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Product Market Competition, Insider Trading, and Stock Market Efficiency

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ABSTRACT

How does competition in firms' product markets influence their behavior in equity markets? Do product market imperfections spread to equity markets? We examine these questions in a noisy rational expectations model in which firms operate under monopolistic competition while their shares trade in perfectly competitive markets. Firms use their monopoly power to pass on shocks to customers, thereby insulating their profits. This encourages stock trading, expedites the capitalization of private information into stock prices and improves the allocation of capital. Several implications are derived and tested.

HOW DOES COMPETITION in firms' product markets influence their behavior in equity markets? Do product market imperfections spread to equity markets? These questions are increasingly of interest as product markets are becoming more competitive in many countries thanks to the relaxation of impediments to trade and barriers to entry.[1] In this paper, we analyze these questions using a noisy rational expectations model in which firms operate under monopolistic competition while their shares trade in perfectly competitive markets.

The model is guided by recent empirical work showing that stock returns are affected by the intensity of product market competition. Gaspar and Massa (2005) and Irvine and Pontiff (2009) document that more competitive firms have more volatile idiosyncratic returns, and Hou and Robinson (2006) show that such firms earn higher risk-adjusted returns. The model is also guided by a direct examination of the data. Our starting point is the finding in Gaspar and Massa (2005) that analysts' earnings forecasts about firms operating in more competitive industries are more dispersed. Since differences in opinions

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[1] Such changes may have an impact on equity markets. For example, the rise in idiosyncratic return volatility (Morck, Yeung, and Yu (2000), Campbell et al. (2001)) may be related to the deregulation of the economy (Gaspar and Massa (2005), Irvine and Pontiff (2009)).

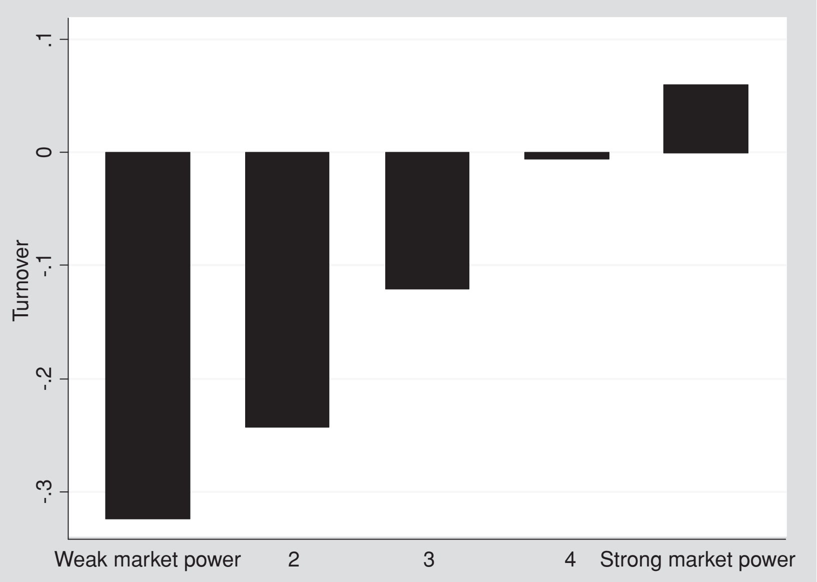

Figure 1. Market power and turnover. This figure shows stock turnover across market power groups. Turnover is defined as the log of the ratio of the number of shares traded during a year to the number of shares outstanding. Firms are sorted every year from 1996 to 2005 into market power quintiles. Market power is measured as the excess price–cost margin (PCM). The PCM or Lerner index is defined as operating profits (before depreciation, interest, special items, and taxes) over sales (Compustat annual data item 12). Operating profits are obtained by subtracting from sales the cost of goods sold (item 41) and general and administrative expenses (item 178). If data are missing, we use operating income (item 178). The excess price–cost margin is constructed as the difference between the firm's PCM and the PCM of its industry. The industry PCM is the value-weighted average PCM across firms in the industry where the weights are based on market share (sales over total industry sales) and industries are defined using two-digit SIC classifications.

are usually a motivation for trading, we expect to find a greater volume of trade for these firms. To analyze this conjecture, we sort firms on their market power and measure the average trading volume in each group.[2] As Figure 1 shows, we find the opposite of our conjecture. Stocks in the bottom market power quintile are traded less frequently than those in the top quintile. A possible explanation for the mismatch between belief heterogeneity and trading volume is that the opinions examined in Gaspar and Massa (2005)—analysts' forecasts—are not representative of the overall market but of informed investors who trade differently. We explore this possibility by studying trades initiated by insiders—officers of firms who presumably have access to privileged information. Figure 2, in the spirit of Figure 1, reveals that their trading volume is again larger in firms with more market power. Thus, it appears that investors scale

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[2] Our data and methodology are described in Section V, where we confirm that the results we presented graphically in this Introduction are statistically significant and robust to the inclusion of other factors including firm size.

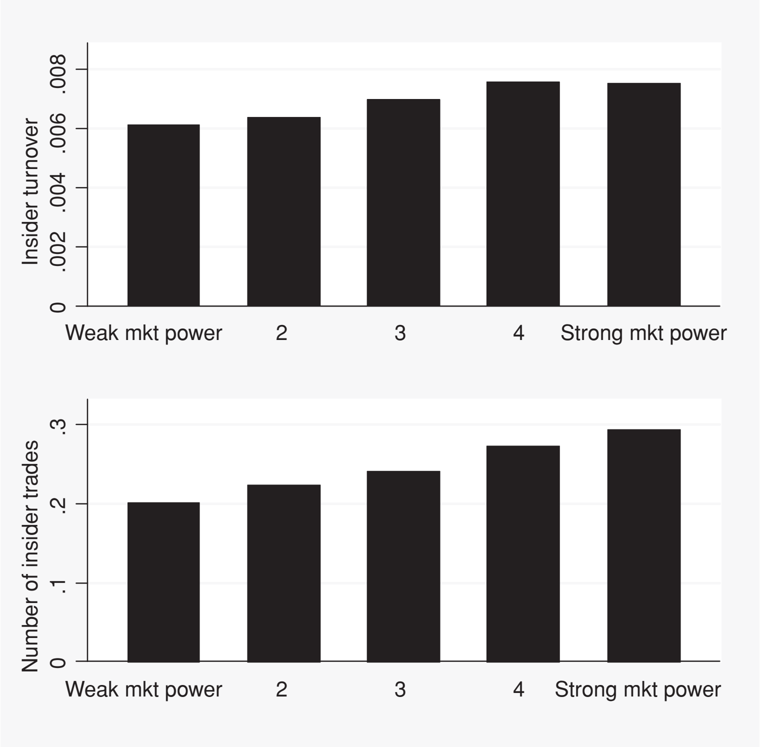

Figure 2. Market power and insider trading. This figure shows insider trading activity across market power groups over the 1996 to 2005 period. In the top panel, insider trading activity is measured as the log of the ratio of a firm's annual total insider trading dollar volume to the firm's market capitalization, and it is denoted Insider turnover. In the bottom panel, it is measured as the log of the ratio of the firm's annual number of insider trades to the firm's number of active insiders and is denoted Number of insider trades. Insider trades are open market transactions, excluding sells, initiated by the top five executives of a firm (CEO, CFO, COO, President, and Chairman of board). Active insiders are defined as executives who have reported at least one transaction in any of the sample years. Firms are sorted every year from 1996 to 2005 into market power quintiles. Market power is measured as the excess price–cost margin or Lerner index (see Figure 1).

down their trading of more competitive stocks even when they have superior information.

The enhanced trading activity, especially among informed investors, for firms enjoying more market power raises the possibility that fundamental information is more quickly capitalized into their stock price. To investigate this hypothesis, we measure the stock price reaction to earnings announcements across market power groups. Earnings of closely followed firms are anticipated long before their official release so their prices do not react to announcements. In contrast, announcements by remotely followed firms provide useful information that causes investors to revise their valuation and stock prices to adjust. Figure 3 shows that firms with more market power experience smaller price changes at announcements after controlling for standard risk factors,

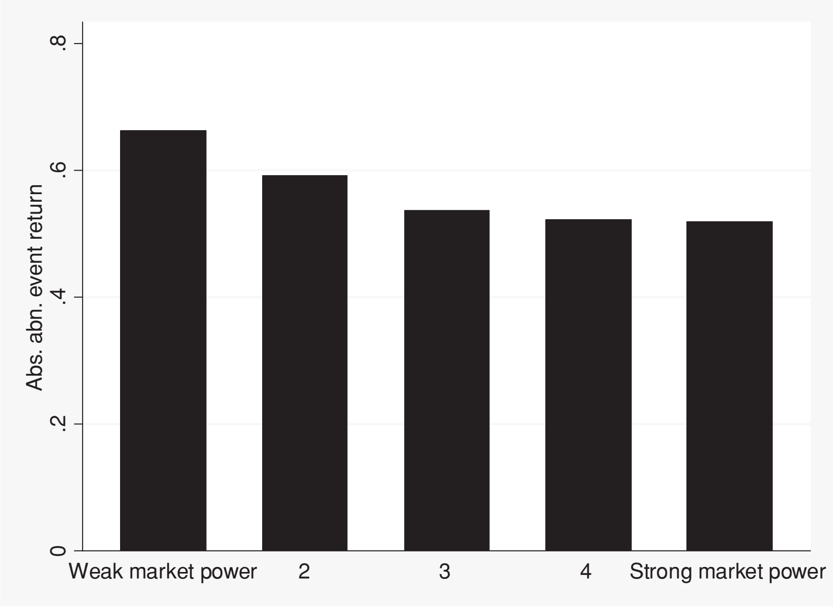

Figure 3. Market power and stock price informativeness. This figure shows stock price informativeness across market power groups. Informativeness is measured as the absolute abnormal return surrounding an earnings announcement. Abnormal returns are the residuals from the Fama–French three-factor model. For every firm, we regress stock returns on the market, size, and book-to-market factors over an estimation window extending from $t = -250$ to $t = -5$ relative to the earnings announcement day 0. We estimate the residuals over an event window ranging from $t = -2$ to $t = +2$. Then, we sum their absolute value on each day of the event window to measure the stock price reaction to the announcement. Finally, we average the absolute abnormal returns estimates obtained from each announcement during a year to get an annual measure. Firms are sorted every year from 1996 to 2005 into market power quintiles. Market power is measured as the excess price–cost margin or Lerner index (see Figure 1).

suggesting that their prices are more informative. This is consistent with our previous finding that insiders in these firms trade more aggressively, which speeds up the incorporation of information into prices.[3] To summarize the evidence, monopoly power in product markets reduces the dispersion of earnings forecasts (Gaspar and Massa (2005)) but stimulates trading, including that by insiders, and enhances the informativeness of stock prices (Figures 1–3). In addition, it lowers risk-adjusted expected returns (Hou and Robinson (2006)) and idiosyncratic return volatility (Gaspar and Massa (2005), Irvine and Pontiff (2009), Chun et al. (2008)).

The contribution of this paper is to present a rational expectations model that explains these observations and provides further insights into how product market competition interacts with information asymmetries. Ours is similar to most models of trading under asymmetric information in competitive stock markets (e.g., Grossman and Stiglitz (1980)) but for one difference: Our firms sell goods in an imperfectly competitive product market. Specifically, they operate under monopolistic competition. Each firm owns a unique patent to produce a good, the demand for which is imperfectly elastic, so the firm enjoys some market power. Firms are subject to random productivity shocks. Investors do not observe these shocks but are endowed with private information. Trading causes private information to be reflected in stock prices but only partially because noise precludes their full revelation. Product market power plays an important role in an uncertain environment. It allows firms to insulate their profits from shocks by passing the shocks on to their customers. Firms that face a captive demand for their good can hedge their profits effectively. But more competitive firms yield more risky profits, even though they face the same amount of technological uncertainty (the variance of productivity shocks is independent of the degree of competition). As Hicks (1935 p. 8) puts it, "the best of all monopoly profits is a quiet life." This insight drives our results.

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[3] In a similar vein, Hoberg and Phillips (2009) document that, in less competitive industries, analyst forecasts are less positively biased and stock returns comove less with the market.

Because the profits of firms with more market power are less risky, investors trade their stock in larger quantities (even though their private signals about productivity are just as accurate). These larger trades, in turn, expedite the incorporation of private information into prices. The improved accuracy of public information—stock prices are more informative—further encourages investors to trade. It also makes their profit and productivity forecasts less dispersed as they rely more on public information and less on their own private signals. Thus, investors disagree less but trade more, and stock prices are more informative, in line with the evidence presented above.[4]

Furthermore, firms with more market power have less volatile, and on average lower returns. These effects obtain in imperfect competition models regardless of information asymmetries simply because their profits are less risky. The novel aspect emphasized here is that monopoly power also exerts an indirect influence through the informativeness of prices, which further reduces volatility and expected returns, even after adjusting for risk. Indeed, stock prices of more monopolistic firms track future profits more closely, allowing returns to absorb a smaller fraction of shocks.[5] The ratio of expected excess returns to their standard deviation—a measure of expected returns adjusted for risk, known as the Sharpe ratio—is reduced too, indicating that the informational effect of market power is stronger on the risk premium than on risk. These results suggest that product market deregulation amplifies return volatility not only because it deprives firms from a hedge but also because public information, conveyed by stock prices, is less accurate.[6]

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[4] This finding may explain why stock picking appears to be declining in the United States since the 1960s (Bhattacharya and Galpin (2005)) as competition in product markets intensifies (Gaspar and Massa (2005), Irvine and Pontiff (2009), Chun et al. (2008)).

[5] When information is perfect, for example, prices reflect technology shocks perfectly while returns equal the risk-free rate.

[6] These findings are consistent with the dramatic increases in idiosyncratic return volatility (Morck et al. (2000), Campbell et al. (2001)) that occurred in the United States following the deregulation of product markets (Gaspar and Massa (2005), Irvine and Pontiff (2005), Chun et al.

The effects considered so far are essentially financial—they involve trades, prices, and returns. An important contribution of the paper is to show that they extend to real variables when firms raise new capital. In that case, investors not only value firms, but also determine how much capital firms are to receive. We find that fresh capital—the proceeds from share issuances—is more efficiently distributed when firms have more market power. The reason is that their stock prices are more informative so investors can easily identify the better technologies to channel more funds to. In other words, informational efficiency feeds back to real efficiency. Thus, competition, rather than the lack thereof, generates an inefficiency when it interacts with information asymmetries. That is, product market imperfections, rather than spreading to equity markets, tend to limit stock market imperfections.[7]

Our paper relates to several important strands of literature. It is part of the research agenda that links industrial organization to financial markets. Starting with the work of Titman (1984) and Brander and Lewis (1986), scholars have established, both theoretically and empirically, that firms' capital structure and the intensity of competition in firms' product market are jointly determined.[8] In particular, debt can be used strategically to relax informational constraints. In Poitevin (1989), for example, debt signals to investors that a firm entering a market dominated by a monopoly has high value, while in Chemla and Faure-Grimaud (2001) it induces buyers with a high valuation to reveal their type to a durable good monopolist.

Less is known about how other financial variables such as trading volume and the informativeness of stock prices are related to market power. Perotti and von Thadden (2003) argue that a firm's dominant investors can limit the informativeness of its stock price by being opaque, which in turn mitigates product market competition. In Stoughton, Wong and Zechner (2001), consumers infer product quality from the stock price, so a high-quality entrant has an incentive to go public to expose itself to speculators' attention. Tookes (2007) is most closely related to our work. She examines trading and information spillovers across competing stocks and shows that informed agents prefer to trade shares in a more competitive firm, even if their information is not specifically about this firm but about a competitor. In her setting, agents are risk-neutral and capital-constrained so they seek the stock with the greatest sensitivity to shocks. In contrast, we assume that agents are risk-averse and characterize how the risk-return trade-off varies with a firm's market power.

Our paper also belongs to the large body of research on trading under asymmetric information. This literature studies the impact of information on

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(2006)). They are also in line with Hou and Robinson (2006), who document that firms in more competitive industries earn higher returns after adjusting for risk.

[7] In our setting, product market power does not generate a net social gain. Rather, it reduces the social loss. This is because our solution technique assumes that shocks are small. Hence, stock prices and investments differ only slightly from those obtained in a riskless economy.

[8] For example, firms may choose low leverage ratios to guarantee that they will be able to service their products (Titman (1984)) or high leverage ratios to commit to aggressive operating strategies through limited liability provisions (Brander and Lewis (1986)).

financial variables. To the best of our knowledge, the role of product market power has not yet been examined in this context. Our paper contributes in particular to the subset of this literature that emphasizes the real benefits of informational efficiency. In our model, stock prices reflect the quality of firms' investment opportunities and help investors channel capital to the better ones.[9]

The remainder of the paper is organized as follows. Section I describes the economy. Section II solves for the equilibrium and Section III studies how it is affected by competition. Section IV considers extensions to the baseline model. Section V confronts the model with the data. Section VI concludes. Proofs are provided in the Appendix.

I. The Economy

Ours is a standard rational expectations model of competitive stock trading under asymmetric information (e.g., Grossman and Stiglitz (1980)) but for one important difference: Firms in our setting enjoy monopoly power in their product market. The economy consists of two sectors, a final and an intermediate goods sector. Intermediate goods are used as inputs in the production of the final good. They are produced by firms operating under monopolistic competition and subject to technology shocks. These shocks are not observed but investors receive private signals about them. Monopolies' stocks trade competitively on the equity market. Their prices reflect private signals but only partially because of the presence of noise. Prices in turn guide investors in their portfolio allocations. Time consists of two periods. In the investment period ($t = 1$), markets open and investors observe their private signals and trade. In the production period ($t = 2$), intermediate and final goods are produced and agents consume. The model is further defined as follows.

A. Technologies

A.1. Intermediate Good Sector

There are M monopolies operating in the intermediate good sector. Monopoly m ($m = 1$ to M) is the *exclusive* producer of good m. Its production is determined by a risky technology that displays constant returns to capital:

$$Y^m \equiv A^m K_0 \quad \textit{for all } m = 1, \ldots, M$$

where A^m is a technology shock specific to firm m and K_0 is the book value of its capital stock. Firms are endowed with an arbitrary capital stock K_0, which cannot be adjusted. Our analysis focuses on the interplay between competition in the product market and information asymmetries in the equity market, for which the initial capital stock is irrelevant. We allow firms to change their capital stock in the last section of the paper, where they raise fresh capital. We assume that the M intermediate monopolies are entirely financed with public equity.

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[9] See, for example, Dow, Goldstein, and Guembel (2006) and the references therein.

Goods are produced and then firms are liquidated in the production period ($t = 2$). Thus, if firm m sells Y^m goods at a price of Q^m, its value at $t = 2$ is $\Pi^m = Q^m Y^m$. The technology shocks A^m ($m = 1$ to M) are assumed to be lognormally distributed and independent from one another. Market power allows firms to insulate their profits from productivity shocks. They increase goods' prices in times of shortage (bad shock) and decrease them in times of abundance (good shock). This behavior complicates modeling under rational expectations because it leads to stock payoffs that are not linear in shocks. As a result, the extraction of information from equilibrium stock prices can no longer be solved in closed form.[10] For this reason, we resort to a small-risk expansion. We assume that the productivity shocks are small and log-linearize firms' reactions to these shocks. Specifically, we assume that $\ln A^m \equiv a^m z$, where a^m can be interpreted as the growth rate of technology m and z is a scaling factor, and $a^m z$ is normally distributed with mean zero and precision h_a/z (variance z/h_a). The model is solved in closed form by driving z toward zero. Peress (2004) demonstrates the convergence and the accuracy of such an approximation in a noisy rational expectations economy. Throughout the paper, we assume that the scaling factor z is small enough for the approximation to be valid.

A.2. Final Good Sector

Intermediate goods are used as inputs in the production of the final good. Many identical firms compete in the final good sector and aggregate to one representative firm. The final good is produced according to a riskless technology,

$$G \equiv \sum_{m=1}^{M} (Y^m)^{1-\omega^m},$$

where G is final output, Y^m is the employment of the m'th type of intermediate good, and ω^m is a parameter between zero and one.[11]

The parameter ω^m is the key parameter of the model. It measures the degree of market power enjoyed by firm m. To see this, note that final good producers set their demand for inputs to maximize profits, $G - \sum_{m=1}^{M} Q^m Y^m$, taking intermediate goods' prices Q^m as given (we use the price of the final good as the numeraire). The resulting demand for input m is $Y^m = [(1-\omega^m)/Q^m]^{1/\omega^m}$.[12] Its elasticity, $-d\ln Y^m/d\ln Q^m$, equals $1/\omega^m$ and declines when ω^m grows. Thus, *the higher ω^m, the less elastic the demand for good m and the more market power firm m exerts.* When ω^m is identical across firms ($\omega^m = \omega$ for all m), it can be interpreted as (the inverse of) the degree of competition in the intermediate goods sector. Indeed, the elasticity of substitution between any two goods m and m', $d\ln(Y^m/Y^{m'})/d\ln(Q^m/Q^{m'})$, equals $1/\omega$. So the inverse of ω measures the extent to which inputs are substitutes for one another, a lower ω indicating more substitutability and a more competitive input market. In the limit when $\omega = 0$, inputs are perfect substitutes and the intermediate goods sector is perfectly competitive.

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[10] Rational expectations models of competitive stock trading under asymmetric information typically assume that preferences display constant absolute risk aversion (CARA) or risk neutrality and that random variables, including payoffs and signals, are normally distributed. Equilibrium stock prices are conjectured to be linear functions of these random variables. The preference assumptions generate stock demands linear in expected payoffs and prices while the normality assumption leads to expected payoffs linear in signals including prices, thus validating the initial guess. The canonical examples are Grossman and Stiglitz (1980) with competitive traders and Kyle (1985) with strategic traders. Alternative assumptions are used, for example, by Ausubel (1990), Rochet and Vila (1994), Barlevy and Veronesi (2000), and Peress (2009). Bernardo and Judd (2000) and Yuan (2005) use numerical solutions to solve more general models.

[11] The final good technology provides a convenient way of aggregating the different goods produced by the monopolies. It is in the spirit of Spence (1976), Dixit and Stiglitz (1977), and Romer (1990), among others, and is used in much of the industrial organization literature.

The main characteristic of market power is that it makes monopoly profits less sensitive to technology shocks. Substituting the demand for intermediate goods into the expression for these profits yields $\Pi^m = (1-\omega^m)(Y^m)^{1-\omega^m}$. Thus, $1-\omega^m$ also measures the elasticity of profits to shocks, $\partial(\ln\Pi^m)/\partial(\ln A^m)$, for a given stock of capital K_0.

B. Assets

Monopolies' equity trades on the stock market. We normalize the number of shares outstanding to one perfectly divisible share. The price of a share of firm m is denoted P^m. To avoid the Grossman–Stiglitz (1980) paradox, we assume that some agents trade stocks for exogenous random reasons, creating the noise that prevents prices from fully revealing private signals. We denote by θ^m the aggregate demand for stock m emanating from these noise traders as a fraction of investors' wealth, that is, θ^m is the number of shares noise traders purchase multiplied by the price of stock m and divided by wealth.[13] We assume that $\theta^m z$ is normally distributed with mean zero and variance $\sigma_\theta^2 z$, and is independent from all other random variables and across stocks. This formulation implies that the level of noise trading is identical across sectors and does not bias our results. There are no short-sales constraints. A riskless asset is available in perfectly elastic supply, allowing investors to borrow and lend freely. The riskless rate of return is denoted $R^f = 1 + r^f z$.

C. Investors

The main decision makers in our economy are investors. There is a continuum of them, indexed by l in the unit interval [0, 1]. They derive utility from the consumption of the final good g. Utility displays constant relative risk aversion

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[12] The demand for input m is independent of the demand for input m' because the final good's production function is separable. This simplifies the analysis substantially.

[13] We derive investors' demand for stocks at the order 0 in z when we solve the model. Accordingly, θ^m represents the order-0 component of noise traders' demand.

(CRRA):

$$U(g) = \frac{g^{1-\gamma} - 1}{1 - \gamma},$$

where $\gamma > 0$ measures relative risk aversion and $\gamma = 1$ corresponds to log utility. Investors are endowed with a portfolio of stocks and bonds. We denote by w and $f^m_{0,l}$ ($m = 1$ to M) agent l's initial wealth and the fraction of wealth initially invested in stock m respectively. We assume for simplicity that investors start with the same initial wealth w, though its composition (the $f^m_{0,l}$'s) may vary arbitrarily. Investors choose new portfolio weights f^m_l in the investment period ($t = 1$) and consume in the production period ($t = 2$).

D. Information Structure

Investors do not observe technology shocks in the intermediate good sector when they rebalance their portfolio ($t = 1$).[14] But they are endowed with some private information. Specifically, investor l receives a private signal s^m_l about firm m's technology shock:

$$s^m_l = a^m + \varepsilon^m_l,$$

where ε^m_l is an error term independent of the firm's profit Π^m and across agents. The term $\varepsilon^m_l z$ is normally distributed with mean zero and precision h_s/z (variance z/h_s). We assume for simplicity that precisions are identical across stocks and investors.

E. Equilibrium Concept

We define the equilibrium concept for this economy, starting from individual maximization (conditions (i) and (ii)) and proceeding to market aggregation (conditions (iii) and (iv)).

(i) In the production stage, final good producers set their demand for intermediate goods to maximize profits taking prices Q^m ($m = 1$ to M) as given. As shown above, this leads to a demand for input m equal to $Y^m = [(1 - \omega^m)/Q^m]^{1/\omega^m}$.

(ii) In the investment stage, investor l sets her portfolio weights f^m_l guided by stock prices P^m($m = 1$ to M) and her private signals s_l. Investors are atomistic and take stock prices as given. Their problem can be expressed formally as:

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[14] The model assumes that investors have private information about the firm's prospects while managers do not. Accordingly managers, unlike investors, do not make any decision. This assumption allows us to focus on the influence of product market competition on investors' incentives to trade and on the aggregation of their dispersed private signals through prices. An alternative interpretation of the model is that managers possess private information that they have already conveyed (possibly imperfectly) to the market. This information is encoded in the prior distribution of technology shocks used by investors. Our focus is on the additional trading and informativeness generated by investors' private signals.

$$\max_{\{f_l^m,\, m=1\,\text{to}\, M\}} E[U(c_l) \mid \mathcal{F}_l] \quad \text{subject to } c_l = \left(R^f + \sum_{m=1}^{M} f_l^m \left(R^m - R^f\right)\right) w, \quad (1)$$

where c_l and $\mathcal{F}_l \equiv \left\{s_l^m, P^m \text{ for } m = 1 \text{ to } M\right\}$ denote agent l's consumption and information set, and R^m and $r^m z = \ln(R^m)$ denote the simple and log returns on stock m. Firm m generates a profit Π^m before being liquidated, yielding a gross stock return of $R^m = \Pi^m / P^m$ (there is one share outstanding). Investors hold a position in every stock, be it long or short, since there are no transactions costs nor short-sales constraints. The return on their portfolio equals $R^f + \sum_{m=1}^{M} f_l^m \left(R^m - R^f\right)$. Their problem is simplified by noting that the final good production function is separable. This implies that the demand for input m is independent from the quantity employed of input m' (as stated in condition (i)), and therefore that the return on stock m is independent from the return on stock m'.[15]

(iii) Intermediate goods' prices $Q^m (m = 1 \text{ to } M)$ clear the market for intermediate goods:

$$[(1 - \omega^m)/Q^m]^{1/\omega^m} = A^m K_0 \qquad \text{for } m = 1 \text{ to } M,$$

where the left-hand side is the demand for good m and the right-hand side its supply.

(iv) Stock prices $P^m (m = 1 \text{ to } M)$ clear the market for stocks:

$$\int_0^1 \frac{w}{P^m} f_l^m \, dl + \frac{w}{P^m} \theta^m = 1 \qquad \text{for } m = 1 \text{ to } M,$$

where the integral and $w\theta^m / P^m$ represent, respectively, the number of shares demanded by investors and noise traders, and the right-hand side is the number of shares outstanding. We are now ready to solve for the equilibrium.

II. Equilibrium Characterization

We discuss the trading and pricing of monopolies' stock. From now on, we consider a generic stock and drop the superscript m when there is no ambiguity to simplify the notation. We guess that stock prices are approximately (i.e., at the order z) log-linear functions of technology and noise shocks, solve for portfolios, derive the equilibrium stock prices, and check that the guess is valid. We express stock prices, profits, and capital as $\bar{P} \exp(pz)$, $\bar{\Pi} \exp(\pi z)$, and $\bar{K} \exp(kz)$ at the order z. Note that $\bar{P}$, $\bar{\Pi}$, and $\bar{K}$ are deterministic constants that measure the value of P, Π, and K when $z = 0$ (in which case $A^m = R^f \equiv 1$ for all m, that is, there is no risk and no value to time). The terms p, π, and k are functions of a and θ that capture the order-z perturbation induced by the shocks and the riskless rate. Our focus throughout the paper is on the interaction of market power with the shocks, which is reflected in the order-z term, that is, p, π, and k.

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[15] Independence across firms implies that shareholders are not better off limiting one firm's output to favor another. Their optimal operating strategy is to maximize profits in all firms.

We begin with a brief discussion of a benchmark economy in which technology shocks, $A = \exp(az)$, are observed perfectly. The equilibrium in this riskless economy is solved in closed form without any approximation, unlike the general case. Given its capital stock K_0, a monopoly generates a profit $\Pi = (1-\omega)K_0^{1-\omega}\exp[(1-\omega)az]$ at $t = 2$ (see Section I.A.2). Its stock trades at $t = 1$ for $P = \Pi/R^f = (1-\omega)K_0^{1-\omega}\exp[(1-\omega)az - r^f z]$. Investors earn the riskless rate on a riskless investment. The following proposition describes the equilibrium when technology shocks are not perfectly observed.

PROPOSITION 1: *There exists a log-linear rational expectations equilibrium characterized as follows.*

- *Shares trade at a price* $P = (1-\omega)K_0^{1-\omega}\exp(pz)$, *where* $p = p_0(\omega) + p_a(\omega)a + p_\theta(\omega)\theta$,

$$p_0(\omega) \equiv \frac{(1-\omega)^2}{h(\omega)}\left(\frac{1}{2} - \frac{\gamma(1-\omega)K_0^{1-\omega}}{w}\right) - r^f, \tag{2}$$

$$p_a(\omega) \equiv (1-\omega)\left(1 - \frac{h_a}{h(\omega)}\right) \geq 0, \quad p_\theta(\omega) \equiv \frac{\gamma(1-\omega)}{h_s}p_a(\omega), \tag{3}$$

$$h_p(\omega) \equiv \frac{h_s^2}{\gamma^2(1-\omega)^2\sigma_\theta^2}, \quad \textit{and} \quad h(\omega) \equiv h_a + h_p(\omega) + h_s. \tag{4}$$

- *Investor l' allocates a fraction f_l of her wealth to each stock such that*

$$f_l = \frac{h_s}{\gamma(1-\omega)}\varepsilon_l - \theta + \frac{(1-\omega)K_0^{1-\omega}}{w}. \tag{5}$$

Proposition 1 confirms our initial guess that prices are approximately log-linear functions of technology and noise shocks. This is illustrated in Figures 4 and 5, which depict p, p_a, and p_θ. The technology shock a appears directly in the price function because individual signals s_l, once aggregated, collapse to their mean, a. The noise shock θ enters the price equation because it represents noise traders' demand. The price P reveals $p_a a + p_\theta\theta = p_a(a + \gamma(1-\omega)\theta/h_s)$, a signal for a with error $\gamma(1-\omega)\theta/h_s$. Investors cannot tell whether the valuation of an expensive stock is justified by a good technology (a large) or by large noise trades (θ large). The function $\mathrm{var}[\gamma(1-\omega)\theta/h_s]/z = \gamma^2(1-\omega)^2\sigma_\theta^2/h_s^2$ measures the noisiness of stock prices and its inverse, h_p, its *informativeness*. Note that $h = z/\mathrm{var}_l(az \mid \mathcal{F}_l)$ measures the total precision of an investor's information. She uses information about profits from three sources, namely, her prior (the

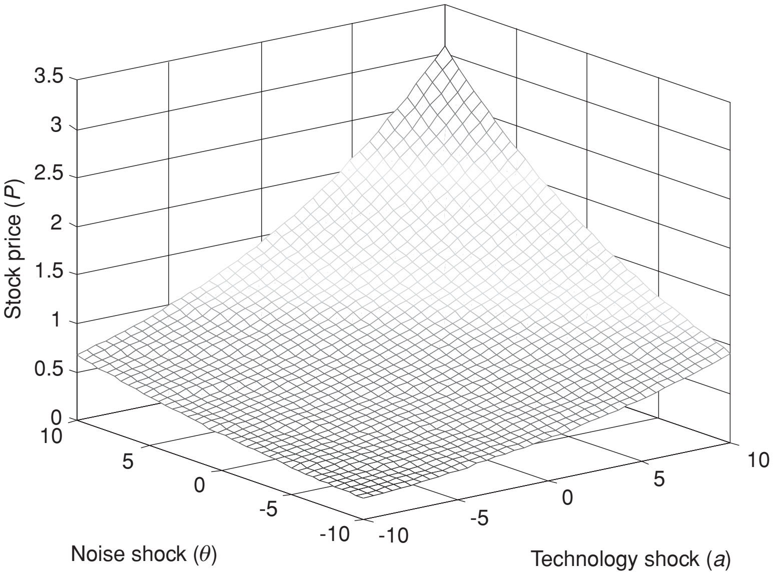

Figure 4. The equilibrium stock price. The stock price is plotted against the realizations of the technology shock a and noise shock θ. The parameters are $\omega = 0.8$, $h_a = 1$, $\sigma_\theta^2 = 0.1$, $r^f = 0.02$, $M = 10$, $w = 0.3$, $\gamma = 1$, $h_s = 0.1$, and $z = 0.1$.

h_a term), the stock price (the h_p term), and her private signal (the h_s term), and their precisions simply add up (equation (4)). The first two sources of information are public and their total precision equals $h_a + h_p$. The equilibrium coincides with that obtained in the riskless benchmark economy when information is perfect ($h = h_s = \infty$, $p_0 = -r^f$, $p_a = (1-\omega)$, and $p_\theta = 0$). Investors hold a position in every stock, be it long ($f_l > 0$) or short ($f_l < 0$). Their portfolio shares are expressed in equation (5) as the average weight across investors (the order-0 component of the firm's profit $(1-\omega)K_0^{1-\omega}$ divided by investors' wealth w), minus noise trades θ tilted by their private signal errors ε_l, scaled by risk aversion γ, the precision of their signal h_s, and one minus market power ω.

III. The Impact of Market Power

In this section we examine how power in firms' product market affects the equilibrium outcome. We start by analyzing trades. From trades follow informativeness of stock prices, dispersion of investors' forecasts, distribution of returns, liquidity, and allocative efficiency.

A. Trading Volume

We study the impact of product market competition on investors' trading activity. Trading volume is measured as the value or the number of shares

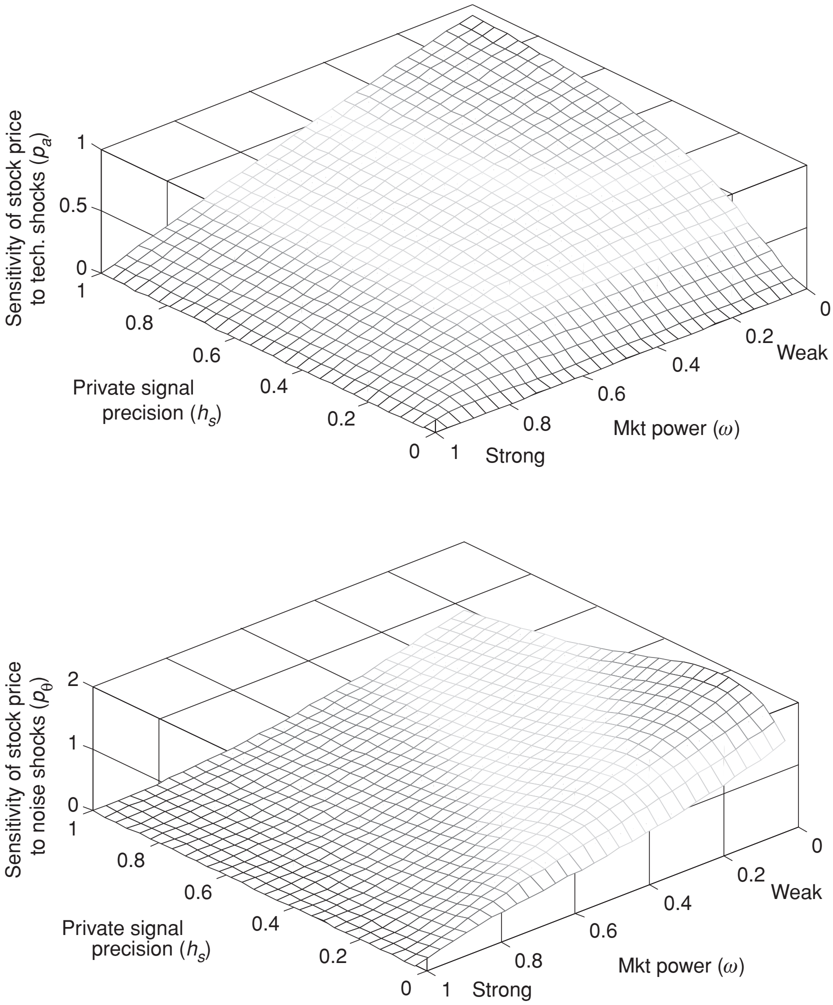

Figure 5. The sensitivities of the stock price to technology and noise shocks. The sensitivities to technology shocks p_a (top panel) and to noise shocks p_θ (bottom panel) are plotted against the precision of private information h_s and the degree of market power ω. The parameters are $h_a = 1$, $\sigma_\theta^2 = 0.1$, $r^f = 0.02$, $M = 10$, $K_0 = 1$, $w = 0.3$, $\gamma = 1$, and $z = 0.1$.

traded, conditional on the distribution of stock endowments (the $f_{0,l}^m$'s) as in Holthausen and Verrecchia (1990). The number of shares traded coincides with the stock's turnover given that there is one share outstanding. The following proposition characterizes the relation between trading volume and market power.

PROPOSITION 2: *Trading volume is larger for firms with more market power.*

The proposition establishes that *market power encourages investors to trade*. This is illustrated in the top left panel of Figure 6. Intuitively,

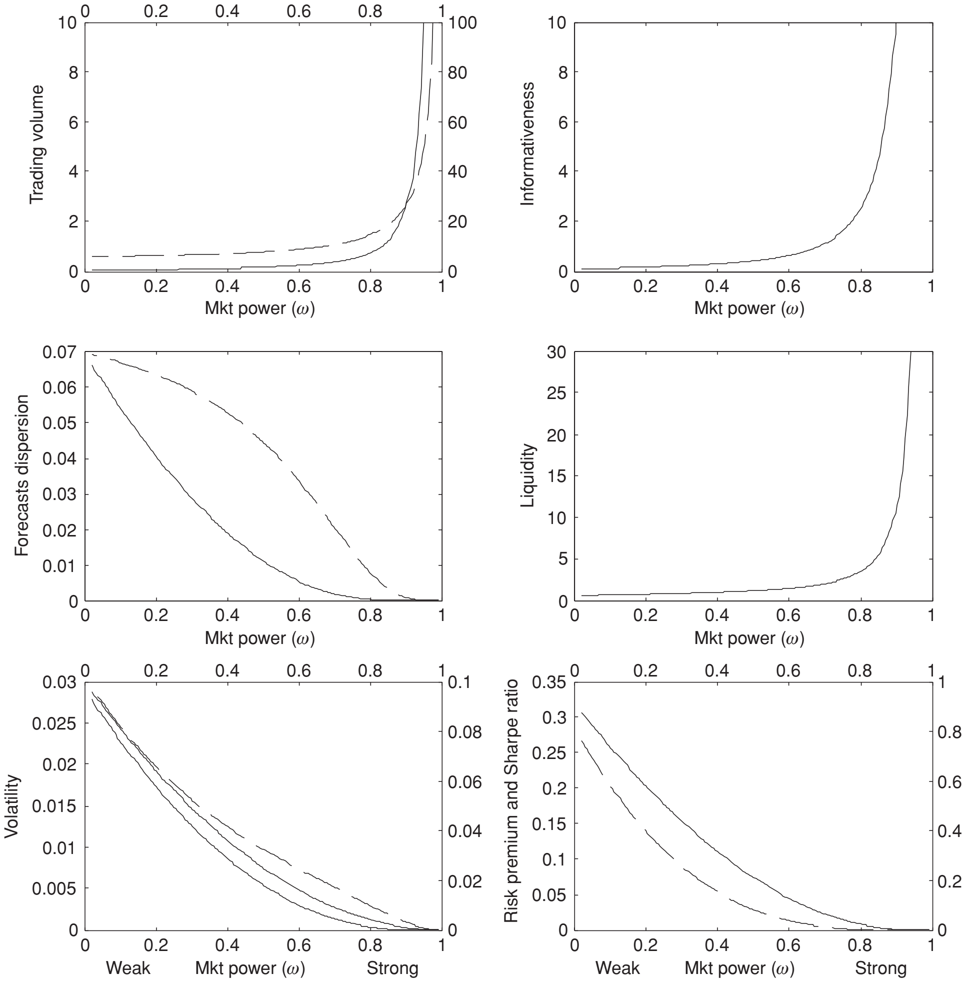

Figure 6. The impact of market power on the equilibrium. ω on the x-axis measures the firm's power in its product market. The top left panel displays the share turnover (solid curve, right scale) and the dollar trading volume (dashed curve, left scale). The top right panel displays the informativeness of stock prices h_p. The middle left panel displays the dispersion of investors' forecasts about the firm's profit (solid line, right scale) and technology shock (dashed line, left scale). The middle right panel displays liquidity $1/p_\theta$. The bottom left panel displays the variance of log profits (solid curve, right scale), the variance of log prices (dashed curve, left scale), and the variance of stock returns (dotted curve, right scale). The bottom right panel displays a firm's risk premium (dashed curve, left scale) and its Sharpe ratio (solid curve, right scale). The parameters are $h_a = 1$, $\sigma_\theta^2 = 0.1$, $r^f = 0.02$, $M = 10$, $K_0 = 1$, $w = 0.3$, $\gamma = 1$, $h_s = 0.1$, and $z = 0.1$.

monopolies are less vulnerable to productivity shocks because they can pass these shocks on to their customers. This makes their profits less risky. Investors are more confident in their profit forecasts (though they trust their productivity forecast just as much) so they trade more aggressively on their private information. Thus, competition erodes insiders' informational advantage.

This is a key implication of the model, from which the next propositions will follow.

It may seem surprising that stocks of more competitive firms are *not* more intensely traded given that their highly sensitive payoff offers a more effective avenue for trading on private information. The reason is that investors are risk-averse and these stocks are also more risky.[16] Were investors risk-neutral and capital-constrained, they would prefer to trade stocks of more competitive firms as in Tookes (2007).[17]

B. Informational Efficiency

The following proposition describes how the increase in informed trading for firms with more market power affects the informativeness of stock prices.

PROPOSITION 3: *Stock prices are more informative when firms enjoy more market power.*

The proposition establishes that market power increases the amount of information that is revealed through prices. Above we show that investors scale up their trades of more monopolistic stocks because of their reduced risk. Consequently, their private signals are more fully capitalized into prices. Thus, *a less efficient product market (in the sense that firms enjoy more monopoly power, that is, face a more captive demand for their product) leads to a more efficient stock market (in the sense that stock prices are more informative).* Putting it differently, stock market imperfections—the extent of information asymmetries—are mitigated by product market imperfections—market power.[18] Proposition 3 is illustrated in the top right panel of Figure 6.

C. Dispersion of Investors' Forecasts

The following proposition shows how the increased accuracy of public information affects the dispersion of investors' forecasts. The dispersion of investors' productivity a, profit π, and return r forecasts are measured for any given firm, conditional on the realization of the productivity and noise shocks a and θ : $\mathrm{var}\left[E(a \mid \mathcal{F}_l) \mid a, \theta\right]$, $\mathrm{var}\left[E(\ln \Pi \mid \mathcal{F}_l) \mid a, \theta\right]$, and $\mathrm{var}\left[E(r \mid \mathcal{F}_l) \mid a, \theta\right]$.

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[16] In our setting, a finite number of stocks with independent returns trade on the stock market. Therefore, risk amounts to the variance of these returns. The variance can be interpreted as a covariance with the market if these stocks are only a subset of available securities. For example, suppose that the return on the market (which encompasses other publicly traded securities, private assets, human capital, etc.) is $r^{\text{market}}z = \sum_{m=1}^{M}(1-\omega^m)a^m z + bz$, where b is a random variable independent of the a^m. Then $\text{cov}(r^{\text{market}}z, r^m z) = (1-\omega^m)^2\text{var}(a^m z) = \text{var}(r^m z)$.

[17] Formally, stock returns can be expressed as $r = \ln(\Pi/P) = (1-\omega)az - pz$, which depends on productivity shocks through $(1-\omega)a$. As $1-\omega$ rises (less market power), returns are more sensitive to these shocks. Expected returns increase by a factor $(1-\omega)$ while their variance increases by a factor $(1-\omega)^2$. Thus, the ratio of expected excess returns to their variance, which determines investors' trades, is magnified by a factor $1/(1-\omega) > 1$. It follows that the dollar trading volume and turnover increase with market power ω.

[18] Formally, prices provide a signal for technology shocks a with error $\gamma(1-\omega)\theta/h_s$ so their precision, which measures the informativeness of prices, equals $h_p = h_s^2/[\gamma^2(1-\omega)^2\sigma_\theta^2]$. It increases when investors trade more (γ lower or ω higher) or when noise traders are less active (σ_θ^2 lower). In particular, prices are perfectly revealing when ω is close to one.

PROPOSITION 4: *Investors' productivity, profit, and return forecasts are less dispersed when firms enjoy more market power.*

Proposition 4 establishes that *the dispersion in investors' productivity, profit, and return forecasts is reduced by market power.* Indeed, investors assign a smaller weight to their private signals and a greater weight to stock prices when their informativeness improves. This results in less disagreement among investors. For example, the dispersion of productivity forecasts equals h_s/h^2, the ratio of the precision of the private signal to the squared precision of total information ($h \equiv h_a + h_p + h_s$). As market power strengthens, h_p rises, inducing investors to rely less on their private signal. Figure 6 shows the forecast dispersion (middle left panel) at different levels of market power.

D. Stock Returns

Market power acts as a hedge that allows firms to pass shocks on to their customers. Hence, profits fluctuate less when firms enjoy more market power. So do stock prices, a discounted version of profits, and returns, which capture the difference between profits and prices. Expected returns are lower too to compensate investors for bearing less risk. These effects obtain in imperfect competition models, regardless of information asymmetries, simply because profits are less risky. The novel aspect emphasized in this paper is that market power also exerts an indirect influence through the informativeness of prices. We focus on these informational effects. The following proposition summarizes the impact of market power on the distribution of stock returns. We consider the volatility of stock returns (unconditionally and conditional on stock prices), the conditional volatility of profits, the expected excess stock return and the Sharpe ratio—the ratio of expected excess returns to their standard deviation.

PROPOSITION 5:

- *Firms enjoying more market power have less volatile returns (unconditionally and conditional on public information), lower expected returns, and higher Sharpe ratios. They also have less volatile profits.*
- *Their return and profit volatility, expected return, and Sharpe ratio are reduced further by the improved informativeness of their stock price.*

We know from Proposition 3 that market power enhances how much investors can learn from stock prices. Improved information in turn makes profits conditional on prices less variable. Thus, the informational effect of market power works to dampen profit volatility. The behavior of returns mirrors that of profits. They too are less volatile for more monopolistic firms as a result of the direct effect of market power. Market power's indirect effect through the informativeness of prices decreases return volatility further. This is because, with better information, prices track future profits more closely, leaving returns to absorb a smaller fraction of shocks. In the case of perfect information for example, prices reflect technology shocks perfectly while returns equal the risk-free rate so their variance is zero. The informational impact of market power also reduces expected stock returns and the average Sharpe ratio, indicating that it is stronger on the risk premium than on risk. Thus, the indirect effect of market power through the informativeness of prices magnifies the decrease in profit and return volatility, expected returns, and the Sharpe ratio. The bottom panels of Figure 6 illustrate these findings.

E. Liquidity

We analyze next the impact of market power on liquidity. We use the sensitivity of stock prices to (uninformative) noise shocks, $p_\theta = \partial(\ln P)/\partial(\theta z)$, to capture liquidity as is common in asymmetric information models.

PROPOSITION 6: *Firms enjoying more market power have stock prices that are less sensitive to noise shocks.*

Proposition 6 extends to noise shocks θ the intuition we developed for productivity shocks a: Firms use their market power to shield their profits from shocks, whatever their source. Profits and therefore prices of more monopolistic firms are less vulnerable to noise shocks. Figure 6 (middle right panel) shows graphically that p_θ decreases with ω.

F. Allocative Efficiency

The interplay between imperfections in the product and equity markets has implications that are not only financial as discussed so far but also real. To illustrate this point, we consider firms that raise fresh capital through an equity issuance. Investors not only value these firms, but also determine how much capital they are to receive. An efficient allocation of capital requires that investors channel more funds to more productive technologies (i.e., those with a higher technology shock A), and less funds to less productive technologies. In this section, we investigate how competition influences investors' ability to perform this allocation. As before, firms start with K_0 units of capital and one share outstanding. We assume that firms issue α new shares (an arbitrary positive number), the proceeds of which will serve to expand their asset base. We denote $K = \alpha P$ the amount of capital raised, where P again represents the stock price (P and K are determined endogenously in equilibrium).

As before, we start with the benchmark perfect-information economy. We denote prices, profits, and capital in this economy with a superscript $\mathcal{P}$. Thanks to its expanded capital stock $K_0 + \alpha P^{\mathcal{P}}$, a monopoly generates a riskless profit $\Pi^{\mathcal{P}} = (1-\omega)(K_0 + \alpha P^{\mathcal{P}})^{1-\omega} \exp[(1-\omega)az]$ at $t = 2$. Therefore, its stock trades at $t = 1$ for

$$P^{\mathcal{P}} = \Pi/R^f = (1-\omega)(K_0 + \alpha P^{\mathcal{P}})^{1-\omega} \exp[((1-\omega)a - r^f)z].$$

We search for a solution to this equation of the form $P^{\mathcal{P}} = \bar{P}\exp(p^{\mathcal{P}}z)$, where we neglect terms of order larger than z. It is useful to define a firm's dilution factor as $\delta \equiv \alpha\bar{P}/(K_0 + \alpha\bar{P})$. This factor equals zero when no shares are issued as in the preceding sections, and one when the firm has no other capital but that newly raised. The term $\bar{P}$ is the implicit solution to $\bar{P}(1+\alpha) = (1-\omega)(K_0 + \alpha\bar{P})^{1-\omega}$ and can be expressed in terms of K_0 and δ as

$$\bar{P} = [K_0/(1-\delta)]^{1-\omega}[(1-\omega) - \delta(K_0/(1-\delta))^{\omega}].$$

Moreover, $p^{\mathcal{P}} = [(1-\omega)a - r^f]/(1-\delta+\delta\omega)$[19]. We can check that when no shares are issued ($\delta = 0$), $P^{\mathcal{P}} = (1-\omega)K_0^{1-\omega}\exp[((1-\omega)a - r^f)z]$ as in Section II. The amount of capital raised is $K^{\mathcal{P}} = \alpha P^{\mathcal{P}} = \alpha\bar{P}\exp(p^{\mathcal{P}}z)$. The scaling factor $1/(1-\delta+\delta\omega)$ in the expression for $p^{\mathcal{P}}$ accounts for the fact that the newly issued shares allow firms to expand their asset base: A 1% increase in the amount of capital raised generates a $(1-\omega)$% increase in profits, of which new shares claim a fraction δ. Therefore, a 1% increase in current stock prices reduces investors' return by less than 1%, namely, by $(1-\delta+\delta\omega)$%. Formally, the stock return is $r^{\mathcal{P}} = (1-\omega)(a + \delta p^{\mathcal{P}}) - p^{\mathcal{P}}$ (given that $k^{\mathcal{P}} = p^{\mathcal{P}}$). Since the investment is riskfree, $r^{\mathcal{P}} = r^f$ and $p^{\mathcal{P}}$ follows. The elasticity of investments to technology shocks, $\partial(\ln K^{\mathcal{P}})/\partial(\ln A)$, equals $p_a^{\mathcal{P}}(\omega,\delta) \equiv (1-\omega)/(1-\delta+\delta\omega)$, which is positive, indicating that more capital flows to better firms. We turn to the analysis of the imperfect-information economy.

PROPOSITION 7: *Assume that firms issue α new shares. There exists a log-linear rational expectations equilibrium characterized as follows.*

- *Shares trade at a price $P = \bar{P}\exp(pz)$ such that $p = p_0(\omega,\delta) + p_a(\omega,\delta)a + p_\theta(\omega,\delta)\theta$,*

$$\bar{P} = \left(\frac{K_0}{1-\delta}\right)^{(1-\omega)}\left((1-\omega) - \delta\left(\frac{K_0}{1-\delta}\right)^{\omega}\right),$$

$$p_0(\omega,\delta) \equiv \frac{1}{1-\delta+\delta\omega}\left\{\frac{(1-\omega)^2}{h(\omega)}\left(\frac{1}{2} - \frac{\gamma(1-\omega)K_0^{(1-\omega)}}{w(1-\delta)^{(1-\omega)}}\right) - r^f\right\},$$

$$p_a(\omega,\delta) \equiv \frac{1-\omega}{1-\delta+\delta\omega}\left(1 - \frac{h_a}{h(\omega)}\right) \geq 0,\ p_\theta(\omega,\delta) \equiv \frac{\gamma(1-\omega)}{h_s}p_a(\omega,\delta), \quad (6)$$

  and $h(\omega)$ is defined in Proposition 1.
- *Firms raise $K = \alpha\bar{P}\exp(kz)$ units of capital, where $k = p$.*

The pricing equations presented in Proposition 7 are similar to those of Proposition 1. The only difference is that the coefficients p_0, p_a, and p_θ are now scaled by $1/(1-\delta+\delta\omega)$ to account for the capital base expansion as in the benchmark perfect-information economy. If no new shares are issued, then $\delta = 0$ and the equations coincide with those of Proposition 1. The equilibrium collapses to that of the benchmark economy when information is perfect ($h = h_s = \infty$, $p_0 = -r^f/(1-\delta+\delta\omega)$, $p_a = (1-\omega)/(1-\delta+\delta\omega)$, and $p_\theta = 0$).

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[19] $\bar{P}$ is uniquely defined by this equation.

We analyze next how the accuracy of information h affects the efficiency of investments, holding fixed the degree of market power ω. This will prove useful for understanding the role of market power. The elasticity of investments to technology shocks, $\partial(\ln K)/\partial(\ln A) = p_a(\omega, \delta)$, measures the economy's allocative efficiency: A larger elasticity means that more (less) productive firms attract more (less) capital. The following proposition establishes a link between informational and allocative efficiency.

PROPOSITION 8: *Capital is more efficiently allocated when information is more accurate.*

The elasticity of investments to technology shocks p_a increases with the level of information, holding ω fixed. Hence, *better-informed economies distribute capital more efficiently across firms.* In the perfect information limit ($h = \infty$), the elasticity collapses to $p_a^{\mathcal{P}} = (1-\omega)/(1-\delta+\delta\omega)$ as derived above. It falls to $p_a = (1-\omega)/(1-\delta+\delta\omega)\,(1-h_a/h)$ when information is imperfect. A worsening of information (lower h) pushes it away from its value under perfect information ($1-h_a/h$ further from one). In the limiting case of no information ($h = h_a$), $p_a = 0$ so investments are independent from technology shocks.[20]

We proceed to the impact of market power. Since its intensity influences the informativeness of prices (Proposition 3), market power affects the efficiency of investments. To assess its impact, we need to neutralize the direct effect of market power, which can be identified in the perfect information case. The elasticity of investments with respect to technology shocks equals $p_a^{\mathcal{P}} \equiv (1-\omega)/(1-\delta+\delta\omega)$ when information is perfect. We are interested in the indirect effect of market power on allocative efficiency, which we measure relative to the perfect-information benchmark as $p_a/p_a^{\mathcal{P}}$. We establish the following result.

PROPOSITION 9: *Capital is more efficiently allocated when firms enjoy more market power.*

Proposition 9 shows that imperfect competition has an efficiency impact through the distribution of capital across firms. It combines Proposition 2, which establishes that the informativeness of stock prices improves as market power strengthens, with Proposition 8, which shows that information improves the quality of investments. Formally, $p_a/p_a^{\mathcal{P}}$ rises with market power ω. Thus, the social loss of market power is tempered by improvements in the capital

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[20] Proposition 8 also makes apparent the informational role of the stock market. It can best be understood by comparison to an economy in which prices do not convey any information. In such an economy, investors' total precision (the combined precisions of price and private signals) is reduced to $h_a + h_s < h$ and the elasticity of investments to technology shocks to $[1 - 1/(1 + h_s/h_a)](1-\omega)/(1-\delta+\delta\omega) < p_a$. (The equilibrium in this economy can be derived from the general case by driving the volatility of noise, σ_θ^2, to infinity to make stock prices uninformative.) The allocation of capital is not as efficient, though the same private signals were observed.

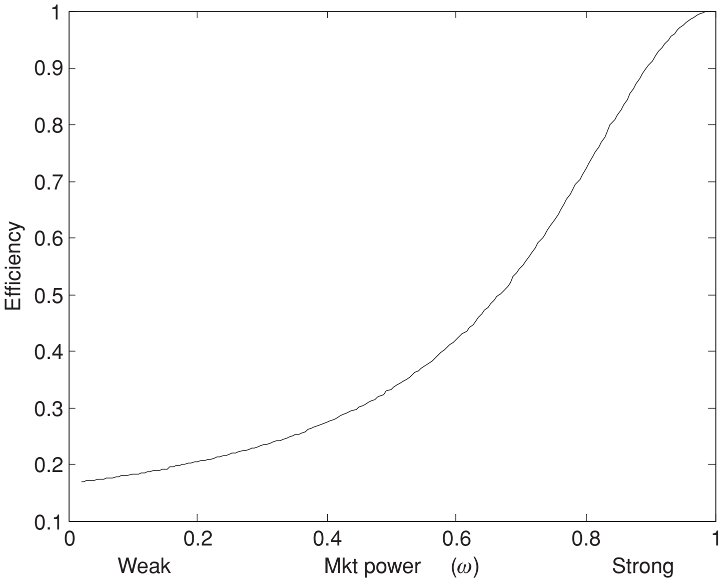

Figure 7. The impact of market power on the economy's allocative efficiency. The plot displays the efficiency of investments $p_a/p_a^{\mathcal{P}}$. ω on the x-axis measures the firm's power in its product market. The dilution factor is $\delta = 0.1$, and the other parameters are $h_a = 1$, $\sigma_\theta^2 = 0.1$, $r^f = 0.02$, $M = 10$, $K_0 = 1$, $w = 0.3$, $\gamma = 1$, $h_s = 0.1$, and $z = 0.1$.

allocation.[21] Putting it differently, *competition, rather than the lack thereof, results in an inefficiency.* This effect, illustrated in Figure 7, results from the interaction of monopoly power in the product market with informational frictions in the equity market.

The proposition implies that the deregulation of product markets has an additional effect that operates through the stock market. Opening product markets reduces the information content of stock prices, which damages the efficiency of the capital allocation within these markets. This finding has implications for policy design. It suggests that product market reforms should not be conducted in isolation but in combination with stock market reforms. Since product market competition can hurt stock markets, policies aimed at improving financial efficiency, such as the liberalization of the financial sector, should be implemented simultaneously.[22]

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[21] The social loss stems from the fact that monopoly power induces firms to produce fewer goods and sell them at prices that exceed their marginal cost. On the other hand, a literature initiated by Schumpeter (1912) argues that competition is detrimental to innovation because it reduces the monopoly rents that reward it. Our findings reinforce the Schumpeterian view: Competition implies that good ideas struggle to attract capital, which further weakens the incentives to innovate. Empirically, Chun et al. (2008) show that competition boosts the volatility of firms' productivity.

[22] This recommendation echoes that of interest group models of financial development such as Rajan and Zingales (2003). They suggest that incumbent firms oppose financial development because it breeds competition. They argue that deregulation should take place in both product and financial markets to overcome the resistance from these groups.

IV. Discussion and Extensions

In this section we explore various extensions of the model. First, we allow investors to learn from firms' past performance. Next, we discuss the role of noise trading. Finally, we examine whether our findings generalize to factors other than product market competition such as leverage.

A. Learning from Past Profits

So far, investors' information consists of their private signals and stock prices. In this section, we allow investors to learn about technology shocks from firms' past profits. We assume that firms operate at $t = 0$, during a period that precedes the trading round ($t = 1$). The profit firm m generates at that time is $\Pi_0^m = (1-\omega^m)(A_0^m K_0)^{1-\omega^m} = (1-\omega^m)(K_0)^{1-\omega^m}\exp[(1-\omega^m)a_0^m z]$, where $A_0^m \equiv \exp(a_0^m z)$ denotes its technology shock at $t = 0$.

To connect past and future profits, we make two assumptions about firm m's technology shock and profit in period 0. First, we assume that technology shocks display some persistence. Therefore, past shocks are informative about future shocks. Specifically, we assume that

$$a_0^m = \rho a^m + \eta^m, \tag{7}$$

where ρ is a positive parameter and η^m is an error term, that is independent of a^m, of all other random variables, and across firms, and is normally distributed with mean zero and precision h_η/z (variance z/h_η). The parameters ρ and h_η control the persistence of shocks: The correlation between a_0^m and a^m equals $1/\sqrt{1+h_a/(\rho^2 h_\eta)}$, which increases with ρ or h_η. In particular, current shocks are unrelated to past shocks if ρ or h_η equals zero.

Second, we assume that profits in period 0 are imperfectly reported. Thus, the past profit provides a noisy signal for $(1-\omega^m)a_0^m$, denoted π_0^m (all the other components of the past profit are deterministic). Specifically, firm m reports

$$\pi_0^m = (1-\omega^m)a_0^m + \nu^m, \tag{8}$$

where ν^m is an error term that is independent of a_0^m, of all other random variables, and across firms, and is normally distributed with mean zero and precision h_ν/z (variance z/h_ν). Observing π_0 is equivalent to observing a signal $a_0^m + \nu^m/(1-\omega^m)$ about a_0^m. This signal is less accurate for a firm that enjoys more market power (the precision of the signal $(1-\omega^m)^2 h_\nu$ is lower when ω^m is larger). This is once again because firms use their market power to insulate profits from shocks, thus weakening the link from productivity to profits.

As before, we consider from now on a generic stock and drop the superscript m to simplify notations. Substituting equation (7) into equation (8) yields $\pi_0 = (1-\omega)\rho a + (1-\omega)\eta + \nu$. Thus, observing π_0 is equivalent to observing a signal about a, namely, $a + u$ were $u \equiv (\eta + \nu/(1-\omega))/\rho$. The precision of this signal is denoted h_{π_0} and equals

$$h_{\pi_0}(\omega) = \frac{\rho^2}{1/h_\eta + 1/[(1-\omega)^2 h_\nu]}.$$

Note that h_{π_0} increases with ρ and h_η as past shocks are more correlated to current shocks, and with h_ν as the reporting error shrinks, but it decreases with ω as firms exert their market power to hedge profits. In particular, the signal is uninformative when $\omega = 1$ because the profit at $t = 0$ is unrelated to the shock at $t = 0$ and hence to the shock at $t = 1$.

Finally, we note that this extension reverts to the model solved so far when ρ, h_η, or h_ν equals zero. In that case, past profits do not provide any information about future profits. The following proposition describes the equilibrium.

PROPOSITION 10: *There exists a log-linear rational expectations equilibrium in which shares trade at a price* $P = (1-\omega)K_0^{1-\omega}\exp(pz)$, *where*

$$p = p_0(\omega) + p_{\pi_0}(\omega)u + p_a(\omega)a + p_\theta(\omega)\theta, \quad u \equiv a + (\eta + \nu/(1-\omega))/\rho, \tag{9}$$

$$p_0(\omega) \equiv \frac{(1-\omega)^2}{h(\omega)}\left(\frac{1}{2} - \frac{\gamma(1-\omega)K_0^{1-\omega}}{w}\right) - r^f, \quad p_a(\omega) \equiv (1-\omega)\left(1 - \frac{h_a}{h(\omega)}\right), \tag{10}$$

$$p_\theta(\omega) \equiv \frac{(1-\omega)^2}{h(\omega)}\left(1 + \frac{h_s}{\gamma^2(1-\omega)^2\sigma_\theta^2}\right), \quad p_{\pi_0}(\omega) \equiv \frac{(1-\omega)h_{\pi_0}}{h(\omega)}, \tag{11}$$

$$h_p(\omega) \equiv \frac{h_s^2}{\gamma^2(1-\omega)^2\sigma_\theta^2}, \quad h_{\pi_0}(\omega) = \frac{\rho^2}{1/h_\eta + 1/[(1-\omega)^2 h_\nu]}, \tag{12}$$

and

$$h(\omega) \equiv h_a + h_{\pi_0}(\omega) + h_p(\omega) + h_s. \tag{13}$$

The pricing equations resemble those in Proposition 1. They are altered in two ways. First, the price is now a function of the past profit. The corresponding signal error u enters with a weight p_{π_0}. Naturally, p_{π_0} rises with the precision of the signal h_{π_0}, so it decreases when market power ω rises. In particular, $p_{\pi_0} = 0$ when $\omega = 1$ because the past profit is then uninformative. Second, investors' total precision h is larger by the amount h_{π_0}, the precision of the new signal (comparing equation (13) to equation (4)). This extra term makes h nonmonotonic in market power ω. Hence, two opposing forces are at work as market power strengthens. On the one hand, more market power implies a more informative stock price (h_p is higher, as in Proposition 3). On the other hand, it means a less informative past profit (h_{π_0} is lower). This trade-off is illustrated in the top left panel of Figure 8, which shows that market power is not unambiguously beneficial to stock market efficiency. Informational and

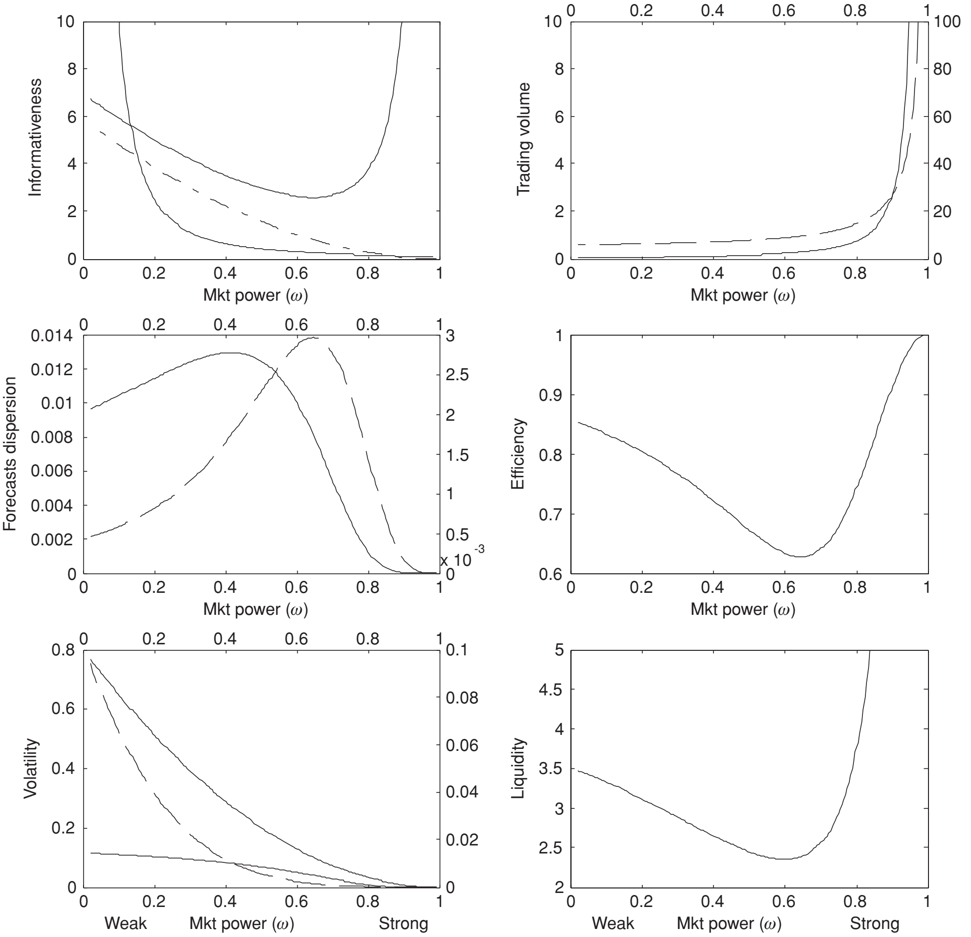

Figure 8. The impact of market power on the equilibrium when a firm's past profit is informative about its technology shock. ω on the x-axis measures the firm's power in its product market. The top left panel displays the total precision of public signals (solid line) and its breakup between the information revealed by stock prices (h_p, dashed line) and that revealed by firms' past performance (h_{π_0}, dash-dotted line). The top right panel displays the share turnover (solid curve, right scale) and the dollar trading volume (dashed curve, left scale). The middle left panel displays the dispersion of investors' forecasts about the firm's profit (solid line, right scale) and technology shock (dashed line, left scale). The middle right panel displays allocative efficiency $p_a/p_a^{\mathcal{P}}$. The bottom left panel displays the variance of log profits (solid curve, right scale), the variance of log prices (dashed curve, left scale), and the variance of stock returns (dotted curve, right scale). The bottom right panel displays liquidity $1/p_\theta$. The parameters are $h_a = 1$, $\sigma_\theta^2 = 0.1$, $r^f = 0.02$, $M = 10$, $K_0 = 1$, $w = 0.3$, $\gamma = 1$, $h_s = 0.1$, $h_\nu = 0.1$, $h_\eta = 0.01$, $\rho = 0.8$, and $z = 0.1$.

allocative efficiency are hurt by market power ω for low values of ω because much information from the past profit is lost. They improve for high values of ω because much information from the stock price is gained. Similarly, volatility and liquidity are nonmonotonous functions of market power. The exception is trading volume, which continues to grow with ω. This is because the past profit is a public signal so it does not generate differences in opinions and hence trading.[23]

B. Noise Trading

Our analysis of market power assumes that it cannot influence the intensity of noise trading, that is, that σ_θ^2 is not a function of ω. One may ask how our findings are affected by this assumption. It is not clear a priori how noise trading would change with market power. On the one hand, if noise stems from the trades of rational agents subject to liquidity needs, then it may strengthen in firms with more market power as these agents build up a precautionary position in less volatile stocks. On the other hand, if noise is generated by risk-neutral capital-constrained investors whose private signals contain systematic errors, then it may be larger in stocks with less market power as these agents trade more aggressively stocks that are more sensitive to their signal.

If we suppose that noise trading is more intense among firms with more market power (e.g., noise originates in liquidity shocks), then speculative trades in these stocks are more easily concealed, which encourages informed trading. In this case, our findings on trading activity are strengthened: The volume of informed trading and total volume increase even more than when σ_θ^2 is independent of ω. But the impact of market power on informativeness is now ambiguous since both informed and noise trading are more intense. It follows that the impacts on dispersion of forecasts and allocative efficiency are also ambiguous. If we suppose instead that noise trading is less intense among firms with more market power (e.g., noise originates in correlated signal errors), then the results are reversed: Informed and total trading grow with ω less than when σ_θ^2 is independent of ω and may even be reduced in more monopolistic firms. The net effects on informational and allocative efficiency are again ambiguous.

C. Leverage

Product market competition influences investors' trading behavior because it affects the probability distribution of the cash flows firms generate. More competitive firms offer payoffs that are more sensitive to shocks and therefore riskier (their variance is larger), so their stock is less actively traded. We expect the same argument to carry over to firms with higher operational or financial leverage. It is well known that firms for which operating costs are predominantly fixed (e.g., firms with large R&D expenditures) or those that finance themselves mostly with debt offer payoffs, are more sensitive to shocks and therefore more volatile. Investors will therefore be less prone to trade their stock.

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[23] Indeed, investors' portfolio shares do not depend on u, the error in the past profit signal. They are still given by equation (5).

The argument applied to financial leverage has interesting implications for security design. Asymmetric information is generally an important concern for issuers. As Boot and Thakor (1993) show, firms find it optimal to split claims to their cash flows into "informationally insensitive" and "informationally sensitive" claims, such as debt and equity. This partition stimulates informed trading (in the informationally sensitive security) and the collection of costly private information.[24] Our findings differ from those of Boot and Thakor (1993). While investors in Boot and Thakor (1993) favor the more informationally sensitive securities, they shy away from them in our framework. This is because traders in Boot and Thakor (1993) are risk-neutral and capital-constrained, whereas here they are risk-averse and free to borrow. In Boot and Thakor (1993), splitting claims avoids the need for traders to tie their limited funds to securities with known payoffs, from which they have little to gain, and allows them to concentrate instead on assets with the greatest information asymmetries. Putting it differently, they trade the most informationally sensitive securities because they are the riskiest, while they avoid trading them in our model precisely because they are the riskiest. These contrasting results illustrate the importance of investors' attitude toward risk and financing constraints to the design of securities. In the next section, we confront the model with data.

V. Empirical Evidence

In this section, we test whether some of the model's predictions are supported empirically. We describe in turn the sample formation, the methodology and variable construction, and the results.

A. Sample

Our sample consists of over 5,000 U.S. firms followed over a decade. It starts from all NYSE-, Amex-, and NASDAQ-listed securities that are contained in the CRSP-Compustat Merged database for the period 1996 to 2005. We retain stocks with share codes 10 or 11, remove financial companies and regulated industries, and winsorize variables at the 1% level. The resulting sample contains 28,172 firm-year observations and 5,497 different firms with an average of 5 years of data for each firm. We obtain corporate data and earnings announcement dates from Compustat, daily stock returns from CRSP, and insider trades from Thomson Financial.

B. Methodology and Variables

We conduct a test of Propositions 2 and 3, which predict that firms operating in more competitive industries have a lower volume of trade and less informative stock prices. For that purpose, we need proxies for market power, trading volume and stock price informativeness. We describe them in turn. Table I presents descriptive statistics.

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[24] Our paper treats the precision of traders' information as exogenous, unlike Boot and Thakor (1993). Nevertheless, investors' propensity to trade is suggestive of how valuable private information is.

- Market power: We proxy for a firm's market power using its price–cost margin or Lerner index, defined as the firm's operating profit margin (sales minus costs divided by sales).[25] Following Gaspar and Massa (2005), we subtract the industry average price–cost margin to control for structural differences across industries unrelated to the degree of competition.[26] The resulting excess price–cost margin (the difference between a firm's operating profit margin and the average of its industry) captures a firm's ability to price goods above marginal cost, adjusting for industry-specific factors unrelated to market power. A larger price–cost margin indicates stronger market power (weaker competition).
- Trading volume: To measure trading volume, we use a stock's turnover, defined as the log of the ratio of the number of shares traded during a year to the number of shares outstanding. We also examine the trades initiated by insiders to capture informed trading. The Thomson Financial Insider Filing database compiles all insider activity reported to the SEC. Corporate insiders include those that have "access to non-public, material, insider information" and are required to file SEC form 3, 4, and 5 when they trade in their companies stock. We follow most studies (e.g., Seyhun 1986, Lakonishok and Lee (2001), Beneish and Vargus (2002)) by limiting insider trades to open market transactions initiated by the top five executives (CEO, CFO, COO, President, and Chairman of Board), as they are more likely to possess private information, and by excluding sells, because they are more likely to be driven by hedging rather than information motives (e.g., when options' vesting periods expire). We measure insider trading activity in two ways: first, as the log of the ratio of a firm's annual total insider trading dollar volume to the firm's market capitalization, denoted "Insider turnover"; and second, as the ratio of the log of the firm's annual number of insider trades to the number of its active insiders, denoted "Number of insider trades." Active insiders are defined as executives who

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[25] The price–cost margin is used in Lindenberg and Ross (1981), Gaspar and Massa (2005), and most of the empirical industrial organization literature. Alternative proxies based on asset or sales concentration such as the Herfindahl–Hirschman index are industry- rather than firm-specific. Moreover, because data are limited to U.S. public firms, they do not account for private nor foreign firms. This is especially problematic given that our sample (1996 to 2005) covers a period of intense global competition.

[26] Specifically, the price–cost margin (PCM) is defined as operating profits (before depreciation, interest, special items, and taxes) over sales (Compustat annual data item 12). Operating profits are obtained by subtracting from sales the cost of goods sold (item 41) and general and administrative expenses (item 178). If data are missing, we use operating income (item 178). The excess price–cost margin is constructed as the difference between the firm's PCM and the PCM of its industry. The industry PCM is the value-weighted average PCM across firms in the industry where the weights are based on market share (sales over total industry sales) and industries are defined using two-digit SIC classifications.

Table I

Descriptive Statistics

This table presents summary statistics for the variables used in the empirical study. The sample starts from all NYSE-, Amex-, and NASDAQ-listed securities that are contained in the CRSP-Compustat Merged database for the period 1996 to 2005. We retain stocks with share codes 10 or 11, remove financial companies and regulated industries, and winsorize variables at the 1% level. *Market power* is measured as the excess price–cost margin (PCM) or Lerner index. The PCM is defined as operating profits (before depreciation, interest, special items, and taxes) over sales (Compustat annual data item 12). Operating profits are obtained by subtracting from sales the cost of goods sold (item 41) and general and administrative expenses (item 178). If data are missing, we use operating income (item 178). The excess price–cost margin is constructed as the difference between the firm's PCM and the PCM of its industry. The industry PCM is the value-weighted average PCM across firms in the industry, where the weights are based on market share (sales over total industry sales) and industries are defined using two-digit SIC classifications. *Size* is measured as the log of firms' assets. *Illiquidity* is measured using the Amihud (2002) illiquidity ratio and equals the ratio of a stock's absolute return to its dollar trading volume in a day, averaged over all days in a year, and scaled by 10^6. *Return on assets* is defined as income before extraordinary items (item 18) over total assets. *Leverage* is computed as total long-term debt (item 9) divided by total assets (item 6). *Market-to-book* is the ratio of the market value of equity (year-end stock price times the number of shares outstanding) to its book value. Book equity is constructed as stockholder's equity (item 216, or 60 + 130, or 6-181, in that order) plus balance sheet deferred taxes and investment tax credit (item 35) minus the book value of preferred stock (item 56, or 10, or 130, in that order). *Turnover* is defined as the log of the ratio of the number of shares traded during a year to the number of shares outstanding. Insider trades are open market transactions, excluding sells, initiated by the top five executives of a firm (CEO, CFO, COO, President, and Chairman of Board). *Insider trading activity* is measured in two ways: first, as the log of the ratio of a firm's annual total insider trading dollar volume to the firm's market capitalization, denoted *Insider turnover*; second, as the ratio of the log of the firm's annual number of insider trades to the number of its active insiders, denoted *Number of insider trades*. Active insiders are defined as executives who have reported at least one transaction in any of the sample years. *Stock price informativeness* is measured as (the inverse of) the absolute abnormal return surrounding an earnings announcement. Abnormal returns are measured as the residuals from the Fama–French three-factor model, obtained by regressing for every firm stock returns on the market, size, and book-to-market factors over an estimation window extending from $t = -250$ to $t = -5$ relative to the earnings announcement day 0. We estimate the residuals over an event window ranging from $t = -2$ to $t = +2$. Then, we sum the absolute value of abnormal returns on each day of the event window. Finally, we average the absolute abnormal returns estimates obtained from each announcement during a year to get an annual measure. We also report the average absolute raw return over the event window.

	Mean	Median	Std. Dev.	Min.	Max.	*N*
Number of years per firm	5.125	4	3.321	1	10	5,497
Market power	0.142	0.115	0.119	−0.107	3.614	26,264
Size	5.607	5.516	1.891	0.501	11.743	26,946
Illiquidity	4.792	0.053	44.737	0.000	3 194	28,103
Return on assets	0.029	0.045	0.374	−43	2.188	26,972
Market-to-book	−0.380	1.923	555	−90,022	6,365	26,495
Leverage	0.191	0.143	0.206	0.000	3.862	26,816
Turnover	−0.127	−0.076	1.006	−6.529	10.313	26,405
Insider turnover	0.007	0.001	0.025	0.000	1.051	26,795
Number of insider trades	0.246	0.147	0.337	0.000	4.868	24,676

(continued)

Table I—*Continued*

	Mean	Median	Std. Dev.	Min.	Max.	N
Abs. 5-day raw return around earnings announcements	0.151	0.135	0.078	0.000	0.845	24,827
Abs. 5-day abn. return relative to the three-factor model around earnings announcements	0.149	0.133	0.078	0.009	0.855	24,827

have reported at least one transaction in any of the sample years (Ke, Huddart, and Petroni (2003)).

- Earnings announcements: We use the stock price reaction to earnings announcements to assess the informativeness of stock prices. Large (small) price changes are indicative of remotely (closely) followed firms, as shown by numerous studies starting with Beaver (1968). We measure the absolute abnormal return over a 5-day window centered on days earnings are announced. Abnormal returns are defined relative to the Fama–French (1993) three-factor model.[27] We sum their absolute value on each day of the event window to measure the stock price reaction to the announcement, and take the average over all announcements in a year to obtain an annual measure (consistent with our proxy for market power and other control variables).

We examine the impact of market power in separate panel regressions for turnover, insider trading, and stock price informativeness. We correct standard errors for serial and cross-sectional correlation using year and firm clusters.[28] Our regressions include controls for several factors, such as firm size, equity market-to-book ratio, liquidity, profitability, and leverage, that may be associated with trading activity or with reactions to announcements.[29]

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[27] Specifically, absolute abnormal returns surrounding an earnings announcement are defined as $\sum_{t=-2}^{+2}|u_t^m|$, where $t = -2, -1, 0, +1$, and +2 count trading days relative to the announcement day 0 for firm m, $u_t^m = R_t^m - (\alpha_0^m + \alpha_{mkt}^m MKT_t + \alpha_{SMB}^m SMB_t + \alpha_{HML}^m HML_t)$, R_t^m is the return on firm m's stock on day t, and MKT_t, SMB_t, and HML_t are respectively the returns on the market, size and book-to-market factors on day t. The coefficients α_0^m, α_{mkt}^m, α_{SMB}^m, and α_{HML}^m are estimated for every firm over a window ranging from $t = -250$ to $t = -5$.

[28] We correct standard errors using the procedure outlined in Thompson (2006) and Cameron, Gelbach, and Miller (2006)).

[29] Firm size is measured as the log of firms' total assets (Compustat item 6). Leverage is computed as total long-term debt (item 9) divided by assets. The market-to-book ratio is defined as the ratio of the market value of equity (year-end stock price times the number of shares outstanding) to its book value. Book equity is constructed as stockholder's equity (item 216, or 60 + 130, or 6 − 181, in that order) plus balance sheet deferred taxes and investment tax credit (item 35) minus the

Table II

Market Power and Turnover

This table presents results of annual panel regressions of turnover on market power and other firm characteristics over the 1996 to 2005 period. Turnover is defined as the log of the ratio of the number of shares traded during a year to the number of shares outstanding. Market power is measured as the excess price–cost margin or Lerner index. The absolute values of *t*-statistics are displayed below the coefficient estimates. They are based on standard errors clustered both by firm and year. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, for the two-tailed hypothesis test that the coefficient equals zero. See Table I for the variable definitions.

	Turnover							
Market power	0.896	0.537	0.420	0.364	0.582	2.117	1.340	1.458
	4.78***	4.17***	3.54***	2.93***	4.67***	4.55***	3.24***	3.37***
Market power × Size						−0.270	−0.156	−0.148
						3.99***	2.55**	2.30**
Size		0.125	0.101	0.103	0.130	0.162	0.123	0.151
		4.40***	3.51***	3.57***	4.54***	4.84***	3.70***	4.54***
Illiquidity			−0.010	−0.009	−0.009		−0.009	−0.009
			6.74***	6.77***	6.81***		6.64***	6.70***
Return on assets			0.166	0.502	−0.006		0.154	−0.047
			1.69*	3.32***	0.030		1.70*	0.290
Market-to-book				5.396	3.511			2.768
				2.99***	2.11**			1.610
Leverage					−0.941			−0.946
					12.10***			12.10***
Constant	−0.254	−0.899	−0.724	−0.737	−0.725	−1.105	−0.847	−0.840
	4.70***	5.36***	4.40***	4.48***	4.35***	5.50***	4.40***	4.29***
Observations	25,798	25,791	25,732	25,462	25,389	25,791	25,732	25,389
R^2	0.011	0.059	0.091	0.093	0.120	0.062	0.092	0.121

C. Results

As a preliminary, we sort firms every year into five groups based on their market power and measure within each group, the average turnover, insider activity, and price reaction to announcements. The results are presented in Figures 1 to 3. The figures reveal that trading activity, including that initiated by insiders, is higher for firms with more market power and that the price of such firms reacts less to announcements. The panel regressions, displayed in Tables II to IV, confirm the visual impression of the figures after controlling for other factors. The coefficient on market power is statistically significant across all specifications with the same sign (positive for the turnover and insider

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book value of preferred stock (item 56, or 10, or 130, in that order). Profitability is measured as the return on assets and is defined as income before extraordinary items over total assets. Finally, we proxy for the lack of liquidity using Amihud's (2002) illiquidity ratio, defined as the ratio of a stock's absolute daily return to its daily trading volume, averaged over all days in a year and scaled by 10^6. It captures the absolute percentage price change per dollar of trading volume, that is, the price impact of trades, and is correlated with illiquidity proxies obtained from microstructure data (see Amihud (2002)).

Table III

Market Power and Insider Trading

This table presents results of annual panel regressions of insider trading on market power and other firm characteristics over the 1996 to 2005 period. In Panel A, insider trading activity is measured as the log of the ratio of a firm's annual total insider trading dollar volume to the firm's market capitalization, and it is denoted Insider turnover. In Panel B, it is measured as the log of the ratio of the firm's annual number of insider trades to the firm's number of active insiders and is denoted Number of insider trades. Market power is measured as the excess price–cost margin or Lerner index. The absolute values of t-statistics are displayed below the coefficient estimates. They are based on standard errors clustered both by firm and year. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively, for the two-tailed hypothesis test that the coefficient equals zero. See Table I for the variable definitions.

Panel A: Insider Turnover

Market power	0.004	0.006	0.005	0.003	0.003	0.020	0.018	0.014
	2.37**	3.69***	3.58***	1.89*	1.75*	3.92***	4.18***	3.17***
Market power × size						−0.002	−0.002	−0.002
						3.39***	3.55***	3.18***
Size		−0.001	−0.001	−0.001	−0.001	0.000	0.000	0.000
		7.21***	6.94***	6.74***	5.50***	2.27**	2.70***	2.34**
Illiquidity			0.000	0.000	0.000		0.000	0.000
			0.250	0.060	0.060		0.130	0.050
Return on assets			0.004	0.012	0.012		0.004	0.011
			1.450	6.42***	6.29***		1.450	6.04***
Market-to-book				0.130	0.130			0.121
				8.12***	8.12***			7.68***
Leverage					0.000			0.000
					0.050			0.120
Constant	0.006	0.010	0.010	0.010	0.009	0.008	0.008	0.008
	12.75***	14.77***	14.13***	13.79***	13.87***	8.29***	8.63***	8.58***
Observations	26,040	26,031	25,970	25,676	25,597	26,031	25,970	25,597
R^2	0.000	0.002	0.003	0.004	0.004	0.003	0.003	0.005

Panel B: Number of Insider Trades

Market power	0.230	0.228	0.204	0.160	0.184	0.484	0.391	0.327
	6.41***	6.52***	5.67***	5.35***	5.93***	4.85***	4.24***	3.74***
Market power × size						−0.043	−0.031	−0.024
						3.25***	2.53**	1.92*
Size		0.001	−0.001	0.000	0.003	0.007	0.003	0.006
		0.250	0.460	0.050	1.100	2.21**	1.150	2.06**
Illiquidity			−0.001	−0.001	−0.001		−0.001	−0.001
			5.47***	5.66***	5.76***		5.34***	5.51***
Return on assets			0.080	0.299	0.239		0.078	0.232
			1.430	4.24***	3.34***		1.430	3.27***
Market-to-book				3.987	3.761			3.651
				3.86***	3.52***			3.43***
Leverage					−0.107			−0.108
					4.83***			4.83***
Constant	0.215	0.212	0.223	0.214	0.216	0.177	0.198	0.197
	13.65***	12.57***	13.60***	12.92***	13.17***	9.01***	10.34***	10.09***
Observations	23,091	23,080	23,037	22,743	22,674	23,080	23,037	22,674
R^2	0.007	0.007	0.010	0.015	0.018	0.007	0.010	0.018

Table IV

Market Power and Stock Price Informativeness

This table presents results of annual panel regressions of stock price informativeness on market power and other firm characteristics over the 1996 to 2005 period. Informativeness is measured as (the inverse of) the average absolute abnormal return surrounding an earnings announcement (from $t = -2$ to $t = +2$). Abnormal returns are the residuals from the Fama–French three-factor model. Market power is measured as the excess price-cost margin or Lerner index. The absolute values of t-statistics are displayed below the coefficient estimates. They are based on standard errors clustered both by firm and year. The symbols *** and * denote significance at the 1% and 10% levels respectively, for the two-tailed hypothesis test that the coefficient equals zero. See Table I for the variable definitions.

	Stock Price Informativeness									
Market power	−0.096	−0.044	−0.030	−0.013	−0.013	−0.032	−0.190	−0.120	−0.083	−0.112
	8.50***	4.92***	5.93***	1.81*	1.65*	4.26***	8.82***	5.03***	4.48***	7.51***
Market power × size							0.025	0.015	0.012	0.013
							6.15***	3.55***	3.20***	4.75***
Size		−0.017	−0.016	−0.016	−0.016	−0.020	−0.021	−0.018	−0.018	−0.022
		17.06***	16.34***	18.27***	18.06***	35.35***	15.68***	14.78***	15.50***	34.61***
Illiquidity			0.001	0.001	0.001	0.001		0.001	0.001	0.001
			6.14***	6.00***	5.94***	5.07***		6.27***	6.05***	5.05***
Return on assets			−0.034	−0.108	−0.107	−0.099		−0.033	−0.104	−0.095
			1.320	11.59***	10.09***	10.30***		1.310	95.6***	9.69***
Market-to-book				0.365	0.368	0.275			0.427	0.344
				2.91***	3.17***	2.77***			3.46***	3.36***
Leverage					0.003	0.031			0.003	0.031
					0.410	5.97***			0.480	5.99***
Turnover						0.026				0.026
						12.69***				12.73***
Constant	0.160	0.250	0.238	0.241	0.241	0.260	0.269	0.250	0.250	0.270
	32.07***	47.36***	56.45***	58.01***	56.08***	54.57***	35.41***	37.01***	38.06***	46.44***
Observations	23,432	23,417	23,415	23,113	23,040	22,718	23,417	23,415	23,040	22,718
R^2	0.023	0.198	0.237	0.255	0.255	0.375	0.202	0.239	0.256	0.376

trading regressions and negative for the earnings announcements regressions). These findings are consistent with the predictions of Propositions 2 and 3.[30]

The economic magnitude of these effects is relatively modest. Increasing market power by one standard deviation increases turnover, insider turnover, and the number of insider trades respectively by 5% to 10% of a standard deviation, 1% to 3% of a standard deviation, and 6% to 8% of a standard deviation. Stock price informativeness declines by 2% to 14% of a standard deviation. These magnitudes are not so surprising given that the effects are measured over the entire sample of firms. Their significance is likely to vary across firms depending on the extent of information asymmetries and noise trading. In particular, one would suspect the impact of market power to be stronger among firms with more severe information asymmetries, such as smaller firms; firms listed on NASDAQ; and firms with fewer analysts, more individual shareholders, large blockholders, and more R&D expenditures.[31]

For example, an interacted term, *Mkt Power* × *Size*, is included in some of the regressions to examine how the coefficient on market power varies with firm size. The sign of the corresponding estimated coefficient is negative in the turnover and insider trading regressions (Tables II and III) and positive in the informativeness regression (Table IV), suggesting that the impact of market power shrinks with size. This is consistent with the model to the extent that size is inversely related to the accuracy of private information. If information asymmetries are less pervasive among larger firms, then informed trading, overall trading, and stock price informativeness are less sensitive to market power among these firms.

The coefficient estimates on leverage deserve some comment. Their sign is negative in Tables II and III and positive in Table IV, indicating that leverage reduces trading, including that by insiders, and the informativeness of stock prices. These findings are consistent with our discussion of leverage in Section IV.C, where we argue that leverage magnifies risk in the same way that competition does, discouraging trading and limiting the incorporation of information into prices.

VI. Conclusion

We present a model that links investors' trading behavior to the degree of product market competition. Ours is a standard rational expectations model of trading under asymmetric information in competitive stock markets, but for one difference: Firms enjoy monopoly power in their product market. Production is subject to random productivity shocks about which investors receive private signals. The driving force of the model is that monopolies are able to pass shocks on to customers and insulate their profits.

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[30] We confirm that our results are robust to a number of changes in supplementary analyses available in the Internet Appendix in the "Supplements and Datasets" section at http://www.afajof.org/supplements.asp.

[31] Indeed, the model implies that market power interacts with the precision of investors' private signals in the trading volume and informativeness equations. Trading volume is a function of $h_s/(1-\omega)^2$ (see the Appendix), and informativeness h_p is a function of $h_s/(1-\omega)$ (equation (4)). Thus, the influence of market power ω is stronger when the precision of private signals h_s is larger.

We establish the following results about firms that enjoy more market power. (i) Their stock trading volume is larger. As a result, (ii) the incorporation of private information into prices is expedited. Several implications follow: (iii) investors' productivity and earnings forecasts are less dispersed, (iv) stock liquidity is enhanced, (v) volatility of profits and stock returns is dampened, and (vi) expected returns are lower, even after adjusting for risk. Moreover, (vii) when firms issue new shares, capital is more efficiently deployed across more monopolistic firms. Thus, product market imperfections (monopoly power), rather than spreading to equity markets, tend to mitigate stock market imperfections (informational and allocative inefficiencies). These findings are consistent with existing documented facts and we present further supportive evidence. In particular, we report that trading volume, including trades initiated by insiders, and the information content of stock prices are higher for firms with more market power.

Our results are of importance to policy makers and financial economists. They indicate that product market deregulation has implications that extend to equity markets. Therefore, these reforms should not be conducted in isolation but in combination with reforms designed to improve the efficiency of the financial sector. They also shed light on some trends that have been observed in the United States. Idiosyncratic return volatility increased in the post-war period (Morck et al. (2000), Campbell et al. (2001) and, Comin and Philippon (2006)) as competition intensified thanks to deregulation and globalization. Our model suggests that competition worsened the informativeness of stock prices, which also contributed to the volatility increase.

In our attempt to link industrial organization to the informational properties of stocks in a rational expectations framework, we omitted several points for simplicity. First, the structure of product markets is taken as given, when in fact it is endogenous. If more productive firms raise more capital in a more efficient equity market, they will be disproportionately large and enjoy more market power. This calls for a model in which the degree of competition and the properties of stock prices are jointly determined in equilibrium. Second, the precision of investors' information is exogenous to the model. In practice, they may adjust their research effort to the stocks' riskiness. The effect of competition on signal precision is unclear. On the one hand, information about more competitive stocks is less useful if they are traded less. On the other hand, increased competition exposes stockholders to more risk, making information more useful. Finally, the number of firms in the market is fixed. Endogenizing the listing decision would shed light on the joint impact of the informational and competitive environments on firms' incentives to go public. Recent empirical work suggests that firms operating in industries characterized by more competition and more information asymmetry are less likely to do an IPO (Chemmanur, He, and Nandy (2006)). These questions are left for future research.

Appendix: Proofs

Proof of Proposition 1 (Stock prices): The proof of Proposition 1 builds on Peress (2004). We guess that equilibrium prices are given by equations (2) to (4) and solve for an investor's optimal portfolio by driving z toward zero. The first step is to relate stock returns to technology shocks.

- Stock returns

For a given stock of capital K_0, intermediate goods prices are determined by the market clearing condition, $A^m K_0 = ((1-\omega^m)/Q^m)^{1/\omega^m}$. The resulting monopoly profits equal $\Pi^m = Y^m Q^m = (1-\omega^m)(A^m K_0)^{1-\omega^m}$. Since there is one share outstanding, the gross stock return is $R^m = \Pi^m / P^m$. Writing $P^m = \bar{P}^m \exp(p^m z)$ implies that

$$R^m = (1-\omega^m)K_0^{1-\omega^m}/\bar{P}^m \exp[((1-\omega^m)a^m - p^m)z].$$

When $z = 0$ (no risk), $R^m = (1-\omega^m)K_0^{1-\omega^m}/\bar{P}^m$ and $R^f = 1$. Stocks are riskless so $\bar{P}^m = (1-\omega^m)K_0^{1-\omega^m}$. Thus, the log return on stock m is $r^m z = \ln(R^m) = (1-\omega^m)a^m z - p^m z$. The second step is to estimate the mean and variance of stock returns using the equilibrium prices and private signals s_l^m.

- Signal extraction

We guess that prices are approximately normally distributed and given in equation (2), that is, $p^m z = p_0 z + p_a \xi^m z + o(z)$, where $\xi^m \equiv a^m + \mu^m \theta^m$, μ^m is a constant to be determined and $o(z)$ captures terms of order larger than z. The conditional mean and variance of $a^m z$ for agent l are

$$\mathrm{var}(a^m z \mid \mathcal{F}_l) = \frac{z}{h^m} \quad \text{and} \quad E(a^m z \mid \mathcal{F}_l) = \left(a_\xi^m \xi^m + a_s^m s_l^m\right)z$$

where

$$h_0^m \equiv h_a + \frac{1}{\mu^{m2}\sigma_\theta^2}, \; h^m \equiv h_0^m + h_s, \, a_\xi h^m \equiv \frac{1}{\mu^{m2}\sigma_\theta^2} = h_p^m, \; \text{and } a_s h^m \equiv h_s.$$

The variance $\mathrm{var}(a^m z \mid \mathcal{F}_l)$ falls as the precisions of the private and public signals, specifically h_s and $1/(\mu^{m2}\sigma_\theta^2)$, increase. $E(a^m z \mid \mathcal{F}_l)$ is a weighted average of priors, public and private signals, where the weight on the private signal (the public signal) is increasing in h_s (in $1/(\mu^{m2}\sigma_\theta^2)$). The conditional mean and variance of stock excess returns follow

$$E\left(r^m z \mid \mathcal{F}_l\right) = E((1-\omega^m)a^m z \mid \mathcal{F}_l) - p^m z$$

and

$$\mathrm{var}(r^m z \mid \mathcal{F}_l) = \mathrm{var}((1-\omega^m)a^m z \mid \mathcal{F}_l).$$

We next turn to the investor's portfolio choice

- Individual portfolio choice

Agent l, endowed with wealth w, forms her portfolio to maximize $E[\frac{c_l^{1-\gamma}-1}{1-\gamma} \mid \mathcal{F}_l]$ subject to $c_l = w\exp(r_l z)$, where $r_l z = \ln[R^f + \sum_{m=1}^{M} f_l^m(R^m - R^f)]$ is investor l's log portfolio return. Note that $r_l z$ is approximately normal when z is small (e.g., Campbell and Viceira (2002)). Therefore,

$$\begin{aligned} E\big[\big(c_l^{1-\gamma}-1\big)/(1-\gamma) \mid \mathcal{F}_l\big] &= E_l\big[\big\{w^{1-\gamma}\exp((1-\gamma)r_l z) - 1\big\}/(1-\gamma) \mid \mathcal{F}_l\big] \\ &= \big\{w^{1-\gamma}\exp\big[(1-\gamma)E(r_l z \mid \mathcal{F}_l) \\ &\quad + (1-\gamma)^2 \operatorname{var}(r_l z \mid \mathcal{F}_l)/2)\big] - 1\big\}/(1-\gamma) + o(z), \end{aligned}$$

where

$$E(r_l z \mid \mathcal{F}_l) = \sum_{m=1}^{M}\big\{f_l^m(E(r^m z \mid \mathcal{F}_l) - r^f z) + f_l^m(1 - f_l^m)\operatorname{var}(r^m z \mid \mathcal{F}_l)/2\big\} + o(z)$$

and

$$\operatorname{var}(r_l z \mid \mathcal{F}_l) = \sum_{m=1}^{M} f_l^{m2}\operatorname{var}_l\big(r^m z \mid \mathcal{F}_l\big) + o(z).$$

Maximizing $E[(c_l^{1-\gamma}-1)/(1-\gamma) \mid \mathcal{F}_l]$ with respect to f_l^m leads to the fraction of wealth allocated to stock m (at the order 0 in z):

$$f_l^m = \frac{E(r^m z \mid \mathcal{F}_l) - r^f z + \operatorname{var}\big(r^m z \mid \mathcal{F}_l\big)/2}{\gamma \operatorname{var}\big(r^m z \mid \mathcal{F}_l\big)} + o(1). \tag{A1}$$

Substituting the above expressions for $E(r^m z \mid \mathcal{F}_l)$ and $\operatorname{var}(r^m z \mid \mathcal{F}_l)$ yields

$$f_l^m = \frac{1}{(1-\omega^m)\gamma}\left\{h_s s_l^m + \frac{1}{\mu^{m2}\sigma_\theta^2}\xi^m - \frac{h^m}{(1-\omega^m)}\big(p + r^f\big) + \frac{(1-\omega^m)}{2}\right\} + o(1). \tag{A2}$$

The final step involves aggregating stock demands and clearing the market.

- Market clearing

We multiply equation (5) by investors' income w and sum over all investors to obtain investors' aggregate demand for stock m (at the order 0 in z):

$$\begin{aligned} \int_0^1 f_l^m w\,dl = \frac{w}{(1-\omega^m)\gamma}&\left\{a^m h_s + \int_0^1 h_s \varepsilon_l^m dl + \frac{1}{\mu^{m^2}\sigma_\theta^2}\xi^m \right. \\ &\left. - \frac{h^m}{(1-\omega^m)}(p^m + r^f) + \frac{(1-\omega^m)}{2}\right\} + o(1) \end{aligned} \tag{A3}$$

since $\int_0^1 h^m dl = h^m$ and $\int_0^1 h_s a^m dl = a^m h_s$. Applying the law of large numbers to the sequence $\{h_s \varepsilon_l^m\}$ of independent random variables with the same mean zero leads to $\int_0^1 h_s \varepsilon_l^m dl = 0$ (see He and Wang (1995) for more details). Finally, the market clearing condition for stock m is $(\int_0^1 f_l^m dl + \theta^m)w/P^m = 1$. The left-hand side is the total demand for stock m, which consists of investors' and noise traders' demands. The right-hand side is the supply of shares. Plugging in the expression for investors' demand and dropping terms of order z and above yields $\mu^m = \gamma(1-\omega^m)/h_s$. The equilibrium prices given in Proposition 1 follow. They are linear in a^m and θ^m as guessed. Finally, rearranging equation (A2) leads to equation (5). Q.E.D

Proof of Proposition 2 (Trading volume): Since an agent's informational trades are worth $w|f_l - f_{l,0}|/2$, the average value of trades, motivated by information, equals $V_I \equiv \int_0^1 \frac{w}{2}|f_l - f_{l,0}|dl$. The factor 1/2 avoids double counting trades. The difference $f_l - f_{l,0}$ is approximately normally distributed so $V_I = \frac{w}{2}\sqrt{\frac{2}{\pi}\text{var}(f_l - f_{l,0})}$ (e.g. He and Wang (1995)). Replacing f_l with its expression in equation (5) yields $V_I = \frac{w}{2}\sqrt{\frac{2}{\pi}}\sqrt{\frac{h_s}{\gamma^2(1-\omega)^2} + \sigma_\theta^2} + o(1)$, conditional on $f_{l,0}$. Noise traders generate a trading volume on average equal to $E(\frac{1}{2}w\,|\theta|) = \frac{w}{2}\sqrt{\frac{2}{\pi}}\sqrt{\sigma_\theta^2}$. Adding information- and noise-motivated trades leads to a (dollar) total trading volume $V = \frac{w}{2}\sqrt{\frac{2}{\pi}}(\sqrt{\frac{h_s}{\gamma^2(1-\omega)^2} + \sigma_\theta^2} + \sqrt{\sigma_\theta^2}) + o(1)$. Turnover is obtained by dividing by the stock's market capitalization, $(1-\omega)K_0^{1-\omega} + o(1)$ (the firm has only one share outstanding), and equals $V_T \equiv V/((1-\omega)K_0^{1-\omega}) + o(1)$. To assess the impact of market power on trading volume, it suffices to differentiate V and V_T with respect to ω. Doing so implies that $\partial V/\partial\omega > 0$ and $\partial V_T/\partial\omega > 0$, as Proposition 2 establishes. Q.E.D.

Proof of Proposition 3 (Stock price informativeness): The informativeness of prices is defined as $h_p = h_s^2/(\gamma^2(1-\omega)^2\sigma_\theta^2)$. Clearly, $\partial h_p/\partial\omega > 0$ so market power enhances the informativeness of prices. Q.E.D.

Proof of Proposition 4 (Dispersion of investors' forecasts): We showed in the proof of Proposition 1 that investors' productivity forecasts equal $E(a \mid \mathcal{F}_l) = a_{0l} + a_\xi \xi + a_s s_l$. The dispersion of these forecasts across investors, for a given firm (i.e., for a given realization of the shocks a and θ) is measured by

$$\begin{aligned} D \equiv \text{var}[E(a \mid \mathcal{F}_l) \mid a, \theta] &= \text{var}(a_s s_l \mid a, \theta) = \text{var}(a_s \varepsilon_l) = a_s^2 \text{var}(\varepsilon_l) \\ &= (h_s/h)^2/h_s/z = h_s/z/h^2/z. \end{aligned}$$

To assess the impact of market power on D, it suffices to note that h is increasing in ω and therefore that D is decreasing in ω. Similarly, investors profit and return forecasts equal $E(\pi \mid \mathcal{F}_l) = E((1-\omega)a \mid \mathcal{F}_l)$ and $E(r \mid \mathcal{F}_l) = E((1-\omega)a \mid \mathcal{F}_l) - p$ so their dispersions, conditional on a and θ, equal $(1-\omega)^2 D$. Since D is decreasing in ω, $(1-\omega)^2 D$ is too. Thus, investors make less dispersed forecasts about the productivity, profit, and return of more monopolistic firms. Q.E.D.

Proof of Proposition 5 (Distribution of stock returns):

- Expected stock returns

The expected excess (simple) return on a stock equals

$$\begin{aligned} E(R) - R^f &= E[E(rz \mid \mathcal{F}_l) - r^f z + \mathrm{var}(rz \mid \mathcal{F}_l)/2] \\ &= E(rz) - r^f z + \mathrm{var}(rz \mid \mathcal{F}_l)/2 \\ &= (-p_0 - r^f + (1-\omega)^2/h/2)z \\ &= \gamma(1-\omega)^3 K_0^{1-\omega} z/(hw) + o(z) \end{aligned}$$

because

$$\mathrm{var}(rz \mid \mathcal{F}_l) = \mathrm{var}((1-\omega)az \mid \mathcal{F}_l) = (1-\omega)^2 z/h$$

from the proof of Proposition 1. We note that $E(R) - R^f$ is identical across investors and firms with the same market power. The numerator, $(1-\omega)^3 K_0^{1-\omega}$, reflects the direct effect of ω on the expected excess return. The indirect effect of ω operates through h in the denominator. Like the direct effect, it tends to reduce expected returns: As ω increases, information improves (h increases) so expected returns fall.

- Sharpe ratios

The average Sharpe ratio is identical across investors and firms with the same market power. It equals

$$\begin{aligned} SR \equiv E\{[E(R \mid \mathcal{F}_l) - R^f]/\sqrt{\mathrm{var}(rz \mid \mathcal{F}_l)}\} &= [E(R) - R^f]/\sqrt{\mathrm{var}(rz \mid \mathcal{F}_l)} \\ &= \gamma(1-\omega)^3 K_0^{1-\omega}\sqrt{z}/(hw)/\sqrt{(1-\omega)^2/h} \\ &= \gamma(1-\omega)^2 K_0^{1-\omega}\sqrt{z}/w/\sqrt{h}. \end{aligned}$$

Again, the direct effect of ω (the $(1-\omega)^2 K_0^{1-\omega}$ term in the numerator) decreases the Sharpe ratio and the indirect effect through the informativeness of prices ($\sqrt{h}$ in the denominator) decreases it further.

- Stock return volatility

As noted above, the conditional variance of stock returns equals

$$\mathrm{var}(rz \mid \mathcal{F}_l) = \mathrm{var}((1-\omega)az \mid \mathcal{F}_l) = (1-\omega)^2 z/h.$$

The unconditional variance is $\mathrm{var}(rz) = \mathrm{var}[E(rz \mid \mathcal{F}_l)] + E[\mathrm{var}(rz \mid \mathcal{F}_l)]$, where

$$E[\mathrm{var}(rz \mid \mathcal{F}_l)] = E[\mathrm{var}((1-\omega)az \mid \mathcal{F}_l)] = (1-\omega)^2 z/h.$$

To compute $\mathrm{var}[E(rz \mid \mathcal{F}_l)]$, we note that

$$\begin{aligned} E(rz \mid \mathcal{F}_l) &= E((1-\omega)az - pz \mid \mathcal{F}_l) = E((1-\omega)az \mid \mathcal{F}_l) - pz \\ &= \left[\xi/\left(\mu^2\sigma_\theta^2\right) + h_s s_l\right]z/h - (p_0 + p_a\xi)z + o(z) \end{aligned}$$

(recall from the proof of Proposition 1 that $\xi \equiv a + \mu\theta$ and $\mu = \gamma(1-\omega)/h_s$). Thus, $E(rz \mid \mathcal{F}_l) = (1-\omega)[h_s(\varepsilon_l - \mu\theta)]z/h - p_0 z$ and $\mathrm{var}[E(rz \mid \mathcal{F}_l)] = (1-\omega)^2(h_s + \gamma^2(1-\omega)^2\sigma_\theta^2)z/h^2 + o(z)$. Adding the two terms yields $\mathrm{var}(rz) = (1-\omega)^2(h + h_s + \gamma^2(1-\omega)^2\sigma_\theta^2)z/h^2 + o(z)$. Again the indirect effect of ω through the informativeness of prices appears in the h terms. Differentiating $\ln \mathrm{var}(rz)$ with respect to h yields

$$\partial(\ln \mathrm{var}(rz))/\partial h = -\left(h + 2h_s + 2\gamma^2(1-\omega)^2\sigma_\theta^2\right)z/\left(h + h_s + \gamma^2(1-\omega)^2\sigma_\theta^2\right)/h < 0.$$

Thus, the increase in h generated by strengthening market power reduces the volatility of stock returns.

- Profit volatility

We compute the volatility of log profits (we take logs to factor out the order-0 term), conditional on stock prices. Here,

$$\mathrm{var}(\ln \Pi \mid P) = \mathrm{var}((1-\omega)az \mid P) = (1-\omega)^2 z/(h_a + h_p).$$

Higher informativeness h_p, caused by an increase in market power, reduces the volatility of profits beyond the direct effect of market power. Q.E.D.

Proof of Proposition 6 (Liquidity): In the model, liquidity represents the sensitivity of stock prices to (uninformative) noise shocks and is measured by

$$p_\theta = \gamma(1-\omega)p_a/h_s = \gamma(1-\omega)^2(1 - h_a/h(\omega))/h_s.$$

To assess the impact of competition on liquidity, we differentiate p_θ with respect to $\omega : \partial \ln p_\theta/\partial\omega = -2/(1-\omega) + h_a(\partial h/\partial\omega)/(1 - h_a/h)/h^2$. Plugging in $\partial h/\partial\omega = 2h_s^2/(\gamma^2(1-\omega)^3\sigma_\theta^2)$ yields

$$\partial \ln p_\theta/\partial\omega = -2\left[(1 - h_a/h) - h_a h_s^2/(\gamma^2(1-\omega)^2\sigma_\theta^2 h^2)\right]/(1 - h_a/h)/(1-\omega).$$

Since the denominator is positive, we focus on the numerator. It can be written as

$$-2\left[h(h - h_a) - h_a(h - h_a - h_s)\right] = -2\left[(h - h_a)^2 + h_a h_s\right] < 0.$$

Hence, $\partial \ln p_\theta/\partial\omega < 0$ and stock prices of more monopolistic firms are less sensitive to noise shocks, that is, are more liquid. In particular, prices are independent from noise shocks when ω is close to one. Q.E.D.

Proof of Proposition 7 (Stock prices when shares are issued): The proof follows that of Proposition 1 except that the stock of capital is now endogenous. The amount of new capital raised equals the value of the α new shares, that is,

$K = \alpha P$. The expanded capital stock, $K_0 + K$, allows a monopoly to generate a profit

$$\Pi = YQ = (1-\omega)(A(K_0+K))^{1-\omega}.$$

Since there are $1+\alpha$ shares outstanding, the resulting gross stock return is

$$R = \Pi/(P(1+\alpha)) = (1-\omega)[A(K_0+\alpha P)]^{1-\omega}/(P(1+\alpha)).$$

We express stock prices as $P = \bar{P}\exp(pz)$ and expand returns around $z = 0$. We obtain

$$R = (1-\omega)(K_0+\alpha\bar{P})^{1-\omega}/(\bar{P}(1+\alpha))\exp[(1-\omega)az - (1-\delta+\delta\omega)pz] + o(z)$$

where $\delta \equiv \alpha\bar{P}/(K_0+\alpha\bar{P})$ is the dilution factor. When $z = 0$ (no risk), $R = 1$ so $\bar{P}$ is the solution to $\bar{P}(1+\alpha) = (1-\omega)(K_0+\alpha\bar{P})^{1-\omega}$. Therefore, the log stock return is $rz = \ln(R) = [(1-\omega)a - (1-\delta+\delta\omega)p]z + o(z)$. The subsequent steps are identical to those that compose the proof of Proposition 1. We solve the signal extraction and portfolio problems of an investor who observes p and s_l. We aggregate stock demands using the law of large numbers, add noise trades, and equate the total demand to the total supply of shares, $1+\alpha$. The resulting stock price p is linear in a and θ as guessed. Its expression is provided in Proposition 7. Q.E.D.

Proof of Propositions 8 and 9 (Allocative efficiency): Differentiating equation (6) defining $p_a(\omega,\delta)$ with respect to h holding ω fixed yields

$$\partial p_a/\partial h = (1-\omega)/(1-\delta+\delta\omega)/h_a/h^2.$$

Thus, p_a increases with h: Investments are more efficient when information is more accurate. Similarly, we can measure the efficiency of investments using $p_a/p_a^{\mathcal{P}} = 1 - h_a/h$ to factor out the direct effect of ω. Since h increases with ω (Proposition 3) and $p_a/p_a^{\mathcal{P}}$ increases with h, $p_a/p_a^{\mathcal{P}}$ increases with ω. Hence, capital is more efficiently allocated across more monopolistic firms. Q.E.D.

Proof of Proposition 10 (Learning from past profits): The proof is identical to that of Proposition 1, except that investors observe an additional public signal π_0. We guess that the stock price is approximately given in equation (9), that is, $pz = p_0 z + p_{\pi_0}\xi_{\pi_0}z + p_\xi\xi_p z + o(z)$, where $\xi_p \equiv a + \mu\theta$($\mu$ is a constant to be determined) and $\xi_{\pi_0} \equiv a + u$. Thus, observing p and π_0 is equivalent to observing ξ_p and ξ_{π_0}. Based on her information set $\mathcal{F}_l \equiv \{s_l, \xi_p, \xi_{\pi_0}$ for all stocks$\}$, the conditional mean and variance of az for agent l are:

$$\mathrm{var}(az \mid \mathcal{F}_l) = \frac{z}{h} \quad \text{and} \quad E(az \mid \mathcal{F}_l) = (a_{\xi_p}\xi + a_s s_l)z,$$

where

$$h \equiv h_a + h_{\pi_0} + h_p + h_s,\ a_{\xi_p}h \equiv h_p = \frac{1}{\mu^2\sigma_\theta^2},\ a_{\xi_{\pi_0}}h \equiv h_{\pi_0},\ \text{and } a_s h \equiv h_s.$$

The conditional mean and variance of excess stock returns follow from $rz = (1-\omega)az - pz$. Investors' stock demand is given by equation (A1), which yields after substitution

$$f_l = \frac{1}{(1-\omega)\gamma}\left\{h_s s_l + h_p \xi_p + h_{\pi_0}\xi_{\pi_0} - \frac{h}{(1-\omega)}\left(p + r^f\right) + \frac{(1-\omega)}{2}\right\} + o(1).$$

Aggregating stock demands and clearing the market leads to $\mu = \gamma(1-\omega)/h_s$ as in Proposition 1, to the expressions given in Proposition 10, and to equilibrium prices linear in ξ_p and ξ_{π_0} as guessed. Q.E.D.

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