration, between 50% and 80%. Unlike the steady increase in the size of institutional investors over the past 20 years, the concentration levels have been relatively stable over time. Of course, given the increase in total ownership of the sector, the largest players have increased their presence in the market, which makes their impact potentially much more significant.

Our final evidence presents the distribution of ownership with respect to institutions' informa-

[7]This number reaches almost 80% when we aggregate ownership using market weights of individual firms.

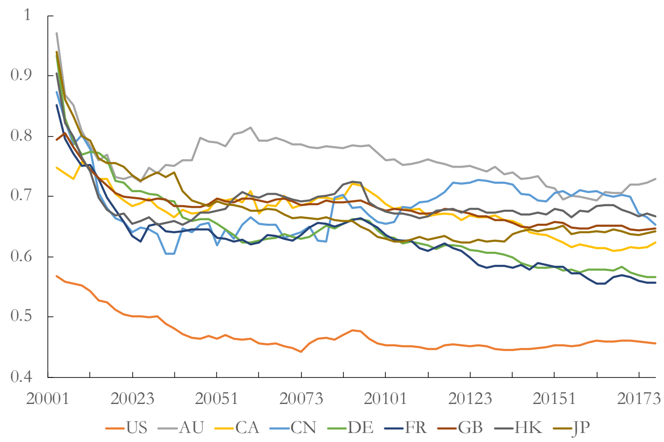

Figure 2: Top-5 investors as a share of total institutional ownership.

tion. We define active investors as those engaged in information acquisition and passive investors as those who strictly invest in pre-defined index portfolios. The latter group includes both index mutual funds and ETFs. Since identifying passive funds in the global context is difficult, we use the evidence from the Investment Company Institute (ICI) Fact Book. This source restricts our analysis to the US market alone, though we believe that similar patterns are likely in other markets as well. We calculate the share of passive ownership in total stock ownership of institutional investors and present the results for the period 1993–2017 in Figure 3. We observe a significant increase in passive ownership over time. While in mid–1990's passive funds accounted for less than 5% of the institutional equity market size in the US, this share has increased to 45% by 2017. In fact, as of December 2020, passive funds hold a greater share of equities than active funds do.

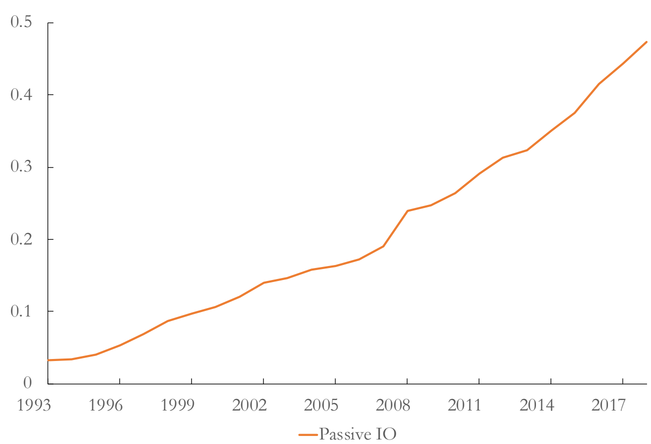

Figure 3: Passive ownership as a share of total institutional ownership.

3 Model

In this section, we set up a model of information and portfolio choices of investors who are constrained in their capacity to process information about asset payoffs. We allow for asset heterogeneity in the supply process and fundamental volatility, and investors to differ in their information capacity and size.[8] Specifically, some of the investors are large, meaning that their trades have price impact, which they internalize. In equilibrium, this affects their information and portfolio choices as well.

Setup A unit continuum of investors is divided into two groups. One group, which we call the *competitive fringe*, has mass $\lambda_0 < 1$ of atomistic uninformed investors, denoted (collectively) by $j = 0$.[9] The second group consists of l-many *oligopolists*, indexed by $j \in \{1, ..., l\}$, each having positive information capacity K_j and size λ_j, such that $\sum_{j=0}^{l} \lambda_j = 1$. The sizes of oligopolists parameterized by λs map monotonically into ownership and hence, in our experiments, we use them as proxies for ownership shares. Oligopolists are large in the sense that they have positive mass, and hence price impact, which they internalize. Each investor solves an information capacity allocation problem and portfolio choice problem to maximize the expectation of mean-variance utility over end-of-period wealth, with a common risk aversion coefficient, $\rho > 0$.[10]

The financial market consists of a risk-free asset, with price normalized to 1 and net payoff r, and $n > 1$ risky assets, indexed by i, with prices p_i and independent payoffs $z_i = \bar{z} + \varepsilon_i$, with $\varepsilon_i \sim N(0, \sigma_i^2)$.[11] The risk-free asset is in unlimited supply, and each risky asset has supply $\bar{x}_i$, which is subject to stochastic shocks $\nu_i \sim N(0, \sigma_{xi}^2)$, independent of payoffs and across assets. The shocks are meant to reflect non-optimizing noise traders, who trade for reasons orthogonal to prices and payoffs (e.g., liquidity, hedging, or life-cycle reasons).[12]

[8]In the numerical section, we specifically focus on supply heterogeneity, but our results apply more generally. As a robustness, we have also calculated results from a model with asset heterogeneity in the form of fundamental volatility, the factor that also provides a clear ranking of the returns from learning about an asset. The conclusions from the experiments are qualitatively similar.

[9]The presence of fringe investors allows us to naturally construct experiments in which we vary the size of the overall large investors sector share relative to the total. Crucially, in contrast to Kyle (1989), the presence of competitive fringe ensures the existence of an equilibrium for an arbitrary number of strategic traders.

[10]The mean-variance utility assumption is standard in the literature and is known to provide tractability to the model, allowing for at least partial analytical characterization of equilibrium. As a result of this assumption, our model does not feature wealth effects. In terms of preference heterogeneity, our numerical solution can easily allow for risk aversion heterogeneity among investors, but that is a dimension we do not pursue in this paper.

[11]Under the assumption of independence of signals across assets, independence of payoffs occurs without loss of generality, as asset payoffs can be easily orthogonalized under such assumptions. For a discussion of this issue, see Van Nieuwerburgh and Veldkamp (2010).

[12]In principle, for versions of our model with multiple oligopolists, the introduction of noise traders is not strictly

Investors know the distributions of all shocks, but not the realizations (ε_i, ν_i). Prior to making their portfolio decisions, oligopolistic investors can obtain information about some or all of the risky asset payoffs in the form of private signals. All investors can learn from prices as well. The quality of the private signals is constrained by each investor's capacity to process information, $K_j > 0$, which places a limit on the reduction of uncertainty about asset payoffs. We model the constraint as a capacity for entropy reduction (Shannon (1948)), following the work of Sims (2003). Higher capacity can be interpreted as having more resources to gather and process news about different assets, and it translates into signals that track the realized payoffs with higher precision. Investors choose how to allocate attention across different assets. After observing their private signals, all investors also observe the price and update their beliefs (without using information capacity). Prices adjust endogenously to clear markets. Oligopolists are strategic and directly reason through the market clearing equation in order to determine their own price impact as well as how much to update their beliefs from the price signal.

Trading strategy We assume (and verify as an equilibrium) that the portfolio strategy of each investor $j \geq 0$ for each asset i takes the form of a linear demand schedule which depends on their private signal about that asset, s_{ji}, and the price p_i, (as in Kyle (1989)):[13]

$$q_{ji} = \beta_{0ji} + \beta_{1ji}s_{ji} - \beta_{2ji}rp_i. \tag{1}$$

Here, β_{1ji} measures the response of quantity demanded by oligopolist j in response to his private signals.[14] The price coefficient β_{2ji} measures the responsiveness of the quantity demanded to the price.

Given their posterior beliefs, $(\mu_{ji}, \hat{\sigma}^2_{ji})$, each investor chooses a trading strategy, summarized by $\{\beta_{0ji}, \beta_{1ji}, \beta_{2ji}\}_{i=1,\ldots,n}$, as a best response to the other investors' trading strategies $\{\beta_{0ki}, \beta_{1ki}, \beta_{2ki}\}_{k\neq j,i=1,\ldots,n}$, conditional on other oligopolists' learning choices. Hence, for every

necessary, as the noise in oligopolists' signals will always show up in the price, preventing perfect revelation of fundamentals (Vives (2011) shows that noise traders can be eliminated under certain conditions). By maintaining noise traders, however, we ensure that the models considered in the NRE literature remain as special cases of this model. We also have asymmetries in learning equilibria, so some assets will only be learned about by one oligopolist. When that happens, without noise traders, the oligopolist's signal is perfectly revealed in the price.

[13]This is in line with the contributions of Vives (2011), Vives (2014), and Kyle (1989). Here, additionally to those papers, we must allow for heterogeneous βs, because the oligopolists will generically have endogenously heterogeneous information. This flexible setup encompasses demand schedule competition if oligopolist j takes other oligopolists' βs as given and also Cournot competition if oligopolist j takes other oligopolists' qs as given. The Cournot case is equivalent to setting $\beta_{2ki} = 0$ in equation (4).

[14]As we show below, in our setup, the posterior mean is equal to the signal s_{ji}.

learning choice by oligopolists, the $\{\beta_{0ji}, \beta_{1ji}, \beta_{2ji}\}_{j=0,...,l,i=1,...,n}$ are a Nash equilibrium.

For the demand schedules submitted by investors to be part of a Nash equilibrium, they must be consistent with utility maximization. Given posterior beliefs of an investor j, $(\mu_{ji}, \hat{\sigma}^2_{ji})$, after observing private signals (for oligopolists) and the price signal (for all investors), utility maximization is:

$$U_j = \max_{\{q_{ji}\}_{i=1}^n} E[W] - \frac{\rho}{2}V[W] \quad s.t. \quad W = (1+r)\bar{W} + \sum_{i=1}^n q_{ji}(z_i - rp_i), \tag{2}$$

where the expectation and variance are conditional on the investor j's information set. Without loss of generality, we normalize initial wealth $\bar{W}$ to zero. The solution to the above problem depends on whether the investor is an oligopolist ($j > 0$) or a member of the competitive fringe ($j = 0$). In particular, the *demand of an oligopolist* j for asset i depends on the degree of impact oligopolist j has on the price of asset i, captured by dp_i/dq_{ji}, introducing a wedge into the otherwise standard CARA demand function:

$$q_{ji} = \frac{\mu_{ji} - rp_i}{\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}}. \tag{3}$$

Oligopolists internalize their price impact when making their trading decisions, given (1), which, together with market clearing, implies:

$$\frac{dp_i}{dq_{ji}} = \frac{\lambda_j}{r\sum_{k\neq j}\lambda_k\beta_{2ki}}. \tag{4}$$

The impact that oligopolist j has on the market price depends positively on his size λ_j, and negatively on the sizes of the other investors, as well as on the responsiveness of other investors' quantities to the price, captured by β_{2ki}. Intuitively, an increase in an oligopolist j's quantity implies that the equilibrium price goes up by *less* if an increase in the price induces other investors' quantities to drop by more (that is, if they have high β_{2ki}'s). In other words, if the other investors' demands are very price-elastic, that makes oligopolist j's price impact smaller.

Finally, demand by the *competitive fringe investors* does not induce price movement and hence their optimization implies:

$$q_{0i} = \frac{\mu_{0i} - rp_i}{\rho\hat{\sigma}^2_{0i}}. \tag{5}$$

Private signals We assume that all oligopolists observe their own private signals and then the price, which they use to update their beliefs without using additional information capacity. The choice of the vector of private signals $s_j = (s_{j1}, ..., s_{jn})$ about the vector of payoffs $z = (z_1, ..., z_n)$ is subject to a capacity constraint $I(z; s_j) \leq K_j$, where $I(z; s_j)$ quantifies the reduction in entropy of the payoffs conditional on the signals (defined below). For analytical tractability, we assume that the signals s_{ji} are independent across assets and investors. In this case, the total quantity of information obtained by an investor based on private signals is the sum of quantities of information obtained for each individual asset, $I(z_i, s_{ji})$. We can think of the information problem as a decomposition of each payoff into the signal component s_{ji} and a residual component δ_{ji} that represents the information loss because of the investor's capacity constraint. That is, $z_i = s_{ji} + \delta_{ji}$. If the signal and the residual are independent, then posterior beliefs are also normally distributed random variables. In particular, an investor j's posterior beliefs about asset i's payoff, after observing the private signal, are distributed according to

$$z_i | s_{ji} \sim \mathcal{N}(\xi_{ji}, \eta_{ji}^2),$$

where the posterior mean and variance are given by Bayes' rule:

$$\xi_{ji} = \bar{z} + \frac{cov(z_i, s_{ji})}{var(s_{ji})}(s_{ji} - \bar{z}) = s_{ji},$$

$$\eta_{ji}^2 = \sigma_i^2 - \frac{cov^2(z_i, s_{ji})}{var(s_{ji})},$$

and $\bar{z}$ stands for the signal's unconditional mean. We define $\alpha_{ji} \equiv \frac{\sigma_i^2}{\eta_{ji}^2}$ to be an investor j's learning choice for each asset. Given a private signal's structure, the information contained in a signal is given by

$$I(z_i, s_{ji}) = \frac{1}{2} \log \left(\prod_{i=1}^{n} \alpha_{ji} \right),$$

which gives rise to the capacity constraint:

$$\prod_{i=1}^{n} \alpha_{ji} \leq e^{2K_j},$$

Price signal All investors submit demand schedules that condition on the price p_i, which is equivalent to them observing the price explicitly. Therefore, as long as processing the information contained in the price does not take any information capacity, investors will use the observation of the price, and update their beliefs according to Bayes' rule, which gives posterior beliefs with mean and variance given by:

$$\begin{aligned}\mu_{ji} &= s_{ji} + \frac{cov_j(z_i,p_i)}{var_j(p_i)}(p_i - E_j[p_i]), \qquad (6)\\ \hat{\sigma}^2_{ji} &= \frac{1}{\alpha_{ji}}\sigma_i^2 - \frac{cov_j^2(z_i,p_i)}{var_j(p_i)}.\end{aligned}$$

where the subscript j denotes the conditionality of each moment on the observed signal s_{ji}, which in the case of the competitive fringe is uninformative, and $\xi_{0i} = \bar{z}$. Note that the update is investor specific, because after observing the private signals, the covariance, variance, and expectation of the price vary across investors.

Given (3) and (5), the demand schedule choices of investors, conditional on information choices $\{\alpha_{ji}\}_{i=1,\dots,n;j=1,\dots,l}$, can be summarized by a fixed point $\{\beta_{0ji},\beta_{1ji},\beta_{2ji}\}_{i=1,\dots,n;j=0,\dots,l}$ of the system:[15]

$$\beta_{0ji} = \frac{-\frac{\gamma_{ji}}{\Delta_i}\left(-\bar{x}_i + \sum_{k=0}^{l}\lambda_k\beta_{0ki} + \sum_{k\neq j}\lambda_k\beta_{1ki}\frac{1}{\alpha_{ki}}\bar{z}\right)}{\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}} \qquad (7)$$

$$\beta_{1ji} = \frac{1-\frac{\gamma_{ji}}{\Delta_i}\left(\lambda_k\beta_{1ji} + \sum_{k\neq j}\lambda_k\beta_{1ki}(1-1/\alpha_{ki})\right)}{\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}}, \qquad (8)$$

$$\beta_{2ji} = \frac{1-\gamma_{ji}/r}{\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}}, \qquad (9)$$

where $\frac{dp_i}{dq_{ji}} = \frac{\lambda_j}{r\sum_{k\neq j}\lambda_k\beta_{2ki}}$ is the price impact of investor $j \geq 1$ on asset i, $\gamma_{ji} \equiv \frac{cov_j(z_i,p_i)}{var_j(p_i)}$ is used by agents to update their beliefs after observing the price using Bayes rule, and $\Delta_i \equiv r\sum_{j=0}^{l}\lambda_j\beta_{2ji}$ is the market sensitivity to the price weighted by size. Importantly, for the fringe, $\frac{dp_i}{dq_{0i}} = 0$. It is straightforward to see that all coefficients are decreasing in price impact (meaning that demand is lower as trades impact prices more). Further, as the overall market responds more to prices (higher levels of Δ_i), traders' demands increase as well. We present the details of the derivation of oligopolist utility and explicit maximization problem in Appendix A.2.[16]

[15] We provide detailed derivations in Appendix A.1.

[16] We do not need to set up the ex-ante utility of the fringe investors since they make no information allocation choice, as $K_0 = 0$.

3.1 Equilibrium

Denote $\bar{\alpha} = \{\alpha_{ji}\}_{i=1,...,n;j=1,...,l}$ and $\bar{\alpha}_{-j} = \{\alpha_{ji}\}_{i=1,...,n;j=1,...,j-1,j+1,...,l}$. Let $\bar{\beta}(\bar{\alpha}) = \{\beta_{0ij}, \beta_{1ij}, \beta_{2ij}\}_{i=1,...,n;j=0,...,l}$ be a solution to (7)-(9) for a given information choice $\bar{\alpha}$.[17] For $i = 1, ..., n$ and $j = 0, ..., l$, an equilibrium consists of information and quantity choices of the fringe and oligopolists $\{\alpha_{ji}, q_{ji}\}$, the demand schedules choices $\bar{\beta}(\bar{\alpha})$, and price p_i, such that

1. $\alpha_{0i} = 1$, and for every $j \geq 1$, $\{\alpha_{ji}\}_{i=1,...,n}$ maximizes ex-ante expectation of utility in (2), given $\bar{\beta}(\bar{\alpha})$ and $\bar{\alpha}_{-j}$. That is, each oligopolist's information choice is a best response to the other oligopolists' information choices, while all the oligopolists internalize the effect of their information choices on the equilibrium behavior of everyone's quantities captured by β's .

2. $\bar{\beta}(\bar{\alpha})$ satisfies (7)-(9) for every feasible $\bar{\alpha}$ and $j \geq 0$. That is, given information choices and β of the other investors, each investor's quantity choices are optimal.

3. q_{ji} is given by (1) for all i and $j \geq 0$.

4. For all realizations of shocks z_i and private signals s_{ji}, the price p_i clears the market for all i, that is,
$$\sum_{j=0}^{l} \lambda_j q_{ji} = x_i.$$

It is a known problem in the literature (e.g., Lambert, Ostrovsky, and Panov (2018)) that allowing for asymmetric strategies—in our case in learning and trading—introduces a significant level of complexity to the model, precluding analytical characterization of equilibrium existence. In our general setup, each oligopolist faces a different residual demand function that depends on other oligopolists' strategies, and chooses potentially different slopes of their demand schedules due to the fact that information is endogenously asymmetric as well. For that reason, we resort to characterizing the predictions of the general model numerically in Section 5, while at the same time we verify that the optimality conditions are satisfied with a very high numerical precision for all our solutions.[18]

[17] In principle, there may be more than one $\bar{\beta}$ solution to the fixed point (7)-(9). However, in our numerical examples, we always find a unique positive solution.

[18] Our model has two layers of strategic interactions among oligopolists, in terms of their learning and trading strategies. Hence, uniqueness of equilibrium allocations is not guaranteed in general. In the parameterization we use in the numerical section, we find the learning strategy and best responses by always starting the solution algorithm from the largest oligopolist. We find that the algorithm finds the same solution independent of the initial guess. We also find that the allocation changes smoothly as we change parameters, suggesting that we are focusing on a single equilibrium outcome.

3.2 Price Informativeness

Following the work of Bai, Philippon, and Savov (2016), we define price informativeness as the covariance of the price with the fundamental shock, normalized by the variance of the price. Given this definition, price informativeness in our model can be expressed as

$$PI_i = \frac{cov(p_i, z_i)}{\sigma_{pi}} = \frac{\sigma_i \sum_{j=1}^{l} \omega_{ji} \frac{\alpha_{ji}-1}{\alpha_{ji}}}{\sqrt{\frac{\sigma_{xi}^2}{\sigma_i^2} + \left[\sum_{j=1}^{l} \omega_{ji} \frac{\alpha_{ji}-1}{\alpha_{ji}}\right]^2 + \sum_{j=1}^{l} \omega_{ij}^2 \frac{\alpha_{ji}-1}{\alpha_{ji}^2}}}, \tag{10}$$

where

$$\omega_{ji} \equiv \frac{\partial \lambda_j q_{ji}}{\partial s_{ji}} = \lambda_j \beta_{1ji}$$

is the responsiveness of an oligopolist's total demand for asset i to his private signal s_{ji}, which we term *the information pass-through*. The PI measure maps well to our theory as the square root of the reduction in the variance of posterior beliefs of a Bayesian agent who learns from the price.[19]

The endogenous terms ω_{ji} and α_{ji} enter the expression for price informativeness above in an intuitive way. First, holding constant learning choices captured by α_{ji}, price informativeness is impacted by the degree to which demand choices of the oligopolists change in response to signals via the ω_{ji}s. If the oligopolists adjust their demand a lot in response to private signals, that is, they have high ω_{ji}s, price informativeness will increase due to higher covariance term $\omega_{ji}\frac{\alpha_{ji}-1}{\alpha_{ji}}$. At the same time, higher responsiveness of quantities to private signals means that any errors in the signals also show up in oligopolists' demand, which decreases price informativeness via the terms $\omega_{ij}^2\frac{\alpha_{ji}-1}{\alpha_{ji}^2}$ in the denominator. These terms capture the noise in oligopolist signals. In the numerical section, we isolate the effect of changing ω_{ji}s on price informativeness and term it *the information pass-through channel*. Second, for a given information pass-through, price informativeness is affected by learning choices captured by α_{ji}s. They increase price informativeness by increasing the covariance of the price with the fundamental via the terms $\omega_{ji}\frac{\alpha_{ji}-1}{\alpha_{ji}}$, but also affect the noise in the price via the residual noise in private signals through the terms $\omega_{ij}^2\frac{\alpha_{ji}-1}{\alpha_{ji}^2}$.[20] When we isolate the impact of learning choices on price informativeness, we refer to these effects as *the learning channel*.

[19]See Appendix A.3 for details.

[20]These terms are non-monotonic in α: increasing for $\alpha < 2$, then decreasing.

4 Characterizing Price Informativeness

Below, we present an analytical characterization of the impact of different market structures on price informativeness. We focus on two extremes in terms of the market power: *perfect competition*, where we assume that investors are atomless, followed by the case of a *monopoly* with a single large informed investor. We show that in the perfectly competitive case, price informativeness grows monotonically with the size of informed investor sector. Then, we show that in the monopolistic case, price informativeness is hump shaped in the size of the monopolist, driven by the information pass-through channel. In Section 5, we present numerical results for the general oligopoly case, where we show that the intuition from the monopoly case considered here holds in the model.

Perfect Competition In this section, we assume that all investors are perfectly competitive price takers, with fraction λ_1 having positive capacity $K > 0$, and fraction $\lambda_0 = 1 - \lambda_1$ having zero capacity. Both types of investors learn from prices without using informational capacity. We guess and later verify that agents choose one asset to spend all of their informational capacity on–meaning that each asset has two types of investors: informed investors who have spent all their capacity on that asset, and uninformed investors who have not. Investors solve the standard portfolio allocation problem, given their posterior beliefs, which results in optimal portfolio holdings given by:

$$q_{ji} = \frac{\mu_{ji} - rp_i}{\rho \hat{\sigma}^2_{ji}},\ j = 0, 1 \tag{11}$$

where μ_{ji} and $\hat{\sigma}^2_{ji}$ are the mean and variance of investors' posterior beliefs after observing their private signals (in case of informed investors) and the price, given by (6).

Given the optimal portfolio holdings as a function of posterior beliefs, the ex-ante optimal distribution of signals maximizes the ex-ante expected utility:

$$E_0[U_j] = \frac{1}{2\rho} \sum_{i=1}^{n} \frac{E_0 \left(\mu_{ji} - rp_i\right)^2}{\hat{\sigma}^2_{ji}}, \tag{12}$$

where the choice of the vector of signals $s_j = (s_{j1}, ..., s_{jn})$ about the vector of payoffs $z = (z_1, ..., z_n)$ is subject to a capacity constraint $I(z; s_j) \leq K_j$. Following Admati (1985), we conjecture and later verify that prices are

$$p_i = a_i + b_i \varepsilon_i - c_i \nu_i, \tag{13}$$

where coefficients a_i, b_i, c_i are determined in equilibrium. Summarizing learning choices by $\alpha_{1i} \equiv \frac{\sigma_i^2}{\hat{\sigma}_{1i}^2}$, we can express the maximization problem of an informed investor as[21]

$$\max \sum_{i=1}^{n} G_i \alpha_{1i} \quad \text{subject to} \quad \frac{1}{2}\sum_{i=1}^{n} \log(\alpha_{1i}) \leq K_1,$$

where

$$G_i \equiv \frac{(\overline{z} - ra_i)^2}{\sigma_i^2} + (1 - rb_i)^2 + r^2 c_i^2 \frac{\sigma_{xi}^2}{\sigma_i^2}. \tag{14}$$

The linear objective function and concave functional form of the constraint implies that each competitive investor $j = 1$ specializes in learning only about one asset. For the remaining assets, that investor's holdings are determined by prior beliefs. In equilibrium, all assets that are learned about provide the same gain G_i, and all other assets offer strictly lower gains. The equilibrium of the competitive economy can be summarized by the mass of informed agents that learn about asset i, $\hat{\lambda}_i \geq 0, \forall i$, with $\sum_{i=1}^{n} \hat{\lambda}_i = \lambda_1$.

We can use the market clearing condition to derive the price coefficients and express G_i as a function of fundamentals and learning choices only, leading to Proposition 1, which states that investors have preference to learn about assets that are in large supply ($\bar{x}_i$) or are more volatile (σ_{xi}^2 or σ_i^2). Additionally, G_is depend on λ_1 only through $\hat{\lambda}_i$, and $dG_i/d\hat{\lambda}_i < 0$. As a consequence, and given $\sum_i \hat{\lambda}_i = \lambda_1$, we have (for proof, see Appendix A.5):

Proposition 1. *The following statements hold in equilibrium:*

1. *The shadow value of information, G_i, is increasing in $\bar{x}_i$, σ_{xi}^2, and σ_i^2.*

2. *For all assets $i = 1, ..., n$, $\frac{d\hat{\lambda}_i}{d\lambda_1} \geq 0$, with strict inequality for assets that are learned about.*

Price informativeness in the competitive model is given by:

$$PI_i = \frac{b_i \sigma_i^2}{\sqrt{b_i^2 \sigma_i^2 + c_i^2 \sigma_{xi}^2}} = \frac{\sigma_i^2}{\sqrt{\sigma_i^2 + (\frac{c_i}{b_i})^2 \sigma_{xi}^2}}.$$

Using the price coefficients derived in Appendix A.5, we have

$$\frac{c_i}{b_i} = \frac{\rho \sigma_i^2}{\hat{\lambda}_i (\alpha_i - 1)}.$$

[21]For detailed derivation of (14), see Appendix A.4.

Since all investors allocate their full capacity to a single asset, the average learning choice of investors learning about asset i, denoted α_i above, is equal to e^{2K_1}, and price informativeness is strictly monotonic in $\hat{\lambda}_i$. Hence, Proposition 1 implies:

Corollary 1. $\frac{dPI_i}{d\lambda_1} \geq 0\, \forall i$, *with strict inequality if the asset is learned about* ($\hat{\lambda}_i > 0$).

Summarizing the competitive model, each individual asset's price informativeness is a strictly monotonic function of the size of the informed competitive investor sector, λ_1, and thus so is the average price informativeness.

Monopoly Our second analytical case is that of a single large informed investor ($l = 1$) of size λ_1. In this case, the price impact term simplifies to $\frac{dp_i}{dq_{ji}} = \frac{\lambda_1}{r(1-\lambda_1)\beta_{20i}}$ and the β terms of the monopolist are $\beta_{01i} = 0$, and $\beta_{11i} = \beta_{21i} \equiv \beta_i$, as there is no additional information in the price over and above that coming from the private signal of the monopolist (and hence the monopolist does not update from the price, that is, $\gamma_{1i} = 0$). We simplify the notation and denote the monopolist's learning choice as α_i. In this setting, price informativeness is:

$$PI_i = \frac{cov(p_i, z_i)}{\sigma_{pi}} = \frac{\sigma_i \lambda_1 \beta_i \frac{\alpha_i - 1}{\alpha_i}}{\sqrt{\frac{\sigma_{xi}^2}{\sigma_i^2} + \left[\lambda_1 \beta_i \frac{\alpha_i - 1}{\alpha_i}\right]^2 + \lambda_1^2 \beta_i^2 \frac{\alpha_i - 1}{\alpha_i^2}}}, \tag{15}$$

where the information pass-through term, $\lambda_1 \beta_i$, is given by

$$\lambda_1 \beta_i = \frac{\lambda_1 (1 - \lambda_1) \beta_{20i} \alpha_i}{\rho (1 - \lambda_1) \sigma_i^2 \beta_{20i} + \lambda_1 \alpha_i}. \tag{16}$$

In equilibrium, the information pass-through is always non-negative, but non-monotonic, converging to zero as λ_1 tends to the boundary values of 0 or 1. The following Proposition summarizes this result (proof is in Appendix A.6):

Proposition 2. *In the monopoly case,* $\lim_{\lambda_1 \to \{0,1\}} PI_i = 0$.

Proposition 2 implies that the non-monotonicity of the information pass-through is going to contribute to the potential non-monotonicity of price informativeness on an asset-by-asset basis, and quantitatively it can contribute to the non-monotonicity of the average price informativeness. Further, for very small or very large λ_1, information pass-through is the only determinant of the shape of price informativeness, as it converges to zero independent of the learning choices of the monopolist. This result stands in contrast to the competitive case, in which price informativeness is strictly monotonic.

5 Numerical Analysis

The analytical results in Section 4 provide insights into the relationship between market size and price informativeness. However, they focus on special cases. In particular, the case of a monopolist may be limiting for the robustness of some of our results, especially those involving strategic interactions of learning choices among oligopolists. Further, it does not allow us to study the richer distributional forces, such as the effects of market concentration. To address these issues, we generalize our setting to a full oligopolistic model. We provide a set of numerical results from the solution to the equilibrium of the model in order to document the response of price informativeness to the changing size and concentration of the oligopolistic sector, as well as the growth of passive sector. As we show below, our numerical results on market power are consistent with those in Section 4.

In our simulations, we choose parameters with two goals in mind: they have to be empirically relevant and the resulting solution needs to involve some degree of learning. We set parameter values such that the benchmark model exhibits: (i) learning about all assets for at least some size distributions, (ii) aggregate oligopoly holdings of between 50% and 70%, and (iii) market excess real return of around 7% (the average over the 1980–2018 period). These targets pin down the size parameter λ_0 (averaged across simulation), the risk aversion coefficient ρ, and the common informational capacity K_j. The risk-free rate is set to match 2.5% real return on 3-month T-bills. The rest of the parameters do not have empirical targets, so we set them arbitrarily and verify the robustness of our results to different choices. We set the payoff distribution to $\bar{z} = 10$ and $\sigma_i = 1.35$ for all i, the number of assets $n = 10$, and the number of oligopolists $l = 2$.[22] Risky assets are heterogeneous in their supply size, $\bar{x}_i$, which we interpolate linearly between 1 and 7, and σ^2_{xi}, for which we target a coefficient of variation of 0.2, for all i.[23] We allow λ_0 and $\{\lambda_j\}_{j=1}^{l}$ to vary across experiments. We summarize the parameter values in Table 1.

The simulation generates equilibrium levels of price informativeness, and oligopoly holdings size and concentration for each asset. In our experiments, we use λs as proxies for stock ownership

[22] The last choice is largely dictated by the computational tractability. $l = 2$ is the minimum number of oligopolists which allows us to speak about the effects of size, concentration, and passive ownership on price informativeness. Experiments with greater values of l do not alter our conclusions but limit the range of sizes we can consider.

[23] We have also studied asset heterogeneity in terms of payoff volatility, with no qualitative difference in the results.

Table 1: Parameter values.

Parameter	Symbol	Value
Mean payoff	$\bar{z}_i$	10
Supply	$\bar{x}_i$	$\in [1,7]$, linear distribution across i
Number of assets, oligopolists	n, l	$10, 2$
Risk-free rate	$r-1$	2.5%
Vol. of noise shocks	σ_{xi}	target coefficient of variation of 0.2 for all i
Vol. of asset payoffs	σ_i	1.35 for all i
Risk aversion	ρ	0.93
Information capacities	K_j	4 for all j except growth in passive investing experiment
Investor masses	λ_0, λ_j	depending on experiment

shares. While not exactly the same, the λ shares map monotonically into ownership shares and hence give us a basis to interpret changes in λs as changes in relative ownership. We report the effects of different market structures on aggregate price informativeness. We present the average and the cross-section of price informativeness, as well as the decomposition into the *learning channel* implied by endogenously changing α_{ji}s in response to different market structures, and the *information pass-through channel* implied by changing ω_{ji}s, consistent with equation (10). Notably, in all the experiments, we do not change the aggregate amount of information in the economy (the maximum quality and number of signals that investors receive does not change), which means that all the effects we find are solely due to changing information choices arising from different market structures.

5.1 Size of the Oligopoly Sector

In our first experiment, we examine the response of price informativeness to changes in the total size of the oligopoly sector, $\sum_{j=1}^{n} \lambda_j \equiv 1 - \lambda_0$, while holding the concentration of the sector fixed. Specifically, we fix the relative distribution of λ_js so that the larger oligopolist is always six times larger than the smaller one for each iteration. We solve the model with respect to different values of $1 - \lambda_0$, ranging from 20% (small oligopoly sector) to 95% (large oligopoly sector). Our experiment can inform several types of regulation, such as limits on entry or limits on a per-agent size in a given market.

Figure 4 presents the relationship between the size of the oligopoly sector and aggregate price informativeness. In the figure, each point corresponds to one solution of the model. We observe that price informativeness exhibits a hump-shaped relationship with the sector size. This result implies an interior solution for optimal oligopoly sector size from the perspective of maximizing price informativeness.

As the size of the sector increases, in equilibrium, oligopolists endogenously adjust both their learning choices, captured by the learning channel (α_{ji}), as well as their choices of how much to trade on their information, captured by the information pass-through channel (ω_{ji}). To provide more detail on the relative importance of each channel, we show their independent contributions to overall price informativeness. Our analysis indicates that the information pass-through channel is responsible for the hump-shaped response of price informativeness to increasing size. This nonlinearity is a result of two competing forces that enter information pass-through: first, increasing the size of an oligopolist mechanically pushes information pass-through up via a pure effect of λ_j; second, increasing the oligopolists' size increases their price impact, and reduces their β_{1ji} – oligopolists trade less aggressively on their signals. When oligopolists are small relative to the market, the increase in λ_j outweighs the decrease in β_{1ji}, leading to an increasing information pass-through and hence price informativeness. However, above a certain size, oligopolists lower their β_{1ji} more than one-to-one with their size increase, reducing information pass-through and price informativeness. Intuitively, at small sizes, oligopolists can trade relatively freely without moving the price, but the larger they get, the larger the price impact of their trades, which reduces the benefit of trading on private information. Consequently, fixing the information pass-through to the value corresponding to a large size of the sector significantly lowers price informativeness and removes its hump-shape.

The effect due to the learning channel is smaller but it is still quantitatively significant. Notably, pure relocation of learning implies an increasing price informativeness as size of the oligopolistic sector increases. This is due to the fact that a larger oligopolists' size implies more diversification of learning, which increases average price informativeness, as information is produced about a larger set of assets.[24] Additionally, the model that allows both for the endogenous learning and the changing information pass-through results in higher price informativeness, as is evidenced by the finding that fixing the learning channel to the value associated with a large size of the oligopolistic sector lowers price informativeness by up to 20%.

In Figure 5, we show the results of our size experiment for individual assets that are cross-

[24] In the model, there is also an opposing force arising from a strategic substitutability in learning: as more assets are learned about, oligopolists find it beneficial to choose different subsets of assets to learn about, which reduces information about individual asset payoffs on the intensive margin. Quantitatively, the extensive-margin diversification benefit of size dominates.

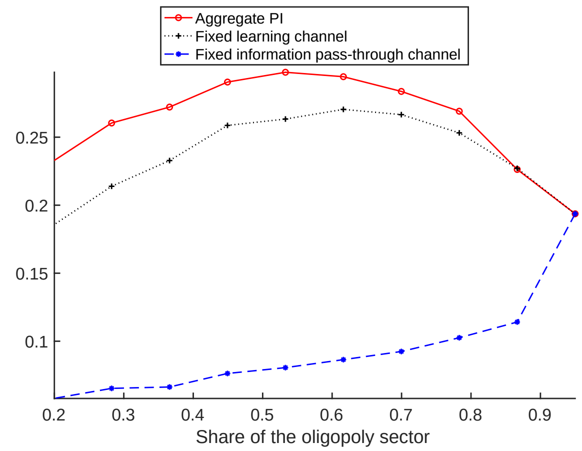

Figure 4: Decomposition of price informativeness and the oligopoly sector size, $\sum_{j=1}^{l} \lambda_j$.

sectionally different in terms of their supply. The driving force in the cross-section is the interplay between the extensive and intensive margins of learning. On the extensive margin, since the marginal benefit of learning is increasing in asset supply, there is a clear preference for learning: high-supply assets are learned about first. On the intensive margin, all assets that are learned about, are subject to the similar effects we showed for the aggregate size effects. The strength of each effect determines the ultimate relationship between size and price informativeness. For our simulation, high-supply assets (e.g., assets $8-10$) observe a hump shape between size and price informativeness, the result driven by information pass-through. In turn, low-supply assets (e.g., assets $1-4$) are affected more by the extensive margin of α_{ji}s. As the assets enter the pool of assets that is learned about, their price informativeness increases significantly. At the same time, as some oligopolists start learning about these assets, they necessarily devote less capacity to the high-supply assets, which exacerbates the drop in those assets' price informativeness.

5.2 Concentration of the Oligopoly Sector

In our second experiment, we study the consequences of a change in the concentration of the oligopoly sector for price informativeness, a novel analysis that is possible to carry out in the oligopoly setup. We define concentration as the ratio of λ_1 to $\lambda_1 + \lambda_2$, where λ_1 is the size of the larger oligopolist. Next, holding the size of the oligopoly sector constant at 55% (the value that maximizes aggregate price informativeness), we vary the ratio between 52% (low concentration) and 92% (high concentration). Figure 6 presents the aggregate PI, as well as its decomposition in

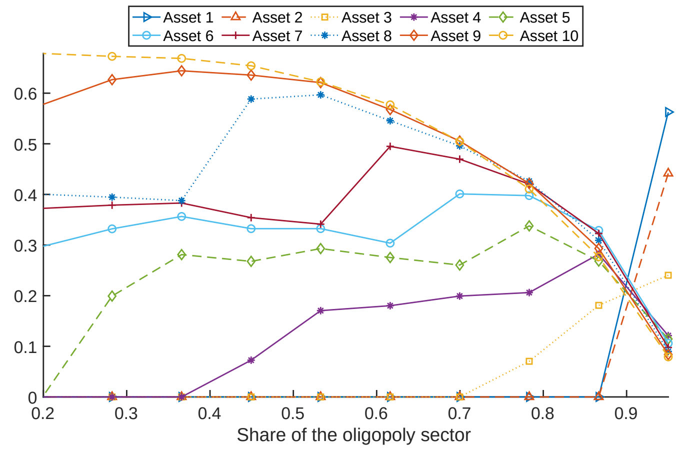

Figure 5: Asset-level price informativeness and the oligopoly sector size, $\sum_{j=1}^{l} \lambda_j$.

which we keep the learning channel and the information pass-through channel fixed at the levels implied by the lowest-concentration scenario.

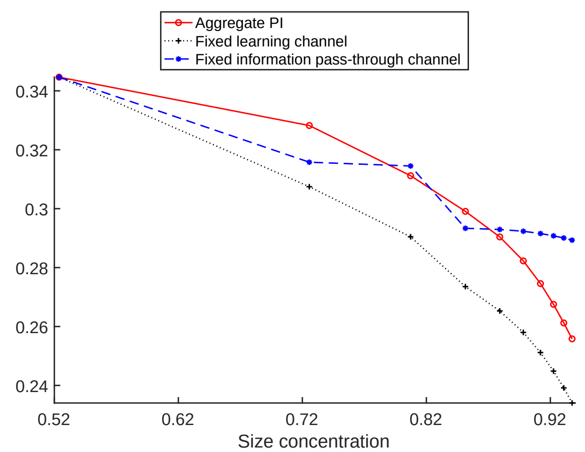

Figure 6: Aggregate price informativeness decomposition and the size concentration, $\frac{\lambda_1}{\lambda_1+\lambda_2}$.

The figure shows that the average price informativeness is decreasing in the size concentration. It also illustrates that both the response of the learning channel and the information pass-through channel contribute to decreasing price informativeness. Similar to the size experiment, the quantitative impact of the information pass-through channel is more significant. Intuitively, a high level of concentration leads to a polarization of sizes, and hence a lower information pass-through for *both* the large and small-size oligopolists, driven by the previously established hump-shaped relationship between size and pass-through. This logic is evident from the scenario in which we fix the learning channel: changes in information pass-through alone imply an even steeper drop in price informativeness as we increase concentration. For the scenario in which information pass-through is fixed at the low concentration level, our analysis also indicates a decreasing price informativeness. The mechanism involves a reallocation of learning by both the growing and the shrinking oligopolist. A larger oligopolist diversifies his learning more, which benefits average price informativeness, while a smaller oligopolist specializes, which hurts average price informativeness. The net effect is a decrease in price informativeness, with the changes in slope of the fixed information pass-through line happening due to changes in the extensive margin of learning.

In Figure 7, we additionally present the overall impact of concentration on price informativeness on an asset-by-asset basis. We can see that, within our parametrization, the aggregate effect comes from price informativeness decreasing for most assets rather than from changes in the number of assets learned about. This is because the number of assets learned about is largely dependent on the total size of the oligopolistic market—something we keep constant in this experiment. It should be noted that at an individual oligopolist level, the extensive margin of learning is still operational in this experiment. However, as Figure 7 illustrates, across the different concentration levels, at least one oligopolist is learning about a constant set of assets.

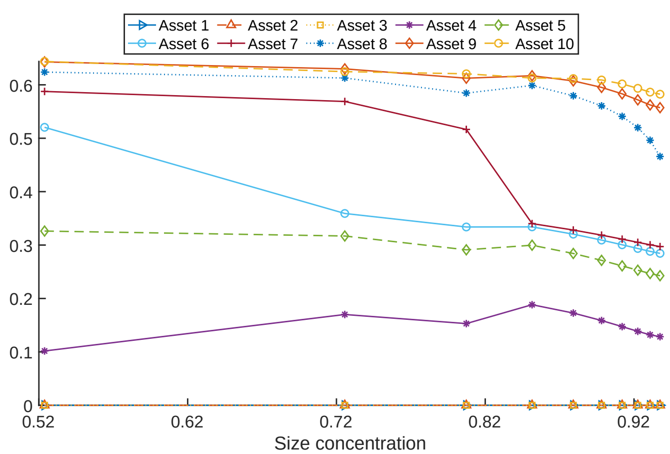

Figure 7: Asset-level price informativeness and the size concentration, $\frac{\lambda_1}{\lambda_1+\lambda_2}$.

5.3 Growth in Passive Investing

The distinct importance of oligopolistic traders comes from two sources: their informational advantage and their large size. While all oligopolists exert price impact, not all of them necessarily use informationally intensive trading strategies. To explore the consequences of this tradeoff for price informativeness, we introduce a large passive investor, defined as one who does not produce his own information about asset payoffs.[25] We analyze the model outcomes resulting from an increase in the size of the passive investor relative to that of the active investor. For our experiment, we set $K_1 = 0$ and $K_2 = 9.5$, and vary the size of the passive investor relative to that of the active investor between 0.01 and 10, while keeping the sum of sizes constant, at 55%. We present the results for aggregate and cross-sectional effects in Figures 8 and 9, respectively.

We document a number of novel results. First, PI is mildly hump-shaped and generally decreases with the size of the passive sector: As the active oligopolist's size shrinks, his information pass-through initially goes up and then decreases, which results in the same shape of price informativeness, consistent with the intuition developed in previous sections. This effect is supported by the counterfactual price informativeness in which information-pass-through is fixed. In Figure 8, we can observe that the shape of price informativeness response in that case does not exhibit a humped shape. Second, as the active oligopolist is getting smaller, he becomes more specialized in learning – reduces the number of assets he learns about – which increases price informativeness of the high-supply assets, and reduces price informativeness of the low-supply assets, as is shown in Figure 9. Notably, without this reallocation of learning, the PI curve would have been higher and much more hump-shaped: the fixed learning channel curve in Figure 8 illustrates this point.

The cross-sectional patterns of price informativeness, illustrated in Figure 9, are particularly noteworthy. Specifically, the response of price informativeness to the growth of passive investor share is heterogeneous across assets. Price informativeness of large-supply assets (e.g., $6 - 10$) goes up as the active oligopolist decides to specialize in those, while price informativeness of small-supply assets (e.g., $1-5$) decreases. This result is reminiscent of a similar heterogeneity documented empirically in Farboodi et al. (2020). Our framework links these responses to the growth in passive investing.

[25] We model passive investors as price-sensitive agents (they learn from prices) who do not have any information capacity of their own, which is consistent with Grossman and Stiglitz (1980). There are other ways to define passive investors, but the two characteristics that we believe are consistent across the definitions are that passive investors do not produce information, and that they care about price impact when trading. If these two characteristics are preserved, other formulations of passive investors (not being able to learn from prices, buying market shares, etc) will preserve our results.

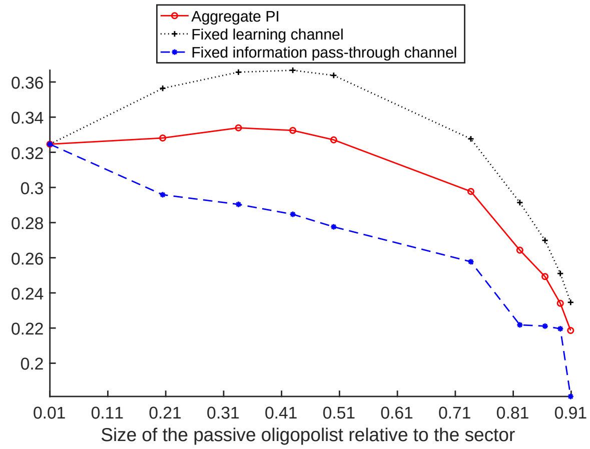

Figure 8: Price informativeness decomposition and the size of passive oligopolist.

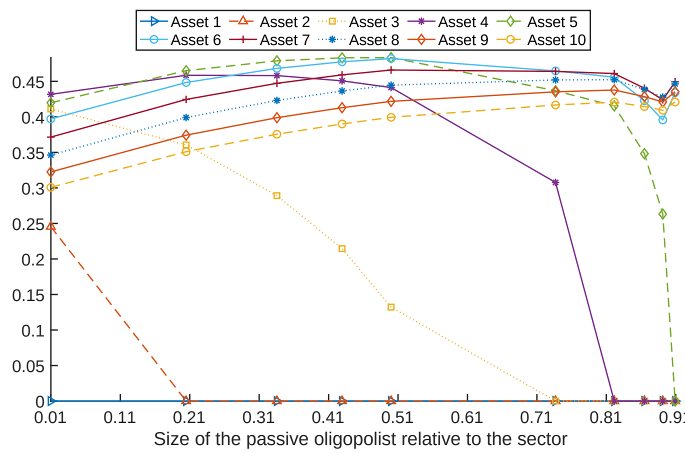

Figure 9: Asset-level price informativeness and the size of passive oligopolist.

5.4 The Role of Endogenous Learning

One of the novelties of our framework is that it features endogenous information choices together with quantity choices. The contrasting model with a fixed information structure is similar in spirit to Kyle (1989), in that the effect of market power on price informativeness depends entirely on the adjustment of quantities. To demonstrate the importance of modeling endogenous learning choices, in Figures 10–12, we present the results from our three experiments—size, concentration, and the active/passive split—for the benchmark and exogenous information models. In the exogenous information case, we endow oligopolists with the α_{ji} choices that are solutions to the benchmark model for one of the parameterizatons in each experiment, and eliminate the possibility of re-optimization along the learning dimension. The response of the fixed information model is driven entirely by information pass-through and hence the intuition is similar to our discussion of the fixed learning channel decomposition for the full model. However, it is important to note that the information pass-through response is endogenously influenced by the information choices, and therefore the exogenous information results in this section and the fixed learning channel results in the previous subsections are qualitatively and quantitatively different.

Figure 10 presents the results for the size experiment. Depending on the choice of α_{ji} (case 1 or 2), one solution of the fixed information model coincides with that of the benchmark model. However, comparison of the predictions across the three models implies that the specific choice of the information structure significantly impacts the size of the oligopoly sector that maximizes price informativeness. In particular, for both exogenous information cases, the maximum is at 45%. Compared to 53% maximum for the benchmark model, fixing the information structure can lead to an understatement of the optimal oligopoly share by up to 20% relative to the endogenous information model.

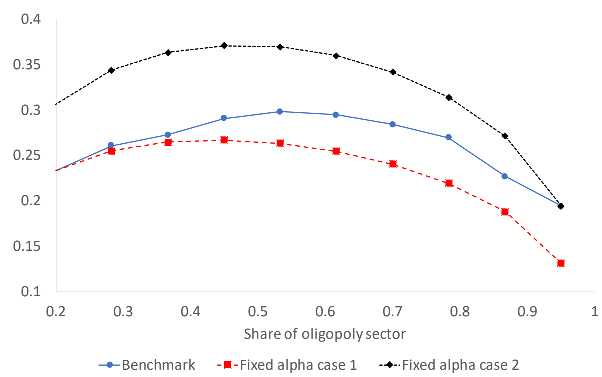

Figure 10: Price informativeness with endogenous (benchmark) and exogenous (fixed alpha) information choice as a function of the oligopoly sector share of the market.

The comparison for the concentration experiment is presented in Figure 11. In this case, the conclusions are even starker. Exogenous learning choices can produce an interior optimal concentration (case 1 in Figure 11 gives a maximum at 72%) while the benchmark model indicates that concentration always hurts price informativeness.

Finally, the experiment on the growth of the passive investor (Figure 12) provides similar conclusions to the size experiment. The two exogenous cases obtain their maxima of price informativeness at 72% and 42% of ownership share of the passive oligopolist relative to the oligopolistic sector.

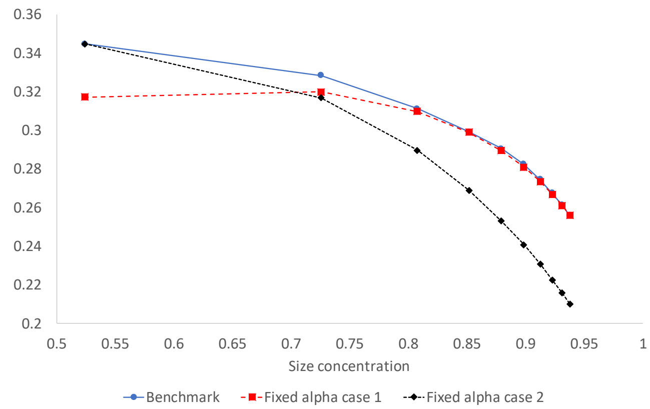

Figure 11: Price informativeness with endogenous (benchmark) and exogenous (fixed alpha) information choice as a function of size concentration.

These levels are an overstatement of the optimal passive oligopolist share, in excess of 100%, relative to the endogenous information model-implied 33% share.

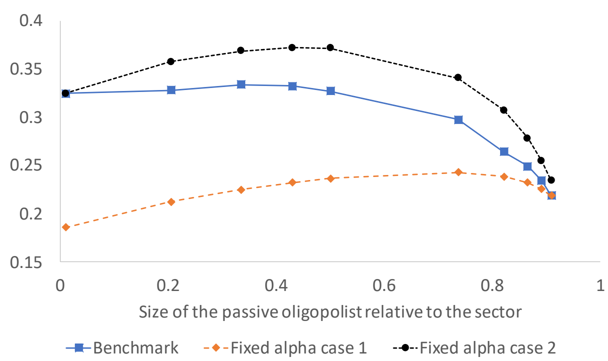

Figure 12: Price informativeness with endogenous (benchmark) and exogenous (fixed alpha) information choice as a function of passive oligopolist's size relative to the entire oligopolistic sector.

In sum, depending on the specific choice of the exogenous information structure, the conclusions about the impact of size, concentration, or passive ownership on price informativeness can be dramatically different. Hence, considering a fully endogenous adjustment of quantities *and* information choices when studying price informativeness is crucial for drawing conclusions about the efficiency of different ownership structures.

6 Concluding Remarks

Equities are overwhelmingly held by more sophisticated investors, and ownership is especially concentrated among the largest investors. This skewed ownership structure has triggered an active discussion among financial regulators and industry participants over its implications for welfare and financial stability. Proponents of regulation have argued in favor of reduced power for large institutions, while critics of such reforms argue that the information such institutions imbue into prices makes market concentration a worthwhile tradeoff. In the absence of a well-specified economic model and a properly specified objective function, it is difficult to shed light on the argument and understand how to quantify the tradeoffs of a more concentrated marketplace, where there can be concentration in assets under management, as well as in capacity for fundamental research.

This paper takes a step towards addressing this issue by developing a general equilibrium model in which asymmetric information, asymmetric market power, and asset heterogeneity are important determinants of the informational efficiency that regulators might want to maximize. While regulators' objective functions can take different forms, we believe that the setting in which informational content of prices is of a planner's interest is appropriate to characterize the world of equity ownership.[26] Our theory makes a methodological contribution in generalizing models of asymmetric information (building on, for example, Kyle (1989)), by explicitly modeling endogenously acquired information in the presence of asymmetric market power and nontrivial heterogeneities across investors and assets.

Contrary to common wisdom, our results suggest that an intermediate size of the institutional sector maximizes the information contained in prices. Our numerical simulations confirm that for ownership levels equal to those currently found in the U.S., average price efficiency is positively related to the levels of large ownership but negatively related to its concentration. Further, we show that average price informativeness across assets can be maximized for admissible values of ownership and concentration. This result suggests that policy makers should consider concentration in addition to size when constructing policies to maximize price efficiency.

Our model applies to settings that involve a rich cross-section of assets, informational asymmetries across oligopolistic agents, and differences in market power. At a broad, policy level, the model can be also fruitfully used in discussions of market transparency and access to information. At the same time, the model naturally abstracts from other dimensions relevant for policy makers, such as investment costs or sectoral fund flows given that the size distribution is an input in our analysis. We also abstract from endogenous changes in market structure due to entry and exit, which could change the aggregate amount of information in the economy. Finally, we omit any issues related to optimal asset management contracts. We leave these issues for future research.

[26] Most analyses of price informativeness in the literature show that price informativeness enhances efficiency of markets (Vives (2011), Vives (2014), Rostek and Weretka (2012), and Lambert et al. (2018)). A notable exception to this result is Vives (2017).

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A Appendix

A.1 Derivation of Equations (7)-(9)

The price observed by oligopolist k is

$$p_i \sum_{j=0}^{l} \lambda_j r \beta_{2ji} = -x_i + \lambda_k \beta_{1ki} s_{ki} + \sum_{j=0}^{l} \lambda_j \beta_{0ji} + \sum_{j=-k} \lambda_j \beta_{1ji} s_{ji}.$$

With $\Delta_i \equiv r \sum_{j=0}^{l} \lambda_j \beta_{2ji}$, we can write:

$$p_i = -\frac{1}{\Delta_i} x_i + \frac{1}{\Delta_i} \lambda_k \beta_{1ki} s_{ki} + \frac{1}{\Delta_i} \sum_{j=0}^{l} \lambda_j \beta_{0ji} + \frac{1}{\Delta_i} \sum_{j=-k} \lambda_j \beta_{1ji} s_{ji}$$

The conditional distribution of the signal s_{ji} is Normal, with mean $\bar{z} + (1 - \frac{1}{\alpha_{ji}})\varepsilon_i$ and variance $(1 - \frac{1}{\alpha_{ji}})\frac{1}{\alpha_{ji}}\sigma_i^2$, and hence, denoting $\zeta_{ji} \equiv s_{ji} - E(s_{ji}|z_i)$, we can write:

$$cov_k(z_i, p_i) = \frac{1}{\Delta_i} \sum_{j=-k} \lambda_j \beta_{1ji} cov_k(s_{ji}, z_i) = \frac{1}{\Delta_i} \sum_{j=-k} \lambda_j \beta_{1ji} cov_k((1 - \frac{1}{\alpha_{ji}})\varepsilon_i + \zeta_{ji}, \varepsilon_i) =$$

$$= \frac{1}{\Delta_i} \sum_{j=-k} \lambda_j \beta_{1ji} cov_k((1 - \frac{1}{\alpha_{ji}})\varepsilon_i, \varepsilon_i) = \frac{1}{\Delta_i} \sum_{j=-k} \lambda_j \beta_{1ji} (1 - 1/\alpha_{ji}) \eta_{ki}^2$$

$$= \frac{1}{\Delta_i} \frac{1}{\alpha_{ki}} \sum_{j=-k} \lambda_j \beta_{1ji} (1 - 1/\alpha_{ji}) \sigma_i^2$$

We note that the covariance of oligopolist k depends both on his own learning choices as well as the learning choices of the other oligopolists. This is also true for the variance of the price:

$$var_k(p_i) = (\frac{1}{\Delta_i})^2 \sigma_{xi}^2 + (\frac{1}{\Delta_i})^2 var_k(\sum_{j=-k} \lambda_j \beta_{1ji} (\bar{z}_i + (1 - \frac{1}{\alpha_{ji}})\varepsilon_i + \zeta_{ji})) =$$

$$= (\frac{1}{\Delta_i})^2 \sigma_{xi}^2 + (\frac{1}{\Delta_i})^2 \frac{1}{\alpha_{ki}} \sigma_i^2 \left[\sum_{j=-k} \lambda_j \beta_{1ji} (1 - \frac{1}{\alpha_{ji}}) \right]^2 + (\frac{1}{\Delta_i})^2 \sum_{j=-k} \lambda_j^2 \beta_{1ji}^2 (1 - \frac{1}{\alpha_{ji}}) \frac{1}{\alpha_{ji}} \sigma_i^2)$$

$E_{ki}[p_i|s_{ki}]$ is given by (omitting the conditioning on the signal notation)

$$E_{ki}[p_i] = -\frac{1}{\Delta_i} \bar{x}_i + \frac{1}{\Delta_i} \lambda_k \beta_{1ki} s_{ki} + \frac{1}{\Delta_i} \sum_{j=0}^{l} \lambda_j \beta_{0ji} + \frac{1}{\Delta_i} \sum_{j=-k} \lambda_j \beta_{1ji} (\bar{z}_i + (1 - 1/\alpha_{ji})(s_{ki} - \bar{z}_i))$$

$$E_{ki}[p_i] = s_{ki} \frac{1}{\Delta_i} \left[\lambda_k \beta_{1ki} + \sum_{j \neq k} \lambda_j \beta_{1ji} (1 - 1/\alpha_{ji}) \right] - \frac{1}{\Delta_i} \bar{x}_i + \frac{1}{\Delta_i} \sum_{j=1}^{l} \lambda_j \beta_{0ji} + \frac{1}{\Delta_i} \sum_{j=-k} \lambda_j \beta_{1ji} 1/\alpha_{ji} \bar{z}_i$$

Denote:

$$\Gamma_{ki} = -\frac{1}{\Delta_i} \bar{x}_i + \frac{1}{\Delta_i} \sum_{j=0}^{l} \lambda_j \beta_{0ji} + \frac{1}{\Delta_i} \sum_{j=-k} \lambda_j \beta_{1ji} 1/\alpha_{ji} \bar{z}_i$$

and

$$\theta_{ki} = \frac{1}{\Delta_i}\left[\lambda_k\beta_{1ki} + \sum_{j\neq k}\lambda_j\beta_{1ji}(1-1/\alpha_{ji})\right]$$

Plugging these results in (3), we get

$$q_{ji} = \frac{\mu_{ji} - rp_i}{\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}},$$
$$\mu_{ji} = s_{ji} + \frac{cov_j(z_i, p_i)}{\sigma^2_{pji}}(p_i - E_{ji}[p_i])$$
$$\hat{\sigma}^2_{ji} = \frac{1}{\alpha_{ji}}\sigma^2_i - \frac{cov^2_j(z_i, p_i)}{var_j(p_i)^2}$$

With $\gamma_{ji} \equiv cov_j(p_i)/\sigma^2_{pji}$, we can further write

$$q_{ji}(\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}) = s_{ji} + \gamma_{ji}p_i - rp_i - \gamma_{ji}(s_{ji}\theta_{ji} + \Gamma_{ji})$$

$$q_{ji}(\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}) = -\gamma_{ji}\Gamma_{ji} + s_{ji}(1-\gamma_{ji}\theta_{ji}) - r(1-\gamma_{ji}/r)p_i$$

Given that and equation (1), we obtain the fixed point for betas:

$$\begin{aligned}
\beta_{0ji} &= \frac{-\gamma_{ji}\Gamma_{ji}}{\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}} \\
\beta_{1ji} &= \frac{(1-\gamma_{ji}\theta_{ji})}{\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}}, \\
\beta_{2ji} &= \frac{1-\gamma_{ji}/r}{\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}}, \\
\frac{dp_i}{dq_{ki}} &= \frac{\lambda_k}{\sum_{j=-k}\lambda_j r\beta_{2ji}}.
\end{aligned}$$

A.2 Utility Maximization

The ex-ante information decision follows the maximization problem:

$$E_0U_j = \sum_{i=1}^{n} E_0(\hat{\mu}_{ji} - rp_i)^2\frac{\frac{\rho}{2}\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}}}{(\rho\hat{\sigma}^2_{ji} + r\frac{dp_i}{dq_{ji}})^2}$$

Using market clearing:

$$p_i = -\frac{1}{\Delta_i}x_i + \frac{1}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{0ji} + \frac{1}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{1ji}s_{ji},$$

where $\Delta_i \equiv r\sum_{j=0}^{l}\lambda_j\beta_{2ji}$, we compute $E_{ji}(\mu_{ji} - rp_i)^2 = \widehat{R}^2_i + \widehat{V}_{ji}$, where $\widehat{R}_i$ and $\widehat{V}_{ji}$ denote the ex-ante mean and variance of expected excess returns,

$$\hat{R}_i = E_{ji}(\mu_{ji} - rp_i) = \frac{r}{\Delta_i}x_i - \frac{r}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{0ji} + \bar{z} - \frac{r}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{1ji}\bar{z}$$

$$= \frac{r}{\Delta_i}x_i - \frac{r}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{0ji} + \bar{z}(1 - \frac{r}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{1ji})$$

We now compute

$$\hat{V}_{ji} = var(\mu - rp_i) = var(\mu_{ji}) + var(rp_i) - 2rcov(\mu_{ji}, p_i)$$

We obtain

$$\begin{aligned}
var(\mu_{ji}) &= var(s_{ji} + \gamma_{ji}(p_i - E_j[p_i])) \\
&= var(s_{ji}) + \gamma_{ji}^2 var(p_i) + \gamma_{ji}^2 var_j(E(p_i)) + 2\gamma_{ji}cov(s_{ji}, p_i) - 2\gamma_{ji}cov(s_{ji}, E_j(p_i)) - 2\gamma_{ji}^2 cov(p_i, E_j(p_i)) \\
&= var(s_{ji} + \gamma_{ji}(p_i - E_j[p_i]) = var(s_{ji}) + \gamma_{ji}^2 var(p_i) - 2\gamma_{ji}cov(s_{ji}, p_i) = \\
&= (1 - 1/\alpha_{ji})\sigma_i^2 + \gamma_{ji}^2\left(\frac{1}{\Delta_i}\right)^2\left(\sigma_{ix}^2 + \sum_{k=0}^{l}\lambda_k^2\beta_{1ki}^2(1 - 1/\alpha_{ki})\sigma_i^2\right) \\
&- 2\gamma_{ji}\frac{1}{\Delta_i}\lambda_j\beta_{1ji}(1 - 1/\alpha_{ji})\sigma_i^2 \\
var(rp_i) &= r^2 var(p_i) = \left(\frac{r}{\Delta_i}\right)^2\left(\sigma_{ix}^2 + \sum_{k=1}^{l}\lambda_k^2\beta_{1ki}^2(1 - 1/\alpha_{ki})\sigma_i^2\right) \\
2rcov(\mu_{ji}, p_i) &= 2rcov(s_{ji} + \gamma_{ji}(p_i - E_j[p_i]), p_i) = 2rcov(s_{ji}, p_i) + 2r\gamma_{ji}var(p_i) - 2r\gamma_{ji}cov(p_i, E_j(p_i)) = \\
&= 2\frac{r}{\Delta_i}\lambda_j\beta_{1ji}(1 - 1/\alpha_{ji})\sigma_i^2 + 2r\gamma_{ji}\left(\frac{1}{\Delta_i}\right)^2\left(\sigma_{ix}^2 + \sum_{k=0}^{l}\lambda_k^2\beta_{1ki}^2(1 - 1/\alpha_{ki})\sigma_i^2\right)
\end{aligned}$$

Summing up:

$$\begin{aligned}
\hat{V}_{ji} &= var(s_{ji}) + \gamma_{ji}^2 var(p_i) + \gamma_{ji}^2 var_j(E(p_i)) + 2\gamma_{ji}cov(s_{ji}, p_i) - 2\gamma_{ji}cov(s_{ji}, E_j(p_i)) - 2\gamma_{ji}^2 cov(p_i, E_j(p_i)) + r^2 var(p_i) \\
&\quad -2r[cov(s_{ji}, p_i) + \gamma_{ji}var(p_i) - \gamma_{ji}cov(p_i, E_j(p_i))] \\
&= var(s_{ji}) + [\gamma_{ji}^2 + r^2 - 2r\gamma_{ji}]var(p_i) + \gamma_{ji}^2 var_j(E(p_i)) + 2[\gamma_{ji} - r]cov(s_{ji}, p_i) \\
&\quad -2\gamma_{ji}cov(s_{ji}, E_j(p_i)) - 2\gamma_{ji}[\gamma_{ji} - r]cov(p_i, E_j(p_i))
\end{aligned}$$

where

$$var(s_{ji}) = (1 - 1/\alpha_{ji})\sigma_i^2$$

$$var_j(p_i) = \left(\frac{1}{\Delta_i}\right)^2\left(\sigma_{ix}^2 + \sum_{k=1}^{l}\lambda_k^2\beta_{1ki}^2(1 - 1/\alpha_{ki})\sigma_i^2\right)$$

$$var_j(E(p_i)) = \theta_{ji}^2(1 - 1/\alpha_{ji})\sigma_i^2 = \theta_{ji}^2 var(s_{ji})$$

$$cov_j(s_{ji}, p_i) = \frac{1}{\Delta_i}\lambda_j\beta_{1ji}(1 - 1/\alpha_{ji})\sigma_i^2 = \frac{1}{\Delta_i}\lambda_j\beta_{1ji}var(s_{ji})$$

$$cov_j(s_{ji}, E_j(p_i)) = \theta_{ji}(1 - 1/\alpha_{ji})\sigma_i^2 = \theta_{ji}var(s_{ji})$$

$$cov_j(p_i, E_j(p_i)) = \theta_{ji}cov_j(s_{ji}, p_i) = \theta_{ji}\frac{1}{\Delta_i}\lambda_j\beta_{1ji}var(s_{ji})$$

Plugging in:

$$\hat{V}_{ji} = var(s_{ji})[1 + \theta_{ji}^2\gamma_{ji}^2 + 2(\gamma_{ji} - r)\frac{1}{\Delta_i}\lambda_j\beta_{1ji} - 2\gamma_{ji}\theta_{ji} - 2\gamma_{ji}[\gamma_{ji} - r]\theta_{ji}\frac{1}{\Delta_i}\lambda_j\beta_{1ji}] + [\gamma_{ji} - r]^2 var(p_i)$$

Finally, since the competitive fringe investors have zero capacity, they only optimize along the quantity dimension, not the learning dimension, and hence it is not necessary to derive their ex-ante utility.

A.3 Derivation of Equation (10)

Using market clearing:

$$p_i = -\frac{1}{\Delta_i}x_i + \frac{1}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{0ji} + \frac{1}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{1ji}s_{ji} = -\frac{1}{\Delta_i}x_i + \frac{1}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{0ji} + \frac{1}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{1ji}[\bar{z}_i + (1 - \frac{1}{\alpha_{ji}})\varepsilon_i + \zeta_{ji}],$$

Given that, we have

$$cov(p_i, z_i) = \frac{1}{\Delta_i}\sum_{j=0}^{l}\lambda_j\beta_{1ji}(1 - \frac{1}{\alpha_{ji}})\sigma_i^2$$

and

$$var(p_i) = \sigma_i^2\frac{1}{\Delta_i^2}\left[\frac{\sigma_{xi}^2}{\sigma_i^2} + \left(\sum_{j=0}^{l}\lambda_j\beta_{1ji}(1 - \frac{1}{\alpha_{ji}})\right)^2 + \sum_{j=0}^{l}\lambda_j^2\beta_{1ji}^2\frac{\alpha_{ji} - 1}{\alpha_{ji}^2}\right]$$

Then, PI equals (the coefficient $\frac{1}{\Delta_i}$ cancels out and $\alpha_{0i} = 1$)

$$PI_i = \frac{cov(p_i, z_i)}{\sigma_{pi}} = \frac{\sigma_i\sum_{j=1}^{l}\lambda_j\beta_{1ji}\frac{\alpha_{ji}-1}{\alpha_{ji}}}{\sqrt{\frac{\sigma_{xi}^2}{\sigma_i^2} + \left[\sum_{j=1}^{l}\lambda_j\beta_{1ji}(1 - \frac{1}{\alpha_{ji}})\right]^2 + \sum_{j=1}^{l}\lambda_j^2\beta_{1ji}^2\frac{\alpha_{ji}-1}{\alpha_{ji}^2}}}$$

Notice that $\lambda_j\beta_{1ji} = \frac{\partial\lambda_j q_{ji}}{\partial s_{ji}}$ is the reaction of the total quantity an oligopolist is purchasing with respect to the private signal, which we term the information pass-through. Defining information pass-through as

$$\omega_{ji} \equiv \frac{\partial\lambda_j q_{ji}}{\partial s_{ji}}.$$

results in equation (10)

$$PI_i = \frac{cov(p_i, z_i)}{\sigma_{pi}} = \frac{\sigma_i\sum_{j=1}^{l}\omega_{ji}\frac{\alpha_{ji}-1}{\alpha_{ji}}}{\sqrt{\frac{\sigma_{xi}^2}{\sigma_i^2} + \left[\sum_{j=1}^{l}\omega_{ji}(1 - \frac{1}{\alpha_{ji}})\right]^2 + \sum_{j=1}^{l}\omega_{ji}^2\frac{\alpha_{ji}-1}{\alpha_{ji}^2}}}.$$

A.4 Derivation of Equations (14) and (14)

In this section, we focus solely on the informed investors ($j = 1$). Their information choice solves

$$\max_{\{\hat{\sigma}_{ji}^2\}_{i=1}^{n}} U_0 \equiv \frac{1}{2\rho}\sum_{i=1}^{n}\frac{E_0\left(\mu_{ji} - rp_i\right)^2}{\hat{\sigma}_{ji}^2} \tag{17}$$

subject to the relative entropy constraint

$$\prod_{i=1}^{n}\frac{\sigma_i^2}{\hat{\sigma}_{ji}^2} \leq e^{2K_1}. \tag{18}$$

Hence, the gain from learning about a particular asset is the same across all competitive investors. To derive the above, note that the objective is:

$$U_0 = \frac{1}{2\rho}\sum_{i=1}^{n}\frac{\widehat{R}_i^2 + \widehat{V}_i}{\hat{\sigma}_{ji}^2},$$

where

$$\widehat{R}_i \equiv E_0\left(\mu_{ji} - rp_i\right) = \bar{z} - rE_0(p_i) = \bar{z} - ra_i,$$

and

$$\widehat{V}_i \equiv V_0\left(\mu_{ji} - rp_i\right) = var\left(\mu_{ji}\right) + r^2\sigma_{pi}^2 - 2rcov\left(\mu_{ji}, p_i\right).$$

Let α_{ji} denote the learning choice of the particular maximizing investor, while α_i the learning choice of all investors learning about asset i (which are of mass m_i). Given that each investor's solution is going to be a corner, in equilibrium $\alpha_{ji} = \alpha_i = e^{2K_1}$. With this notation in hand, we have:

$$var\left(\mu_{ji}\right) = var(s_{ji} + \frac{cov(z_i,p_i)}{\sigma_{pi}^2}(p_i - E_j[p_i])) = (1 - \frac{1}{\alpha_{ji}})\sigma_i^2 + \frac{cov^2(z_i,p_i)}{\sigma_{pi}^4}[var(p_i) + b_i^2(1 - \frac{1}{\alpha_i})\sigma_i^2]$$

$$+2\frac{cov(z_i,p_i)}{\sigma_{pi}^2}[cov(s_{ji},p_i) - cov(s_{ji},E(p_i)) - \frac{cov(z_i,p_i)}{\sigma_{pi}^2}cov(p_i,E(p_i)]$$

$$= (1 - \frac{1}{\alpha_i})\sigma_i^2 + \frac{cov^2(z_i,p_i)}{\sigma_{pi}^4}[var(p_i) + b_i^2(1 - \frac{1}{\alpha_i})\sigma_i^2]$$

$$+2\frac{cov(z_i,p_i)}{\sigma_{pi}^2}[b_i(1 - \frac{1}{\alpha_i})\sigma_i^2 - b_i(1 - \frac{1}{\alpha_i})\sigma_i^2 - \frac{cov(z_i,p_i)}{\sigma_{pi}^2}b^2(1 - \frac{1}{\alpha_i})\sigma_i^2]$$

$$= (1 - \frac{1}{\alpha_i})\sigma_i^2 + \frac{cov^2(z_i,p_i)}{\sigma_{pi}^4}[var(p_i) - b_i^2(1 - \frac{1}{\alpha_i})\sigma_i^2]$$

$$= (1 - \frac{1}{\alpha_i})\sigma_i^2 + \frac{cov^2(z_i,p_i)}{\sigma_{pi}^4}[c^2\sigma_{xi}^2 + b_i^2\frac{1}{\alpha_i}\sigma_i^2]$$

Given that the conditional variance of the price is: $c^2\sigma_{xi}^2 + b_i^2\frac{1}{\alpha_i}\sigma_i^2$, we have

$$var(\mu_{ji}) = (1 - \frac{1}{\alpha_i})\sigma_i^2 + \frac{cov^2(z_i,p_i)}{\sigma_{pi}^2}$$

Now for the covariance:

$$cov(\mu_{ji},p_i) = cov(s_{ji} + \frac{cov(z_i,p_i)}{\sigma_{pi}^2}(p_i - E_j[p_i]),p_i) = cov(s_{ji},p_i) + \frac{cov(z_i,p_i)}{\sigma_{pi}^2}var(p_i) - \frac{cov(z_i,p_i)}{\sigma_{pi}^2}cov(E(p_i),p_i)$$

$$= cov(s_{ji},p_i) + \frac{cov(z_i,p_i)}{\sigma_{pi}^2}[var(p_i) - b_i^2(1 - \frac{1}{\alpha_i})\sigma_i^2]$$

$$= b_i(1 - \frac{1}{\alpha_i})\sigma_i^2 + cov(z_i,p_i) = b_i(1 - \frac{1}{\alpha_i})\sigma_i^2 + b\frac{1}{\alpha}\sigma_i^2 = b\sigma_i^2$$

$$\hat{V} \quad = \quad (1 - \frac{1}{\alpha_i})\sigma_i^2 + \frac{cov^2(z_i,p_i)}{\sigma_{pi}^2} + r^2b^2\sigma_i^2 + r^2c^2\sigma_{xi}^2 - 2rb\sigma^2$$

And the ex-ante expected utility is:

$$U_0 \quad = \quad \frac{1}{2\rho}\sum_i\left[(\bar{z} - ra_i)^2 + \sigma_i^2 + r^2b^2\sigma_i^2 + r^2c^2\sigma_{xi}^2 - 2rb\sigma^2 - \left[\frac{1}{\alpha_i}\sigma_i^2 - \frac{cov^2(z_i,p_i)}{\sigma_{pi}^2}\right]\right]\frac{1}{\frac{1}{\alpha_{ji}}\sigma_i^2 - \frac{cov^2(p_i,z_i)}{\sigma_{pi}^2}}$$

Which becomes

$$U_0 = \frac{1}{2\rho}\sum_i [(\bar{z} - ra_i)^2 + \sigma_i^2 + r^2b^2\sigma_i^2 + r^2c^2\sigma_{xi}^2 - 2rb\sigma^2] \frac{1}{\frac{1}{\alpha_{ji}}\sigma_i^2 - \frac{cov^2(p_i,z_i)}{\sigma_{pi}^2}} + const.$$

Consider now $\frac{1}{\alpha_{ji}}\sigma_i^2 - \frac{cov^2(p_i,z_i)}{\sigma_{pi}^2}$. Given that $p_i = a_i + b_i\varepsilon_i - c\nu_i$, we have

$$\frac{1}{\alpha_{ji}}\sigma_i^2 - \frac{cov^2(p_i,z_i)}{\sigma_{pi}^2} = \frac{1}{\alpha_{ji}}\sigma_i^2 - \frac{b^2\frac{1}{\alpha_{ji}^2}\sigma_i^4}{b^2\frac{1}{\alpha_{ji}}\sigma_i^2 + c^2\sigma_{xi}^2}$$

$$= \frac{\frac{1}{\alpha_{ji}}\sigma_i^2(b^2\frac{1}{\alpha_{ji}}\sigma_i^2 + c^2\sigma_{xi}^2) - b^2c\frac{1}{\alpha_{ji}^2}\sigma_i^4}{b^2\frac{1}{\alpha_{ji}}\sigma_i^2 + c^2\sigma_{xi}^2} = \frac{\frac{1}{\alpha_{ji}}\sigma_i^2c^2\sigma_{xi}^2}{b^2\frac{1}{\alpha_{ji}}\sigma_i^2 + c^2\sigma_{xi}^2}$$

Given that, the maximization problem becomes

$$\begin{aligned}
U_0 &= \frac{1}{2\rho}\sum_i [(\bar{z} - ra_i)^2 + \sigma_i^2 + r^2b^2\sigma_i^2 + r^2c^2\sigma_{xi}^2 - 2rb\sigma^2] \frac{b^2\frac{1}{\alpha_{ji}}\sigma_i^2 + c^2\sigma_{xi}^2}{\frac{1}{\alpha_{ji}}\sigma_i^2c^2\sigma_{xi}^2} + const. \\
&= \frac{1}{2\rho}\sum_i [(\bar{z} - ra_i)^2 + \sigma_i^2 + r^2b^2\sigma_i^2 + r^2c^2\sigma_{xi}^2 - 2rb\sigma^2] \left[\frac{b^2}{c^2\sigma_{xi}^2} + \frac{1}{\frac{1}{\alpha_{ji}}\sigma_i^2}\right] + const. \\
&= \frac{1}{2\rho}\sum_i G_i\alpha_{ji} + const.
\end{aligned}$$

where

$$G_i = \frac{(\bar{z} - ra_i)^2}{\sigma_i^2} + (1 - rb_i)^2 + r^2c^2\frac{\sigma_{xi}^2}{\sigma_i^2}$$

So, the objective is linear in α_{ji}, subject to constraint

$$\prod_i \alpha_{ji} \leq e^{2K_1}.$$

A.5 Proof of Proposition 1

First, we need to derive the shadow value of information G_i as function of fundamentals and information choices. Start with demand for asset i from investor j who choses learning α_{ji}:

$$\begin{aligned}
q_{ji} &= \frac{\mu_{ji} - rp_i}{\rho\hat{\sigma}_{ji}^2}, \\
\mu_{ji} &= s_{ji} + \frac{cov_j(z_i,p_i)}{\sigma_{pji}^2}(p_i - E_j[p_i]) \\
\hat{\sigma}_{ji}^2 &= \frac{1}{\alpha_{ji}}\sigma_i^2 - \frac{cov_j^2(z_i,p_i)}{\sigma_{pji}^2}
\end{aligned}$$

where

$$cov_j(z_i,p_i) = b_i\frac{\sigma_i^2}{\alpha_{ji}}$$

$$\sigma_{pji}^2 = b_i^2\frac{\sigma_i^2}{\alpha_{ji}} + c_i^2\sigma_{xi}^2$$

Plugging in for the posterior variance and mean, we get

$$\begin{aligned} q_{ji} &= \frac{b^2\sigma_i^2\frac{1}{\alpha_{ji}}+c_i^2\sigma_{xi}^2}{c_i^2\sigma_i^2\sigma_{xi}^2\frac{1}{\alpha_{ji}}}(\mu_{ji}-rp_i)=\frac{b^2\sigma_i^2\frac{1}{\alpha_{ji}}+c_i^2\sigma_{xi}^2}{c_i^2\sigma_i^2\sigma_{xi}^2\frac{1}{\alpha_{ji}}}(s_{ji}+\frac{b\sigma_i^2\frac{1}{\alpha_{ji}}}{b^2\sigma_i^2\frac{1}{\alpha_{ji}}+c_i^2\sigma_{xi}^2}[p_i-a_i-b_i(s_{ji}-\bar{z})]-rp_i) \\ &= \frac{1}{\rho}\left[s_{ji}\frac{\alpha_{ji}}{\sigma_i^2}+\frac{b_i}{c_i^2\sigma_{xi}^2}(p_i-a_i+b_i\bar{z})-\frac{b^2\sigma_i^2\frac{1}{\alpha_{ji}}+c_i^2\sigma_{xi}^2}{c_i^2\sigma_i^2\sigma_{xi}^2\frac{1}{\alpha_{ji}}}rp_i\right] \end{aligned}$$

Let $\hat{\lambda}_i$ be the mass of agents learning about asset i, with $\sum_i \hat{\lambda}_i = \lambda_1$. Denote the average quantity of the learning agents as $\hat{q}_i$ and the average quantity of the non-learning agents as q_i. Then, market clearing is

$$x_i = \hat{\lambda}_i\hat{q}_i + (1-\hat{\lambda}_i)q_i$$

The cross-sectional average of the signal is $\bar{z}+(1-\frac{1}{\alpha_i})\varepsilon_i$, where α_i is the common value of alpha that learning agents choose (due to the solution being a corner, as we show in A.4). Then, market clearing becomes

$$\rho x_i = \hat{\lambda}_i\left[\frac{\alpha_i}{\sigma_i^2}(\bar{z}+(1-\frac{1}{\alpha_i})\varepsilon_i)-\frac{b^2\sigma_i^2\frac{1}{\alpha_{ji}}+c_i^2\sigma_{xi}^2}{c_i^2\sigma_i^2\sigma_{xi}^2\frac{1}{\alpha_{ji}}}rp_i\right]+(1-\hat{\lambda}_i)\left[\frac{1}{\sigma_i^2}\bar{z}-\frac{b^2\sigma_i^2+c_i^2\sigma_{xi}^2}{c_i^2\sigma_i^2\sigma_{xi}^2}rp_i\right]+\frac{b_i}{c_i^2\sigma_{xi}^2}(p_i-a_i+b_i\bar{z})$$

Using

$$\hat{\lambda}_i\frac{b^2\sigma_i^2\frac{1}{\alpha_{ji}}+c_i^2\sigma_{xi}^2}{c_i^2\sigma_i^2\sigma_{xi}^2\frac{1}{\alpha_{ji}}}+(1-\hat{\lambda}_i)\frac{b^2\sigma_i^2+c_i^2\sigma_{xi}^2}{c_i^2\sigma_i^2\sigma_{xi}^2}=\frac{b_i^2\sigma_i^2+c_i^2\sigma_{xi}^2(\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i))}{c_i^2\sigma_i^2\sigma_{xi}^2}$$

the market clearing becomes

$$\rho x_i = \bar{z}[\frac{\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i}{\sigma_i^2}+\frac{b_i^2}{c_i^2\sigma_{xi}^2}]+\frac{\hat{\lambda}_i(\alpha_i-1)}{\sigma_i^2}\varepsilon_i-\frac{b_i}{c_i^2\sigma_{xi}^2}a_i-\frac{-b_i\sigma_i^2+rb_i^2\sigma_i^2+rc_i^2\sigma_{xi}^2(\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i))}{c_i^2\sigma_i^2\sigma_{xi}^2}p_i$$

and then

$$p_i\left[\frac{rb_i^2}{c_i^2\sigma_{xi}^2}+\frac{r(\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i)}{\sigma_i^2}-\frac{b_i}{c_i^2\sigma_{xi}^2}\right]=-\rho(\bar{x}_i+\nu_i)+\bar{z}[\frac{\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i}{\sigma_i^2}+\frac{b_i^2}{c_i^2\sigma_{xi}^2}]+\frac{\hat{\lambda}_i(\alpha_i-1)}{\sigma_i^2}\varepsilon_i-\frac{b_i}{c_i^2\sigma_{xi}^2}a_i$$

We get

$$\frac{b_i}{c_i}=\frac{\hat{\lambda}_i(\alpha_i-1)}{\rho\sigma_i^2}$$

and

$$\frac{1}{c_i}=\frac{1}{\rho}\left[r\frac{\hat{\lambda}_i^2(\alpha_i-1)^2}{\rho^2\sigma_i^4\sigma_{xi}^2}+r\frac{(\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i)}{\sigma_i^2}-\frac{\hat{\lambda}_i(\alpha_i-1)}{\rho\sigma_i^2\sigma_{xi}^2}\frac{1}{c_i}\right]$$

and so

$$c_i=\frac{\rho+\frac{\hat{\lambda}_i(\alpha_i-1)}{\rho\sigma_i^2\sigma_{xi}^2}}{r\frac{\hat{\lambda}_i^2(\alpha_i-1)^2}{\rho^2\sigma_i^4\sigma_{xi}^2}+r\frac{(\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i)}{\sigma_i^2}}=\frac{\rho\sigma_i}{r}\frac{\hat{\lambda}_i(\alpha_i-1)+\rho^2\sigma_i^2\sigma_{xi}^2}{\hat{\lambda}_i^2(\alpha_i-1)^2+(1-\hat{\lambda}_i+\hat{\lambda}_i\alpha_i)\rho^2\sigma_i^2\sigma_{xi}^2}$$

Then

$$b_i=\frac{\hat{\lambda}_i(\alpha_i-1)}{r}\frac{\hat{\lambda}_i(\alpha_i-1)+\rho^2\sigma_i^2\sigma_{xi}^2}{\hat{\lambda}_i^2(\alpha_i-1)^2+(1-\hat{\lambda}_i+\hat{\lambda}_i\alpha_i)\rho^2\sigma_i^2\sigma_{xi}^2}$$

so that

$$1-rb_i=\frac{\rho^2\sigma_i^2\sigma_{xi}^2}{\hat{\lambda}_i^2(\alpha_i-1)^2+(1-\hat{\lambda}_i+\hat{\lambda}_i\alpha_i)\rho^2\sigma_i^2\sigma_{xi}^2}$$

Finally

$$a_i = \frac{-\rho\bar{x}_i + \bar{z}[\frac{\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i}{\sigma_i^2} + \frac{b_i^2}{c_i^2\sigma_{xi}^2}] - \frac{b_i}{c_i^2\sigma_{xi}^2}a_i}{\frac{rb_i^2}{c_i^2\sigma_{xi}^2} + \frac{r(\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i)}{\sigma_i^2} - \frac{b_i}{c_i^2\sigma_{xi}^2}}$$

$$a_i r\left[\frac{b_i^2}{c_i^2\sigma_{xi}^2} + \frac{(\hat{\lambda}_i\alpha_i + 1 - \hat{\lambda}_i)}{\sigma_i^2}\right] = -\rho\bar{x}_i + \bar{z}[\frac{\hat{\lambda}_i\alpha_i + 1 - \hat{\lambda}_i}{\sigma_i^2} + \frac{b_i^2}{c_i^2\sigma_{xi}^2}]$$

$$ra_i = \bar{z} - \frac{\rho\bar{x}_i}{\frac{b_i^2}{c_i^2\sigma_{xi}^2} + \frac{(\hat{\lambda}_i\alpha_i+1-\hat{\lambda}_i)}{\sigma_i^2}}$$

and

$$\bar{z} - ra_i = \frac{\rho^3\sigma_i^4\sigma_{xi}^2\bar{x}_i}{\hat{\lambda}_i^2(\alpha_i-1)^2 + (1-\hat{\lambda}_i+\hat{\lambda}_i\alpha_i)\rho^2\sigma_i^2\sigma_{xi}^2}$$

Given the price coefficients, we can express G_i as a function of the masses of agents learning about asset i:

$$G_i = \rho^2\sigma_i^2\sigma_{xi}^2\frac{\rho^2\sigma_i^2\sigma_{xi}^2 + \rho^4\sigma_i^4\sigma_{xi}^2\bar{x}_i^2 + (\hat{\lambda}_i(\alpha_i-1) + \rho^2\sigma_i^2\sigma_{xi}^2)^2}{[\hat{\lambda}_i^2(\alpha_i-1)^2 + (1-\hat{\lambda}_i+\hat{\lambda}_i\alpha_i)\rho^2\sigma_i^2\sigma_{xi}^2]^2}.$$

To see **Part 1** of the proposition, note is that obviously, G_i is increasing in $\bar{x}_i$. Second, it is increasing in σ_{xi}^2. The partial derivative is

$$\frac{\partial G_i}{\partial\sigma_{xi}^2} =$$

$$\rho^2\sigma_i^2\frac{\hat{\lambda}_i^4(\alpha_i-1)^4 + 3\hat{\lambda}_i^3(\alpha_i-1)^3\rho^2\sigma_i^2\sigma_{xi}^2 + \rho^6\sigma_i^6\sigma_{xi}^6 + \hat{\lambda}_i(\alpha_i-1)\rho^6\sigma_i^6\sigma_{xi}^6 + \hat{\lambda}_i^2(\alpha_i-1)^2\rho^2\sigma_i^2\sigma_{xi}^2(1+\rho^2\sigma_i^2(3\sigma_{xi}^2+2\bar{x}_i^2))}{[\hat{\lambda}_i^2(\alpha_i-1)^2 + (1-\hat{\lambda}_i+\hat{\lambda}_i\alpha_i)\rho^2\sigma_i^2\sigma_{xi}^2]^3} > 0$$

Finally, the partial derivative with respect to asset's fundamental volatility is

$$\frac{\partial G_i}{\partial\sigma_i^2} = \frac{\rho^2\sigma_{xi}^2}{((-1+\alpha_i)^2\hat{\lambda}_i^2 + (1+(-1+\alpha_i)\hat{\lambda}_i)\rho^2\sigma_i^2\sigma_{xi}^2)^3}\times$$

$$[(\alpha_i-1)^4\hat{\lambda}_i^4 + 3(\alpha_i-1)^3\hat{\lambda}_i^3\rho^2\sigma_i^2\sigma_{xi}^2 + \rho^6\sigma_i^6\sigma_{xi}^4(\sigma_{xi}^2+\bar{x}_i^2) + (\alpha_i-1)\hat{\lambda}_i\rho^6\sigma_i^6\sigma_{xi}^4(\sigma_{xi}^2+\bar{x}_i^2)$$
$$+(\alpha_i-1)^2\hat{\lambda}_i^2\rho^2\sigma_i^2\sigma_{xi}^2(1+3\rho^2\sigma_i^2(\sigma_{xi}^2+\bar{x}_i^2))] > 0$$

That means that the investors, ceteris paribus, have preferences towards asset with high and noisy supply, and high volatility of returns.
For **Part 2**, it is enough to show that the shadow value of learning about asset i are decreasing in the mass of agents learning about that asset, i.e. $\frac{\partial G_i}{\partial\hat{\lambda}} < 0$:

$$\frac{\partial G_i}{\partial\hat{\lambda}} =$$

$$-2(\alpha_i-1)\rho^2\sigma_i^2\sigma_{xi}^2\frac{((\alpha_i-1)^3\hat{\lambda}_i^3 + 3(\alpha_i-1)^2\hat{\lambda}_i^2\rho^2\sigma_i^2\sigma_{xi}^2 + \rho^6\sigma_i^6\sigma_{xi}^4(\sigma_{xi}^2+\bar{x}^2) + (\alpha_i-1)\hat{\lambda}_i\rho^2\sigma_i^2\sigma_{xi}^2(1+\rho^2\sigma_i^2(3\sigma_{xi}^2+2\bar{x}^2)))}{[\hat{\lambda}_i^2(\alpha_i-1)^2 + (1-\hat{\lambda}_i+\hat{\lambda}_i\alpha_i)\rho^2\sigma_i^2\sigma_{xi}^2]^3} < 0$$

A.6 Proof of Proposition 2

Proof. It is enough to show that information pass-through given by (16):

$$\lambda_1\beta_i = \frac{\lambda_1(1-\lambda_1)\beta_{20i}\alpha_i}{\rho(1-\lambda_1)\sigma_i^2\beta_{20i} + \lambda_1\alpha_i}.$$

converges to 0. Using β_{20i} from (9) gives:

$$\beta_{20i} = \frac{1 - \frac{cov_0(z_i,p_i)}{rvar_0(p_i)}}{\rho(\sigma_i^2 - \frac{cov_0^2(z_i,p_i)}{var_0(p_i)})} = \frac{rvar_0(p_i) - cov_0(z_i, p_i)}{\rho(\sigma_i^2 var_0(p_i) - cov_0^2(z_i, p_i))},$$

is bounded from above, since the derivations in Appendix A.1 imply that $cov_0^2(z_i, p_i)$ is strictly smaller than $\sigma_i^2 var_0(p_i)$. This and boundedness of α_i immediately implies that

$$\lim_{\lambda_i \to \{0,1\}} \lambda_1 \beta_i = 0.$$

□