Information Markets and the Comovement of Asset Prices

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Abstract

Traditional asset pricing models predict that covariance between prices of different assets should be lower than what we observe in the data. This paper introduces markets for information that generate high price covariance within a rational expectations framework. When information is costly, rational investors only buy information about a subset of the assets. Because information production has high fixed costs, competitive producers charge more for low-demand information than for high-demand information. The low price of high-demand information makes investors want to purchase the same information that others are purchasing. When investors price assets using a common subset of information, news about one asset affects the other assets' prices; asset prices comove. The cross-sectional and time-series properties of comovement are consistent with this explanation.

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The high covariance of asset prices, relative to the covariance of their fundamentals, seems to defy rational explanation (Pindyck and Rotemberg, 1993; Barberis, Shleifer and Wurgler, 2005). Many take this 'excess covariance,' or comovement, to be evidence of investor irrationality. This paper explores whether information observed by investors, but not known to the econometrician, is a possible source of comovement. Information-driven comovement has not been widely accepted because, without data on investors' information, it cannot be tested directly. To circumvent this problem, the paper derives a micro-founded theory of a competitive information market and shows that, in equilibrium, investors purchase the kind of information that generates comovement. Indirect implications of the theory provide a basis for testing the information-driven comovement hypothesis. Documented time-series and cross-sectional patterns of comovement, news provision and analyst coverage support the model's predictions.

To see how news could generate comovement, consider the following example. Suppose the payoff to asset A was equal to the sum of normally-distributed payoffs from two uncorrelated assets B and C. If investors purchase information about the current-period payoff to A, but not information about B and C, then when A's payoff rises, investors will attribute some of the increase to B and some to C. Because they infer that the valuations of both assets rose, both prices will rise. If A's payoffs fall, the prices of B and C will both fall. Prices of B and C will covary, even though investors know their payoffs are uncorrelated. The common source of information adds a new common shock to the prices of B and C, which causes apparent excess covariance in their prices.

A signal must have two features to produce comovement: It must contain information about the value of many assets, and it must be observed by many investors. An information-based explanation therefore raises two questions.

Question 1: Why would many investors buy the same signals? A noisy rational expectations model with a fixed cost for purchasing information (e.g. a multiple-signal version of Grossman and Stiglitz, 1980) would predict the opposite: Investors should want signals that other investors are not purchasing. Other investors' signals can be deduced (imperfectly) by observing asset prices. Investors prefer the higher-information-content signals that others don't observe. With fixed-price information, the demand for a given signal is a strategic substitute.

Introducing markets for information creates a strategic complementarity that works through the market price for information. Information is a non-rival good with a high fixed cost of discovery and a low marginal cost of replication. Producing a small number of copies of a piece of information is very expensive, on a per-unit basis. Information that is mass-produced can be produced cheaply and sold at a low price. We see this price pattern in reality: A copy of the Wall Street Journal costs less than an investment newsletter, which costs less than hiring an analyst to provide proprietary information. This decreasing price in quantity generates the complementarity in information purchasing. Introducing this complementarity into a Grossman-Stiglitz environment causes many but not all investors to buy common information, because the information that others buy is less valuable, but cheap.

Question 2: Will investors coordinate on observing a signal that can cause asset prices to comove? It is possible that investors would cluster their information demand on some signal, simply because it was inexpensive, for exogenous reasons. But exogenous information prices could not generate comovement, except by unlikely coincidence, because the cheapest signals may not predict the values of many assets. In an information market, suppliers must provide the highest-value signals to be competitive. Since signals that predict many assets' values generate more expected profit for investors, market forces induce suppliers to sell these types of signals to many investors. These signals are the ones most capable of causing many prices to comove.

Section 1 sets up a noisy rational-expectations model with markets for assets and information. Section 2 shows that with fixed-cost information, investors' information is dispersed; one information shock affects a small fraction of investors' beliefs and generates a small amount of comovement. With information markets, investors observe largely common signals that predict many assets' payoffs; a shock to one signal can be a shock to the beliefs of a large number of investors and can move the prices of many other assets in lock step. Numerical results show that common information shocks raise asset price correlations 40% above the correlation predicted by a model where investors observe all signals, and 30% above what a fixed-cost information model would predict. The first finding highlights the difficulty in explaining comovement, using only portfolio rebalancing effects (as in Kodres and Pritsker 2002). Like liquidity (Calvo 1999) and wealth effects (Kyle and Xiong 2001), rebalancing can be significant in a crisis, when asset values change greatly, but generates only minor responses to normal market fluctuations. The second result, that comovement with endogenous-cost information exceeds that with fixed-cost information, highlights the importance of information markets. Simply adding uninformed investors (as in King and Wadhwani 1990) cannot generate large covariances. These statements about comovement in asset prices hold true for asset returns as well. Section 2.7 explains why.

By analyzing the determinants of information acquisition, the model can explain time-series and cross-sectional properties of comovement. Section 3 builds a model where demand for information varies endogenously and shows that investors purchase more information about high-value assets. The abundant information reduces comovement. This result is consistent with (1) time-series evidence, which shows excess covariance is countercyclical and (2) cross-sectional evidence, which shows excess covariance is stronger in emerging markets (Morck, Yeung and Yu, 2000). This result differs from Ribeiro and Veronesi's (2002) because they hold the information flow fixed and vary the uncertainty of priors over the business cycle, whereas this model generates time-varying information provision. Cyclical variation in information flow is documented by Veldkamp (2005): When a market's assets are valuable, news about that market is abundant in the financial press. Finally, Campbell, Lettau, Malkiel and Xu (2001) show that between 1967-97, comovement decreased in the U.S.; Morck et. al. confirm this result in emerging markets. Adding a falling information cost to the model can produce this decline

The empirical literature on comovement has uncovered many facts that support a link between comovement and incomplete information. The enactment of disclosure requirements in December 1980 created a natural experiment in which information became less costly and more abundant. Fox et.al. (2003) show that this legal reform caused a decline in comovement, just as predicted by the theory. At an international level, Li, Morck, Fan and Yeung (2004) argue there is more demand for production of information pertaining to countries with larger scope for foreign investment. They show that these countries have the least comovement. Also exhibiting low comovement are countries with more developed financial analysis industries and a free press (Bushman, Piotroski and Smith, 2004). At the firm level, having more institutional investors, who are likely to acquire richer information sets, reduces comovement; asset prices that exhibit high comovement contain little information about future earnings (both facts from Durnev, et.al. 2003).

The most direct support for the model comes from Hameed, Morck and Yeung (2005). Using CRSP and IBES data (1984-2003), they find that firms whose fundamentals are good predictors of many other firms' fundamentals are covered by more analysts (after controlling for firm size). In other words, analysts are providing exactly the kind of information that can produce comovement, a prediction that is unique to the information markets explanation (see proposition 6). Furthermore, firms with more analyst coverage have returns that predict more of the variation in other firms' returns, after controlling for covariance in fundamentals. This result suggests investors are doing what agents in the model do: They use more information about one firm's return to better predict another firm's return. This information ends up being incorporated into both returns and makes one a more accurate predictor of the other. Since analysts covered only 18% of firms, many returns are potentially predicted this way and are susceptible to comovement. In industries where a higher proportion of firms are covered, the effect of an additional analyst on comovement is shown to be less. This finding confirms proposition 5, that the comovement effect diminishes when more signals are observed.

Although the effects of information markets are explored in the context of an asset market, the results carry two general messages relevant to macro and international economics. Message one is: the information agents choose to see can alter relationships between macro aggregates. The literature applying global games to monetary economics (Woodford 2002), business cycles (Angeletos and Pavan 2004, Lorenzoni 2004), and financial crises (Morris and Shin 1998), has made great inroads explaining observed responses to macroeconomic shocks, by adding private information. Analyzing information markets yields predictions about how public or private observed information will be, as well as which particular signals will be observed. Both the signal observed and how many people observe it are important determinants of aggregate covariance. Message two is: information frictions fall with the value of the assets involved, be they financial assets, physical capital, or currency. The reason is that information has increasing returns in an asset's value. One signal can forecast the payoff of $1 of asset value or $100. As the value of an asset rises, it comprises a larger share of the average investor's portfolio, and information about it becomes more valuable. If agents choose how much information to acquire, then when asset values are low, information will be scarce and information frictions will be strong.

1 Model

The model is in the spirit of Grossman and Stiglitz (1980). It adds multiple assets with correlated payoffs and replaces Grossman and Stiglitz' constant information price with an endogenous price, set in an information market with increasing returns.

Preferences and Technology Time is discrete and lasts two periods ($t = 1, 2$). There is a large finite number N of two-period-lived, ex-ante identical agents. They have constant absolute risk aversion preferences over period-2 wealth (W).

$$U(W) = E[-e^{-\alpha W}] \tag{1}$$

There are two types of assets: one riskless asset with payoff $r > 1$ and three risky assets indexed by i with payoff u_i. Risky asset payoffs have a learnable component θ_i and an idiosyncratic component $\epsilon_i \sim iidN(0, \sigma_\epsilon^2)$.

$$u_i = \theta_i + \epsilon_i \tag{2}$$

Payoffs can be interpreted as the price plus dividends, at some future date, or as the intrinsic value of the firm, following Merton (1973). The random shocks (θ_i, ϵ_i) are changes to the value of the firm. Some of these changes (θ_i) can be learned about, before they are publicly revealed. Public revelation could take the form of a quarterly earnings report, for example. After the information is public, it would be reflected in either the firm's dividend or its price.

Information Agents have identical prior beliefs about the learnable component of θ_i:

$$\theta_i \sim N(\mu_i, \sigma_\theta^2) \quad \text{and} \quad E[(\theta_i - \mu_i)(\theta_j - \mu_j)] = \sigma_{ij} \geq 0 \;\; \forall i, j : \; i \neq j. \tag{3}$$

At the start of period 1, agent a chooses whether or not to buy information about each asset. The information reveals the learnable component of next period's asset payoff (θ_i). Although the value of θ_i can be learned exactly, it is a noisy signal of the true asset payoff u_i, which is not known to any agents until period 2. The restriction that covariances are non-negative does not carry any great importance. It simply avoids the problem of having to consider excess negative covariance.

Asset Markets There are three risky assets. Risky asset m has price P_m; the riskless asset price is normalized to one. The per capita supply of each risky asset x_i is normally distributed: $x_i \sim N(\bar{x}, \sigma_x^2)$, with no covariance between asset supplies. This supply is never observed. However, agents who know θ_i can infer the value of x_i from the price. The role of the supply shocks is to prevent price from perfectly revealing θ_i to uninformed agents.

Information Markets Three features of information markets are crucial. First, information is produced according to a fixed-cost technology. A signal θ_i can be discovered at the beginning of period 1 at a per-capita fixed cost χ. This can be interpreted as the cost of hiring a journalist to interview people and find primary sources of information. The information, once discovered, can be distributed to other traders at zero marginal cost. Second, reselling purchased information is forbidden. The realistic counterpart to this assumption is intellectual property law that prohibits copying a publication and re-distributing it for profit. Third, there is free entry. Any agent can discover information at any time.

Information suppliers compete on price in a perfectly contestable market.[1] Profits from information discovery depend on the price charged and demand for information, given the pricing strategies of other agents. One way to ensure that the market is contestable is to force agents to choose prices in a first stage and choose entry in a second stage. This is a reasonable way to think of news markets where the price of the periodical is fixed well in advance and then editors decide whether or not to supply a story. By supplying the story, they would be entering the market for that piece of information.

Let $\Psi_{ai} = 1$ if agent a decides to discover information about asset i and $\Psi_{ai} = 0$ otherwise. Let the fraction of the population that demands information about asset i from producer a, be λ_{ai}. This depends, among other things, on the price producer a charges c_{ai}, and on all other posted prices for information. The objective of the information producer is to maximize profit. If he produces information, that profit is price times per-capita demand,

[1] This market structure is used because it produces a simple pricing formula. Veldkamp (2005) shows that Cournot or monopolistically competitive markets produce similar results.

minus per capita cost, multiplied by the size of the population:

$$\pi_a = \sum_{i=1}^{3} \Psi_{ai}(c_{ai}\lambda_{ai} - \chi)N. \tag{4}$$

The fraction of agents that purchase information about asset i, from any supplier, is the sum demands for each supplier: $\lambda_i = \sum_a \Psi_{ai}\lambda_{ai}$.

Order of Events

1. All agents begin with wealth W_0, and prior beliefs given by (3).

   - Agents decide what price to set for information. Given all prices, they decide whether to discover information about each asset.
   - For each asset i, agents choose whether to purchase information that reveals θ_i.
   - Informed and uninformed agents demand D_i^I and D_i^U units of each risky asset i.

2. Payoffs are received. Agent a derives utility from terminal wealth W_a.

Equilibrium

Given an initial wealth W_0, prior beliefs (3), idiosyncratic payoff shocks ϵ_i, and risky asset supplies x_i, an equilibrium is a set of agents' risky asset demands $\{D_{ai}\}_a$, a fraction of investors who purchase information λ_i, asset prices P_i, and information prices c_i, for each asset i, such that

1. Given prices $\{P_i, c_i\}$, agents choose whether to buy information about asset i ($I_{ai} = 1$), or not ($I_{ai} = 0$), and choose asset demands to maximize expected utility (1), subject to their budget constraint,

$$W_a = rW_{0a} + \sum_{i=1}^{3} (D_{ai}u_i - r(P_iD_{ai} - I_{ai}c_i)) + \pi_a. \tag{5}$$

2. Information supply (d_{ai})and pricing strategies (c_{ai}) are a subgame perfect Nash equilibrium. They maximize equation (4). If there are multiple Nash equilibria, information

suppliers coordinate on the equilibrium that generates the highest total welfare for information purchasers.[2]

3. The markets for risky assets and information clear.

2 Information Provision and Price Covariance

To highlight the fundamental forces in the model, this section solves a series of simpler models. Sections 2.1-2.3 examine what patterns of information demand generate comovement. The signals investors observe must forecast other assets' payoffs well (section 2.1); most investors must observe the same set of signals (section 2.2), and this set of signals must be small (section 2.3). Section 2.4 shows that the market allocation of information exhibits the right features to generate comovement. Sections 2.5 and 2.6 document numerical results for the full model.

2.1 Exogenous Information Supply

A simple starting case is where all agents observe information about one asset ($[\lambda_1, \lambda_2, \lambda_3] = [1, 0, 0]$). Since endogenizing information supply with competitive information markets will cause agents to cluster their information demands, and this is the extreme form of clustering, it is a useful benchmark.[3] Results will compare the covariance of asset prices in this model with two alternatives. A no-information price ($[\lambda_1, \lambda_2, \lambda_3] = [0, 0, 0]$) measures the value of an asset, based on its known fundamentals, such as past earnings announcements. Covariance in no-information prices is the simplest measure fundamentals-based covariance. A full-information price ($[\lambda_1, \lambda_2, \lambda_3] = [1, 1, 1]$) measures the value of an asset, based on its realized fundamentals. If realized changes in fundamentals are interpreted as earnings announcements, then full-information price covariance is earnings covariance times $\frac{1}{R^2}$ (see equation 8). Most empirical researchers use realized earnings or dividend covariance to mea-

[2]In a monopolistic competition model where information supply was not perfectly competitive and suppliers could earn some profit, this would be the highest-profit outcome. See Veldkamp (2005) for an analysis of such a model. In most cases, coordinating on other equilibria would affect which assets comove, but not the aggregate extent of comovement. Since the issue of multiple equilibria is a tangential one here, the possibility is ruled out, by assumption.

[3]Ribeiro and Veronesi (2002) employ a similar information structure.

sure covariance of fundamentals. The main result is that when the payoff covariance of two assets is sufficiently low, price covariance in this model will exceed both benchmark measures of covariance.

To describe prices, vector notation is useful. Let P, θ, u, and x, without i subscripts, denote 3×1 vectors with the price, learnable payoff, total payoff, and supply of each of the three assets. Let Σ be the 3×3 variance-covariance matrix of θ with diagonal entries σ_θ^2 and off-diagonals σ_{ij}^2.

When agents all have the same information set, the vector of prices takes the following form:

$$P = \frac{1}{r}\left(E[\theta] - \alpha \text{Var}[u]x\right) \tag{6}$$

where the expectation and variance-covariance matrix are conditional on the information set of the agents. This standard pricing equation comes from rearranging the investors' first order condition: the partial derivative of $E[-e^{-aW}]$, where W is given by (5), with respect to asset demand D_{im}.

Full Information With full information, θ_i is known for all assets i and each asset's price can be written as

$$P_i^{FI} = \frac{1}{r}\left(\theta_i - \alpha x_i \sigma_\epsilon^2\right). \tag{7}$$

The covariance between the prices of assets 2 and 3 is

$$cov(P_2^{FI}, P_3^{FI}) = \frac{\sigma_{23}}{r^2}. \tag{8}$$

No Information With no information, all knowledge about θ_i is based on prior beliefs.

$$P^{NI} = \frac{1}{r}\left(\mu - \alpha(\Sigma + \sigma_\epsilon^2 I)x\right). \tag{9}$$

The covariance between the prices of assets 2 and 3 is

$$cov(P_2^{NI}, P_3^{NI}) = \frac{\alpha^2 \sigma_x^2}{r^2}\left(\sigma_{12}\sigma_{13} + 2\sigma_{23}(\sigma_\theta^2 + \sigma_\epsilon^2)\right) \tag{10}$$

Prices are determined mostly by prior beliefs. The only random element that can generate covariance in no-information prices is the asset supply. Supply shocks move prices and generate covariance when agents rebalance their portfolio in response. This *portfolio rebalancing effect* is documented by Kodres and Pritsker (2002).

Information About One Asset When agents all observe θ_1, the price of asset 1 is the full information price P_1^{FI}. The prices of assets 2 and 3 change. For assets $i \epsilon \{2,3\}$, the expected value of θ_i conditional on observing θ_1 is

$$E[\theta_i|\theta_1] = \mu_i + \frac{\sigma_{1i}}{\sigma_\theta^2}(\theta_1 - \mu_1). \tag{11}$$

The price and the payoffs of the asset that investors learn about will always have the same covariance with all other assets. This is because the optimal inference weights the innovation to θ_1 by its covariance with asset i. An optimal linear forecast always matches this moment. When investors learn about asset 1, there will be no comovement between assets 1 and 2, or assets 1 and 3, in excess of their payoff covariance. The interesting comparison will be across the covariances of asset prices 2 and 3.

The vector of prices will be

$$P = \frac{1}{r}(E[\theta|\theta_1] - \alpha V^I x_m) \tag{12}$$

where V^I is the conditional variance-covariance of asset payoffs.

$$V^I = Var[u|\theta_1] = \begin{bmatrix} \sigma_\epsilon^2 & 0 & 0 \\ 0 & \sigma_\theta^2 + \sigma_\epsilon^2 - \frac{\sigma_{12}}{\sigma_\theta^2} & \sigma_{23} - \frac{\sigma_{12}\sigma_{13}}{\sigma_\theta^2} \\ 0 & \sigma_{23} - \frac{\sigma_{12}\sigma_{13}}{\sigma_\theta^2} & \sigma_\theta^2 + \sigma_\epsilon^2 - \frac{\sigma_{13}}{\sigma_\theta^2} \end{bmatrix} \tag{13}$$

The covariance between prices P_2 and P_3, is

$$cov(P_2, P_3) = \frac{1}{r^2}\left[\frac{\sigma_{12}\sigma_{13}}{\sigma_\theta^2} + \alpha^2\sigma_x^2 V_{23}^I(V_{22}^I + V_{33}^I)\right] \tag{14}$$

If an investor observes a θ_1 that is 1 unit higher than he expected it to be, then he will revise his beliefs about θ_2 and θ_3 upward by $\frac{\sigma_{12}}{\sigma_\theta^2}$ and $\frac{\sigma_{13}}{\sigma_\theta^2}$, respectively. The covariance generated by these inferences is $\frac{\sigma_{12}\sigma_{13}}{\sigma_\theta^2}$. If making inferences based on observations of signal one generates more covariance than the covariance between fundamentals (σ_{23}), then excess price covariance results. The last term arises because investors rebalance their portfolios to manage risk. The left panel of figure 1 shows the region of parameter values that generate excess covariance.

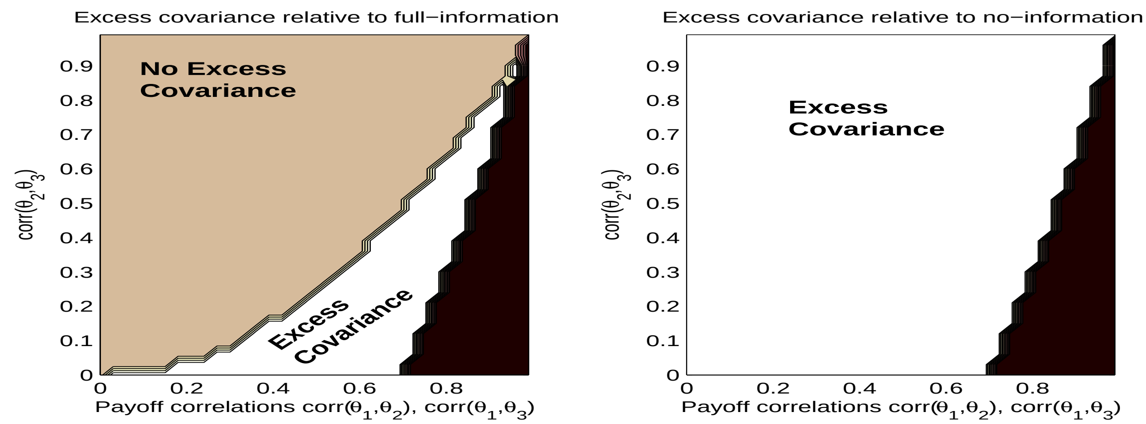

Figure 1: Regions of covariance parameters that generate excess price covariance between assets 2 and 3 relative to a full-information and a no-information benchmark. Axis labels are correlations ($\sigma_{ij}/\sigma_\theta^2$). Black region covers inadmissable parameters that produce non-positive variance-covariance matrices. Parameters: $r = 1.02$, $\mu = 1$, $\rho = 0.86$, $\sigma_\theta^2 = 0.1^2$, $\bar{x} = 1$, $vx = 0.5$, $\sigma_\epsilon = 0.13^2$, $a = 1.5$.

Proposition 1 ***Comovement Relative to Full Information:*** *For sufficiently small payoff and asset supply variances ($\sigma_x^2(V_{22}^I + V_{33}^I) < \frac{1}{\alpha^2}$), if $\sigma_{23} < \frac{\sigma_{12}\sigma_{13}}{\sigma_\theta^2}$, then the covariance of asset prices 2 and 3 is higher than it would be given full information: $cov(P_2, P_3) > cov(P_2^{FI}, P_3^{FI})$*

Proof: The result follows from equations (8) and (14). □

The covariance restriction $\sigma_{23} < \frac{\sigma_{12}\sigma_{13}}{\sigma_\theta^2}$ can be restated in terms of correlations: The payoff correlation of assets 2 and 3 must be less than the product of each asset's correlation with the purchased information. The restriction on sufficiently small variances ensures that portfolio rebalancing effects do not swamp the information effect. It is likely to be satisfied for high-frequency price movements. It is even satisfied when the model is calibrated to yearly data. (See section 2.6.) This illustrates why portfolio rebalancing might be a better model of a crisis, where payoff variance σ_θ is large. In these highly-volatile environments, portfolio rebalancing is a bigger effect than the information effect. However, an information market theory is better positioned to explain comovement in day-to-day fluctuations, because in less-volatile environments, portfolio rebalancing effects are negligible.

The requirement that payoff covariance between assets (σ_{23}) be small for their prices to covary fits with the empirical excess correlation literature which focuses on covariance between assets that appear unrelated. Pindyck and Rotemberg's (1993) original comovement test works with groups of assets whose earnings, after removing aggregate macroeconomic factors, have statistically insignificant correlation. It is exactly between these kinds of assets where payoff correlation is very low that the excess correlation generated by common information has the largest effect.

Proposition 2 ***Comovement Relative to No Information:*** *If*

$$\sigma_{23} < \frac{\sigma_{12}\sigma_{13}}{\sigma_\theta^2} + \frac{\sigma_{12}\sigma_{13}}{\sigma_{12}^2 + \sigma_{13}^2}\left(\frac{1}{\alpha^2\sigma_x^2} - 3\sigma_\theta^2 - 2\sigma_\epsilon^2\right), \tag{15}$$

then the covariance of asset prices 2 and 3 is higher than it would be given no information: $cov(P_2, P_3) > cov(P_2^{NI}, P_3^{NI})$

Proof: The result follows from comparing equations (10) and (14). □

If the point of comparison is instead a no-information price, where agents only observe past states and prices, then the conditions for excess price covariance are weaker. When payoff and asset supply variances ($\sigma_\theta^2, \sigma_\epsilon^2, \sigma_x^2$) are small, the second term is large and positive. With small variances, price covariance exceeds its no-information level, no matter which asset is learned about. (See figure 1, right panel.)

2.2 Introducing Asymmetric Information

Next, consider the case where θ_1 is observed by a fraction λ_1 of the investors. As before, no investors see θ_2 or θ_3. As soon as investors have different information sets, some will look to the price level as a signal of the information observed by others. Since the observed value of θ_1 will affect informed traders' demand for all three assets, all three asset prices are informative signals for the uninformed. This section describes how uninformed agents solve their signal extraction problem and how the degree of asymmetry changes the extent of comovement.

There are two problems that must be solved simultaneously. The first is: how do prices depend on fundamentals θ and x? The second problem is to deduce what the optimal set of beliefs are for each type of agent, upon observing the price vector P. When preferences are exponential and all random shocks are normally distributed, the asset prices that solve this fixed point problem are linear.

Proposition 3 ***Asset prices*** *are a linear function of the observed signal* θ_1 *and the asset supply shock* x*:* $P = A + B\theta_1 + C(x - \bar{x})$.

The proof and formulae for A, B (3×1 vectors) and C (a 3×3 matrix) are in appendix A. Information demand shows up in asset prices because all three coefficients A, B and C depend on the fraction of informed agents λ_1.

Given a form for asset prices, we can now ask how the prices change when the amount of information λ_1 varies. Assuming that no agents are informed about assets 2 and 3, increasing the number of agents that observe information about asset 1 will increase price covariance. Excess covariance is generated by people observing information about asset 1 and making correlated inferences about assets 2 and 3. The more people making these inferences, the more prices covary.

Proposition 4 ***Informing more agents increases comovement.*** *If (15) holds and no agents observe signals* θ_2 *or* θ_3*, then there exists a non-empty set* Λ *inside* $[0, 1]$ *such that for all* $\lambda_1 \epsilon \Lambda$*,* $cov(P_2, P_3)$ *is increasing in* λ_1.

Proof: Proofs of this and all further propositions are in appendix A.

Figure 2 shows a numerical example where, as the fraction of the population that observes θ_1 rises, so does the excess covariance of prices 2 and 3. As more people become informed, the asset prices reveal more information, and investors make stronger inferences about the appropriate prices of assets 2 and 3, based on the signal θ_1.

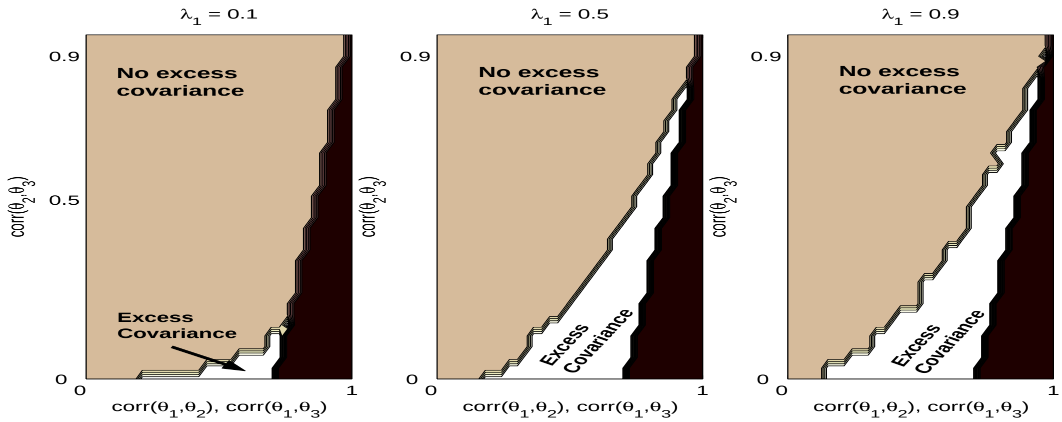

Figure 2: Regions of excess covariance, relative to full-information prices, for three values of λ_1, the fraction of the population that is informed. Increasing the number of informed agents increases the range of parameters that generate excess covariance. Axis labels are correlations ($\sigma_{mn}/\sigma_\theta^2$). By assumption, $\sigma_{12} = \sigma_{13}$. Black region covers inadmissable parameters that produce non-positive variance-covariance matrices. Parameters: $r = 1.02$, $\mu = 1$, $\rho = 0.86$, $\bar{x} = 1$, $vx = 0.5$, $a = 1.5$, $\sigma_\theta^2 = 0.1^2$, $\sigma_\epsilon^2 = 0.13^2$.

2.3 Comovement with Multiple Signals

Section 2.2 demonstrated that as purchases of a given signal rise (information demand deepens), comovement increases. In contrast, the next result shows that as more signals are purchased (information demand broadens), comovement declines. As the variety of signals purchased rises, asset prices approach their full-information levels and excess covariance disappears.

Proposition 5 ***Comovement Falls When More Signals Are Observed.*** *If all agents buy signal 1 ($\lambda_1 = 1$), no agents buy signal 3 ($\lambda_3 = 0$), and $\sigma_{23} < \frac{\sigma_{12}\sigma_{13}}{\sigma_\theta^2}$, then $cov(P_2, P_3)$ is decreasing in λ_2 over some non-empty interval $\Lambda \subset (0, 1)$.*

If information becomes more abundant, there are two competing effects. More people becoming informed about one asset increases excess covariance. But, if information demand starts spilling over into other assets, price covariance falls. Price covariance can arise where there are two assets whose values are not directly observed by some agents, but are being inferred on the basis of some common information. In the simple case where there are three assets, this means that comovement arises primarily when only one asset is being learned about. When investors start learning about two assets, only one price is being determined based on inference, and comovement cannot arise. As the number of assets (N_A) grows, comovement will still be strongest when most agents observe one signal. In that case there are $(N_A - 1)$ assets all being priced based on the same signal. As more signals are observed, fewer assets are susceptible to comovement, and the ones that are will be priced based on more nuanced, and less common information. The comovement effect will diminish and eventually disappear when $(N_A - 1)$ signals are observed. In short, excess price covariance arose because of an incomplete information problem. When information becomes more complete, the effect disappears.

To illustrate these effects, consider three assets whose dividend correlations suggest that they are good candidates for generating excess price covariance: Nordstrom (retailer), Pitney-Bowes (business services) and Sysco (food services). Pitney and Sysco both have high dividend correlation with Nordstrom (0.705 and 0.500), and a low correlation with each other (0.201). Investors who learned about the future value of Nordstrom could use that information to make strong inferences about two companies, Pitney and Sysco, that have little to do with each other. If investors hold all three assets and learn primarily about Nordstrom, demand for Pitney and Sysco should be high when news about Nordstrom is good and low when Nordstrom news is bad. Pitney and Sysco prices will covary more than a standard valuation model would predict (proposition 1). The more widespread the information about Nordstrom becomes, the stronger the covariance should be (proposition 4). But if many investors learn about Pitney and Sysco, comovement will disappear (proposition 5). Comovement depends delicately on the information acquisition choice. The next section shows why information markets will supply information, like that about Nordstrom, that generates comovement.

2.4 Properties of the Information Market

Comovement is strongest when investors buy mostly the same signals, and the signals they buy have strong covariance with the other asset payoffs. In equilibrium, information markets provide signals with exactly these features. Signals that can forecast many payoffs accurately are the signals that investors get the highest utility from and that competitive producers supply. But signals that other agents observe are less valuable. Therefore, with fixed-cost information, investors would demand different signals and comovement would be low. But with endogenous-cost information markets, investors will buy high-demand information, even though it is less valuable, because it is cheap. Information demand will be concentrated and comovement high. Not only is it possible for costly information to produce comovement, the most surprising result is that the forces at work in information markets make this outcome quite likely.

Terminal wealth W is a product of two variables that, in period 1, are normally distributed: profit $(u - rp)$ and portfolio holdings q. Since utility is exponential, expected utility is given by the moment-generating function of a quadratic normal variable.

Proposition 6 ***Highest value signal.*** *Observing signal $i^\star$ increases expected utility more than any other signal if $i = i^\star$ minimizes the determinant $|Var[u|\theta_i, p]|$.*

Proof: See appendix A.

Consider the simple case where all agents are either learning θ_i or not observing any signal. Then, the conditional variance $Var[u|\theta_i, p] = Var[u|\theta_i]$: the price level is only revealing a noisy signal of θ_i because that is the only private information known to any market participants. Therefore, conditioning on θ_i makes knowing p redundnant. This 3×3 matrix is defined for $i = 1$ in (13), and is defined analogously for $i = \{2, 3\}$. Its determinant is the generalized conditional variance:

$$|Var[u|\theta_i]| = \left(\sigma_\theta^2 + \sigma_\epsilon^2 - \frac{\sigma_{ij}}{\sigma_\theta^2}\right)\left(\sigma_\theta^2 + \sigma_\epsilon^2 - \frac{\sigma_{ik}}{\sigma_\theta^2}\right) - \left(\sigma_{jk} - \frac{\sigma_{ij}\sigma_{ik}}{\sigma_\theta^2}\right)^2. \tag{16}$$

The most valuable signal is the i that makes this quantity the lowest. Since a variance-covariance matrix is positive semi-definite, this determinant is always positive. The smallest values for the first two terms are achieved when σ_{ij} and σ_{ik} are large. Large σ_{ij}, σ_{ik} will also maximize the quantity subtracted if $\sigma_{jk} - \frac{\sigma_{ij}\sigma_{ik}}{\sigma_\theta^2} < 0$. This tells us that the most valuable signal is one that has high covariance with the other signals (σ_{ij}, σ_{ik} large). Proposition 1 tells us that excess covariance arises when $\frac{\sigma_{ij}\sigma_{ik}}{\sigma_\theta^2}$ is larger than σ_{jk}. So, this signal with the highest covariances with the other two signals is the signal most capable of generating excess covariance and the first signal that information markets will supply. Agents value most the signals with this highest potential to cause asset prices to comove.

Proposition 6 also reveals how one agent's information choice affects another's value for information. As noted a moment ago, when all agents either don't learn or learn the same θ_i, information embodied in asset prices becomes redundant information to informed agents. But, if this agent purchased some other signal θ_j, he would then have two relevant pieces of information, θ_j and prices, which would tell him something about the θ_i that others observed. In many situations, buying information like θ_j that other agents are not observing is the most valuable because it produces the lowest conditional variance $|Var[u|\theta_i, p]|$. This is a strategic substitutability in information acquisition. Since comovement falls when agents learn many different signals, information markets will have to fight against substitutability if the model is to have any hope of generating significant asset price comovement.

So far, the analysis has focused on the benefit of information. The complementarity in information acquisition arises from information costs.

Proposition 7 ***Information price.*** *In equilibrium, information suppliers will price all information at its average cost.*

Proof: Free entry at the stage where information prices are set ensures zero profit for information suppliers. If they made profits, other suppliers would have an incentive to discover information. That would not be an equilibrium. Zero profit means that the price of information times the quantity demanded equals the cost of discovery: $c_{ai}\lambda_{ai} = \chi$. Thus, each information supplier prices at average cost $c_{ai} = \chi/\lambda_{ai}$. $\square$

The fact that the price of information declines in the fraction of people who buy it is critical because it creates a complementarity: Investors want to buy the same information because that information is cheap. This cross-investor complementarity differs from Admati and Pfleiderer's (1987) cross-signal complementarity. In their model, when an investor observes a signal, that same investor values other signals more. Observing more signals reduces comovement. In this model, cross-investor complementarity leads investors to purchase the same signals as other investors. Observing common signals strengthens comovement.

Equilibrium information demand determined reflects both the complementarity of information created by its endogenous price and the strategic substitutability embodied in its ability to reduce conditional variance. Since all agents are identical ex-ante, the fraction of agents that purchase signal i, $\lambda_i \epsilon (0, 1)$ is an equilibrium when all agents are indifferent between buying signal i or not: $E[u(W^I)] = E[u(W^U)]$ where W^I and W^U denote the wealth of informed and uninformed agents. If there is no such indifference point, then $\lambda_i = 0$ or 1. In the numerical example that follows, the fraction of informed agents will be 0 or in $(0, 1)$, telling us that substitutability is still playing an important role in determining information demand. However, complementarity is crucial in creating enough homogeneity in information demand to allow the model to quantitatively approach the levels of comovement observed in the data.

Unfortunately, the equilibrium information allocation cannot be neatly characterized analytically. Although asset prices (derived in the appendix) can be solved numerically, they are not closed-form.[4] To explore equilibrium information provision, we turn to numerical simulation results.

2.5 Calibration and Simulation

To make the numerical results realistic, model parameters match yearly asset pricing moments from the S&P 500. The variance of prior beliefs σ_θ determines both the Sharpe ratio and the equity premium. This model, like most, cannot match both statistics. The benchmark ($\sigma_\theta^2 = 0.1^2$) is an intermediate value that generates a Sharpe ratio of 2.6 and a 3% equity premium. Section 3.1 explores a range of values between 0.025^2 and 0.2^2. The idiosyncratic payoff shock ϵ makes payoffs more volatile, but is never learned and therefore never incorporated into prices. Therefore, $\sigma_\epsilon^2 = 0.13^2$ matches the ratio of return variance to price variance (0.62 in the data). The variance of the asset supply shock σ_x^2, together with the cost of information, determines how much information will be held in equilibrium. For excess covariance to have a fighting chance in a three-asset model, most agents must purchase one signal in equilibrium. Therefore ($\sigma_x^2 = 0.5$) and $\chi = 0.1$ were chosen so that the average number of signals purchased is 0.95. With a larger number of assets, the range of parameters that would generate comovement would grow substantially. (See section 2.6.) The real return on a risk-free asset is 2%. Absolute risk aversion a is 1.5, producing an average relative risk aversion of 4.5. The mean asset payoff and average number of shares per capita do not affect second moments. They are both set to 1.

[4] The problem is distinct from the one-asset solution method employed in Grossman and Stiglitz (1980). Models where information is exogenous (e.g. Kodres and Pritsker 2001) or where signals are independent across agents (Admati 1985) also do not run into these technical dilemmas.

The remaining parameters are the correlations of the three assets' payoffs. There are no corresponding population moments, only specific examples. Payoff correlations are set equal to the correlation of dividends of the three S&P500 firms discussed in section 2.3: Nordstrom, Pitney-Bowes and Sysco. These firms are chosen because the high correlation of Pitney and Sysco with Nordstrom (0.705 and 0.500), and their low dividend correlation with each other (0.201), satisfy the conditions for propositions 1 and 2 to hold, given the other calibrated parameters. The goal for the model is then to match the extent of the price and return comovement between Pitney and Sysco.

Optimal information choices are computed by simulating a 20-agent market and computing expected utility with each signal combination. An equilibrium is a set of information portfolios such that no agent would achieve a higher utility with any other signal, given the signals other agents are holding. The search algorithm begins with an initial guess and then lets agents optimize sequentially, holding other agents' information fixed, until no agent wants to change his portfolio.

2.6 Numerical Results: Information Portfolios and Comovement

Three interesting features of optimal information portfolios stand out: information demand is clustered; the optimal signals maximize comovement, and information demand can shift suddenly. These features are illustrated in the top panel of figure 3. Vertical slices of the graph depict an equilibrium information portfolio for a given payoff variance. Moving to the right on the graph, payoff variance σ_θ^2 rises. When payoffs are less predictable, information becomes more valuable and agents buy more signals.

When agents start buying signals, a large fraction of the population all buy signal 1 (Nordstrom). This is the clustering of information demand, concentrated on a small number of signals, that ensures that the same shocks to signals get passed on to prices of all three assets. As variance rises, agents switch from buying signal 1 to buying signals 2 and 3 (Pitney and Sysco), to eventually buying all 3 signals. The reason for this pattern is that Nordstrom has the highest correlation with the other two assets. To predict the payoffs of all three assets based on one signal, Nordstrom has the strongest predictive power. When buying two signals, signals Pitney and Sysco are optimal because they are both good at predicting

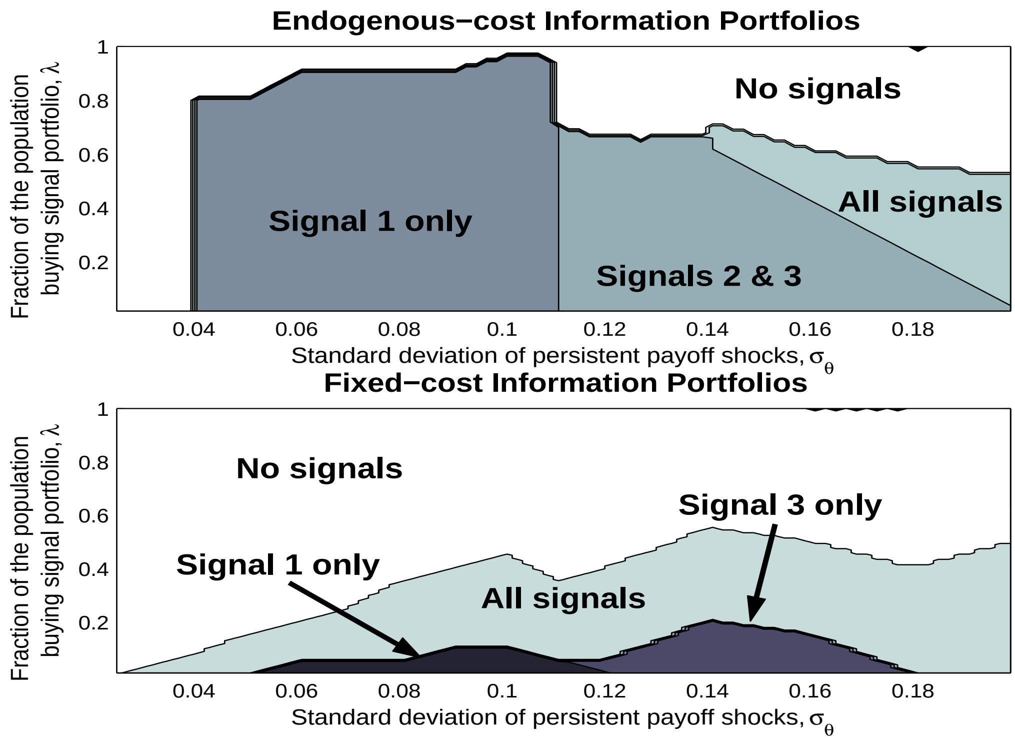

Figure 3: Distribution of information portfolios over the population, for varying levels of asset payoff risk. For a given variance parameter, a vertical slice of this graph describes what fraction of the population buys each signal. With information markets, demand is concentrated on a smaller set of signals.

Nordstrom. More generally, when information is not very valuable, it is optimal to purchase a few signals that are highly correlated with many assets. When information demand rises, a more diversified information portfolio that focuses on hard-to-predict assets yields higher payoffs.

Contrast the portfolios purchased from information markets with the bottom panel of figure 3, where the cost of information is fixed.[5] The average number of signals per person is not very different in the two models. But, instead of having many agents concentrate their demand on a small number of signals, agents buy many signals. Agents diversify their information portfolios when information costs are fixed because information that is not already held and not already reflected in the price is more valuable. Recall that excess covariance is strongest when a large fraction of agents hold the same small subset of signals.

[5]The price of a signal in the fixed-information-cost model is equal to the average signal price paid in the endogenous cost model: $\chi/0.8$.

Thus, diversity of information in the fixed-cost model dampens the common shocks to prices and washes away most excess price covariance.

How much comovement can these information portfolios generate? When the payoff variance is $\sigma_\theta^2 = 0.1^2$, as in the calibrated model, then 95% of agents purchase signal 1 and excess covariance is 0.0015. Since covariance rises partly because the variance of price changes, it is useful to isolate comovement by looking at correlations. The correlation between the prices of assets 2 and 3 is 43% higher than it would be if agents had a full set of signals, and is 108% higher than the correlation in the asset payoffs. Comovement is present, even when there is full information, because agents rebalance the risk in their portfolios in response to news, affecting their demand for unrelated assets. However, this effect is tiny.

With the fixed information cost portfolio, comovement still appears, but is only 7.1% higher than for the full-information price. The reason correlation is so low is that when different agents hold different information portfolios, they make different prediction errors about asset values that cancel each other out in the market price. Only when many agents are making the same inference errors will comovement be strong.

The extent of the correlation in the asset price still does not match the correlation in the prices of Sysco and Pitney, in the data example (excess of 108% in the model vs. 161% in the data). However, some of that price covariance could be explained by forces absent in this model, such as macroeconomic fluctuations that affect the stochastic discount factor used to price all assets.

The analysis has focused on the simplest possible case, where there are three assets. This can be relaxed. As long as there are two or more assets being priced by the same noisy signal, excess covariance can arise. With three assets, excess covariance disappears when two signals are observed, because there is only one asset left being priced with noisy information. With more assets, the range of parameters that generates excess covariance will grow. If there were 100 assets, investors could purchase information about 99 of them before all excess covariance disappeared. (See section 2.3.)

Information regime shifts The shift between a market focus on a few important summary statistics and a more nuanced approach to evaluating many individual assets can happen quite suddenly. The sudden switch is because of the endogenous information price.

If the price per signal were constant, regardless of how many people bought it, then information demand would be a continuous function that gradually declined as σ_θ^2 fell. With an endogenous information price, few people purchasing θ_1 makes the signal very expensive. When an increase in the variance makes information more valuable and demand rises, the price of information falls. This causes a discrete shift to a regime where many investors buy the signal and this is optimal because the signal is very cheap.

Sudden shifts in the information sets of many agents can rationalize a separate set of puzzling asset pricing facts. Key statistics or economic quantities whose announcements clearly move asset prices during one period, may later become almost useless predictors of price changes. Hong and Stein's (2003) case study of Amazon equity found that traders writing about and trading on data about the number of clicks on Amazon's webpage, suddenly shifted in 2000, to writing about and trading based on earnings announcements. In foreign exchange markets, Cheung and Chinn's (2001) surveys reveal that traders' reliance on different macro indicators varies substantially over time.

Information regimes shifts could be triggered by small events and would have large consequences for the cross-section of asset prices. A market-wide shift in the patterns of information demand would change conditional covariances (conditional betas), as well as the conditional variances which determine assets' risk premia.

2.7 Return Comovement

Much of the empirical work on comovement has focused on returns. So far, the discussion has revolved around price comovement because returns are ratios of normal variables, which are much less tractable than normally distributed prices. With the numerical simulation, computing return comovement is easy. Return correlation is almost 100 times higher than in a full-information model; correlation between the return ($\frac{u_{mt}}{P_{mt}}$) on assets 2 and 3 is 28%, while for the fixed-cost information and full information models, the correlation is almost zero ($< 0.3\%$).

To understand why the model generates such large return comovement, consider an alternative notion of return used in the asymmetric information literature: $(u - rp)$ is the profit earned on a risky asset, in excess of what would have been earned by investing the same amount in a riskless bond. Consider a simple environment where all agents observe the same information. Using the price formula in (12), profit is

$$u - rp = u - E[u] + \alpha Var[u]x. \tag{17}$$

The first term represents expectation error and the second portfolio rebalancing. As in section 2.6, portfolio rebalancing generates very little comovement. The ability of expectation errors to generate comovement depends crucially on what information is being used to form expectations.

The key feature of the model that produces return comovement is having signals that contain both asset-specific and market-wide information. Suppose an investor learns about asset 1 and uses θ_1 to forecast the payoff to asset 2. We can decompose θ_1 and θ_2 into a common component κ and asset-specific components τ_1 and τ_2 and (using equation 11) express expectation errors for asset 2 as $\kappa + \tau_2 + \epsilon_2 - \frac{\sigma_{12}}{\sigma_\theta^2}(\kappa + \tau_1)$. A similar expression for the expectation error of asset 3's payoff will also contain τ_1. The asset-1-specific payoff that shows up in the expectation errors causes returns of assets 2 and 3 to covary.

This effect is similar to an errors-in-variables problem in econometrics. In the previous example, what investors really want to know in order to forecast asset 2's payoff is κ: the common component. The θ_1 they observe is a noisy signal about the common factor. The noise is the asset-specific information that is also contained in θ_1, but is not useful for forecasting other payoffs. When agents use a variable with noise to form beliefs (linear forecasts) of many asset values, the noise causes the expectations errors (residuals) to be correlated. Since asset returns are determined by expectation errors, and the learning process is generating extra correlation in these errors, returns comove.

Peng and Xiong (2005) argue that investors must be overconfident because rational agents with limited information sets cannot generate comovement in returns. This is true when signals are about common factors in asset prices. When signals reveal common factors, inference errors contain only non-common or idiosyncratic risk, which by definition does not comove. In the example above, if the signal was κ ($\tau_1 = 0$), then the signal covariance with u_2 would be equal to the signal's variance, so $\frac{\sigma_{12}}{\sigma_\theta^2} = 1$; the expectation error would be $\tau_2 + \epsilon_2$, which is asset-specific risk. Since expectation errors do not comove, and portfolio rebalancing effects are small, returns do not comove when rational agents learn about common components of asset payoffs.

3 Other Predictions of the Theory

3.1 Business Cycle Variation in Comovement

Patterns of comovement change over the business cycle. In particular, comovement is higher in recessions than in booms (Ribeiro and Veronesi, 2002). Can the model match this fact?

A Dynamic Model Consider a dynamic model with the same period utility function, endowments, asset market and information market structure as before. Each period, new assets are issued that pay off $u_{it} = \theta_{it} + \epsilon_{it}$ at the end of the period, where $\epsilon_{it} \sim i.i.d.\, N(0, \sigma_\epsilon^2)$, as before. Each generation of overlapping assets is related to the previous generation through persistence in the θ_{it} process. For simplicity, no assets are multi-period lived. Suppose that the learnable component of asset payoffs follows a discrete-time persistent process that has a mean-variance relationship similar to a geometric Brownian motion:

$$\theta_{it} = (1-\rho)\mu_i + \rho\theta_{i(t-1)} + \theta_{i(t-1)}\eta_{it}. \tag{18}$$

The (3×1) vector of innovations η_t are jointly normally distributed: $\eta_t \sim N(0, \Sigma)$, where the diagonal elements are denoted σ_θ^2.

Risk, the standard deviation of future payoffs divided by the current asset value (σ_θ), stays constant, while the total variance ($\theta_{i(t-1)}^2 \sigma_\theta^2$) of the payoff fluctuates. As with a geometric Brownian motion, the probability of a given percentage increase or decrease in payoffs is unchanging. At the end of each period t, the components of payoffs u_{it}, θ_{it} and ϵ_{it} become public information.

Equilibrium At every date t, each agent a chooses information $\{I_{a1t}, I_{a2t}, I_{a3t}\}$ and asset demands $\{D_{a1t}, D_{a2t}, D_{a3t}\}$ to maximize (2), subject to the budget constraint (5), taking as given the payoff process (18) and the choices of other agents. Information supply and pricing strategies are a subgame perfect Nash equilibrium. The markets for risky assets and information clear.

Calibration The new parameter, the payoff autocorrelation parameter ρ is 0.86, matching the price autocorrelation.[6] The variance of innovations to θ_t is the dynamic counterpart to prior uncertainty about θ in the static model. Therefore, the calibrated value of σ_θ^2 remains the same.

Results Consider recessions as times when asset values (θ_{t-1}) are low. When asset values are low, information provision falls. Since incomplete information is the source of comovement, recessions are times when comovement is strong.

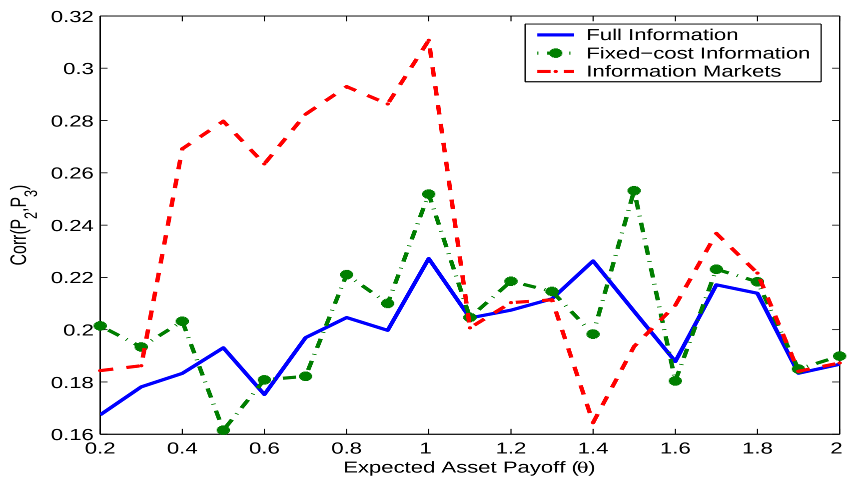

Figure 4: Asset price correlations for full-information, fixed-cost information, and market for information models. Excess correlation is the distance between the dotted and starred lines with the solid line. Information markets make excess correlation rise and then fall with asset payoffs.

Figure 4 shows how the correlation between the prices of assets 2 and 3 changes as the expected asset payoff (denoted θ) grows. The difference between information market and full-information asset price correlation is the measure of comovement. Correlations are more appropriate than covariances for this comparison, because the entire environment is becoming more volatile as θ grows. When asset values are very low, no signals are purchased. Prices based on past observations exhibit low correlation. Likewise, when asset values are high, agents buy two or three signals. When there are not two assets whose prices are determined by inference, price correlation is roughly the same as with full-information. Only in the intermediate range (θ between 0.3 and 1.1), where most agents are buying one signal, can

[6]Since a positive trend in prices will inflate their correlation as well as their variance, I first detrend prices using a loglinear trend. The data is yearly returns and average price levels for the S&P 500 index 1946-2004.

the covariance between two prices exceed the full-information covariance. The mean asset payoff is $\theta = 1$. Therefore, price correlation is higher when asset prices are below average, than when they are above average.

Proposition 6 is the key to understanding why demand for signals falls when asset values fall. It says that the value of information depends on its ability to reduce total payoff variance. Total payoff variance depends on risk (Σ) and the value of the asset at risk ($\theta_{i(t-1)}$). Risk stays constant, while asset values fall in recession and rise in booms.[7] Wilson (1975) shows that when a firm becomes more valuable, information about that firm also becomes more valuable. The same is true for assets in this setting. One piece of information can be used to evaluate a small or large amount of asset value; agents get more benefit from information that is used to evaluate more asset value. When the total value of an asset rises, some investors must hold that additional asset value, in order for the asset market to clear. Therefore, there will be more aggregate demand for information about high-value assets and more total information provision when many assets are highly-valued, in a boom.

A variety of cross-sectional and time series data supports this positive relationship between asset value and information provision. Shiller (2000) cites more Reader's Guide articles about the stock market, and higher investment club membership as evidence of more desire for information in bull markets. Emerging market news in the Financial Times (23 markets, 1989-2002) is abundant when and where payoffs are volatile and asset values are high (Veldkamp 2005). High-value firms have more analyst coverage (Hong, Lim, Stein, 2000). These large firms' asset prices contain more information about future earnings (Collins, Kothari and Rayburn, 1987).

Increasing information provision when asset values are high has two competing effects on comovement. One effect is to make more people learn about the same subset of assets. If the fraction of informed people rises, existing comovement will be made stronger (proposition 4). The other effect is to make information available about a broader class of assets. This would reduce the extent to which investors use information about one asset to make inference about

[7]Risk in the annual S&P 500 index (1946-2003) is counter-cyclical, rather than constant. However, total volatility (what determines information value) is procyclical. Detrended prices are positively correlated with the total volatility of both prices (0.75) and prices plus dividends (0.72), where total volatility is measured as the squared change in the detrended levels. This relationship also holds for emerging market indices (Veldkamp, 2005).

others and reduce the extent of comovement (proposition 5). If broadening the information set is a stronger force than enlarging the size of the informed population, then as payoffs and risk rise, comovement will fall; prices will exhibit countercyclical comovement. From figure 3, it is clear that more variance has a much stronger effect on the number of signals purchased than on the number of informed agents.

Of course, choosing a different mean for σ_θ could easily produce the opposite conclusion, that comovement increases in good times. However, extending this logic to a larger class of assets makes the conclusion more robust. Comovement will be strongest when all investors use only one signal to price all assets. As the number of signals rises, and investors construct more accurate forecasts of payoffs, comovement falls. It is only the case where people switch from seeing no signals to seeing one signal that comovement increases with the information supplied. Certainly in the U.S., the idea that investors stop learning anything about equity markets in downturns seems implausible. If investors buy fewer signals in downturns, but still buy at least one signal, then downturns should be times of high comovement.

3.2 Twin Stocks and Habitat Comovement

Twin stocks are identical financial claims that trade on two different markets, at two different prices. Twin stocks comove more with their own market than with their twin (Froot and Dabora 1999). Hardouvelis, La Porta and Wizman (1994) document a similar pattern for closed-end country funds: They have higher covariance with the market they are traded in than with the market where their underlying assets are traded. Barberis, Schleifer and Wurgler (2005) document this effect more broadly, calling it "habitat-based comovement." They show that there is a common factor in returns of assets traded by a common set of investors. They call that factor sentiment. In this model, that factor is information.

If an asset in this model trades on a market with other assets (called US assets), and a claim to the same sequence of payoffs is traded in another market with different (UK) assets, the prices of the two identical financial claims can differ substantially. As in Barberis et.al., the analysis starts from the observation that "many investors choose to trade only a subset of all available securities." In many cases, that subset is comprised of securities in an investor's home market. The reason for this home bias, or market segmentation, is left as an open question. Call the twin asset listed on both markets T with prices P_T^{US} and P_T^{UK}. It is a claim to the same payoff in every period and is subject to identical asset supply shocks, in both markets. In each market, there are two additional assets, which are not common. In the US, there are assets $S1$ and $S2$ with prices P_{S1} and P_{S2}. In the UK, there are assets $K1$ and $K2$ with prices P_{K1} and P_{K2}. Investors in each market hold only the assets in their market. Half of US investors buy information about $S1$ and half of UK investors purchase information about $K1$.

	P_T^{US}	P_T^{UK}
Correlation with US market ($P_{S1} + P_{S2}$)	0.73	0.31
Correlation with UK market ($P_{K1} + P_{K2}$)	0.32	0.74

Table 1: Simulated asset markets (US and UK) that have one asset T in common. The payoffs and asset supply shocks for T are identical in both markets. The asset that informed agents learn about has correlation of 0.8 with all the assets in its market: $\sigma_{T,K1} = \sigma_{K2,K1} = \sigma_{T,S1} = \sigma_{S2,S1} = 0.8$. All other combinations of assets have payoff correlations of 0.6. Variance of payoffs and supply shocks are $\sigma_\eta = 1$, $\sigma_\epsilon = 0.7$, $\sigma_x = 0.7$. Half of all investors are informed ($\lambda = 0.5$). 10,000 iterations.

Since the shares of T traded in each market are identical assets, we would expect for them to have the same correlations with each market. Table 1 shows that asset prices are influenced by the prices of other assets being traded in the same market, when information is incomplete. The reason is that these other assets determine what set of information traders purchase. An asset that is traded by people who learn lots of information about US stocks will have more covariance with US stocks and an asset traded by people who learn primarily about UK stocks will have more covariance with UK assets.

3.3 Decreasing Comovement over Time

Asset price comovement has been steadily decreasing in the U.S and emerging markets (Morck, Yeung, Yu 2000). At the same time, information technology has made information collection easier. According to the model, falling information costs can cause a more diverse set of signals to be supplied to investors. Instead of learning about one asset in an industry when information was very expensive, investors now have detailed firm-level information available at low cost. Proposition 5 says that more detailed information brings asset prices closer to full-information pricing, which exhibits no excess covariance.

4 Conclusion

When a piece of information can be used to forecast the value of many different assets, and that information is simultaneously observed by many investors, prices and returns can covary, even if the asset fundamentals are uncorrelated. By supplying the highest-value information, information markets naturally supply signals that can be used to evaluate many assets. When information is supplied at a competitive price, it becomes a strategic complement. Many investors observe the same signals because the signals that others purchase are supplied at a lower price.

Complementarity in information demand can arise in other settings. One way to make information a complement is to alter properties of the asset market: for example, with its distribution of shocks (Barlevy and Veronesi, 2000) or with investors' trading horizons (Froot, Scharfstein and Stein, 1992). While it is possible to generate complementarity in a specific region of the price distribution, or for a particular type of investor, it is an uphill battle because financial assets are rival goods. Investors want to hold low-demand assets because they have lower prices. Since investors want to learn about assets they expect to hold, they want to learn low-demand information as well. In this paper, complementarity in information demand comes from the information market, instead of the asset market. Complementary arises in the simplest competitive market. The non-rival nature of information makes complementarity in information markets more natural than complementarity arising from properties of asset markets.

There is a whole spectrum of asset-payoff-relevant information that could be sold and could produce comovement. For example, if a component of each asset's payoff were due to movements in the unemployment rate, then discovering and selling unemployment data might be an equilibrium outcome. Alternatively, many assets with uncorrelated payoffs could have correlated prices if investors observe a market index that is a weighted sum of the assets' payoffs. When information is costly, this is exactly the kind of high-value information that markets supply. For comovement to arise, it is not so important what people learn about, as long as the information is relevant for valuing many assets.

By characterizing optimal information portfolios, this paper gives more content to a broad set of models that rely on asymmetric information. Most of these models take their information structures as given and offer predictions, conditional on their information structure. Since we cannot observe information directly, the content of these predictions is unclear. However, with a theory of what information sets rational agents will acquire, these conditional predictions can be made unconditional and therefore more general.

In asset pricing, the literature traditionally assumes symmetric knowledge of all past realizations of prices and dividends. Yet, we know that it is not humanly possible, nor economical to actively track close to 7000 U.S. common stocks. The question of which stocks investors choose to track and what firms they choose to research is crucial to understanding how prices for these assets are formed. Such information choices can alter some of the most basic results in finance. Even diversification can become suboptimal when investors first choose what to learn (Van Nieuwerburgh and Veldkamp, 2005). This paper develops a framework to analyze information choices by investors. Its conclusions provide one more reason why we ought to think carefully about the information choices investors make.

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A Appendix

Proof of Proposition 3

Since this pricing rule will later be used to price assets in the full model, a general pricing result is derived here. With 3 assets, there are 8 possible combinations of signals that an investor can purchase. Let $\tilde{\lambda}$ denote the (8×1) vector whose jth entry $\tilde{\lambda}_j$ describes the fraction of agents who purchase the jth combination of signals. Agents can choose to purchase any combination of signals.[8]

The solution involves first postulating a linear rule for risky asset prices

$$P = A + B(\theta - \mu) + C(x - \bar{x}).$$

Since this is a rational expectations equilibrium, agents include prices in their information set when they update beliefs about θ. Each agent solves a Kalman filtering problem to obtain expectations of θ, as well as the variance of that expectation. While the price rule comprises the observation equation and is common to all agents, the state equation depends on the agent's information set $\mathcal{F}_i$, which contains the signals they purchase, as well as equilibrium prices.

$$\eta = E[\eta|\mathcal{F}_i] + Var[\eta|\mathcal{F}_i]^{1/2}\nu \tag{19}$$

where $\nu \sim N(0, 1)$.

To solve for the coefficients A, B, and C, and verify that price is linear, use the asset market clearing condition. The first-order condition of the utility maximization problem tells us that each agent's asset demand depends on their conditional expectation and variance of the assets' payoffs, as well as on the price $D_i = (a\, Var[u|\mathcal{F}_i])^{-1} (E[u|\mathcal{F}_i] - rP)$. These conditional expectations and variances are the same for all agents who observe the same set of signals. Total asset demand is therefore a weighted sum of demands of each group of investors, where the weights are their shares of the population $\tilde{\lambda}_j$. Setting total asset demands equal to supply and rearranging yields the equilibrium price equation

$$P = \frac{1}{r} V_\lambda \left(\sum_{j=1}^{8} \tilde{\lambda}_j Var[u|\mathcal{F}_j]^{-1} E[u|\mathcal{F}_j] - ax\right)$$

where $V_\lambda = (\sum_j \tilde{\lambda}_j Var[u|\mathcal{F}_j]^{-1})^{-1}$.

The conditional variances $Var[u|\mathcal{F}_j]$ and equilibrium information demands $\tilde{\lambda}$ can be deduced from knowing the structure of the problem. The only variables that depend on the signals θ are the conditional expectations $E[u|\mathcal{F}_j]$. Since Bayesian updating of normal priors with normal signals involves forming a linear combinations of those signals and prior beliefs, $E[u|\mathcal{F}_j]$ will be a linear function of the signal θ. Since P is linear in $E[u|\mathcal{F}_j]$, P will be a linear function of θ as well.

This pricing equation can be rewritten as a linear function of $(\theta - \mu)$ and $(x - \bar{x})$. Matching coefficients yields implicit solutions for A, B and C. where B and C solve

$$B = [\lambda r V_I^{-1} + (1 - \lambda) V_U^{-1}(rI - K)]^{-1} \lambda V_I^{-1} B \tag{20}$$

$$C = \frac{-a\sigma_x^2}{r} [\lambda r V_I^{-1} + (1 - \lambda) V_U^{-1}(rI - K)]^{-1}. \tag{21}$$

The term K is the Kalman gain: $K = \Sigma B'(B\Sigma B + \sigma_x^2 CC')^{-1}$. Σ is the prior variance-covariance matrix. It has diagonal elements σ_θ^2 and (i, j)th element, σ_{ij}, for $i \neq j$. The variance of asset payoffs (u), conditional on observed prices, for the uninformed agent is $V_U = \Sigma - KB\Sigma + \sigma_\epsilon^2 I$. Finally, A is the expected price.

$$A = \frac{1}{r}(\mu - aV_\lambda \bar{x}) \tag{22}$$

The coefficients B and C cannot be solved for explicitly. However, a numerical algorithm that begins with a guess for B and C and then iterates on equations 20 and 21 until convergence, will produce a solution.

[8]This solution method is similar to that used by Admati (1985). However, this problem is distinct because Admati's agents receive signals that independent. All agents in this model who choose to see a signal about asset i observe the same signal.

Proof of Proposition 4

If (15) holds, then $cov(P_2, P_3)$ is higher when $\lambda_1 = 1$ than when $\lambda_1 = 0$. Price covariance with $\lambda \epsilon (0, 1)$ is

$$E[PP'] = B\Sigma B' + \sigma_x^2 CC'. \tag{23}$$

Note that (20), (21) and (23) are all continuous functions of λ. The covariance of P_2 and P_3 is the (2,3) entry of the $E[PP']$ matrix. If this covariance is higher at $\lambda = 1$ than at $\lambda = 0$ and varies continuously in λ for all $\lambda \epsilon (0, 1)$, then there must be some region $\Lambda \subset (0, 1)$ where covariance in increasing in Λ. □

Proof of Proposition 5

Proof: If $\lambda_2 = 1$, the price of asset 2 is the full-information price $P_2 = \frac{1}{R}(\theta_2 - a\sigma_\epsilon^2 x_2)$. The price of asset 3 is $\frac{1}{R}(E[\theta_3|\theta_1, \theta_2] - aV_3 x_2)$, where $V_3 = \sigma_\theta^2 - \Sigma(1:2,3)'\Sigma(1:2,1:2)^{-1}\Sigma(1:2,3)$. The covariance between these two prices is

$$\begin{aligned} cov(P_2, P_3) &= E[\eta_2 E[\eta_3|\eta_1, \eta_2]] + \rho^2 E[\theta_2\theta_3] \\ &= \sigma_{23} + \tfrac{\rho^2}{1-\rho^2}\sigma_{23} = \tfrac{1}{1-\rho^2}\sigma_{23} \end{aligned}$$

which is the same as the covariance between full-information prices. Proposition 1 shows that when $\sigma_{23} < \frac{\sigma_{12}\sigma_{13}}{\sigma_\eta^2}$, then the price covariance when $[\lambda_1, \lambda_2, \lambda_3] = [1, 1, 0]$. is less than when $[\lambda_1, \lambda_2, \lambda_3] = [1, 0, 0]$. Therefore, by continuity of price covariance in λ (established proposition 4), there must be some non-empty region Λ where cov(P_2, P_3) is decreasing in λ_2. □

Proof of proposition 6

In a setting with an identical asset market and information structure, Admati and Pfleiderer (1987, proposition 3.1) show that traders' expected ex-ante utility, excluding information costs, is

$$E[U(W)] = -\frac{|Var[u|\theta_i, p]|^{1/2}}{|Var[u - rp]|^{1/2}} exp\left(-\frac{1}{\rho}W_{0a} - \frac{1}{2}E[\theta - rp]'(Var[u - rp])^{-1}E[\theta - rp]\right). \tag{24}$$

where $|\cdot|$ denotes a matrix determinant. The fact that information is purchased from a market in this setting, and not in Admati and Pfleiderer only affects its price. Since the term inside the exponential and the unconditional variance $Var[u-rp]$ do not depend on learned information, the information that maximizes expected utility is the i that minimizes $|Var[u|\theta_i, p]|$ term. □