Social Networks and Financial Markets

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Abstract

We explore a competitive financial market with costly information acquisition in which investors can learn both from market prices and from each other. Learning from others involves direct observation of a network of sources as well as an information production externality that generates increasing aggregate returns to scale. Price informativeness depends on a new object we term the "information mesh," which reflects both the total information collected by investors and the network interconnectedness. The magnitude of production externalities governs the response of the information mesh to information costs and network depth.

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1 Introduction

Over the past couple of decades, widespread use of the internet has significantly altered learning dynamics and the transmission of knowledge. In the case of the financial industry, this has led to a relative surge of non-price mechanisms of information transmission as simple and efficient alternative channels for learning.

Such non-price mechanisms of information transmission include financial media services such as Bloomberg or Reuters, and external consulting services such as Deloitte or McKinsey & Company, which offer rich databases used in forecasting returns. Perhaps most relevant, though, are both direct or indirect communications among investors themselves via e-mail, social networks, or slack channels. The importance of direct communication of this sort is likely the reason why financial institutions have historically tended to agglomerate in particular metropolitan areas, such as New York City or London.

In this paper, we explore the consequences of exogenous non-price social networks for price efficiency and return volatility in a financial environment in the tradition of Grossman and Stiglitz (1980). We consider a model of a financial market with costly information acquisition in which investors can learn about the payoff of a risky asset from prices, their own idiosyncratic signals, and the signals of others in their 'network' of sources. Learning from others affects information acquisition in two ways. First, an investor can directly learn by freely observing signals produced by others in his network of sources. Second, information acquisition effort exerted by sources in an investor's network reduces the marginal cost to that investor of producing his own signal.

This latter effect gets at the idea that an investor learns more than just the realization of other's signals. He can take advantage of information processing others have already done and use his energy to 'search elsewhere.' To focus on the asset-pricing implications of this assumption and keep the model relatable to the tradition of Grossman and Stiglitz (1980), we represent this 'spatial' searching as a positive information production externality resembling the investment dynamics in Farmer and Benhabib (1994) or Farmer and Guo (1994). This externality implies simultaneously diminishing returns to individual investment and increasing returns to scale in the aggregate. Its strength is expressed in terms of a scalar parameter, ι. When $\iota > 0$, investors' marginal costs in information production decrease in response to the efforts of others. When $\iota = 0$, investors can observe the signals of others in their network, but their learning efforts are independent.

The model offers a couple of interesting insights. First, it draws a new distinction between total information and a new metric we call the "information mesh." The former aggregates the information collection efforts undertaken by investors. The latter adjusts this figure to account for the interconnectedness of the network of information sources. Two markets can coincide in the total information but differ in their information meshes: The information mesh will be thicker, i.e., have a higher value, in an economy in which the (same set of) idiosyncratic signals are more widely distributed throughout the network.

The distinction, not present in a standard Grossman model without networks, is highly relevant. The information mesh is the more meaningful metric of the two, as it governs price informativeness, return volatility, and the correlation across investor portfolios in equilibrium. Moreover, it is often the case that total information and the information mesh move in opposite directions in response to key fundamentals. For instance, an expansion of an investors' circle of sources can often reduce total information (as a result of more free-riding) but nevertheless thicken the information mesh. Thus, market prices can become more informative even as total information decreases.

Second, the response of market informativeness to information costs/network size depends crucially on the magnitude of information production externalities. When these externalities are small, increases in network size generally make prices more informative; but when they are large, free-riding can become so severe that the information mesh shrinks and with it price informativeness. Thus when production externalities are large, our model generates predictions similar to those of Han and Yang (2013), in whose work price informativeness is always falling with network size. However, our model, with certain values of information production externalities, can also accommodate the empirical findings of Halim et al. (2019), who show that networks tend to enhance the ability of asset prices to reflect fundamental information. These authors conjecture that the discrepancies between their results are due to different network structures. We show instead that differences could be driven by the magnitude of information production externalities.

1.1 Related Literature and Contribution

This paper contributes to the literature on informational efficiency in financial markets spawned by Grossman (1976) and Grossman and Stiglitz (1980), who posit an environment in which investors can learn from prices but not from each other and who assume that some unlearnable uncertainty exists to preclude prices being fully revealing. Just a few examples in this literature include Verrecchia (1982), Admati (1985), Peress (2004), Dow and Gorton (2006), Van Nieuwerburgh and Veldkamp (2009, 2010), Mackowiak and Wiederholt (2009), Banerjee (2011), Valchev (2017), and Pavan et al. (2022). Our study extends this literature by incorporating networks into a model of costly information production and by generating new predictions linking social communication to market efficiency and volatility.

The most related papers to ours are Halim et al. (2019) and Han and Yang (2013), who also explore financial markets with costly information and social networks. The former is an empirical study using laboratory experimental data, and the latter is the only other theoretical paper to our knowledge to study the effect of social communication on financial market outcomes when information is endogenously acquired at a cost. There are several differences between Han and Yang (2013) and ours and in ways that shed light on the empirical findings of Halim et al. (2019). First is how information acquisition is treated. In Han and Yang (2013), becoming informed is a binary decision and an indifference condition between being informed and uninformed closes the model by allowing for the fraction of informed investors to adjust to clear markets. In our framework, all investors are equally informed in equilibrium and information acquisition instead happens on the intensive margin.

The second difference is that network groups are mutually exclusive in Han and Yang (2013) but can partially overlap in our model. The third and most critical difference, though, is the presence of information production externalities, which are key to the dynamics in our model but are absent in Han and Yang (2013). In particular, we find that the strength of these externalities govern the market response to network expansion or information cost reduction. This finding can shed light on the empirical results by Halim et al. (2019) that seem to contrast with Han and Yang (2013).

Given that a core driver of our results is related to investors' ability to observe and mimic other investors in a social network, our paper is also related to a literature on investor herding and mimicking behavior, e.g., Hong and Stein (1999), Chari and Kehoe (2003, 2004), Veldkamp (2006a), and Gu (2011) among others.

The information production externality in our model generates a complementarity in information-acquisition activity. Many other works have argued that such information complementarities emerge in alternative settings. García and Strobl (2010) show that the marginal value of information can increase in the number of agents who acquire it, depending on how an investor's marginal utility of consumption is related to other investors' consumption. Other sources of the complementarity include short-term trades (Froot et al. (1992); Chamley (2007)), fixed costs in information production (Veldkamp (2006b)), correlation of noise in supply and fundamentals (Barlevy and Veronesi (2007)), the presence of an additional dimension of supply information (Ganguli and Yang (2009)), feedbacks between financial markets and the value of traded securities (Goldstein et al. (2013)), or investors being ambiguity averse (Mele and Sangiorgi (2015)).

2 Model Description

2.1 Market Structure

We consider a financial market in the tradition of Grossman and Stiglitz (1980) in which investors attempt to infer an asset's payoff by direct means, i.e., information acquisition, as well as market prices. Some aggregate unobservable noise, in this case a supply shock, obscures perfect revelation by prices. We add into this structure a social network amongst investors that allows for the transmission of some of their information via non-price mechanisms.

There are two assets traded in the market. One is a risky asset that pays a stochastic dividend, $\theta \sim \mathcal{N}\left(\bar{\theta}, \frac{1}{\kappa}\right)$ and the other yields a gross, risk-free return $R > 0$. The risk-free asset price is normalized to unity. The risky asset supply is random and distributed, $a \sim \mathcal{N}\left(\bar{a}, \frac{1}{\beta}\right)$.

On the other side of the market there is a unit continuum of investors, each denoted by $i \in [0, 1]$ and small enough to have no strategic incentives. These investors are rational and update their beliefs according to Bayes' rule. Following Grossman and Stiglitz (1980), they receive private signals about the underlying fundamental, θ, but can infer nothing about the risky asset supply a except through the price. They make bids contingent on both realized prices and their private information to maximize their utility post-private-signal realization. Each has an initial stock of risk-free assets, w_0.

The price of the risky asset adjusts to clear markets and can depend only on these aggregate fundamentals. It is given by a function $q(a, \theta)$. Following Grossman and Stiglitz (1980), investors observe the price and can use it to infer information, but they directly observe neither θ nor a.

2.2 Information Structure

Investors observe a countable number of private signals of the dividend, θ and all private signals conditional on θ are independent. Each investor, i, receives one 'non-mimickable' private signal, ξ_i, given

$$\xi_i = \theta + \nu_i$$

where $\nu_i \sim \mathcal{N}\left(0, \frac{1}{\chi}\right)$, i.e., χ is the *precision* of the non-mimickable private signal, which is taken to be exogenous. These signals follow the tradition of Grossman and Stiglitz (1980) insofar as no other agent $j \neq i$ is privy to the realization of ξ_i and thus cannot condition bids on it.

In addition to a non-mimickable private signal, each investor can construct a *mimickable* private signal,

$$z_i = \theta + \epsilon_i$$

where $\epsilon_i \sim \mathcal{N}\left(0, \frac{1}{\eta_i}\right)$ and $\eta_i \geq 0$ is the precision of the signal. Importantly, the precision of this signal is *chosen by the investor* in a way we'll describe shortly.

The mimickability of z_i enters in two ways. First, investor i gets to observe the realizations (and precisions) of the mimickable signals, z_j, of $M - 1 \geq 1$ other investors for some integer M. We assume that investor i can observe (and condition bids on) his own signal plus those of investors in his network which we will refer to as his *sources* and index by $i/2$, $i/3$, $\ldots$, i/M. All of his sources will also be indexed in $[0, 1]$. This particular network structure is designed to eliminate strategic incentives. The subset of i's mimickers will always be countable, investor i could never hope to influence market prices by swaying the mimicry of others.

This network structure also allows for partial but not complete overlap of different investors across their source networks. Some investors will have completely disjointed information networks, such as $i = 0.5$ and $j = 1/\pi$ while some others will exhibit non-trivial overlap. For instance, consider two investors: $i = 0.5$ and $j = 0.25$. In this case, j is one of i's sources, but not the other way round. Further, if taken individually, their source networks share some but not all sources. Consider the case where $M = 5$.

$$\left\{\frac{1/2}{k}\right\}_{k=1}^{5} = \left\{\frac{1}{4}, \frac{1}{6}, \frac{1}{8}, \frac{1}{10}, \frac{1}{12}\right\}$$
$$\left\{\frac{1/4}{k}\right\}_{k=1}^{5} = \left\{\frac{1}{8}, \frac{1}{12}, \frac{1}{16}, \frac{1}{20}, \frac{1}{24}\right\}$$

In this case, investors 1/2 and 1/4 share two common sources, $\{1/8, 1/12\}$, but each have three of their own distinct sources.

The second way mimickability plays a role is through a production externality. In particular, whenever (1) the number of sources in the network grows or (2) the extant source network produces more mimickable information, it lowers the cost of i in producing his own mimickable information. In particular, we follow the approach of Farmer and Benhabib (1994) or Farmer and Guo (1994) and assume that mimickable information produced by others (both on the intensive and extensive margins) reduces the cost (and marginal cost) of investor i in producing mimickable information. In particular,

$$C\left(\eta_i; \{\eta_{i/k}\}_{k=2}^{M}\right) = \frac{\eta_i^p}{p\left(M \times \frac{1}{M-1}\sum_{k=2}^{M}\eta_{i/k}\right)^{\iota}} \tag{1}$$

where $p > 1$ and $\iota > 0$. The idea behind this cost function is straightforward. The individual i's production of more accurate signals faces a convex cost governed by the curvature parameter p, but that cost (and the implied marginal cost) is lowered if either (1) the total number sources (including himself), M, increases or (2) the average information produced by other sources increases. The curvature parameter ι governs the size of these externalities. Information cost is given in terms of information units, e.g., bits. We assume a constant per-unit disutility of information, λ, such that the total information disutility is $\lambda C\left(\eta_i; \{\eta_{i/k}\}_{k=2}^{M}\right)$.

In addition to these private signals, investors can also infer information from the price itself, which in equilibrium will serve as a noisy aggregate signal of the dividend as well.

It is most convenient to express the investors' problem working backward in time. We follow Kacperczyk et al. (2016) and Valchev (2017) and assume that investment behavior conditional on a given information set is determined by maximizing a mean-variance utility function as follows

$$U_i\left(\xi_i, \{z_{i/k}\}_{k=1}^M, q|\{\eta_{i/k}\}_{k=1}^M\right) = \max_{b_i} \; \alpha\mathbb{E}\left[\tilde{c}_i|\xi_i, \{z_{i/k}, \eta_{i/k}\}_{k=1}^M, q\right] - \frac{\alpha^2}{2}Var\left(\tilde{c}_i|\xi_i, \{z_{i/k}, \eta_{i/k}\}_{k=1}^M, q\right) \quad (2)$$

$$c_i = \left[w_0 - qb_i\right]R + b_i\theta$$

The objects of the expectation are random variables denoted with a tilde and are taken with respect to the investor's information set at the time. There are no financial frictions here and investors are allowed to short the risky asset.

Moving backward from the investment decision, the ex-ante utility in the information design problem is given by the payoff of a Nash game in the information acquisition, wherein each investor takes the signal precisions of the other investors as given.

$$U_i\left(\{\eta_{i/k}\}_{k=2}^M\right) = \max_{0\leq\eta_i\leq\bar{\eta}} \; \mathbb{E}\left[U_i\left(\tilde{\xi}_i, \{\tilde{z}_{i/k}\}_{k=1}^M, \tilde{q}|\{\eta_{i/k}\}_{k=1}^M\right)\right] - \lambda C\left(\eta_i; \{\eta_{i/k}\}_{k=2}^M\right) \quad (3)$$

Notice that the information cost applies only to mimickable information production as the non-mimickable private information is exogenous. Also, while investors can make bids contingent on price realizations, they cannot make information acquisition decisions based on it. This is consistent with the idea of price-contingent bids as being limit orders that must be placed ahead of time.[1]

As Problems 2 and 3 are convex, the solution to this problem is a *best-response* function that we define as

$$\eta_i^* = G_I\left(\{\eta_{i/k}\}_{k=2}^M\right) \quad (4)$$

2.3 Market Clearing

The price, $q(a,\theta)$, must adjust to clear markets in all possible aggregate states, i.e.,

$$a = \int_0^1 \int\int\cdots\int b_i^*\left(\xi_i, \{z_{i/k}^*\}_{k=1}^M, q(a,\theta)|\{\eta_{i/k}^*\}_{k=1}^M,\right) f(z_i|\theta)dz_i \ldots f(z_{i/M}|\theta)dz_{i/M} f(\xi_i|\theta)d\xi_i di \quad (5)$$

[1]The cap on information acquisition is merely a technical condition. In practice we will set $\bar{\eta}$ high enough that it never binds in equilibrium.

where b_i^* is the solution to the investment problem, i.e., Equation 2 and η_i^* is the solution to the information game, i.e., the fixed point of the best-response function implied by Equation 3.

2.4 Equilibrium Definition

A **Competitive Equilibrium** will be a price function, $q(a, \theta)$, investment policy functions, b_i^*, and information acquisition level, η^*, such that

1. b_i^* maximizes investor utility in Equation (2).
2. $\eta^* = G_I((M-1)\eta^*)$, i.e., the information acquisition satisfies Equation (4) and agents are homogenous at the information-gathering stage.
3. Markets clear, i.e., Equation (5) holds.
4. The pricing function is linear in its inputs.

As we will show that the equilibrium is unique conditional on η^*, we will distinguish equilibria by their value of η.

3 Analysis

In this section, we formalize a collection of useful and interesting results regarding the model's behavior in equilibrium. Proofs of all propositions can be found in Appendix A.

3.1 Existence and Efficiency

We begin with an existence result.

Proposition 1. *A competitive equilibrium exists. The pricing function is unique conditional on η^*.*

Proposition 1 can be shown by a guess-and-verify approach following Admati (1985). The key insight here is that the linearity of the price in its inputs allows it to be used as a noisy aggregate signal.[2]

[2] In the rare but possible event of equilibrium multiplicity, all results hold in all equilibria.

To help build intuition, we write out the equilibrium price as follows

$$Rq(a, \theta) = A + B \times (a - \bar{a}) + C \times \theta \tag{6}$$

where A, B, and C are expressions dependent on η^*. This is useful because we can interpret the equilibrium price as a signal of the dividend whose imprecision is driven by the independent, aggregate, and mean-zero shock $\tilde{a} - \bar{a}$. Since the various slopes of the pricing function depend on η^*, the degree to which the supply shock obscures this information depends on the equilibrium acquisition of information. This can be seen by re-writing the pricing expression as

$$\frac{Rq}{C} - \frac{A}{C} = \theta + \frac{B}{C}(a - \bar{a}) \tag{7}$$

That is, when investors observe a market price, q, they can transform via a series of constants to arrive an expression that can be interpreted as a signal of the fundamental. This signal will have a precision given by

$$\rho_\theta = \frac{C^2}{B^2}\beta$$

that we will refer to as the *market efficiency* or *price informativeness*. Such terminology is common in the literature.

The first relevant feature of our model is that there is a distinction between *total information* and the *information mesh* for the purpose of price informativeness. **Total information** refers to the integration over all private information collected in the market and is equal to the posterior precision $\chi + \eta^*$. The **information mesh** describes both to how much information is acquired in total *and* the degree to which it is tangled and entwined across the various networks of investors. In particular, it will be given by $\chi + M\eta^*$. Total information and the information mesh play different roles in the model, with the latter generally being more important.

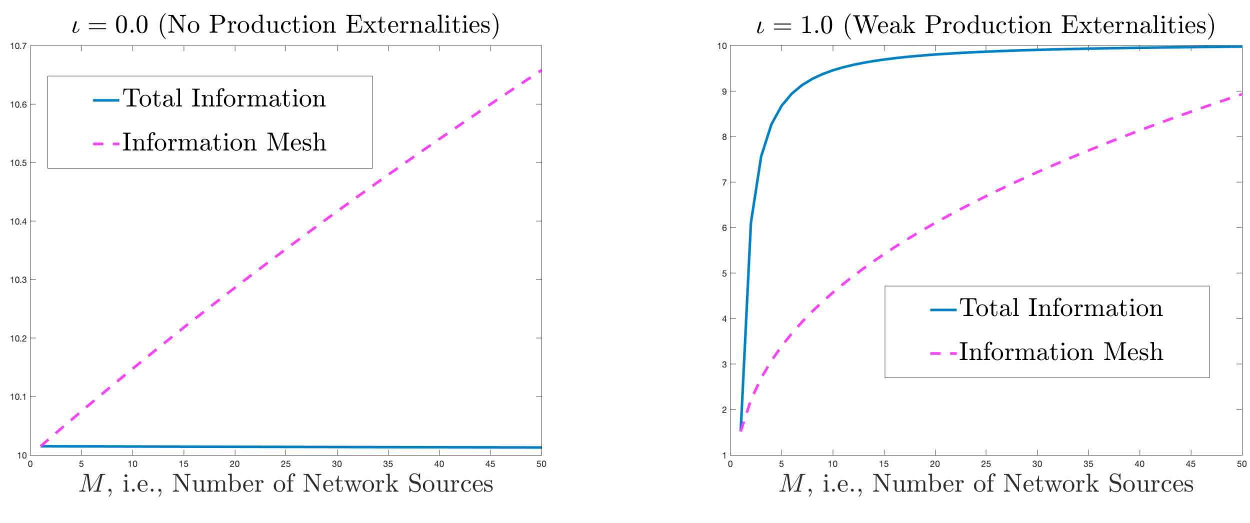
This is seen first in Proposition 2.

Proposition 2. *Market efficiency, ρ_θ, is increasing in the information mesh, but not in total information.*

In a standard Grossman model, market efficiency typically coincides with total information. This is because the price reflects shifts in demand driven by the information acquisition undertaken by individual investors and, in a standard framework, their information is completely private. Here, though, individual information sets are driven both by the accuracy they observe/collect themselves, $\chi + \eta^*$, and the accuracy of the information observed in the rest of the network, $(M-1)\eta^*$. The sum delivers the information mesh.

3.2 Network Comparative Statics

Here, we consider how the equilibrium responds to an increase in the network size. It will turn out that these same comparative static exercises will apply equally to the information cost (see the corollary in the proof of Proposition 3 for details). The example[3] in Figure 1a portrays how changes in network interconnectedness can have opposite impacts on total information and the information mesh when there are no production externalities. In the absence of these externalities, the main impact of the network on investor behavior is to induce mild free-riding: An increase in the network size, via free-riding dynamics, can cause total information to fall mildly. This fall, however, is not so great that it causes the information mesh to attenuate. Rather, the increased interconnectedness of the network more than overcomes the free-riding, thickening the information mesh and, by Proposition 2, increasing market efficiency.



(a) (b)

Figure 1: Comparative Statics: No or Weak Externalities

[3] See Appendix B for the parameterization.

Figure 1b reveals what happens when we add in relatively weak production externalities. We see now both that total information increases and the information mesh thickens with the size of the network. The production externalities induce a positive feedback loop: A wider network reduces investors' marginal costs, which incentivizes them to produce more information, which in turn reduces other investors' marginal costs even further, incentivizing even further production. This feedback loop is eventually brought to a halt by decreasing returns to individual information acquisition.

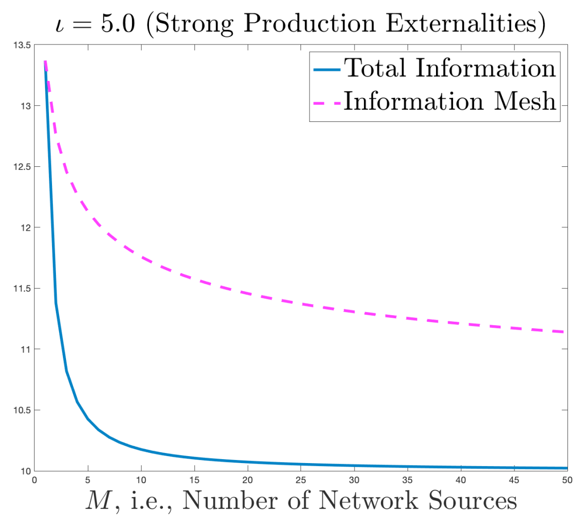


Figure 2: Comparative Statics: Strong Externalities

Interestingly, if we strengthen these externalities significantly as in Figure 2, the feedback loop can work in the opposite direction. An increase in the network size initially leads to a bit of free-riding, which reduces investors' information effort, as in Fig 1a. This reduction in an investor's information effort makes it *more costly* for other investors to acquire information, and so they decrease their effort as well. This continues to cycle, as it did in the weak externalities case, until increasing returns to individual information acquisition eventually kills the feedback loop.

We can provide a sufficient condition to ensure that the feedback effects cause the information mesh to fall as the network gets denser rather than the other way around.

Proposition 3. *If learning from others is sufficiently strong, i.e., $\iota > p+3$, then there exist an information cost $\bar{\lambda} > 0$, below which the information mesh is decreasing in M.*

It is worth noting here that, by changing the production externalities, our model can accommodate both the empirical results of Halim et al. (2019) and the theoretical results of Han and Yang (2013). The former's results hold under weak (or no) production externalities, while the latter's hold under strong production externalities.

4 Conclusion

In this paper, we explored a competitive financial market with endogenous information acquisition and social networks. We demonstrated that the information mesh, not total information, is the critical information variable that governs market efficiency. Further, how the information mesh responds to key parameter changes depends critically on the magnitude of the information production externality.

A natural next step is for empirical researchers to take up the task of exploring some of the model's key predictions. It is easy to show that return volatility or portfolio correlations could be used as a proxy for the information mesh in such exercises.

A Proofs

A.1 Proof of Propositions 1 and 2

Proof. Observe that under mean-variance preferences, the FONC implies that the optimal investment policy has the form

$$b_i^* = \frac{1}{\alpha \mathrm{Var}_i(\tilde{\theta})} \times \left[\mathbb{E}_i\left[\tilde{\theta}\right] - qR\right]$$

where the subscript i denotes an expectation or variance taken with respect to the investor's information set.

To solve for the equilibrium, we follow Admati (1985) and take a guess-and-verify approach. In particular, we conjecture a linear pricing rule of the form

$$Rq(a,\theta) = A + B \times (a - \bar{a}) + C \times \theta$$

for real constants A, B, and C. The first convenient thing about this is that it allows us to treat the price as a signal of θ with the noise coming from the supply shock/noise traders,

$$\frac{Rq}{C} - \frac{A}{C} = \theta + \frac{B}{C}(a - \bar{a})$$

The precision of this signal will be the inverse of the variance of the mean-zero noise, i.e., $\frac{C^2}{B^2}\beta$.

The Gaussian structure of the signals (including the aggregate price) allows for a convenient description of the conditional variances, also described by Veldkamp (2011) among others, i.e.,

$$\theta | \xi_i, \{z_{i/k}\}_{k=1}^M, q \sim \mathcal{N}\left(\frac{\chi\xi_i + \sum_{k=1}^M \eta_{i/k} z_{i/k} + \frac{C^2}{B^2}\beta\left(\frac{Rq}{C} - \frac{A}{C}\right) + \kappa\bar{\theta}}{\chi + \sum_{k=1}^M \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa}, \frac{1}{\chi + \sum_{k=1}^M \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa}\right)$$

Plugging these expressions into the policy function delivers a policy rule in terms of fundamental parameters.

$$b_i^* = \frac{\chi + \sum_{k=1}^M \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa}{\alpha} \times \left[\frac{\chi\xi_i + \sum_{k=1}^M \eta_{i/k} z_{i/k} + \frac{C^2}{B^2}\beta\left(\frac{Rq}{C} - \frac{A}{C}\right) + \kappa\bar{\theta}}{\chi + \sum_{k=1}^M \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa} - qR\right]$$

The goal here is to find the parameters A, B, and C, that ensure market clearing. Given that all private signals conditional on θ are independent, this can be done easily enough by imposing market clearing given this policy function together with the restriction that every agent invests the same η^* as follows:

$$\alpha a = \mathbb{E}_i\left[\chi\tilde{\xi}_i + \sum_{k=1}^{M}\eta_{i/k}\tilde{z}_{i/k} + \frac{C^2}{B^2}\beta\left(\frac{Rq(a,\theta)}{C} - \frac{A}{C}\right) + \kappa\bar{\theta} - Rq(a,\theta)\left(\chi + \sum_{k=1}^{M}\eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)|\theta\right]$$

$$\alpha a = (\chi + M\eta^*)\,\theta + \frac{C^2}{B^2}\beta\left(\frac{Rq(a,\theta)}{C} - \frac{A}{C}\right) + \kappa\bar{\theta} - Rq(a,\theta)\left(\chi + M\eta^* + \frac{C^2}{B^2}\beta + \kappa\right)$$

$$\implies Rq(a,\theta)\times\left[\left(\frac{C^2}{B^2}\right)\frac{\beta}{C} - \left(\chi + M\eta^* + \frac{C^2}{B^2}\beta + \kappa\right)\right] = \alpha a - \kappa\bar{\theta} - (\chi + M\eta^*)\theta + \left(\frac{C^2}{B^2}\right)\frac{\beta A}{C}$$

$$\implies Rq(a,\theta) = \underbrace{\frac{\alpha\bar{a} - \kappa\bar{\theta} + \left(\frac{C^2}{B^2}\right)\frac{\beta A}{C}}{\left(\frac{C^2}{B^2}\right)\frac{\beta}{C} - \left(\chi + M\eta^* + \frac{C^2}{B^2}\beta + \kappa\right)}}_{A} + \underbrace{\frac{\alpha}{\left(\frac{C^2}{B^2}\right)\frac{\beta}{C} - \left(\chi + M\eta^* + \frac{C^2}{B^2}\beta + \kappa\right)}}_{B}\times(a - \bar{a})$$
$$+ \underbrace{\frac{-(\chi + M\eta^*)}{\left(\frac{C^2}{B^2}\right)\frac{\beta}{C} - \left(\chi + M\eta^* + \frac{C^2}{B^2}\beta + \kappa\right)}}_{C}\times\theta$$

This gives us three equations: A equals the first term, B equals the second, and C equals the third. Most immediate in the solution is the term $\frac{C}{B}$ since the denominators of these terms cancel leaving

$$\rho_\theta = \frac{C}{B} = \frac{-(\chi + M\eta^*)}{\alpha} \implies \frac{C^2}{B^2} = \frac{(\chi + M\eta^*)^2}{\alpha^2} \tag{A.1}$$

This term happens to be market efficiency as well given how we interpret the price as a signal. Thus Equation A.1 immediately establishes that Proposition 2 holds in any equilibrium.

With this, we can solve easily for the third term, C, i.e.,

$$C = \frac{-(\chi + M\eta^*)}{\left(\frac{(\chi+M\eta^*)^2}{\alpha^2}\right)\frac{\beta}{C} - \left(\chi + M\eta^* + \frac{(\chi+M\eta^*)^2}{\alpha^2}\beta + \kappa\right)}$$

$$\implies -(\chi + M\eta^*) = \left(\frac{(\chi + M\eta^*)^2}{\alpha^2}\right)\beta - \left(\chi + M\eta^* + \frac{(\chi + M\eta^*)^2}{\alpha^2}\beta + \kappa\right)C$$

$$\implies C = \frac{\chi + M\eta^* + \frac{(\chi+M\eta^*)^2}{\alpha^2}\beta}{\chi + M\eta^* + \kappa + \frac{(\chi+M\eta^*)^2}{\alpha^2}\beta}$$

$$\implies C = \left[1 + \kappa\left[\chi + M\eta^* + \frac{(\chi + M\eta^*)^2}{\alpha^2}\beta\right]^{-1}\right]^{-1}$$

With this, we can solve for B

$$
\begin{aligned}
B &= \frac{-\alpha}{\chi + M\eta^*} C \\
\implies B &= -\frac{\alpha}{\chi + M\eta^*} \times \left[1 + \kappa \left[\chi + M\eta^* + \frac{(\chi + M\eta^*)^2}{\alpha^2}\beta \right]^{-1} \right]^{-1} \\
\implies B &= -\alpha \left[\chi + M\eta^* + \kappa \left[1 + \frac{\chi + M\eta^*}{\alpha^2}\beta \right]^{-1} \right]^{-1}
\end{aligned}
$$

And finally, we can solve for A

$$
\implies A = \frac{\kappa\bar{\theta} - \alpha\bar{a}}{\left(\chi + M\eta^* + \frac{(\chi + M\eta^*)^2}{\alpha^2}\beta + \kappa \right)}
$$

We have shown now that A, B, and C are uniquely determined for a given η^*. We need now only verify that an equilibrium η^* exists. This easily follows by applying Brouwer's fixed point theorem to the equilibrium best-response. G_I is manifestly a continuous function, and it necessarily maps into the compact set, $[0, \bar{\eta}]$, thus ensuring existence. □

A.2 Proof of Proposition 3

Proof. We start by deriving a closed-form expression for the expected utility at the information-acquisition stage.

$$
\begin{aligned}
U_i(q, \{z_{i/k}\}_{i=1}^M, \xi_i) &= \alpha \left[\mathbb{E}_i[\tilde{\theta}] - qR \right] b_i^* - \frac{\alpha^2}{2} b_i^{*2} Var_i(\tilde{\theta}) \\
&= \frac{\left(\mathbb{E}_i[\tilde{\theta}] - qR \right)^2}{2 \times Var_i(\tilde{\theta})} \\
&= \frac{\chi + \sum_{k=1}^M \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa}{2} \times \left[\frac{\chi\xi_i + \sum_{k=1}^M \eta_{i/k} z_{i/k} + \frac{C^2}{B^2}\beta \left(\frac{Rq}{C} - \frac{A}{C} \right) + \kappa\bar{\theta}}{\chi + \sum_{k=1}^M \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa} - qR \right]^2 \\
&= \frac{\left[\chi \left(\xi_i - qR \right) + \sum_{k=1}^M \eta_{i/k} \left(z_{i/k} - qR \right) + \frac{C^2}{B^2}\beta \left(\frac{Rq}{C} - \frac{A}{C} - Rq \right) + \kappa \left(\bar{\theta} - qR \right) \right]^2}{2 \left(\chi + \sum_{k=1}^M \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa \right)}
\end{aligned}
$$

The relevant expression here is essentially the normalized sum of the deviations of all of the realized signals from the realized price plus some price-specific terms and a term that measures the deviation of the realized price from the fundamental. The next step will be to break signals and prices into exogenous shocks

$$
= \frac{\left[\begin{array}{c} \chi\left(\theta+\nu_i-A-B(a-\bar{a})-C\theta\right) \\ +\sum_{k=1}^{M}\eta_{i/k}\left(\theta+\epsilon_{i/k}-A-B(a-\bar{a})-C\theta\right) \\ +\frac{C^2}{B^2}\beta\left(-\frac{A}{C}-\left(1-\frac{1}{C}\right)\left(A+B(a-\bar{a})+C\theta\right)\right) \\ +\kappa\left(\bar{\theta}-A-B(a-\bar{a})-C\theta\right) \end{array}\right]^2}{2\left(\chi+\sum_{k=1}^{M}\eta_{i/k}+\frac{C^2}{B^2}\beta+\kappa\right)}
$$

$$
= \frac{\left[\begin{array}{c} \chi\nu_i+\sum_{k=1}^{M}\eta_{i/k}\epsilon_{i/k} \\ -\left[\chi+\sum_{k=1}^{M}\eta_{i/k}+\frac{C^2}{B^2}\beta\left(1-\frac{1}{C}\right)+\kappa\right]B(a-\bar{a}) \\ +\left[\left(\chi+\sum_{k=1}^{M}\eta_{i/k}+\frac{C^2}{B^2}\beta\right)(1-C)-\kappa C\right]\theta \\ -\left[\left(\chi+\sum_{k=1}^{M}\eta_{i/k}+\frac{C^2}{B^2}\beta+\kappa\right)A-\kappa\bar{\theta}\right] \end{array}\right]^2}{2\left(\chi+\sum_{k=1}^{M}\eta_{i/k}+\frac{C^2}{B^2}\beta+\kappa\right)}
$$

Now we add a zero term in the above square term to get a sum of mean-zero normals squared

$$= \left[\underbrace{\frac{\chi}{\sqrt{2\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)}}}_{\hat{\chi}} \nu_i + \sum_{k=1}^{M} \underbrace{\frac{\eta_{i/k}}{\sqrt{2\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)}}}_{\hat{\eta}_{i/k}} \epsilon_{i/k} \right.$$
$$+ \underbrace{\frac{-\left[\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\left(1 - \frac{1}{C}\right) + \kappa\right] B}{\sqrt{2\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)}}}_{\hat{B}} (a - \bar{a})$$
$$+ \underbrace{\frac{\left[\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\right)(1 - C) - \kappa C\right]}{\sqrt{2\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)}}}_{\hat{C}} (\theta - \bar{\theta})$$
$$\left. + \underbrace{\frac{-\left[\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right) A - \kappa\bar{\theta}\right] + \left[\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\right)(1 - C) - \kappa C\right]\bar{\theta}}{\sqrt{2\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)}}}_{\hat{A}} \right]^2$$

which yields a more convenient expression given by a sum of independent normal random variables.

$$= \left[\hat{A} + \hat{\chi}\nu_i + \sum_{k=1}^{M} \hat{\eta}_{i/k}\epsilon_{i/k} + \hat{B}(a - \bar{a}) + \hat{C}(\theta - \bar{\theta})\right]^2$$

We compute the expected utility given only the precisions of the private signals, $\eta_{i/k}$ for $k = 1, \ldots, M$, by taking an expectation over everything else. Since these are all mean-zero Gaussians with no correlation, everything but the variance terms and $\hat{A}^2$ disappear, leaving us with

$$U_i\left(\{\eta_{i/k}\}_{k=2}^{M}\right) = \max_{\eta_i \geq 0}\ \hat{A}^2 + \frac{\hat{\chi}^2}{\chi} + \sum_{k=1}^{M} \frac{\hat{\eta}_{i/k}^2}{\eta_{i/k}} + \frac{\hat{B}^2}{\beta} + \frac{\hat{C}^2}{\kappa} - \lambda C(\eta_i; \{\eta_{i/k}\}_{k=2}^{M}) \tag{A.2}$$

where λ is the per-unit disutility of information. Expanding this out gives us

$$= \max_{\eta_i \geq 0} \frac{\begin{bmatrix} \chi + \sum_{k=1}^{M} \eta_{i/k} + \left[\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\left(1 - \frac{1}{C}\right) + \kappa\right]^2 B^2/\beta + \\ \left[\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\right)\left(1 - \frac{1}{C}\right) + \kappa\right]^2 C^2/\kappa + \\ \left[\left[\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\right)\left(1 - \frac{1}{C}\right) + \kappa\right] C\bar{\theta} + \left[\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right) A - \kappa\bar{\theta}\right]\right]^2 \end{bmatrix}}{2\left(\chi + \sum_{k=1}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)} - \lambda \frac{\eta_i^p}{p\left(\frac{M}{M-1}\sum_{k=2}^{M} \eta_{i/k}\right)^{\iota}}$$

Now it is important to note here that we do *not* substitute out the A, B, and C terms. In equilibrium, these will be functions of all the η terms, including that belonging to investor i. But investor i does not take this equilibrium effect into account when choosing η_i. Being competitive, they take the whole pricing schedule as given and unaffected by their choice of η_i.

It's also important to note the source of the terms in the denominator, as it seems curious that increasing precision would reduce welfare. The denominator terms stem from the fact that the welfare is a weighted average of the various inverse variances the agent faces. Changing the level of precision not only affects these perceived variances directly, but also endogenously shifts these weights.

This implies a FONC given by

$$\frac{\begin{bmatrix} 1 + 2\left[\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\left(1 - \frac{1}{C}\right) + \kappa\right] B^2/\beta + 2\left[\left(\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\right)\left(1 - \frac{1}{C}\right) + \kappa\right]\left(1 - \frac{1}{C}\right) C^2/\kappa \\ +2\left[\left[\left(\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\right)\left(1 - \frac{1}{C}\right) + \kappa\right] C\bar{\theta} + \left[\left(\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right) A - \kappa\bar{\theta}\right]\right] \times \left[(C-1)\bar{\theta} + A\right] \end{bmatrix} \times 2\left(\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)}{4\left(\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)^2}$$

$$- \frac{\begin{bmatrix} \chi + \sum_{k=1}^{M} \eta_{i/k} + \\ \left[\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\left(1 - \frac{1}{C}\right) + \kappa\right]^2 B^2/\beta + \\ \left[\left(\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\right)\left(1 - \frac{1}{C}\right) + \kappa\right]^2 C^2/\kappa + \\ \left[\left[\left(\chi + \eta_i^* \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta\right)\left(1 - \frac{1}{C}\right) + \kappa\right] C\bar{\theta} + \left[\left(\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right) A - \kappa\bar{\theta}\right]\right]^2 \end{bmatrix} \times 2}{4\left(\chi + \eta_i^* + \sum_{k=2}^{M} \eta_{i/k} + \frac{C^2}{B^2}\beta + \kappa\right)^2} = \lambda \frac{\eta_i^{p-1}}{\left(\frac{M}{M-1}\sum_{k=2}^{M} \eta_{i/k}\right)^{\iota}}$$

We can now substitute in the expressions for A, B, and C, as well as impose the assumption of a homogeneous equilibrium, i.e., $\eta_i = \eta_j = \eta^*$ for any $i \neq j$. Thus the expression above simplifies considerably (with many terms equating to zero or far simpler terms),

$$\frac{\left[1+2\alpha^2\left(\frac{1+\kappa}{\beta(\chi+M\eta^*)}\times\frac{(\chi+M\eta^*+\frac{(\chi+M\eta^*)^2}{\alpha^2}\beta)^2}{(\chi+M\eta^*+\frac{(\chi+M\eta^*)^2}{\alpha^2}\beta+\kappa)^2}+\frac{\bar{a}^2}{\chi+M\eta^*+\frac{(\chi+M\eta^*)^2}{\alpha^2}\beta+\kappa}\right]\right)\left(\chi+M\eta^*+\frac{(\chi+M\eta^*)^2}{\alpha^2}\beta+\kappa\right)}{2\left(\chi+M\eta^*+\frac{(\chi+M\eta^*)^2}{\alpha^2}\beta+\kappa\right)^2}$$

$$-\frac{\left[\chi+M\eta^*+\alpha^2\left(\frac{1+\kappa}{\beta(\chi+M\eta^*)}\times\frac{(\chi+M\eta^*+\frac{(\chi+M\eta^*)^2}{\alpha^2}\beta)^2}{(\chi+M\eta^*+\frac{(\chi+M\eta^*)^2}{\alpha^2}\beta+\kappa)^2}+\bar{a}^2\right)\right]}{2\left(\chi+M\eta^*+\frac{(\chi+M\eta^*)^2}{\alpha^2}\beta+\kappa\right)^2}=\lambda\frac{\eta * p-1}{(M\eta^*)^\iota}$$

If we define $H = M\eta^*$ as the aggregate amount of mimickable information collected, we get the key equilibrium condition

$$H^{\iota-(p-1)}\left[\frac{1+2\alpha^2\left(\frac{1+\kappa}{\beta(\chi+H)}\times\frac{(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta)^2}{(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa)^2}+\frac{\bar{a}^2}{\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa}\right)}{2\left(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa\right)}\right.$$

$$\left.-\frac{\chi+H+\alpha^2\left(\frac{1+\kappa}{\beta(\chi+H)}\times\frac{(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta)^2}{(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa)^2}+\bar{a}^2\right)}{2\left(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa\right)^2}\right]=\frac{\lambda}{M^{p-1}}$$

Careful examination reveals that some $\bar{a}$ terms cancel, which leaves us with the key equilibrium condition that determines mimickable information in the source network.

$$H^{\iota-(p-1)}\left[\frac{1+2\alpha^2\left(\frac{1+\kappa}{\beta(\chi+H)}\times\frac{(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta)^2}{(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa)^2}\right)}{2\left(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa\right)}\right.$$

$$\left.-\frac{\chi+H+\alpha^2\left(\frac{1+\kappa}{\beta(\chi+H)}\times\frac{(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta)^2}{(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa)^2}-\bar{a}^2\right)}{2\left(\chi+H+\frac{(\chi+H)^2}{\alpha^2}\beta+\kappa\right)^2}\right]=\frac{\lambda}{M^{p-1}} \tag{A.3}$$

Any H^* that satisfies this condition will imply an equilibrium with $\eta^* = H^*/M$. Notice here that because λ and M appear only on the right-hand-side we have the following interesting corollary.

Corollary 1. *For any increase in the network size, M, there exists a reduction in information costs that delivers the same equilibrium allocation.*

This implies that we can think about the comparative static exercises in M as comparative statics in λ as well.

Proceeding, we can now see that if M increases, the RHS of this expression must go down. The LHS can be broken into two components: $H^{\iota-(p-1)}$ and the large term in the brackets. To understand these two, we take logs and rename the large, second term $Z(H)$. This implies

$$[\iota - (p-1)] \log(H) + \log(Z(H)) = \log(\lambda) - (p-1)\log(M)$$
$$\implies [\iota - (p-1)] \frac{1}{H}\frac{\partial H}{\partial M} + \frac{Z'(H)}{Z(H)}\frac{\partial H}{\partial M} = -(p-1)\frac{1}{M}$$
$$\implies \frac{\partial H}{\partial M} = \frac{-(p-1)\frac{1}{M}}{[\iota-(p-1)]\frac{1}{H} + \frac{Z'(H)}{Z(H)}}$$

We are thus interested in finding cases wherein

$$[\iota - (p-1)] > \frac{Z'(H)H}{Z(H)} \tag{A.4}$$

This can be done under the sufficient conditions of Proposition 3. To see how, note that $Z(0)$ is some finite number. This implies that $H^{\iota-(p-1)}Z(H)$ goes to zero as H goes to zero provided $\iota > p-1$. Further, $Z(H)$ is quartic in H in the denominator. This implies via L'Hopital's rule that $Z(H)$ goes to infinity as H goes to infinity since $\iota > p+3$ will imply that $H^{\iota-(p-1)}$ is an order greater than 4. The intermediate value theorem thus tells us that for any positive real number, x, there exists at least one H such that $x = H^{\iota-(p-1)}Z(H)$.

This allows us the freedom to change $x = \lambda/M^{p-1}$ and in doing so achieve any desired H value. The strategy here will be to identify regions of λ for which Equation A.4 holds. First, we note that the RHS converges continuously to zero as $H \to 0$, since $Z(0)$ and $Z'(0)$ are finite. This implies that for any sufficiently small $\epsilon > 0$, we can find a strictly positive $\bar{\lambda}$ such that the implied equilibrium H' will satisfy.

$$[\iota - (p-1)] > \epsilon = \frac{Z'(H')H'}{Z(H')}$$

Thus, provided $\iota > p + 3$, we can always find a $\bar{\lambda}$ such that H decreases as M increases.

Now, given that changing M and changing λ have the same impact on H (this is evident from Equation A.3), it is manifestly the case that $\partial H/\partial\lambda$ will have the opposite sign of $\partial H/\partial M$. Thus, if we reduce λ, it will have the same directional effect as increasing M, i.e., H will go down.

As such, starting from $\bar{\lambda}$ and reducing λ will only bring the RHS of Equation A.4 closer to zero. Thus, equation A.4 will hold for any $\lambda \in (0, \bar{\lambda}]$, which gives us Proposition 3. □

B Example Parameters

For the example in Section 3.2, we set $\chi = 10.0$, $\alpha = 2.0$, $\bar{a} = 2.0$, $\beta = 2.0$, $\kappa = 1.0$, $\bar{\theta} = 4.0$, $p = 2.0$, and $\lambda = 1.0$. It can also be shown that these parameters generate a positive relationship between the information mesh and (1) log-return volatility and (2) randomly drawn cross-sectional portfolio correlations.

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