

Financial Markets where Traders Neglect the Informational Content of Prices

Erik Eyster

London School of Economics

Matthew Rabin

Harvard University

Dimitri Vayanos

London School of Economics, CEPR and NBER

August 24, 2015

Abstract: We present a model of a financial market where some traders are “cursed” when choosing how much to invest in a risky asset, failing to fully take into account what prices convey about others’ private information. Cursedness induces traders to weight their private signals more heavily than rational traders. But because they neglect that the price encodes other traders’ information, prices depend less on private signals and more on public signals than rational-expectation-equilibrium (REE) prices. Markets comprised entirely of cursed traders generate more trade than those comprised entirely of rationals; mixed markets can generate even more trade, as rationals employ momentum-trading strategies to exploit cursed traders. We contrast our results to other models of departures from REE and show that per-trader volume with cursed traders increases when the market becomes large, while natural forms of overconfidence predict that volume should converge to zero.

Acknowledgments: We thank Nick Barberis, John Campbell, Kent Daniel, Willie Fuchs, Xavier Gabaix, Tristan Gagnon-Bartsch, Josh Schwartzstein, Andrei Shleifer, Jeremy Stein, seminar participants at Columbia, Humboldt, NYU Stern, UC Berkeley, UC Davis, and Wharton, and participants at the NBER Behavioral Finance Conference, the Paris School of Economics Workshop in Bounded Rationality, the Miami Behavioral Finance Conference, and the Stanford Institute for Theoretical Economics for helpful comments. We also thank Tristan Gagnon-Bartsch and Tarso Mori Madeira for research assistance.

1 Introduction

People might rationally trade financial assets for a variety of non-speculative motives, such as portfolio rebalancing and liquidity. But ever since Milgrom and Stokey (1982), researchers have understood that common knowledge of rationality combined with a common prior precludes purely speculative trade. Even in settings where the presence of non-speculative motives allows for speculation, a rational understanding of the adverse-selection problem causes the overall volume of trade to be constrained by non-speculative motives. In many people’s estimation, trading volume in financial markets greatly exceeds what can be plausibly explained by models applying rational-expectations equilibrium (REE).¹

Researchers have sought to explain excessive trading volume by relaxing the common-prior assumption. Harrison and Kreps (1978) show how non-common priors about an asset’s payoff generate volume in a dynamic model where risk-neutral traders cannot sell the asset short. Scheinkman and Xiong (2003) use Harrison and Kreps’ framework to explore traders who are “overconfident”: all traders observe all signals about the payoff, yet certain traders overestimate the information content of certain signals.² In these complete-information models, trade derives from traders agreeing to disagree about the relationship between payoff and publicly available information; the lack of private information disencumbers traders from the need to invert market prices.³ A second

¹For example, in his presidential address to the American Finance Association, French (2008) notes that the capitalized cost of trading exceeds 10% of market capitalization, and turnover in 2007 was 215%, creating a puzzle that “from the perspective of the negative-sum game, it is hard to understand why equity investors pay to turn their aggregate portfolio over more than two times in 2007” (page 1552).

²Hong, Scheinkman and Xiong (2006) model overconfidence similarly, allowing also for heterogeneous priors, in a model where the number of shares of a risky asset increases over time.

³Other models of trade deriving from differences in beliefs include Varian (1985), where traders have different subjective priors, DeLong, Shleifer, Summers, Waldmann (1990), where symmetrically informed traders disagree because some of them (“noise traders”) misperceive next-period prices for exogenous reasons, as well as Harris and Raviv (1993) and Kandel and Pearson (1995), where traders disagree about the informativeness of public signals. Hong and Stein (2007) summarize this literature. Eyster and Piccione (2013) model traders with incomplete theories of price formation, also in a complete-information setting.

approach incorporates non-common priors into incomplete-information models by assuming that privately informed traders agree to disagree about the precision of traders’ private information. Daniel, Hirshleifer and Subrahmanyam (1998, 2001) and Odean (1998), for example, show how traders’ overconfidence about the precision of their private information can increase trading volume. Similarly, Odean (1998), Banerjee, Kaniel and Kremer (2009), Banerjee and Kremer (2010), and Banerjee (2011) show that when traders downplay the precision of one another’s private signals—which we call *dismissiveness*—volume also increases. In this second class of agreeing-to-disagree models, the presence of private information infuses market prices with information content, and traders are assumed to fully invert market prices to uncover hidden information. Both type of agreeing-to-disagree models depict traders who recognize their disagreements in beliefs and trade based on them.

This paper proposes a different conceptual approach to explaining speculation: people trade because they *neglect* disagreements in beliefs. We capture this idea in a simple and tractable model of markets where some or all traders, when choosing their demands, do not fully attend to the informational content of prices or others’ trades. This approach builds on evidence and modeling that people do not sufficiently heed the information content of others’ behavior—even in the absence of intrinsic disagreements. We draw out several implications of disagreement neglect, and contrast both to REE and to existing alternatives. We show, in particular, that disagreement neglect is key to generate trading volume in large markets with dispersed private information: in its absence, volume per trader converges to zero. Disagreement neglect also enables other cognitive errors such as overconfidence to have a significant effect on prices and volume.

Section 2 outlines the basic model upon which our approach builds. Based on evidence from strategic situations, Eyster and Rabin (2005) define *cursed equilibrium* in Bayesian games by the requirement that every player correctly predicts the behavior of others, but fails to fully attend to its informational content. Cursed equilibrium is meant to capture the intuitive psychology behind the “winner’s curse” in common-values auctions, as well as related phenomena in other strategic settings.⁴ We then illustrate the workings of cursed equilibrium in a simple zero-sum game

⁴Cursedness explains the voluminous evidence on bidders succumbing to the “winner’s curse” in common-

of speculative trade, where its prediction of trade is supported by direct experimental evidence. Moreover, that evidence cannot be accounted for by alternative approaches such as non-common priors over asset values or agreeing to disagree about the informativeness of private signals.

Section 3 introduces our formal set-up, based on Grossman (1976), Hellwig (1980) and Diamond and Verrechia (1981). We consider a market in which traders can exchange a risky for a riskless asset over one period. Each trader observes a public and a private signal about the risky asset’s payoff, with the private signals being independent across traders conditional on that payoff. Random endowments correlated with the asset payoff furnish traders with a non-speculative motive to trade. We define *cursed-expectations equilibrium (CEE)* by the requirement that some traders do not fully extract information from asset prices and call them *partially cursed*. Because CEE transplants the concept of cursed equilibrium from strategic games to price-taking competitive settings, it has the methodological advantage of not having been designed specifically to explain the particular financial-market puzzles that we explore. For tractability, we assume that traders have constant-absolute-risk-aversion (CARA) preferences and that probability distributions are normal.

We begin in Section 4 by analyzing a setting without random endowments, where there is a unique linear REE with no trade and a price that aggregates efficiently all public and private signals (Grossman, 1976). The most important implication of CEE is also the most basic: disagreement neglect produces substantial trade, with volume approaching infinity as the number of agents becomes large. Cursedness distorts not only volume but also prices. Indeed, although each cursed trader relies too much upon his own private signal when estimating the asset payoff, because other traders fail to appreciate how that signal influences the price, private signals enter the price with a smaller weight than in REE and public signals with a larger weight. This makes returns a predictable function of observables: future return depends positively on past return and negatively

values auctions—where the average price paid by the winner exceeds the average value of the object being auctioned—reviewed in Kagel and Levin (2002). Additional evidence consistent with cursedness comes from settings including social learning (Weizsäcker (2010)), voting (Esponda and Vespa (2013)), and trade in positive-sum (Samuelson and Bazerman (1985), Holt and Sherman (1994)) and zero-sum (Carrillo and Palfrey (2011)) environments.

on the public signal in a bivariate regression, and it depends positively on past return in a univariate regression. The univariate-regression result is consistent with the empirical evidence on return momentum.⁵ We show additionally that cursed traders with more precise private signals can be worse off than those with less precise ones because cursedness induces them to trade too aggressively. Finally, we show that markets that include both rational and cursed traders generate more trade than those comprised solely of one type or the other. Intuitively, a cursed trader trades more against someone who does the opposite—a rational trader who exploits the momentum in prices—than against another cursed trader. Moreover, the private information of cursed traders exerts disproportionate influence in such markets because rational traders weight the private signals of cursed traders by inverting the price, whereas fully cursed traders do not weight the private signals of rational traders whatsoever.

The link between non-inference from price and momentum was first shown in Hong and Stein (1999). Some or all of their traders are “newswatchers,” assumed to trade based on signals or news they watch without inverting price to infer unwatched news. Hong and Stein show that prices move predictably when information diffuses gradually, yielding momentum. Our work departs from theirs in several respects: first, by formalizing a general market-equilibrium concept that applies to other information environments as well; second, by relaxing their assumption that traders infer nothing from price to allow for partial inference; third, by analyzing volume, and comparing its level to that predicted by alternative models such as overconfidence.

To compare the qualitative properties of cursed trade to rational trade, in Section 5 we extend our analysis to settings in which traders have random endowments. In this setting, REE trading volume is inverse hump-shaped in the precision of private signals, intuitively because adverse selection reduces rational volume but disappears when everybody knows little due to imprecise signals or is fully informed because of very precise signals (Akerlof (1970), Hirshleifer (1971)). Cursedness produces the exact opposite pattern. CEE trading volume is hump-shaped in the precision of traders’ private information: private information fuels cursed trade and vanishes when either sig-

⁵See Jegadeesh and Titman (1993), and Jegadeesh and Titman (2011) for a recent survey of the empirical evidence on momentum.

nals are very imprecise—everybody knows very little—or when signals are very precise—everybody is fully informed.⁶

In Section 6, we contrast our approach and results to those of overconfidence—where traders exaggerate the precision of their own private signals—and dismissiveness—where traders downplay the precision of other traders’ private signals.⁷ As in the literature, in the model of overconfidence and dismissiveness that we construct for comparison traders are otherwise rational: they understand the mapping between the price and other traders’ private information—but they agree to disagree about the meaning of that information. We show that overconfidence leads to prices that depend too much on private information and too little on public information relative to REE—the exact opposite of our findings with cursed traders. Extreme dismissiveness—every trader regards every other trader’s private signal as pure noise—makes the same prediction as the special case of our model in which no trader gleans any information from price. Less extreme dismissiveness resembles partial cursedness in that traders who downplay the informativeness of others’ signals lead to prices that overweight public signals and underweight private signals.

The predictions of cursedness differ sharply from those of overconfidence and dismissiveness in the case of trading volume and especially for large markets. Whereas the per-trader volume under cursedness increases with the number of traders, per-trader volume under overconfidence or anything other than extreme dismissiveness converges to zero. Intuitively, while each trader thinks he knows more than he does, he understands that the total amount of “valid” information reflected in the price in a large market swamps his own information. Hence, the same no-trade logic that prevails in REE also prevails in large markets of overconfident or dismissive traders; partial

⁶Banerjee (2011) finds that dismissiveness predicts this same pattern relative to REE.

⁷This form of overconfidence does not perfectly correspond to people’s sensation that they are more skilled than they are, as in the work of Malmendier and Tate (2005) on CEOs. Instead, it accords to people thinking “my private signals are better than they are,” which might result from people thinking they are better than others at reading information, making it akin to ego-related overconfidence.

dismissiveness makes very different predictions than partial cursedness.⁸ Excluding the extreme scenario in which people completely dismiss others’ signals (extreme dismissiveness), cursedness is the only explanation we know for large speculative volume in large markets with many different private signals.

In Section 6, we also show how cursedness magnifies overconfidence. In a large market of *cursed* overconfident traders, per-trader volume remains non-negligible. In this sense, cursedness and overconfidence work as complements, and cursedness helps vindicate the basic intuition from the literature that overconfidence can be a significant source of trading volume. Finally, we conjecture some additional implications of cursedness to financial markets. Grossman and Stiglitz (1980) famously described the paradox that in markets in which the price incorporates all available information, traders have no incentive to collect private information. Unlike rational traders who recognize the futility of acquiring private information, cursed traders attracted to speculation in such markets also may misperceive value in information acquisition. Hence, cursedness may help explain why traders demand costly private information even in the informationally richest of settings. By contrast, for the same reason that they barely trade in large markets—they understand that the information contained in the market price overwhelms that contained in their own private signals—overconfident and dismissive traders in large markets should not demand costly private information.

In Section 7, we conclude by describing how cursedness may interact with other biases. As it does with overconfidence and dismissiveness, cursedness may serve as an “enabler” of various cognitive errors to which traders seem to fall prey: many errors matter significantly for prices and volume if and *only if* traders are cursed.

⁸Our finding that the per-trader volume of overconfident trade vanishes in large markets would also hold if all signals in the model were made public as in Scheinkman and Xiong (2003).

2 Cursed Equilibrium

In this section, we use a simple trading game to illustrate Eyster and Rabin's (2005) concept of *cursed equilibrium*, which underlies our concept of *cursed-expectations equilibrium* introduced in Section 3. In the context of this game, we show how cursed equilibrium differs from other theories that have been explored in the finance literature such as non-common priors, overconfidence and dismissiveness. A general definition of cursed equilibrium is in Appendix A.

The trading game works as follows. A seller owns an asset that he knows to be worth s both to himself and to a potential buyer. The buyer does not know s , but believes that it is randomly drawn from $[0, 1]$ with a cumulative distribution function F . The buyer makes the seller a take-it-or-leave-it offer p for the asset.

The seller's optimal strategy is to accept the buyer's offer p if and only if $s \leq p$. In a Bayesian Nash equilibrium the buyer understands this, and so chooses p to maximize $F(p) \times (E[s|s \leq p] - p)$. This objective is the probability $F(p)$ that the seller accepts the offer p , times the buyer's expected surplus from acquiring the asset conditional on seller acceptance. Because $E[s|s \leq p] < p$ for each $p > 0$, the buyer's optimal offer is $p^* = 0$. Thus, no trade occurs, consistent with Milgrom and Stokey's (1982) celebrated result on the absence of speculative trade between rational agents.

In a cursed equilibrium players fail to appreciate the informational content of others' behavior. This does not matter for the seller, who knows s perfectly and hence has nothing to learn, but matters for the buyer. A buyer who is *fully cursed* completely neglects the relationship between the seller's willingness to sell at price p and the seller's private information s , but correctly predicts the probability distribution over the seller's actions. As a consequence, a fully cursed buyer perceives the expected value of an asset traded at price p to be its unconditional expectation, $E[s]$. A fully cursed buyer thus chooses p to maximize $F(p) \times (E[s] - p)$. A *partially cursed* buyer appreciates that the seller's willingness to sell correlates with his private information but underestimates that relationship. A buyer who is partially cursed with coefficient χ perceives the expected value of an asset traded at price p to be $(1 - \chi)E[s|s \leq p] + \chi E[s]$. This is the weighted average of the rational belief with weight $1 - \chi$ and the fully cursed belief with weight χ . In effect, the buyer believes that with probability $1 - \chi$ the seller's decision to sell conveys information about the asset, and

with probability χ it does not. The coefficient χ measures the buyer's naivety: $\chi = 0$ corresponds to full rationality, while $\chi = 1$ corresponds to full cursedness. A χ -cursed buyer thus chooses p to maximize $F(p) \times ((1 - \chi)E[s|s \leq p] + \chi E[s] - p)$. Since $E[s] > 0$, the buyer's optimal offer exceeds zero for any $\chi > 0$. Moreover, since the buyer's objective function is supermodular in (p, χ) for $p \in [0, E[s]]$, Topkis' Theorem implies that p^* increases in χ . In summary, cursedness produces trade in no-trade settings, and the more cursed the buyer, the higher the volume of trade.

Cursed trade derives from people's neglect of disagreement: the buyer neglects how the seller's willingness to trade at p signals beliefs that the object is worth less than p . Researchers have proposed alternative models for speculative trade based on the idea that people are conscious of their disagreement and "agree to disagree." This is modelled as non-common priors about the distribution of asset payoffs, or as disagreement over the information that different signals convey about payoffs. Models of overconfidence assume a specific type of disagreement over signals: people believe that private signals they receive are more precise than private signals others receive. Such a belief may arise because people overestimate the precision of their signals while holding a correct assessment of the precision of others' signals. Alternatively, people may correctly assess the precision of their signals while underestimating the precision of others' signals. Researchers have considered both of these polar cases as well as their combination. We reserve the term overconfidence for the former case (people are overconfident about their ability to gather a precise signal), and use the term dismissiveness for the latter (people are dismissive about others' ability).

One way to identify cursedness in the data, and to distinguish from non-common priors, overconfidence and dismissiveness, is through laboratory experiments. Carrillo and Palfrey (2011) conduct experiments on a trading game that is a variant of the one considered in this section. The main difference is that in their game the buyer also has a private signal b , and the value of the object is some function $v(b, s)$. (The take-it-or-leave-it offer is also made by the seller rather than the buyer.) As in the game considered in this section, the Bayesian Nash equilibrium involves no trade but the cursed equilibrium does. Moreover, neither non-common priors, nor overconfidence, nor dismissiveness can generate trade. Carrillo and Palfrey argue indeed that behavior in their experiments is well explained by cursed equilibrium.

The failure of non-common priors, overconfidence and dismissiveness to generate trade can be seen in the game considered in this section (and the same logic transposes to Carrillo and Palfrey's game). Non-common priors about the distribution of asset payoffs would amount to the buyer and the seller employing different cumulative distribution functions F . This would not yield trade. Indeed, the seller has a dominant strategy that is independent of F , and the offer $p = 0$ is optimal for the buyer regardless of his assessment of F . Overconfidence has no bite because the seller knows s perfectly and so cannot exaggerate further the precision of his private information, while the buyer lacks private information whose precision to exaggerate. Dismissiveness would amount to the buyer believing that the seller has less information than he actually has, e.g., observes a noisy signal about s . Yet, the information structure is announced clearly to all experiment participants.

In Section 6 we examine the relationship between cursedness, overconfidence and dismissiveness within our financial markets model. We show that cursedness yields distinct predictions concerning trading volume and its behavior in large markets.

3 Model, Equilibrium Concept, and Equilibrium Conditions

In this section, we begin by defining cursed-expectations equilibrium in a general version of our model, before making more specific assumptions on traders' utility functions and the distribution of their information that allow us to derive analytically tractable, linear equilibria. There are two periods, 1 and 2, and two assets that pay off in terms of a consumption good in Period 2. One asset is riskless and pays off one unit of the consumption good with certainty. The other asset is risky and pays $d = \bar{d} + \epsilon + \zeta$ units, where $\bar{d}$ is a constant and (ϵ, ζ) are random variables with mean zero. We use the riskless asset as the numeraire, and denote by p the price of the risky asset in Period 1. Our choice of numeraire implies that the price of the risky asset in Period 2 is d and the riskless rate is zero. We assume that the risky asset is in zero supply.

There are N traders who can exchange the two assets in Period 1. Trader $i = 1, \dots, N$ observes the private signal

$$s_i = \epsilon + \eta_i, \tag{1}$$

as well as the public signal

$$s = \epsilon + \theta, \tag{2}$$

which is also observed by all other traders. The random variables $(\{\eta_i\}_{i=1,\dots,N}, \theta)$ have mean zero. The signals are observed in Period 1. They provide information about the component ϵ of the risky asset's payoff but not about ζ .

Trader i starts with a zero endowment of the riskless and the risky assets, and receives an endowment $z_i d$ of the consumption good in Period 2. We refer to z_i as the endowment shock, and assume that it is observed in Period 1 and has mean zero. Through its correlation with d , the endowment generates a hedging motive to trade. When, for example, $z_i > 0$, trader i is exposed to the risk that d will be low and wishes to hedge by selling the risky asset. We assume that the variables $(\epsilon, \zeta, \{\eta_i\}_{i=1,\dots,N}, \theta, \{z_i\}_{i=1,\dots,N})$ are mutually independent.

The budget constraint of trader i is

$$W_i = x_i(d - p) + z_i d, \tag{3}$$

where x_i denotes the number of shares of the risky asset held by the trader in Period 1. We impose no portfolio constraints, e.g., on short sales or leverage, and allow x_i to take any value in $\mathbb{R}$.

Traders maximize expected utility of consumption in Period 2. We denote by $u_i(W_i)$ the utility of trader i . If the trader is rational, he maximizes the expected utility

$$\mathbb{E}[u_i(x_i(d - p) + z_i d) | \{s_i, s, z_i, p\}],$$

where we use (3) to substitute for W_i . A rational trader conditions his estimate of the asset payoff d on his private signal, the public signal, the endowment shock, and the price. A fully cursed trader completely neglects the relationship between the price and other traders' information, and maximizes the expected utility

$$\mathbb{E}[u_i(x_i(d - p) + z_i d) | \{s_i, s, z_i\}],$$

which differs from the rational expected utility because there is no conditioning on the price. To derive the objective of a partially cursed trader, we proceed as in Section 2 with a slight modification

for tractability. Following the definition in Section 2, if trader i is χ_i -cursed, he maximizes the expected utility

$$(1 - \chi_i)E[u_i(x_i(d - p) + z_id)|\{s_i, s, z_i, p\}] + \chi_i E[u_i(x_i(d - p) + z_id)|\{s_i, s, z_i\}],$$

which is the weighted average of the rational expected utility with weight $1 - \chi_i$ and the fully cursed expected utility with weight χ_i . For tractability, we employ the geometric average of utilities instead of the arithmetic average, hence modifying trader i 's objective to

$$E[u_i(x_i(d - p) + z_id)|\{s_i, s, z_i, p\}]^{1-\chi_i} E[u_i(x_i(d - p) + z_id)|\{s_i, s, z_i\}]^{\chi_i}.$$

As in the case of the arithmetic average, $\chi_i = 0$ corresponds to rationality, $\chi_i = 1$ to full cursedness, and intermediate values of χ_i to traders who appreciate the information content of the price but only partially. The demand function of partially cursed traders always lies between the rational and the fully cursed demand functions.

Our definition of cursed-expectations equilibrium combines utility maximization under cursed expectations with market clearing. As in the case of REE, the equilibrium involves a price function p that depends on all the random variables in the model. These are the private signals $\{s_i\}_{i=1,\dots,N}$, the public signal s , and the endowment shocks $\{z_i\}_{i=1,\dots,N}$.

Definition 1 A price function $p(\{s_i\}_{i=1,\dots,N}, s, \{z_i\}_{i=1,\dots,N})$ and demand functions $\{x_i(s_i, s, z_i, p)\}_{i=1,\dots,N}$ are a cursed-expectations-equilibrium (CEE) if:

(i) (**Optimization**) For each trader $i = 1, \dots, N$, and each (s_i, s, z_i, p) ,

$$x_i \in \arg \max_x \{E[u_i(x(d - p) + z_id)|\{s_i, s, z_i, p\}]^{1-\chi_i} E[u_i(x(d - p) + z_id)|\{s_i, s, z_i\}]^{\chi_i}\}, \quad (4)$$

(ii) (**Market Clearing**) For each $(\{s_i\}_{i=1,\dots,N}, s, \{z_i\}_{i=1,\dots,N})$,

$$\sum_{i=1}^N x_i = 0. \quad (5)$$

We next specialize our analysis by making two assumptions, which allow us to derive tractable linear equilibria. First, the variables $(\epsilon, \zeta, \{\eta_i\}_{i=1,\dots,N}, \theta, \{z_i\}_{i=1,\dots,N})$ follow normal distributions,

with variances denoted by $(\sigma_\epsilon^2, \sigma_\zeta^2, \{\sigma_{\eta_i}^2\}_{i=1,\dots,N}, \sigma_\theta^2, \{\sigma_{z_i}^2\}_{i=1,\dots,N})$ and precisions, i.e., the inverses of the variances, denoted by $(\tau_\epsilon, \tau_\zeta, \{\tau_{\eta_i}\}_{i=1,\dots,N}, \tau_\theta, \{\tau_{z_i}\}_{i=1,\dots,N})$. Second, traders have negative exponential, or constant absolute risk aversion (CARA), utility functions: $u_i(W_i) = -\exp(-\alpha_i W_i)$, where α_i is the coefficient of absolute risk aversion.

A linear CEE price function has the form

$$p = \bar{d} + \sum_{i=1}^N A_i s_i + B s - \sum_{i=1}^N C_i z_i, \quad (6)$$

for coefficients $(\{A_i\}_{i=1,\dots,N}, B, \{C_i\}_{i=1,\dots,N})$. For CARA utility, we can write the expectations in (4) as

$$\begin{aligned} & -\mathbb{E}[\exp[-\alpha_i(x_i(d-p) + z_i d)] | I_i] \\ & = -\exp\left[-\alpha_i\left(x_i(\mathbb{E}(d|I_i) - p) + z_i \mathbb{E}(d|I_i) - \frac{1}{2}\alpha_i(x_i + z_i)^2 \text{Var}(d|I_i)\right)\right], \end{aligned} \quad (7)$$

where the information set I_i is equal to $I_{ir} \equiv \{s_i, s, z_i, p\}$ for the second expectation that is exponentiated to $1 - \chi_i$ (where r stands for rational) and to $I_{ic} \equiv \{s_i, s, z_i\}$ for the first expectation that is exponentiated to χ_i (where c stands for fully cursed). The second step in (7) follows because all variables are normally distributed. Substituting (7) into (4) and maximizing, we find the demand function

$$x_i = \frac{(1 - \chi_i)\mathbb{E}(d|I_{ir}) + \chi_i\mathbb{E}(d|I_{ic}) - p}{\alpha_i[(1 - \chi_i)\text{Var}(d|I_{ir}) + \chi_i\text{Var}(d|I_{ic})]} - z_i. \quad (8)$$

The demand function is the solution to a mean-variance problem. The trader's conditional expectation is the weighted average of the rational expectation with weight $1 - \chi_i$ and the fully cursed expectation with weight χ_i . The trader's conditional variance is the same weighted average of the rational and fully cursed variances. The geometric average formulation of utilities ensures that traders' optimization problems retain a tractable mean-variance structure even under partial cursedness. Combining (8) with the market-clearing condition (5), we derive conditions in Proposition 1 so that (6) is an equilibrium price. Proposition 1 does not show existence or uniqueness of $(\{A_i\}_{i=1,\dots,N}, B, \{C_i\}_{i=1,\dots,N})$ satisfying these conditions, both of which are instead demonstrated in the special cases studied in subsequent sections.

To state Proposition 1, we introduce some notation. From the perspective of a rational trader i , the price (6) includes information on (s_i, s, z_i) , which the trader knows, and on $(\{s_i\}_{j \neq i}, \{z_i\}_{j \neq i})$, which he does not. The latter information is summarized in the signal

$$\frac{\sum_{j \neq i} A_j s_j - \sum_{j \neq i} C_j z_j}{\sum_{j \neq i} A_j}, \quad (9)$$

which the trader can extract from the price. Using (1) and (2), we can write this signal as $\epsilon + \xi_i$, where

$$\xi_i \equiv \frac{\sum_{j \neq i} A_j \eta_j - \sum_{j \neq i} C_j z_j}{\sum_{j \neq i} A_j}. \quad (10)$$

We denote the variance of ξ_i by $\sigma_{\xi_i}^2$ and its precision by τ_{ξ_i} .

Proposition 1 *The price (6) is an equilibrium price if and only if $(\{A_i\}_{i=1, \dots, N}, B, \{C_i\}_{i=1, \dots, N})$ satisfy the conditions*

$$\begin{aligned} & \frac{\tau_{\eta_i}(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \chi_i \tau_{\xi_i}) - (1 - \chi_i) \tau_{\xi_i} \frac{A_i}{\sum_{k \neq i} A_k} (\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{\alpha_i [(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}) + \tau_\zeta (\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \chi_i \tau_{\xi_i})]} \\ &= A_i \sum_{j=1}^N \frac{(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \tau_{\xi_j}) - (1 - \chi_j) \tau_{\xi_j} \frac{1}{\sum_{k \neq j} A_k} (\tau_\epsilon + \tau_{\eta_j} + \tau_\theta)}{\alpha_j [(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \tau_{\xi_j}) + \tau_\zeta (\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \chi_j \tau_{\xi_j})]}, \end{aligned} \quad (11)$$

$$\begin{aligned} & \sum_{i=1}^N \frac{\tau_\theta (\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \chi_i \tau_{\xi_i})}{\alpha_i [(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}) + \tau_\zeta (\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \chi_i \tau_{\xi_i})]} \\ &= B \sum_{j=1}^N \frac{(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \tau_{\xi_j})}{\alpha_j [(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \tau_{\xi_j}) + \tau_\zeta (\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \chi_j \tau_{\xi_j})]}, \end{aligned} \quad (12)$$

$$C_i = A_i \alpha_i \frac{(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}) + \tau_\zeta (\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \chi_i \tau_{\xi_i})}{\tau_\zeta \tau_{\eta_i} (\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \chi_i \tau_{\xi_i})}. \quad (13)$$

4 No Endowment Shocks

This section analyzes the model in the case where there are no endowment shocks. This case is derived by setting the variances $\{\sigma_{z_i}^2\}_{i=1, \dots, N}$ of endowment shocks equal to zero. The shocks are then equal to their mean, which is zero. Without endowment shocks, traders lack a hedging motive to trade, and trade can occur only because of the private signals. The price (6) takes the form

$$p = \bar{d} + \sum_{i=1}^N A_i s_i + B s. \quad (14)$$

4.1 All Traders Rational

We begin with the benchmark case where all traders are rational ($\chi_i = 0$ for all i). Proposition 2 shows that the coefficients $(\{A_i\}_{i=1,..N}, B)$ in the price (14), which are characterized by the conditions in Proposition 1, are uniquely determined.

Proposition 2 *Suppose that there are no endowment shocks and all traders are rational. The price (14) is an equilibrium price if and only if*

$$A_i = \frac{\tau_{\eta_i}}{\tau_\epsilon + \sum_{j=1}^N \tau_{\eta_j} + \tau_\theta}, \quad (15)$$

$$B = \frac{\tau_\theta}{\tau_\epsilon + \sum_{j=1}^N \tau_{\eta_j} + \tau_\theta}. \quad (16)$$

There is no trade in equilibrium.

That there is no trade in equilibrium is a manifestation in the context of our model of the no-trade theorem of Milgrom and Stokey (1982). Since traders start with zero endowments in the risky asset and receive no endowment shocks, no-trade is a Pareto-efficient allocation and hence the unique equilibrium outcome.

The coefficients $(\{A_i\}_{i=1,..N}, B)$ with which the private and the public signals enter into the price are proportional to these signals' precisions. Therefore, the price aggregates all the signals efficiently, as in Grossman (1976). The price equals the expected value of the asset payoff d conditional upon all of the signals in the market.

4.2 All Traders Fully Cursed

We next turn to the case where all traders are fully cursed ($\chi_i = 1$ for all i). Proposition 3 shows that the coefficients $(\{A_i\}_{i=1,..N}, B)$ in the price (14) are uniquely determined.

Proposition 3 *Suppose that there are no endowment shocks and all traders are fully cursed. The*

price (14) is an equilibrium price if and only if

$$A_i = \frac{\frac{\tau_{\eta_i}}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}}{\sum_{j=1}^N \frac{\tau_\epsilon + \tau_{\eta_j} + \tau_\theta}{\alpha_j(\tau_\epsilon + \tau_\zeta + \tau_{\eta_j} + \tau_\theta)}}, \quad (17)$$

$$B = \frac{\sum_{j=1}^N \frac{\tau_\theta}{\alpha_j(\tau_\epsilon + \tau_\zeta + \tau_{\eta_j} + \tau_\theta)}}{\sum_{j=1}^N \frac{\tau_\epsilon + \tau_{\eta_j} + \tau_\theta}{\alpha_j(\tau_\epsilon + \tau_\zeta + \tau_{\eta_j} + \tau_\theta)}}. \quad (18)$$

Unlike in the case where all traders are rational, the coefficients $(\{A_i\}_{i=1,\dots,N}, B)$ are not proportional to the precisions of the corresponding signals. Therefore, the price does not aggregate the signals efficiently. Proposition 4 compares the coefficients $(\{A_i\}_{i=1,\dots,N}, B)$ in the rational and fully cursed cases.

Proposition 4 *Suppose that there are no endowment shocks and all traders are fully cursed. Compared to the case where all traders are rational:*

- (i) *The coefficient B with which the public signal enters into the price is larger.*
- (ii) *The sum across traders of the coefficients $\{A_i\}_{i=1,\dots,N}$ with which private signals enter into the price is smaller. The coefficient A_i for any given trader i can be larger or smaller.*
- (iii) *The ratio A_i/B is smaller.*

Intuition for Proposition 4 and other results in this section can be derived from a general property of the price in the absence of endowment shocks. Substituting the demand functions $\{x_i\}_{i=1,\dots,N}$ given by (8) into the market-clearing condition (5), setting $\{z_i\}_{i=1,\dots,N} = 0$, and solving for p , we find:

$$p = \frac{\sum_{i=1}^N \frac{(1-\chi_i)E(d|I_{ir}) + \chi_i E(d|I_{ic})}{\alpha_i[(1-\chi_i)\text{Var}(d|I_{ir}) + \chi_i \text{Var}(d|I_{ic})]}}{\sum_{i=1}^N \frac{1}{\alpha_i[(1-\chi_i)\text{Var}(d|I_{ir}) + \chi_i \text{Var}(d|I_{ic})]}}. \quad (19)$$

The price is thus a weighted average of traders' conditional expectations of the asset payoff d , with trader i 's conditional expectation receiving weight

$$\frac{\frac{1}{\alpha_i[(1-\chi_i)\text{Var}(d|I_{ir}) + \chi_i \text{Var}(d|I_{ic})]}}{\sum_{j=1}^N \frac{1}{\alpha_j[(1-\chi_j)\text{Var}(d|I_{jr}) + \chi_j \text{Var}(d|I_{jc})]}}.$$

The weight is larger for traders who are less risk averse or observe more precise signals. This is because they trade more aggressively on any given discrepancy between the price and their conditional expectation. In the rational case, all traders have the same conditional expectation because they learn from the price, which aggregates all the signals efficiently. Therefore, the price is also equal to that conditional expectation. In the fully cursed case, conditional expectations differ because traders do not learn other traders' signals from the price.

Since fully cursed traders form conditional expectations using fewer signals than rational traders, they attach larger weight to each signal they use. The public signal thus receives larger weight in each trader's conditional expectation than in the rational case, and hence enters the price with a larger coefficient (Result (i) of Proposition 4). The private signal of any given trader i receives larger weight in that trader's conditional expectation but zero weight in all other traders' expectation. When trader i 's risk aversion is low, the first effect dominates and that signal enters the price with a larger coefficient than in the rational case. The second effect dominates, however, when the coefficients are averaged across traders (Result (ii)). Note that when traders are symmetric, the coefficient corresponding to each trader equals the average coefficient, and hence is smaller than in the rational case. Finally, trader i gives the correct weight to his private signal relative to the public signal. Because, however, other traders give zero weight to trader i 's private signal but positive weight to the public signal, the price in the fully cursed case underweights the former signal relative to the latter (Result (iii)).

The results of Proposition 4 have implications for the predictability of asset returns. We define the return of the risky asset between Periods 1 and 2 as the difference between the asset payoff d and the price p . We examine whether this return can be predicted using information available in Period 1, i.e., whether including such information improves the accuracy of a return forecast. When all traders are rational, the return is not predictable based on past information because p is the expectation of d conditional on all the signals available in Period 1.

Proposition 5 *Suppose that there are no endowment shocks and all traders are fully cursed. The bivariate regression*

$$d - p = \gamma_1(p - \bar{d}) + \gamma_2 s + \nu \tag{20}$$

yields coefficients $\gamma_1 > 0$ and $\gamma_2 < 0$. The univariate regressions

$$d - p = \gamma s + \nu, \tag{21}$$

$$d - p = \gamma(p - \bar{d}) + \nu, \tag{22}$$

yield coefficients $\gamma = 0$ and $\gamma > 0$, respectively. All regression coefficients are zero when all traders are rational.

The bivariate regression (20) predicts the asset return between Periods 1 and 2 using the public signal s and the difference between the price p and the unconditional expectation $\bar{d}$ of the asset payoff. The difference $p - \bar{d}$ can be interpreted as the return between a Period 0, in which no signals are observed and the asset trades at $\bar{d}$, and Period 1. Hence, (20) measures the extent to which past return and the public signal predict future return. Since the price p is influenced by the private and the public signals, and (20) controls for the latter, the coefficient γ_1 measures the effect of the private signals.

Because (γ_1, γ_2) are non-zero, the return between Periods 1 and 2 is predictable. Holding the public signal constant, high private signals in Period 1 predict a price rise in Period 2 ($\gamma_1 > 0$). Holding instead the private signals constant, a high public signal in Period 1 predicts a price drop ($\gamma_2 < 0$). The price thus under-reacts to the private signals and over-reacts to the public signal. The under-reaction is consistent with Result (ii) of Proposition 4 that the average coefficient with which the private signals enter into the price is smaller in the fully cursed than in the rational case. The over-reaction is consistent with Result (i) that the coefficient with which the public signal enters into the price is larger in the fully cursed than in the rational case.

The univariate regressions (21) and (22) predict the asset return between Periods 1 and 2 using only the public signal s or only the return between Periods 0 and 1. The coefficient γ in each of these regressions combines the effects of γ_1 and γ_2 . Since γ_1 and γ_2 have opposite signs, the sign of γ is a priori ambiguous.

Since $\gamma = 0$ in the regression (21), the return between Periods 1 and 2 cannot be predicted using the public signal alone, even when traders are fully cursed. This stems from the fact that cursed traders process the limited set of signals that they observe correctly, and the public signal

belongs to that set. The law of iterative expectations thus implies that when a trader's conditional expectation of the asset payoff d is "conditioned down" on the public signal s , it must equal the expectation of d conditional on s . Since the price p equals a weighted average of traders' conditional expectations of d (Eq. (19)), the expectation of p conditional on s equals that of d conditional on s , and so $d - p$ cannot be predicted by s .

The return between Periods 1 and 2 can be predicted based on the return between Periods 0 and 1 only. Since $\gamma > 0$, a high return between Periods 0 and 1 predicts a price rise in Period 2, which means that returns exhibit momentum. Since the price in Period 2 is equal to the asset's payoff, momentum in our model reflects price under-reaction to information. This under-reaction is driven by the price response to the private signals. Because the price under-reacts to information, the return between Periods 0 and 1 has lower variance than when traders are rational. Variance averaged across the return between Periods 0 and 1 and that between Periods 1 and 2 is also lower.

Corollary 1 *Suppose that there are no endowment shocks and all traders are fully cursed. Compared to the case where all traders are rational, the variance of the return between Periods 0 and 1 is lower, and so is the variance averaged across the return between Periods 0 and 1 and that between Periods 1 and 2.*

We next explore the implications of cursedness for trading volume. Since fully cursed traders do not learn others' signals from the price, they trade with each other even without endowment shocks. We define the trading volume generated by trader i as the absolute value of the quantity x_i that the trader trades in equilibrium. Proposition 6 computes expected trading volume in two special cases, and examines how it depends on the precision of private signals.

Proposition 6 *Suppose that there are no endowment shocks and all traders are fully cursed.*

- (i) *When all traders have the same risk-aversion coefficient α and observe private signals with the same precision τ_η , the expected trading volume that each generates is*

$$\frac{\tau_\zeta \sqrt{2(N-1)\tau_\eta}}{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta) \sqrt{\pi N}}. \quad (23)$$

Volume increases in the number of traders N . It is hump-shaped in the common precision τ_η of private signals, with the hump located at $\tau_\eta = \tau_\epsilon + \tau_\zeta + \tau_\theta$.

(ii) When all traders have the same risk-aversion coefficient α and the shock ζ has zero variance, the expected trading volume generated by trader i is

$$\frac{\sqrt{2 [(\tau_\epsilon + \tau_\theta)^2 [\tau_\eta + (N - 2)\tau_{\eta_i}] + (\tau_\epsilon + \tau_\theta) [N\tau_\eta^2 + (N - 2)\tau_{\eta_i}^2] + (N\tau_\eta - \tau_{\eta_i})\tau_\eta\tau_{\eta_i}]} }{\alpha(\tau_\epsilon + \tau_\eta + \tau_\theta)\sqrt{\pi N}}, \quad (24)$$

where τ_η denotes the average precision of private signals. Trader i generates more volume than trader j if and only if he observes a more precise private signal ($\tau_{\eta_i} > \tau_{\eta_j}$).

The intuition why trading volume is hump-shaped in the precision of private signals when traders are symmetric (Case (i) of Proposition 6) is as follows. Under symmetry, the quantity that a trader trades in equilibrium is equal to the difference between his conditional expectation of the asset payoff and the average conditional expectation of all traders, adjusted by his risk aversion and conditional variance. The difference in conditional expectations is zero when private signals have zero precision because traders then do not use them and share the same conditional expectation. It is also zero when private signals have infinite precision because they must then reveal the same information. For intermediate values of precision the dispersion in conditional expectations is positive, making volume hump-shaped in the common precision τ_η of private signals.

Adjusting by risk aversion and conditional variance preserves the hump-shaped pattern. The hump is located at a larger value of τ_η , and so the adjustment causes volume to be increasing in τ_η over a larger interval. This is because an increase in signal precision reduces traders' conditional variances, hence making traders less uncertain and more eager to trade.

Case (ii) of Proposition 6 allows signal precision to differ across traders. Traders' conditional expectations can then differ both because of the private signals and because each trader weights the public signal differently when forming his expectation. For analytical simplicity we eliminate the shock ζ about which traders cannot learn by setting its variance to zero. For $\sigma_\zeta^2 = 0$, the hump in trading volume in Case (i) occurs for $\tau_\eta = \infty$, and so volume is always increasing in τ_η . Proposition 6 shows that the same comparison applies in the cross section: traders who observe more precise signals generate more volume than those observing less precise signals.

When traders are symmetric, the per-trader volume increases in market size as measured by the number N of traders. This is because the weight that each trader's private signal receives in the trader's conditional expectation is independent of N while the weight that it receives in the price converges to zero when N becomes large. Hence, each trader's beliefs become more discordant with price as N increases. Since per-trader volume increases in N , aggregate volume converges to infinity when N becomes large: cursedness produces large volume in large markets.

We finally compute traders' expected utilities and examine how they depend on the precision of private signals. We evaluate expected utility in the ex-ante sense, before signals appear (Period 0). We also focus on the true expected utilities, i.e., compute the expectation under the true joint distribution of the signals and the price, rather than the distribution perceived by cursed traders.

Proposition 7 *Suppose that there are no endowment shocks, all traders are fully cursed and have the same risk-aversion coefficient α , and the shock ζ has zero variance. The expected utility of trader i is*

$$-\frac{1}{\sqrt{1 + \frac{(\tau_\epsilon + \tau_\theta)^2 [N\tau_{\eta_i} - (2N-1)\tau_\eta] - (\tau_\epsilon + \tau_\theta) [N(2N-1)\tau_\eta^2 - 2N(N+1)\tau_\eta\tau_{\eta_i} + (N-2)\tau_{\eta_i}^2] - (N\tau_\eta - \tau_{\eta_i})\tau_\eta\tau_{\eta_i}}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)^2(\tau_\epsilon + N\tau_\eta + \tau_\theta)}}}, \quad (25)$$

where τ_η denotes the average precision of private signals. A trader i who observes a more precise signal than a trader j ($\tau_{\eta_i} > \tau_{\eta_j}$) has higher expected utility if

$$(\tau_\epsilon + \tau_\theta)^2 + 2(N+1)(\tau_\epsilon + \tau_\theta)\tau_\eta - \tau_\eta^2 > 0. \quad (26)$$

When (26) fails, there exist $\tau_{\eta_i} > \tau_{\eta_j}$ such that trader i has lower expected utility than trader j .

Proposition 7 shows that fully cursed traders who observe more precise signals can be worse off relative to those observing less precise signals. This is not a manifestation of the standard result that asymmetric information makes traders worse off by destroying trading opportunities (Akerlof (1970), Hirshleifer (1971)). Indeed, the standard result compares expected utilities when traders are uninformed to those when some traders become informed and equilibrium prices change. Proposition 7 compares instead expected utilities of two traders who differ in the precision of their information, are present in the market at the same time, and face the same equilibrium price.

To explain how signal precision affects expected utility, we consider a trader who observes a completely uninformative private signal. Because the trader does not learn from the price, he falls victim to trading against others' private signals, e.g., buys when others observe negative signals. If the trader observes instead an informative signal, less of that trading occurs because his signal is better aligned with others' signals, e.g., is more likely to be negative when others' signals are negative. At the same time, a new effect appears: because the trader does not learn from the price, he trades overly aggressively on his signal and takes on excessive risk. When the second effect dominates, traders with more precise signals are worse off relative to those with less precise signals.

According to (26), the second effect dominates when the average precision τ_η of private signals is high, but the first effect dominates when the number N of traders is large. Intuitively, when precision is high, signals are essentially identical and information is symmetric. As a consequence, returns are not predictable (the regression coefficients in Proposition 5 are zero) and trading against others' signals does not generate a loss. Hence, the first effect disappears. When instead the market is large, returns remain predictable. Indeed, even though the price aggregates a large number of signals and provides highly precise information, cursed traders neglect that information and rely only on their own signals.

4.3 Intermediate Cases

We next analyze two intermediate cases between the polar extremes of rationality and full cursedness studied in the previous sections.

4.3.1 Partially Cursed Traders

The first intermediate case is when all traders are partially cursed with the same cursedness coefficient χ . For analytical simplicity, we assume that traders also have the same risk-aversion coefficient α and observe private signals with the same precision τ_η . Thus, the price (14) takes the form

$$p = \bar{d} + A \sum_{i=1}^N s_i + Bs. \quad (27)$$

Proposition 9 shows that the coefficients (A, B) are uniquely determined, and examines how these coefficients as well as trading volume depend on χ .

Proposition 8 *Suppose that there are no endowment shocks and all traders are partially cursed with the same cursedness coefficient χ , risk aversion coefficient α , and private signal precision τ_η . The price (27) is an equilibrium price if and only if*

$$A = \frac{\tau_\eta \{ [N - (N - 1)\chi] (\tau_\epsilon + \tau_\theta) + N\tau_\eta \}}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)}, \quad (28)$$

$$B = \frac{\tau_\theta \{ \tau_\epsilon + [1 + \chi(N - 1)] \tau_\eta + \tau_\theta \}}{(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)}. \quad (29)$$

The coefficient A decreases in χ and the coefficient B increases in χ . The expected trading volume that each trader generates is

$$\frac{\chi\tau_\zeta(\tau_\epsilon + N\tau_\eta + \tau_\theta)\sqrt{2(N - 1)\tau_\eta}}{\alpha(\tau_\zeta\{\tau_\epsilon + [1 + \chi(N - 1)]\tau_\eta + \tau_\theta\} + (\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta))\sqrt{\pi N}} \quad (30)$$

Volume increases in χ and N .

As traders become more cursed (χ increases), the private signals enter the price with a smaller coefficient A , the public signal enters with a larger coefficient B , and trading volume increases. The results on (A, B) are consistent with the comparisons between rationality and full cursedness derived in Proposition 4. Note that per-trader volume under partial cursedness increases in the number N of traders. This result, which also holds under full cursedness, implies that aggregate volume converges to infinity when N becomes large.

4.3.2 Rational and Fully Cursed Traders

The second intermediate case is when some traders are rational and some are fully cursed. We denote by N_r and N_c , respectively, the number of rational and fully cursed traders, and by R and C the sets of these traders. For analytical simplicity we assume that traders within each group have the same risk-aversion coefficient and private-signal precision. We denote by α_r and $\tau_{\eta r}$ the risk-aversion coefficient and private-signal precision for a rational trader, and by α_c and $\tau_{\eta c}$ the

same quantities for a fully cursed trader. The price (14) takes the form

$$p = \bar{d} + A_r \sum_{i \in R} s_i + A_c \sum_{i \in C} s_i + Bs. \quad (31)$$

Proposition 9 shows that the coefficients (A_r, A_c, B) are uniquely determined.

Proposition 9 *Suppose that there are no endowment shocks, and there are N_r rational traders with risk-aversion coefficient α_r and private-signal precision $\tau_{\eta r}$, and N_c fully cursed traders with risk-aversion coefficient α_c and private-signal precision $\tau_{\eta c}$. The price (31) is an equilibrium price if and only if*

$$A_r = xA_c, \quad (32)$$

$$A_c = \frac{\frac{N_r \tau_\xi}{\alpha_r [(N_r - 1)x + N_c] (\tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta + \tau_\xi)} + \frac{\tau_{\eta c}}{\alpha_c (\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)}}{\frac{N_r (\tau_\epsilon + \tau_{\eta r} + \tau_\theta + \tau_\xi)}{\alpha_r (\tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta + \tau_\xi)} + \frac{N_c (\tau_\epsilon + \tau_{\eta c} + \tau_\theta)}{\alpha_c (\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)}}, \quad (33)$$

$$B = \frac{\frac{N_r \tau_\theta}{\alpha_r (\tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta + \tau_\xi)} + \frac{N_c \tau_\theta}{\alpha_c (\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)}}{\frac{N_r (\tau_\epsilon + \tau_{\eta r} + \tau_\theta + \tau_\xi)}{\alpha_r (\tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta + \tau_\xi)} + \frac{N_c (\tau_\epsilon + \tau_{\eta c} + \tau_\theta)}{\alpha_c (\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)}}, \quad (34)$$

where

$$\tau_\xi \equiv \frac{[(N_r - 1)x + N_c]^2 \tau_{\eta r} \tau_{\eta c}}{(N_r - 1)x^2 \tau_{\eta c} + N_c \tau_{\eta r}}, \quad (35)$$

and $x \in (0, \frac{\tau_{\eta r}}{\tau_{\eta c}})$ is the unique solution of

$$x = \frac{\alpha_c N_c \tau_{\eta r} (\tau_{\eta r} - x \tau_{\eta c}) (\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)}{\alpha_r \tau_{\eta c} \left\{ [(N_r - 1)x^2 \tau_{\eta c} + N_c \tau_{\eta r}] (\tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta) + [(N_r - 1)x + N_c]^2 \tau_{\eta r} \tau_{\eta c} \right\}}. \quad (36)$$

Since the fully cursed traders are symmetric, their private signals enter the price with the same weight, and equal weighting is efficient because the signals have the same precision. At the same time, the price gives too much weight to the signals of the fully cursed traders relative to those of the rational traders. Indeed, since $x = \frac{A_r}{A_c} < \frac{\tau_{\eta r}}{\tau_{\eta c}}$, the precision-adjusted coefficient $\frac{A_r}{\tau_{\eta r}}$ with which the rational traders' signals enter the price is smaller than its counterpart $\frac{A_c}{\tau_{\eta c}}$ for fully cursed traders. The intuition is that conditional expectations of rational traders give weight to both their own signals and those of fully cursed traders, while conditional expectations of fully cursed traders give weight to their own signals only.

We next characterize the trading activity of rational and fully cursed traders, and do so by regressing their signed volume on past return. A positive regression coefficient means that a trader buys following a price rise, and is hence a momentum trader. A negative coefficient means instead that a trader buys following a price decline. When traders are symmetric (all rational or all fully cursed), the regression coefficients are zero for all traders because of symmetry and because aggregate signed volume is zero. When instead some traders are rational and some are fully cursed, the regression coefficients are non-zero. Recall from Proposition 5 that returns in a market with fully cursed traders exhibit momentum because the price under-reacts to the private signals. Rational traders exploit this predictability, buying when the price goes up, hence acting as momentum traders. Fully cursed traders, by contrast, do the opposite because they neglect that high prices signal positive private information.

Proposition 10 *Suppose that there are no endowment shocks, and there are N_r rational traders with risk-aversion coefficient α_r and private-signal precision $\tau_{\eta r}$, and N_c fully cursed traders with risk-aversion coefficient α_c and private-signal precision $\tau_{\eta c}$. The univariate regression*

$$x_i = \gamma_i(p - \bar{d}) + \nu, \tag{37}$$

yields coefficient $\gamma_i > 0$ for $i \in R$ and $\gamma_i < 0$ for $i \in C$.

Because momentum trading adds to trading volume, volume can be higher in a market where some traders are rational and some are fully cursed than in an otherwise identical market where all traders are fully cursed. To show this result, we hold constant the total number N of traders, assume that they all have the same risk-aversion coefficient ($\alpha_r = \alpha_c = \alpha$) and private-signal precision ($\tau_{\eta r} = \tau_{\eta c} = \tau_\eta$), and change the relative numbers of rational and fully cursed traders. We compute expected aggregate trading volume, defined as the sum over all traders of the expected trading volume that each generates.

Proposition 11 *Suppose that there are no endowment shocks, and there are N traders with risk-aversion coefficient α and private-signal precision τ_η . Expected aggregate trading volume is larger when one trader is rational and $N - 1$ are fully cursed than when all N traders are fully cursed,*

under the sufficient condition

$$\frac{1}{N-1} \left(\frac{\tau_\epsilon + N\tau_\eta + \tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} \right)^2 + \left(\frac{2(\tau_\epsilon + \tau_\zeta + N\tau_\eta + \tau_\theta)}{(N-1)(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)} - 1 \right) \frac{\tau_\epsilon + N\tau_\eta + \tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} + \left(\frac{\tau_\epsilon + \tau_\zeta + N\tau_\eta + \tau_\theta}{\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta} \right)^2 < 0. \quad (38)$$

When the shock ζ has zero variance, (38) is satisfied if N exceeds a threshold $\bar{N}$.

When (38) is satisfied, volume is hump-shaped in the number of rational traders: it increases when that number increases from zero to one, and it decreases to zero when rational traders make up all of the market. The increasing region can exist if the number N of traders is large: enough cursed traders are needed so that return predictability is important and induces rational traders to engage in a sizeable amount of momentum trading. Moreover, volume can increase in the number of rational traders even when that number is well above one. Indeed, our numerical calculations indicate that the hump of trading volume can occur at a point where rational traders make up about half of the market.

Taken together, Propositions 8 and 11 imply that a market with some rational and some fully cursed traders is not equivalent in terms of volume to a market with partially cursed traders. Indeed, volume in the latter market is smaller than volume with all traders fully cursed (Proposition 8), which in turn can be smaller than volume in the former market (Proposition 11).

5 Endowment Shocks

In this section we introduce endowment shocks. With endowment shocks, the volume generated by rational traders becomes non-zero and returns become predictable. We derive these properties and compare with the case where traders are fully cursed. For analytical simplicity, we assume that traders have the same risk aversion coefficient α , private-signal precision τ_η , and endowment-shock precision τ_z . Thus, the price (14) takes the form

$$p = \bar{d} + A \sum_{i=1}^N s_i + Bs - C \sum_{i=1}^N z_i. \quad (39)$$

Proposition 12 determines the coefficients (A, B, C) when all traders are rational and when they are all fully cursed.

Proposition 12 *Suppose that there are endowment shocks and all traders have the same risk-aversion coefficient α , private-signal precision τ_η , and endowment-shock precision τ_z . When all traders are rational, the price (39) is an equilibrium price if and only if*

$$A = \frac{\tau_\eta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}}{N \left(\tau_\epsilon + \tau_\eta + \tau_\theta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta} \right)}, \quad (40)$$

$$B = \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}}, \quad (41)$$

and $\frac{C}{A} > 0$ is the unique solution to the cubic equation

$$\left(\tau_z + \frac{C^2}{A^2}\tau_\eta \right) \left(\frac{C}{A}\tau_\zeta\tau_\eta - \alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta) \right) - \alpha(N-1)\tau_\eta\tau_z = 0. \quad (42)$$

When all traders are fully cursed, (A, B, C) are derived from (40)-(42) by setting $\tau_z = 0$.

When all traders are fully cursed, the coefficients A on the private signals and B on the public signal do not depend on the precision τ_z of the endowment shocks. Indeed, because fully cursed traders do not learn from the price, τ_z does not affect the way that the signals and the price enter into their demand function. The coefficients (A, B) for rational traders coincide with those for fully cursed traders when the endowment shocks have infinite variance ($\tau_z = 0$). This is because for $\tau_z = 0$ the price becomes uninformative, and hence rational traders have the same demand function as fully cursed traders. When instead the endowment shocks have zero variance ($\tau_z = \infty$), the coefficients (A, B) for rational traders coincide with their counterparts in Proposition 2.

Endowment shocks do not change the result of Section 4 that the return between Periods 1 and 2 cannot be predicted using the public signal alone. That return, however, becomes predictable using the return between Periods 0 and 1 even when traders are rational. Returns with rational traders and endowment shocks exhibit reversals: a high return between Periods 0 and 1 predicts a price decline in Period 2. If the variance of endowment shocks is large enough, returns with fully cursed traders exhibit reversals as well, otherwise they exhibit momentum as in Section 4. Endowment shocks tend to generate reversals because they cause prices to deviate temporarily from traders' expectations of the asset payoff.

Proposition 13 *Suppose that there are endowment shocks and all traders have the same risk-aversion coefficient α , private-signal precision τ_η , and endowment-shock precision τ_z . When all traders are rational, the univariate regression (22) yields coefficient $\gamma < 0$. When all traders are fully cursed, (22) yields coefficient $\gamma < 0$ if and only if*

$$\frac{\alpha^2(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)^2}{(N-1)\tau_\zeta^2\tau_\eta\tau_z} > 1. \quad (43)$$

The univariate regression (21) yields coefficient $\gamma = 0$ under both rationality and full cursedness.

Endowment shocks generate trading volume even when traders are rational. Rational volume, however, has different qualitative properties than cursed volume. Volume with fully cursed traders and no endowment shocks is hump-shaped in the precision of private signals, as shown in Section 4, and this property extends to endowment shocks. Volume with rational traders, however, is inverse hump-shaped in private-signal precision. The intuition in the rational case is as follows. Starting from the case where precision is zero, an increase in precision reduces volume because it introduces adverse selection (Akerlof (1970), Hirshleifer (1971)). Adverse selection disappears again when precision is infinite because traders' signals are identical.

Proposition 14 *Suppose that there are endowment shocks and all traders have the same risk-aversion coefficient α , private-signal precision τ_η , and endowment-shock precision τ_z . The expected volume that each trader generates increases in the number of traders N both when all traders are rational and when they are fully cursed. Volume is inverse hump-shaped in the common precision τ_η of private signals when all traders are rational, and is hump-shaped when they are fully cursed.*

When the shock ζ about which traders cannot learn has zero variance, the hump in volume with rational traders occurs for $\tau_\eta = \infty$, and so volume is always decreasing in τ_η . Intuitively, when precision is infinite, traders know the asset payoff perfectly: while there is no adverse selection, there are also no gains from risk-sharing. Notice that when ζ has zero variance, the corresponding hump with fully cursed traders also occurs for $\tau_\eta = \infty$, and so volume is always increasing in τ_η .

6 Overconfidence and Dismissiveness

In this section we examine the relationship between cursedness, overconfidence and dismissiveness. We introduce overconfidence and dismissiveness into our model following Odean (1998), like him specializing our model to no endowment shocks and to traders who are symmetric in terms of their risk-aversion coefficient α and private signal precision τ_η . Ruling out endowment shocks allows us to focus on trading volume that is purely driven by traders' cognitive errors.

Following Odean, we capture overconfidence by assuming that each trader incorrectly perceives the precision of his own signal to be $\kappa \times \tau_\eta$, for $\kappa \geq 1$ (and $\kappa = 1$ embedding REE in our analysis below), but correctly perceives the precision of all other traders' signals to be τ_η . Moreover, this belief system is common knowledge: it is common knowledge that each trader thinks he is better informed than all other traders think he is. We also follow Odean by allowing traders to err in a second, conceptually distinct way, namely by underestimating the information content in others' private signals, which we term dismissiveness. Each trader incorrectly perceives the precision of all other traders' signals to be $\gamma \times \tau_\eta$, for $\gamma \in [0, 1]$ (and $\gamma = 1$, together with $\kappa = 1$, embedding REE in our analysis below). This too is common knowledge.

Under the parameter values $\kappa = 1$ and $\gamma = 0$, i.e., no overconfidence and extreme dismissiveness, behavior is the same as under full cursedness ($\chi = 1$). This is because a trader who fails to infer another's signal from the price behaves identically to one who fully infers that signal but erroneously assumes that it has zero precision.⁹ In the rest of this section we identify dismissiveness with $\gamma > 0$, i.e., traders do not view others' signals as completely worthless. We contrast such non-extreme dismissiveness ($\gamma \in (0, 1)$) with full or partial cursedness ($\chi \in (0, 1]$).

Because of symmetry, the price takes the form

$$p = \bar{d} + A \sum_{i=1}^N s_i + Bs. \quad (44)$$

⁹Nevertheless, the notions differ from each other conceptually, leading them to make different predictions outside the confines of our market model. For instance, symmetric, fully dismissive traders would not pay any positive amount to learn one another's private signals, whereas fully cursed traders would value the additional information.

Proposition 15 shows that the coefficients (A, B) are uniquely determined, and examines how they depend on the overconfidence parameter κ and the dismissiveness parameter γ .

Proposition 15 *Suppose that there are no endowment shocks and all traders have the same risk-aversion coefficient α and private-signal precision τ_η . Suppose also that each trader misperceives the precision of his private signal to be $\kappa \times \tau_\eta$ for $\kappa \geq 1$, and the precision of every other trader's signal to be $\gamma \times \tau_\eta$ for $\gamma \in (0, 1]$. The price (44) is an equilibrium price if and only if*

$$A = \frac{[(N-1)\gamma + \kappa]\tau_\eta}{N\{\tau_\epsilon + [(N-1)\gamma + \kappa]\tau_\eta + \tau_\theta\}}, \quad (45)$$

$$B = \frac{\tau_\theta}{\tau_\epsilon + [(N-1)\gamma + \kappa]\tau_\eta + \tau_\theta}. \quad (46)$$

The coefficient A increases in κ and γ . The coefficient B decreases in κ and γ .

Fixing the dismissiveness parameter γ , more overconfidence (larger κ) causes traders to attach larger weight to their own private signals and smaller weight to the public signal when forming conditional expectations. This causes A to increase and B to decrease. Fixing instead the overconfidence parameter κ , more dismissiveness (smaller γ) causes traders to attach smaller weight to other traders' private signals (as revealed by price) and larger weight to the public signal when forming conditional expectations. This causes A to decrease and B to increase. Dismissiveness thus moves A and B from their REE values in the same direction as cursedness does, while overconfidence moves them in the opposite direction.

Overconfidence and dismissiveness yield dramatically different predictions than cursedness about trading volume. Recall from Propositions 6 and 8 that under full or partial cursedness, per-trader volume grows as the market becomes large and hence aggregate volume converges to infinity. Under overconfidence or dismissiveness instead, per-trader volume converges to zero, and aggregate volume converges to a finite limit. Thus, overconfidence or dismissiveness on their own are not sufficient to generate volume in large markets, while cursedness is.

Proposition 16 *Suppose that there are no endowment shocks and all traders have the same risk-aversion coefficient α and private-signal precision τ_η . Suppose also that each trader misperceives*

the precision of his private signal to be $\kappa \times \tau_\eta$ for $\kappa \geq 1$, and the precision of every other trader's signal to be $\gamma \times \tau_\eta$ for $\gamma \in (0, 1]$. The expected volume that each trader generates is

$$\frac{(\kappa - \gamma)\tau_\zeta\sqrt{2(N-1)\tau_\eta}}{\alpha[\tau_\epsilon + \tau_\zeta + [(N-1)\gamma + \kappa]\tau_\eta + \tau_\theta]\sqrt{\pi N}}. \quad (47)$$

Volume declines to zero as the number N of traders grows large. Aggregate volume, summed across traders, converges to a finite limit.

The intuition why per-trader volume converges to zero goes as follows. Overconfident or dismissive traders trade for two reasons: first, each thinks that the price overweights all other traders' signals; second, each thinks that the price underweights his own signal. Since each trader inverts the price to perfectly infer the average signal of all other traders, the price would not change if all private signals were made public. If all signals were public, then each trader's expectation of the asset payoff d would be a weighted average of his own signal, the average signal of other traders, and the public signal s . For any $\kappa \geq 1$ and $\gamma \in (0, 1]$, as N grows large, each trader puts arbitrarily more weight on the average signal of other traders than on his own signal. Hence, the difference between any two traders' expectations of d converges to zero, and so does per-trader volume.¹⁰ Only when $\gamma = 0$, which is observationally equivalent to full cursedness in our model, does per-trader volume not vanish in large markets.

Overconfident per-trader volume disappears in our model because each trader, no matter how overconfident, believes that the information conveyed by price about all other traders' signals trumps his own private signal in a sufficiently large market. This would not happen if traders believed that their private information conveyed something non-negligible beyond the information conveyed by a large-market price. Odean (1998) implicitly makes this assumption by assuming that the N traders in the market observe $M < N$ signals in such a way that $\frac{N}{M} > 1$ observe each signal. He computes volume when $\gamma = 1$ and $N \rightarrow \infty$, but holding M fixed. Whatever the value of M , each signal conveys non-negligible information beyond that conveyed by the set of other signals.

¹⁰The fact that equilibrium prices do not depend upon whether signals are public or private suggests that per-trader volume would be negligible in large markets even in complete-information models of overconfidence (e.g., Sheinkman and Xiong (2003)) if traders are risk averse.

Overconfidence *does* have substantial effects when traders are cursed. Proposition 17 expresses volume when traders are overconfident and cursed. As when traders are cursed but not overconfident, per-trader volume grows as the market becomes large, and hence aggregate volume goes to infinity. Overconfidence produces an additional effect that increases volume even in the large-market limit. Yet it generates non-negligible per-trader volume only when traders are cursed, in which case it amplifies the effect of cursedness. In this sense, overconfidence and cursedness work as complements. Intuitively, when traders fail to infer information from prices, overconfidence magnifies differences in their beliefs, producing even more trade. Although Proposition 17 assumes full cursedness, the same results hold under partial cursedness.

Proposition 17 *Suppose that there are no endowment shocks and all traders have the same risk-aversion coefficient α and private-signal precision τ_η . Suppose also that all traders are fully cursed, and that each misperceives the precision of his private signal to be $\kappa \times \tau_\eta$ for $\kappa \geq 1$. The expected volume that each trader generates is*

$$\frac{\kappa\tau_\zeta\sqrt{2(N-1)\tau_\eta}}{\alpha(\tau_\epsilon + \tau_\zeta + \kappa\tau_\eta + \tau_\theta)\sqrt{\pi N}}. \quad (48)$$

Volume increases in the number of traders N and in the overconfidence parameter κ .

We conclude with the conjecture that overconfident and dismissive traders also differ from cursed traders in their motivation to acquire private information. Grossman and Stiglitz (1980) famously observed that traders have no incentive to acquire information in markets where the price incorporates all available information; since rational traders understand this logic, the fact that anyone collects any private information to influence the price becomes a paradox. Cursedness points at a simple caveat: because in large markets they use their private signals to carry out substantial trading, cursed traders may misperceive benefits to acquiring private information. By contrast, overconfident and dismissive traders, who hardly trade based on their private signals, have essentially no motivation to acquire private information.

7 Discussion and Conclusion

In this paper, we propose a new market equilibrium concept, *cursed expectations equilibrium (CEE)*, in which traders fail to fully infer information from market prices. CEE differs at a conceptual level from agreeing-to-disagree models in which traders have differences of opinion about the informativeness of private signals by virtue of allowing people to appreciate that prices in large markets reveal some information without appreciating that these prices reveal virtually all available information. We show that cursed volume per trader grows with the size of the market, whereas per-trader volume under overconfidence or non-extreme dismissiveness declines to zero. Cursedness is thus key to generate trading volume in large markets with dispersed private information. It also amplifies trading volume due to overconfidence or dismissiveness, thus enabling these biases to have a significant effect. Markets comprised entirely of cursed traders generate more trade than those comprised entirely of rational traders; mixed markets can generate more trade still, as rationals employ momentum-trading strategies to take advantage of cursed traders.

Because cursed traders fail to fully appreciate the information content of market prices, they use their private signals to carry out substantial trading. Consequently, they may exaggerate the benefit of acquiring private information, and this may offer a resolution of the Grossman and Stiglitz (1980) paradox. Overconfidence and dismissiveness do not offer such a resolution: traders prone to these biases barely trade in large markets and hence attribute only a vanishing value to private information.

Extending CEE to a dynamic model would allow us to formally explore information acquisition as well as potentially highlight the role of a second shortcoming in inference from market prices that might affect traders. In a dynamic market, agents in period $t + 2$ may fail to appreciate how those in period $t + 1$ infer private information from prices in period t , as embodied in a solution concept devised by Eyster and Rabin (2010). Suppose that the price is high in both periods t and $t + 1$. If some agents in period $t + 2$ neglect that some of the positive information contained in the period $t + 1$ price is in fact information agents gleaned from the high period t price, then they will overestimate the positive information in the high prices, and push the price up further. This error in inference, which is conceptually distinct from cursedness, may give rise to medium-run

over-reaction to private information.

In Section 6, we showed the necessity in some settings of cursedness to “enable” overconfidence to explain appreciable per-trader volume of trade. We conclude by speculating how cursedness may similarly enable the study of various other biases in asset markets. Researchers have recently proposed that a number of statistical errors may be relevant for financial decisions, including over-inference from small samples (see Rabin (2002) and Rabin and Vayanos (2010)) and non-belief in the law of large numbers (see Benjamin, Rabin, and Raymond (2013)). Predicting the consequences of these and other biases for markets where traders extract information from prices requires additional assumptions about traders’ theories of one another’s errors. Yet, relatively little is known about how people reason about others’ errors. In its extreme, cursedness provides a simple assumption about what people think of others’ errors: they don’t think about them at all. If models of errors are instead closed by assuming that people do agree to disagree about the meaning of private signals, then, much like with overconfidence in Section 6, we suspect that the per-trader volume of trade will be small in information-rich settings where each trader values the sum total of others’ private information far more heavily than his own private signal.

References

- [1] Akerlof, G. 1970, “The Market for ‘Lemons’: Quality Uncertainty and the Market Mechanism”, *Quarterly Journal of Economics* 84(3): 488-500.
- [2] Banerjee, S. 2011, “Learning from Prices and the Dispersion in Beliefs”, *Review of Financial Studies* 24(9): 3025-3068.
- [3] Banerjee, S., Kaniel, R. and I. Kremer 2009. “Price Drift as an Outcome of Differences in Higher Order Beliefs”, *Review of Financial Studies* 22(9): 3707-3734.
- [4] Banerjee, S. and I. Kremer 2010, “Disagreement and Learning: Dynamic Patterns of Trade”, *Journal of Finance* 65(4): 1269-1302.
- [5] Benjamin, D., Rabin, M. and C. Raymond 2013, “A Model of Non-Belief in the Law of Large Numbers”, Mimeo.
- [6] Bernard, V. and J. Thomas 1989, “Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?”, *Journal of Accounting Research* 27(Suppl):1-36.
- [7] Carrillo, J. and T. Palfrey 2011, “No Trade”, *Games and Economic Behavior* 71(1): 66-87.
- [8] Daniel, K., Hirshleifer, D. and A. Subrahmanyam 1998, “Investor Psychology and Security Market under- and Overreactions”, *Journal of Finance* 53(6): 1839-1885.
- [9] Daniel, K., Hirshleifer, D. and A. Subrahmanyam 2001, “Overconfidence, Arbitrage, and Equilibrium Asset Pricing”, *Journal of Finance* 56(3): 921-965.
- [10] DeLong, J., Shleifer, A., Summers, L. and R. Waldmann 1990, “Noise Trader Risk in Financial Markets”, *Journal of Political Economy* 98: 703-738.
- [11] Diamond D. and R. Verrecchia 1981, “Information Aggregation in a Noisy Rational Expectations Equilibrium”, *Journal of Financial Economics* 9: 221-235.
- [12] Esponda, I. and E. Vespa 2013, “Hypothetical Thinking and Information Extraction: Strategic Voting in the Laboratory”, Mimeo, NYU Stern.

- [13] Eyster, E. and M. Piccione 2013, “An Approach to Asset-Pricing Under Incomplete and Diverse Perceptions”, *Econometrica* 81(4): 1483-1506.
- [14] Eyster, E. and M. Rabin 2005, “Cursed Equilibrium”, *Econometrica* 73(5): 1623-1672.
- [15] Eyster, E. and M. Rabin 2010, “Naïve Herding in Rich-Information Settings”, *American Economic Journal: Microeconomics* 2: 221-43.
- [16] French, K. 2008, “Presidential Address: The Cost of Active Investing”, *Journal of Finance* 63(4): 1537-1573.
- [17] Griffin, D. and A. Tversky 1992, “The Weighing of Evidence and the Determinants of Confidence”, *Cognitive Psychology* 24(3): 411-435. r
- [18] Grossman, S. 1976, “On the Efficiency of Competitive Stock Markets when Traders Have Diverse Information”, *Journal of Finance* 31: 573-585.
- [19] Grossman, S. and J. Stiglitz 1980. “On the Impossibility of Informationally Efficient Markets”, *American Economic Review* 70(3): 393-408.
- [20] Harris, M. and A. Raviv 1993, “Difference of Opinion Make a Horse Race”, *Review of Financial Studies* 6: 473-506.
- [21] Harrison, J. M. and D. Kreps 1978, “Speculative Investor Behavior in a Stock Market with Heterogenous Expectations”, *Quarterly Journal of Economics* 93(2): 323-336.
- [22] Hellwig, M. 1980, “On the Aggregation of Information in Competitive Markets”, *Journal of Economic Theory* 22: 477-498.
- [23] Hirshleifer, J. 1971, “The Private and Social Value of Information and the Reward to Inventive Activity”, *American Economic Review* 61(4): 561-574.
- [24] Holt, C. and R. Sherman 1994, “The Loser’s Curse”, *American Economic Review* 84(3): 642-652.

- [25] Hong, H. J. Scheinkman and W. Xiong 2006. “Asset Float and Speculative Bubbles”, *Journal of Finance*, American Finance Association 61: 1073-1117.
- [26] Hong, H. and J. Stein 1999, “A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets”, *Journal of Finance* 54(6): 2143-2184.
- [27] Hong, H. and J. Stein 2007, “Disagreement and the Stock Market”, *Journal of Economic Perspectives* 21(2): 109-128.
- [28] Jegadeesh, N. and S. Titman 1993, “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency”, *Journal of Finance* 48: 65-91.
- [29] Jegadeesh, N. and S. Titman 2011, “Momentum”, *Annual Review of Financial Economics* 3: 493-509.
- [30] Kagel, J. and D. Levin 2002, *Common Value Auctions and the Winner’s Curse*, Princeton University Press.
- [31] Kandel, E. and N. Pearson 1995, “Differential Interpretation of Public Signals and Trade in Speculative Markets”, *Journal of Political Economy* 103: 831-72.
- [32] Malmendier, U. and G. Tate 2008, “Who Makes Acquisitions? CEO Overconfidence and the Market’s Reaction”, *Journal of Financial Economics* 89(1): 20-43.
- [33] Milgrom, P. and N. Stokey 1982, “Information, Trade and Common Knowledge”, *Journal of Economic Theory* 26(1): 17-27.
- [34] Morris, S. 1996, “Speculative Investor Behavior and Learning”, *Quarterly Journal of Economics* 111: 1111-1133.
- [35] Odean, T. 1998, “Volume, Volatility, and Price when all Traders Are Above Average”, *Journal of Finance* 53(6): 1887-1934.
- [36] Rabin, M. 2002, “Inference by Believers in the Law of Small Numbers”, *Quarterly Journal of Economics* 117(3): 775-816.

- [37] Rabin, M. and D. Vayanos 2010, “The Gambler’s and Hot-Hand Fallacies: Theory and Applications”, *Review of Economic Studies* 77: 730-778.
- [38] Samuelson, W. and Bazerman, M. 1985, “The Winner’s Curse in Bilateral Negotiations.” In *Research in Experimental Economics*, vol. 3, Vernon L. Smith, ed., Greenwich, CT: JAI Press.
- [39] Scheinkman, J. and W. Xiong 2003, “Overconfidence and Speculative Bubbles”, *Journal of Political Economy* 111(6): 1183-1219.
- [40] Varian, H. 1989, “Divergence of Opinion in Complete Markets: A Note”, *Journal of Finance* 40: 309-317.
- [41] Weizsäcker, G. 2010, “Do We Follow Others when We Should? A Simple Test of Rational Expectations”, *American Economic Review* 100: 2340-2360.

APPENDIX

A Cursed Equilibrium

Cursed equilibrium is defined in finite Bayesian games of the form

$$(\{A_i\}_{i=1,\dots,N}, \{T_i\}_{i=0,\dots,N}, p, \{u_i\}_{i=1,\dots,N}).$$

For each player $i = 1, \dots, N$, A_i is a finite set of available actions and T_i is a finite set of types, including one, T_0 , for nature. We denote the set of action profiles by $A \equiv \prod_{i=1,\dots,N} A_i$ and the set of type profiles by $T \equiv \prod_{i=0,\dots,N} T_i$. We assume that all players share the common prior probability distribution p over T . Player i 's utility function is $u_i : A \times T \rightarrow \mathbb{R}$.

A strategy for player i , $\sigma_i : T_i \rightarrow \Delta A_i$, specifies a probability distribution over actions for each type. We denote by $\sigma_i(a_i|t_i)$ the probability that type t_i plays action a_i when he follows strategy σ_i . We denote the set of action profiles for players other than i by $A_{-i} \equiv \prod_{j \neq i} A_j$, and the set of type profiles for nature and players other than i by $T_{-i} \equiv \prod_{j \neq i} T_j$. We denote by a_{-i} and t_{-i} generic elements of these sets. We denote by $\sigma_{-i}(a_{-i}|t_{-i})$ the probability that types t_{-i} play action profile a_{-i} when they follow strategy $\sigma_{-i} \equiv \{\sigma_j\}_{j \neq i}$. Finally, we denote by $p(t_{-i}|t_i)$ the distribution of player i 's beliefs about other players' types conditional on his own type t_i . The standard solution concept for these games is Bayesian Nash equilibrium.

Definition 2 *A strategy profile σ is a Bayesian Nash equilibrium if for each player i , each type $t_i \in T_i$, and each a_i^* such that $\sigma_i(a_i^*|t_i) > 0$:*

$$a_i^* \in \arg \max_{a_i \in A_i} \sum_{t_{-i}} p(t_{-i}|t_i) \left(\sum_{a_{-i}} \sigma_{-i}(a_{-i}|t_{-i}) u_i(a_i, a_{-i}; t_i, t_{-i}) \right). \quad (\text{A.1})$$

To define cursed equilibrium, we compute for each type of each player the average strategy of other players, averaged over the other players' types. For type t_i of player i we define

$$\bar{\sigma}_{-i}(a_{-i}|t_i) \equiv \sum_{t_{-i} \in T_{-i}} p_i(t_{-i}|t_i) \cdot \sigma_{-i}(a_{-i}|t_{-i}).$$

This is the marginal probability that other players play action profile a_{-i} , and is derived by averaging over type profiles t_{-i} the probabilities $\sigma_{-i}(a_{-i}|t_{-i})$ that other players play a_{-i} conditional on t_{-i} . We associate to each player i a cursedness parameter $\chi_i \in [0, 1]$.

Definition 3 *A strategy profile σ is a cursed equilibrium if for each player i , each type $t_i \in T_i$, and each a_i^* such that $\sigma_i(a_i^*|t_i) > 0$:*

$$a_i^* \in \arg \max_{a_i \in A_i} \sum_{t_{-i}} p(t_{-i}|t_i) \left(\sum_{a_{-i}} (1 - \chi_i) \sigma_{-i}(a_{-i}|t_{-i}) u_i(a_i, a_{-i}; t_i, t_{-i}) + \chi_i \bar{\sigma}_{-i}(a_{-i}|t_i) u_i(a_i, a_{-i}; t_i, t_{-i}) \right). \quad (\text{A.2})$$

Player i best-responds to beliefs that with probability $1 - \chi_i$ the other players' actions depend on their types (the probability of action profile a_{-i} in (A.2) is conditional on type profile t_{-i}) and with probability χ_i actions do not depend on types (the probability of a_{-i} in (A.2) is the marginal). When $\chi_i = 0$, player i is rational, and his objective is as in Bayesian Nash equilibrium (Eq. (A.1)). When $\chi_i = 1$, player i is fully cursed, and neglects entirely the relationship between the other players' actions and their types. Note that while cursed players fail to map actions to types, they assess correctly the probability distribution of other players' actions.

Applying the definition (A.2) to the trading game considered in Section 2, we find that the buyer's objective is $F(p) \times ((1 - \chi)E[s|s \leq p] + \chi E[s] - p)$: the buyer believes that with probability $1 - \chi$ the seller's decision to sell conveys information about the asset, and with probability χ it does not.

B Proofs

We first prove the following lemma, which we use for proving Proposition 1.

Lemma B.1 *Suppose that the variables $(x, \{y_i\}_{i=1,\dots,K})$ are normal, independent, with mean zero and precisions $(\tau_x, \{\tau_{y_i}\}_{i=1,\dots,K})$. Then, the distribution of x conditional on $\{x + y_i\}_{i=1,\dots,K}$ is normal*

with mean

$$\mathbb{E}(x | \{x + y_i\}_{i=1, \dots, K}) = \sum_{i=1}^K \frac{\tau_{y_i}}{\tau_x + \sum_{j=1}^K \tau_{y_j}} (x + y_i) \quad (\text{B.1})$$

and precision

$$\tau(x | \{x + y_i\}_{i=1, \dots, K}) = \tau_x + \sum_{i=1}^K \tau_{y_i}. \quad (\text{B.2})$$

Proof. The conditional mean and variance can be computed from the regression

$$x = \sum_{i=1}^K \beta_i (x + y_i) + e,$$

where $\{\beta_i\}_{i=1, \dots, K}$ are the regression coefficients and e is the error term. Taking covariances of both sides with $x + y_i$ and noting that $(x, \{y_i\}_{i=1, \dots, K}, e)$ are independent, we find

$$\begin{aligned} \text{Cov}(x, x + y_i) &= \sum_{j=1}^K \beta_j \text{Cov}(x + y_j, x + y_i) \\ \Rightarrow \frac{1}{\tau_x} &= \beta_i \left(\frac{1}{\tau_x} + \frac{1}{\tau_{y_i}} \right) + \sum_{j \neq i} \beta_j \frac{1}{\tau_x} \\ \Rightarrow \beta_i &= \frac{\tau_{y_i}}{\tau_x} \left(1 - \sum_{j=1}^K \beta_j \right). \end{aligned} \quad (\text{B.3})$$

Summing (B.3) across i and solving for $\sum_{j=1}^K \beta_j$, we find

$$\sum_{j=1}^K \beta_j = \frac{\sum_{j=1}^K \tau_{y_j}}{\tau_x + \sum_{j=1}^K \tau_{y_j}}. \quad (\text{B.4})$$

Substituting $\sum_{j=1}^K \beta_j$ from (B.4) into (B.3), we find

$$\beta_i = \frac{\tau_{y_i}}{\tau_x + \sum_{j=1}^K \tau_{y_j}}. \quad (\text{B.5})$$

Since

$$\mathbb{E}(x | \{x + y_i\}_{i=1, \dots, K}) = \sum_{i=1}^K \beta_i (x + y_i),$$

(B.5) implies (B.1). Taking variances of both sides and noting that $(x, \{y_i\}_{i=1,\dots,K}, e)$ are independent, we find

$$\begin{aligned}\text{Var}(x) &= \left(\sum_{i=1}^K \beta_i \right)^2 \text{Var}(x) + \sum_{i=1}^K \beta_i^2 \text{Var}(y_i) + \text{Var}(e) \\ \Rightarrow \frac{1}{\tau_e} &= \frac{1}{\tau_x} \left[1 - \left(\frac{\sum_{i=1}^K \tau_{y_i}}{\tau_x + \sum_{i=1}^K \tau_{y_i}} \right)^2 \right] - \sum_{i=1}^K \frac{1}{\tau_{y_i}} \left(\frac{\tau_{y_i}}{\tau_x + \sum_{j=1}^K \tau_{y_j}} \right)^2 \\ \Rightarrow \frac{1}{\tau_e} &= \frac{1}{\tau_x + \sum_{i=1}^K \tau_{y_i}},\end{aligned}\tag{B.6}$$

where the second step follows from (B.4) and (B.5). Since

$$\tau(x | \{x + y_i\}_{i=1,\dots,K}) = \tau_e,$$

(B.6) implies (B.2). ■

Proof of Proposition 1. We first determine traders' demand functions using (8). Since $d = \bar{d} + \epsilon + \zeta$ and ζ is independent of traders' information I_i ,

$$E(d|I_i) = \bar{d} + E(\epsilon|I_i),\tag{B.7}$$

$$\text{Var}(d|I_i) = \text{Var}(\epsilon|I_i) + \text{Var}(\zeta) = \frac{1}{\tau(\epsilon|I_i)} + \frac{1}{\tau_\zeta}.\tag{B.8}$$

Using Lemma B.1 with $x = \epsilon$, $K = 3$ and $\{y_j\}_{j=1,2,3} = (\eta_i, \eta, \xi_i)$, we find

$$E(d|I_{ir}) = \bar{d} + \frac{\tau_{\eta_i}}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}} s_i + \frac{\tau_\theta}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}} s + \frac{\tau_{\xi_i}}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}} (\epsilon + \xi_i),\tag{B.9}$$

$$\text{Var}(d|I_{ir}) = \frac{1}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}} + \frac{1}{\tau_\zeta}.\tag{B.10}$$

Using Lemma B.1 with $x = \epsilon$, $K = 2$ and $\{y_j\}_{j=1,2} = (\eta_i, \eta)$, we find

$$E(d|I_{ic}) = \bar{d} + \frac{\tau_{\eta_i}}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta} s_i + \frac{\tau_\theta}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta} s,\tag{B.11}$$

$$\text{Var}(d|I_{ic}) = \frac{1}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta} + \frac{1}{\tau_\zeta}.\tag{B.12}$$

Substituting (B.9), (B.10), (B.11) and (B.12) into (8), we can write the demand of trader i as

$$x_i = \frac{\bar{d} + (1 - \chi_i) \frac{\tau_{\eta_i} s_i + \tau_\theta s + \tau_{\xi_i} (\epsilon + \xi_i)}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}} + \chi_i \frac{\tau_{\eta_i} s_i + \tau_\theta s}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta} - p}{\alpha_i \left[(1 - \chi_i) \frac{1}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}} + \chi_i \frac{1}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta} + \frac{1}{\tau_\zeta} \right]} - z_i.\tag{B.13}$$

We next substitute (B.13) into the market-clearing condition (5), use (6) to write p in terms of $(\{s_i\}_{i=1,\dots,N}, s, \{z_i\}_{i=1,\dots,N})$, and use (9) to write $\epsilon + \xi_i$ in terms of $(\{s_i\}_{j \neq i}, \{z_i\}_{j \neq i})$. This yields an equation that is linear in $(\{s_i\}_{i=1,\dots,N}, s, \{z_i\}_{i=1,\dots,N})$. Identifying terms in s_i yields (11). Identifying terms of s yields (12). Identifying terms in z_i yields

$$\begin{aligned} & 1 - \frac{(1 - \chi_i)\tau_\zeta\tau_{\xi_i}\frac{C_i}{\sum_{k \neq i} A_k}(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{\alpha_i[(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}) + \tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta + \chi_i\tau_{\xi_i})]} \\ &= C_i\tau_\zeta \sum_{j=1}^N \frac{(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \tau_{\xi_j}) - (1 - \chi_j)\tau_{\xi_j}\frac{1}{\sum_{k \neq j} A_k}(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta)}{\alpha_j[(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta)(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \tau_{\xi_j}) + \tau_\zeta(\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \chi_j\tau_{\xi_j})]}. \end{aligned} \quad (\text{B.14})$$

Combining (B.14) with (11) yields (13). ■

Proof of Proposition 2. Setting $\chi_i = 0$ for all i , we can simplify (11) to

$$\frac{\tau_{\eta_i} - \tau_{\xi_i}\frac{A_i}{\sum_{k \neq i} A_k}}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i})} = A_i \sum_{j=1}^N \frac{\tau_\epsilon + \tau_{\eta_j} + \tau_\theta + \tau_{\xi_j} - \tau_{\xi_j}\frac{1}{\sum_{k \neq j} A_k}}{\alpha_j(\tau_\epsilon + \tau_\zeta + \tau_{\eta_j} + \tau_\theta + \tau_{\xi_j})} \equiv A_i \mathcal{Z}. \quad (\text{B.15})$$

Since $\{\sigma_{z_i}\}_{i=1,\dots,N} = 0$, (10) implies that

$$\tau_{\xi_i} = \frac{\left(\sum_{j \neq i} A_j\right)^2}{\sum_{j \neq i} \frac{A_j^2}{\tau_{\eta_j}}}. \quad (\text{B.16})$$

Substituting τ_{ξ_i} from (B.16) into the left-hand side of (B.15), we can write (B.15) as

$$\begin{aligned} & \frac{\tau_{\eta_i}}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}) \sum_{j \neq i} \frac{A_j^2}{\tau_{\eta_j}}} \left(\sum_{j \neq i} \frac{A_j^2}{\tau_{\eta_j}} - \frac{A_i}{\tau_{\eta_i}} \sum_{j \neq i} A_j \right) = A_i \mathcal{Z} \\ & \Rightarrow \sum_{j=1}^N \frac{A_j^2}{\tau_{\eta_j}} - \frac{A_i}{\tau_{\eta_i}} \sum_{j=1}^N A_j = \frac{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}) A_i \sum_{j \neq i} \frac{A_j^2}{\tau_{\eta_j}}}{\tau_{\eta_i}} \mathcal{Z}. \end{aligned} \quad (\text{B.17})$$

Multiplying (B.17) by A_i and summing over i , we find

$$0 = \sum_{i=1}^N A_i \sum_{i=1}^N \frac{A_i^2}{\tau_{\eta_i}} - \sum_{i=1}^N A_i \sum_{i=1}^N \frac{A_i^2}{\tau_{\eta_i}} = \sum_{i=1}^N \left[\frac{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta + \tau_{\xi_i}) A_i^2 \sum_{j \neq i} \frac{A_j^2}{\tau_{\eta_j}}}{\tau_{\eta_i}} \right] \mathcal{Z},$$

which implies that $\mathcal{Z} = 0$. Eq. (B.17) then implies that

$$\sum_{j=1}^N \frac{A_j^2}{\tau_{\eta_j}} - \frac{A_i}{\tau_{\eta_i}} \sum_{j=1}^N A_j = 0,$$

which in turn implies that

$$A_i = \lambda \tau_{\eta_i}, \quad (\text{B.18})$$

for a constant λ that does not depend on i . Substituting A_i from (B.18) into (B.16), we find

$$\tau_{\xi_i} = \sum_{j \neq i} \tau_{\eta_j}. \quad (\text{B.19})$$

Substituting (A_i, τ_{ξ_i}) from (B.18) and (B.19) into the definition of $\mathcal{Z}$ in (15), and recalling that $\mathcal{Z} = 0$, we find

$$\begin{aligned} & \left(\sum_{i=1}^N \frac{1}{\alpha_i} \right) \frac{\tau_\epsilon + \sum_{i=1}^N \tau_{\eta_i} + \tau_\theta}{\tau_\epsilon + \tau_\zeta + \sum_{i=1}^N \tau_{\eta_i} + \tau_\theta} - \frac{1}{\lambda} \left(\sum_{i=1}^N \frac{1}{\alpha_i} \right) \frac{1}{\tau_\epsilon + \tau_\zeta + \sum_{i=1}^N \tau_{\eta_i} + \tau_\theta} = 0 \\ \Rightarrow \lambda &= \frac{1}{\tau_\epsilon + \sum_{i=1}^N \tau_{\eta_i} + \tau_\theta}. \end{aligned} \quad (\text{B.20})$$

Eqs. (B.18) and (B.20) imply (15). Eq. (16) follows similarly by substituting τ_{ξ_i} from (B.19) into (12). Substituting $(\epsilon + \xi_i, p, \{A_j\}_{j=1, \dots, N}, B, \tau_{\xi_i})$ from (9), (14), (15), (16) and (B.19) into (B.13) for $\chi_i = 0$, we find that the numerator in (B.13) is zero. Since, in addition $z_i = 0$, trader i 's demand is zero for the equilibrium price. Therefore, there is no trade. ■

Proof of Proposition 3. Setting $\chi_i = 1$ for all i , we can simplify (11) to

$$\frac{\tau_{\eta_i}}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} = A_i \sum_{j=1}^N \frac{\tau_\epsilon + \tau_{\eta_j} + \tau_\theta}{\alpha_j(\tau_\epsilon + \tau_\zeta + \tau_{\eta_j} + \tau_\theta)}. \quad (\text{B.21})$$

Solving for A_i using (B.21) yields (17). Eq. (18) follows similarly from (12). ■

Proof of Proposition 4. Eqs. (16) and (18) imply that (i) holds if

$$\tau_\epsilon + \sum_{i=1}^N \tau_{\eta_i} + \tau_\theta > \frac{\sum_{i=1}^N \frac{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}}{\sum_{i=1}^N \frac{1}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}} = \sum_{i=1}^N w_i(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta), \quad (\text{B.22})$$

where

$$w_i \equiv \frac{\frac{1}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}}{\sum_{i=1}^N \frac{1}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}}.$$

Since the weights $\{w_i\}_{i=1,\dots,N}$ are positive and sum to one, the right-hand side of (B.22) is smaller than

$$\tau_\epsilon + \max_{i=1,\dots,N} \tau_{\eta_i} + \tau_\theta < \tau_\epsilon + \sum_{i=1}^N \tau_{\eta_i} + \tau_\theta,$$

and so (B.22) holds.

Eqs. (15) and (17) imply that the first statement in (ii) holds if

$$\frac{\tau_\theta + \sum_{i=1}^N \tau_{\eta_i} + \tau_\theta}{\sum_{i=1}^N \tau_{\eta_i}} < \frac{\sum_{i=1}^N \frac{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}}{\sum_{i=1}^N \frac{\tau_{\eta_i}}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}} = \sum_{i=1}^N w_i \frac{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta}{\tau_{\eta_i}}, \quad (\text{B.23})$$

where

$$w_i \equiv \frac{\frac{\tau_{\eta_i}}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}}{\sum_{i=1}^N \frac{\tau_{\eta_i}}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}}.$$

Since the weights $\{w_i\}_{i=1,\dots,N}$ are positive and sum to one, the right-hand side of (B.22) is larger than

$$\min_{i=1,\dots,N} \frac{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta}{\tau_{\eta_i}} > \frac{\tau_\theta + \sum_{i=1}^N \tau_{\eta_i} + \tau_\theta}{\sum_{i=1}^N \tau_{\eta_i}},$$

and so (B.23) holds. When traders are symmetric, the first statement in (ii) implies that A_i is smaller in the fully cursed than in the rational case for all i . To show the second statement in (ii), it suffices to show an example where A_i is larger in the fully cursed than in the rational case for some i . Suppose that trader i is much less risk averse than the other traders. Eq. (17) then implies that

$$A_i \approx \frac{\tau_{\eta_i}}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta}$$

in the fully cursed case. This is larger than A_i in the rational case, given by (15).

Eqs. (15), (16), (17) and (18) imply that (iii) holds if

$$\frac{\tau_{\eta_i}}{\tau_\theta} \frac{\frac{1}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}}{\sum_{i=1}^N \frac{1}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}} < \frac{\tau_{\eta_i}}{\tau_\theta},$$

which obviously holds. ■

Proof of Proposition 5. The results for the rational case follow because Proposition 2 implies that

$$p = E(d | \{s_i\}_{i=1, \dots, N}, s), \quad (\text{B.24})$$

which in turn implies that

$$E(d - p | I) = E[d - E(d | \{s_i\}_{i=1, \dots, N}, s) | I] = E(d | I) - E(d | I) = 0,$$

for any information set I consisting of information revealed in Period 1. Since the expectation of $d - p$ conditional on I is zero, the coefficients $(\gamma_1, \gamma_2, \gamma)$ in the regressions (20), (21) and (22) are zero.

We next turn to the fully cursed case. To show the result for regression (21), we follow the argument sketched after the proposition. Taking expectations of both sides of (19) for $\chi_i = 1$ for all i , and noting that $\text{Var}(d | I_{ic})$ is a constant, we find

$$E(p | s) = \frac{\sum_{i=1}^N \frac{E[E(d | I_{ic}) | s]}{\alpha_i \text{Var}(d | I_{ic})}}{\sum_{i=1}^N \frac{1}{\alpha_i \text{Var}(d | I_{ic})}} = \frac{\sum_{i=1}^N \frac{E(d | s)}{\alpha_i \text{Var}(d | I_{ic})}}{\sum_{i=1}^N \frac{1}{\alpha_i \text{Var}(d | I_{ic})}} = E(d | s), \quad (\text{B.25})$$

where the second step follows from the law of iterative expectations because I_{ic} includes s . Eq. (B.25) implies that

$$E(d - p | s) = E(d | s) - E(p | s) = 0. \quad (\text{B.26})$$

The coefficient γ in the regression (21) is proportional to

$$\text{Cov}(d - p, s) = E((d - p)s) - E(d - p)E(s) = E(E(d - p | s)s) - E(E(d - p | s))E(s) = 0,$$

where the second step follows from the law of iterative expectations and last step follows from (B.26).

To show the result for regression (22), we note that γ is proportional to

$$\text{Cov}(d - p, p - \bar{d}) = \left(1 - \sum_{i=1}^N A_i - B\right) \left(\sum_{i=1}^N A_i + B\right) \sigma_\epsilon^2 - \sum_{i=1}^N A_i^2 \sigma_{\eta_i}^2 - B^2 \sigma_\theta^2,$$

where the equality follows from (1), (2) and (14). Substituting $(\{A_i\}_{i=1,\dots,N}, B)$ from Proposition 3, we find that $\text{Cov}(d - p, p - \bar{d})$ has the same sign as

$$\begin{aligned} & \sum_{i=1}^N \frac{\tau_\epsilon}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} \sum_{i=1}^N \frac{\tau_{\eta_i} + \tau_\theta}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} \sigma_\epsilon^2 - \sum_{i=1}^N \frac{\tau_{\eta_i}^2 \sigma_{\eta_i}^2 + \tau_\theta^2 \sigma_\theta^2}{\alpha_i^2(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)^2} \\ &= \sum_{i=1}^N \frac{1}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} \sum_{i=1}^N \frac{\tau_{\eta_i} + \tau_\theta}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} - \sum_{i=1}^N \frac{\tau_{\eta_i} + \tau_\theta}{\alpha_i^2(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)^2}, \end{aligned}$$

which is positive.

To show the result for regression (20), we compute (γ_1, γ_2) . Taking covariances of both sides of (20) with $p - \bar{d}$ and with s , yields respectively

$$\text{Cov}(d - p, p - \bar{d}) = \gamma_1 \text{Var}(p - \bar{d}) + \gamma_2 \text{Cov}(s, p - \bar{d}), \quad (\text{B.27})$$

$$\text{Cov}(d - p, s) = \gamma_1 \text{Cov}(p - \bar{d}, s) + \gamma_2 \text{Var}(s). \quad (\text{B.28})$$

Eqs. (B.27) and (B.28) form a linear system in (γ_1, γ_2) . Its solution is

$$\gamma_1 = \frac{\text{Cov}(d - p, p - \bar{d}) \text{Var}(s) - \text{Cov}(d - p, s) \text{Cov}(s, p - \bar{d})}{\text{Var}(p - \bar{d}) \text{Var}(s) - \text{Cov}(s, p - \bar{d})^2}, \quad (\text{B.29})$$

$$\gamma_2 = -\frac{\text{Cov}(d - p, p - \bar{d}) \text{Cov}(p - \bar{d}, s) - \text{Cov}(d - p, s) \text{Var}(p - \bar{d})}{\text{Var}(p - \bar{d}) \text{Var}(s) - \text{Cov}(s, p - \bar{d})^2}. \quad (\text{B.30})$$

Since $\text{Cov}(d - p, s) = 0$ and $V(s) > 0$, (B.29) implies that $\gamma_1 > 0$. Since $\text{Cov}(d - p, s) = 0$ and $\text{Cov}(p - \bar{d}, s) > 0$, (B.30) implies that $\gamma_2 > 0$. ■

Proof of Corollary 1. The variance of the return $p - \bar{d}$ between Periods 0 and 1 is equal to the variance of p . The comparison between $\text{Var}(p)$ in the rational and fully cursed cases will follow from the identities

$$\begin{aligned} \text{Var}[\mathbb{E}(d | \{s_i\}_{i=1,\dots,N}, s)] &= \text{Var}[\mathbb{E}(d | \{s_i\}_{i=1,\dots,N}, s) - p] + 2\text{Cov}[\mathbb{E}(d | \{s_i\}_{i=1,\dots,N}, s) - p, p] + \text{Var}(p) \end{aligned} \quad (\text{B.31})$$

and

$$\begin{aligned}
\text{Cov} [E(d|\{s_i\}_{i=1,\dots,N}, s) - p, p] &= E[(E(d|\{s_i\}_{i=1,\dots,N}, s) - p)p] - E[E(d|\{s_i\}_{i=1,\dots,N}, s) - p]E(p) \\
&= E[(E(d|p) - p)p] - [E(d) - E(p)]E(p) \\
&= E[\gamma(p - \bar{d})p] \\
&= \gamma \text{Var}(p),
\end{aligned} \tag{B.32}$$

where the second step in (B.32) follows from applying the law of iterative expectations, and the third step follows from (22) and $E(d) = E(p) = \bar{d}$. When traders are fully cursed, (B.32) and Proposition 5 imply that the second term in the right-hand side of (B.31) is positive. Since the first term is also positive, (B.31) implies that

$$\text{Var}[E(d|\{s_i\}_{i=1,\dots,N}, s)] > \text{Var}(p). \tag{B.33}$$

When traders are rational, (B.33) holds as an equality because of (B.24). Therefore, $\text{Var}(p)$ is smaller when traders are fully cursed.

The comparison between $\text{Var}(p) + \text{Var}(d - p)$ in the rational and fully cursed cases will follow similarly from the identities

$$\text{Var}(d) = \text{Var}(d - p) + 2\text{Cov}(d - p, p) + \text{Var}(p) \tag{B.34}$$

and

$$\text{Cov}(d - p, p) = E[\gamma(p - \bar{d})p] = \gamma \text{Var}(p), \tag{B.35}$$

where the first step in (B.35) follows from (22). Eq. (B.35) and Proposition 5 imply that the second term in the right-hand side of (B.34) is positive when traders are fully cursed and zero when they are rational. Since the left-hand side of (B.34) is the same when traders are fully cursed and when they are rational, $\text{Var}(p) + \text{Var}(d - p)$ is smaller when they are fully cursed. ■

Proof of Proposition 6. Substituting p from (14) into (B.13) for $\chi_i = 1$, and using $z_i = 0$, we can write the quantity that trader i trades in equilibrium as

$$x_i = \frac{\tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} \left(\sum_{j=1}^N a_{ij}s_j + b_i s \right), \tag{B.36}$$

where

$$a_{ii} \equiv \frac{\tau_{\eta_i}}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta} - A_i, \quad (\text{B.37})$$

$$a_{ij} \equiv -A_j \quad \text{for } j \neq i, \quad (\text{B.38})$$

$$b_i \equiv \frac{\tau_\theta}{\tau_\epsilon + \tau_{\eta_i} + \tau_\theta} - B. \quad (\text{B.39})$$

Using (1) and (2), we can write (B.36) as

$$x_i = \frac{\tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} \left[\left(\sum_{j=1}^N a_{ij} + b_i \right) \epsilon + \sum_{j=1}^N a_{ij} \eta_j + b_i \theta \right]. \quad (\text{B.40})$$

Since x_i is normal,

$$\begin{aligned} E(|x_i|) &= \sqrt{\frac{2\text{Var}(x_i)}{\pi}} \\ &= \frac{\tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} \sqrt{\frac{2}{\pi} \left[\left(\sum_{j=1}^N a_{ij} + b_i \right)^2 \sigma_\epsilon^2 + \sum_{j=1}^N a_{ij}^2 \sigma_{\eta_j}^2 + b_i^2 \sigma_\theta^2 \right]}, \end{aligned} \quad (\text{B.41})$$

where the second step follows from (B.40).

When $\alpha_i = \alpha$ and $\tau_{\eta_i} = \tau_\eta$ for all i , Proposition 3 implies that

$$A_i = \frac{\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)} \quad \text{for all } i,$$

$$B = \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta}.$$

Substituting into (B.37)-(B.39), we find

$$a_{ii} = \frac{(N-1)\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)},$$

$$a_{ij} = -\frac{\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)} \quad \text{for } j \neq i,$$

$$b_i = 0,$$

$$\sum_{j=1}^N a_{ij} + b_i = 0.$$

Substituting into (B.41), we find (23). The comparative statics follow by differentiating (23) with respect to N and τ_η .

When $\alpha_i = \alpha$ for all i and $\sigma_\zeta^2 = 0$, Proposition 3 implies that

$$A_i = \frac{\tau_{\eta_i}}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)} \quad \text{for all } i, \quad (\text{B.42})$$

$$B = \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta}. \quad (\text{B.43})$$

(These values can be derived as a limit when τ_ζ goes to ∞ .) Substituting into (B.37)-(B.39), we find

$$a_{ii} = \frac{[(N-1)(\tau_\epsilon + \tau_\theta) + N\tau_\eta - \tau_{\eta_i}]\tau_{\eta_i}}{N(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + \tau_\eta + \tau_\theta)}, \quad (\text{B.44})$$

$$a_{ij} = -\frac{\tau_{\eta_j}}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)} \quad \text{for } j \neq i, \quad (\text{B.45})$$

$$b_i = \frac{(\tau_\eta - \tau_{\eta_i})\tau_\theta}{(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + \tau_\eta + \tau_\theta)}, \quad (\text{B.46})$$

$$\sum_{j=1}^N a_{ij} + b_i = \frac{(\tau_{\eta_i} - \tau_\eta)\tau_\epsilon}{(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + \tau_\eta + \tau_\theta)}. \quad (\text{B.47})$$

Substituting into (B.41), and using again $\alpha_i = \alpha$ for all i and $\sigma_\zeta^2 = 0$, we find

$$E(|x_i|) = \frac{\sqrt{2 \left[(\tau_{\eta_i} - \tau_\eta)^2 \tau_\epsilon^2 \sigma_\epsilon^2 + \frac{[(N-1)(\tau_\epsilon + \tau_\theta) + N\tau_\eta - \tau_{\eta_i}]^2 \tau_{\eta_i}^2}{N^2} \sigma_{\eta_i}^2 + \sum_{j \neq i} \frac{(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)^2 \tau_{\eta_j}^2}{N^2} \sigma_{\eta_j}^2 + (\tau_\eta - \tau_{\eta_i})^2 \tau_\theta^2 \sigma_\theta^2 \right]}}{\alpha(\tau_\epsilon + \tau_\eta + \tau_\theta)\sqrt{\pi}}. \quad (\text{B.48})$$

Since the variance is the inverse of the precision, we can write (B.48) as

$$\begin{aligned} E(|x_i|) &= \frac{\sqrt{2 \left[(\tau_{\eta_i} - \tau_\eta)^2 \tau_\epsilon + \frac{[(N-1)(\tau_\epsilon + \tau_\theta) + N\tau_\eta - \tau_{\eta_i}]^2 \tau_{\eta_i}}{N^2} + \sum_{j \neq i} \frac{(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)^2 \tau_{\eta_j}}{N^2} + (\tau_\eta - \tau_{\eta_i})^2 \tau_\theta \right]}}{\alpha(\tau_\epsilon + \tau_\eta + \tau_\theta)\sqrt{\pi}} \\ &= \frac{\sqrt{2 \left[(\tau_{\eta_i} - \tau_\eta)^2 (\tau_\epsilon + \tau_\theta) + \frac{[(N-1)(\tau_\epsilon + \tau_\theta) + N\tau_\eta - \tau_{\eta_i}]^2 \tau_{\eta_i}}{N^2} + \frac{(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)^2 (N\tau_\eta - \tau_{\eta_i})}{N^2} \right]}}{\alpha(\tau_\epsilon + \tau_\eta + \tau_\theta)\sqrt{\pi}}, \end{aligned} \quad (\text{B.49})$$

where the second step follows from the definition of τ_η . Eq. (24) follows from (B.49) by separating quadratic, linear and constant terms in $\tau_\epsilon + \tau_\eta$. Trader i generates more volume than trader j if

and only if the difference between the term inside the squared root in (24) and the corresponding term for j is positive. The difference is

$$\left[(N-2)(\tau_\epsilon + \tau_\theta)^2 + (N-2)(\tau_\epsilon + \tau_\theta)(\tau_{\eta_i} + \tau_{\eta_j}) + (N\tau_\eta - \tau_{\eta_i} - \tau_{\eta_j})\tau_\eta \right] (\tau_{\eta_i} - \tau_{\eta_j}).$$

Since

$$N\tau_\eta - \tau_{\eta_i} - \tau_{\eta_j} = \sum_{k=1}^N \tau_{\eta_k} - \tau_{\eta_i} - \tau_{\eta_j} = \sum_{k \neq i, j} \tau_{\eta_k} > 0,$$

the difference is positive if and only if $\tau_{\eta_i} > \tau_{\eta_j}$. ■

We next prove two lemmas, which we then use to prove Proposition 7.

Lemma B.2 *Let x be an $n \times 1$ normal vector with mean zero and covariance matrix Σ , Z_A a scalar, Z_B an $n \times 1$ vector, Z_C an $n \times n$ symmetric matrix, I the $n \times n$ identity matrix, v' the transpose of a vector v , and $|M|$ the determinant of a matrix M . Then,*

$$E_x \exp \left\{ -\alpha \left[Z_A + Z'_B x + \frac{1}{2} x' Z_C x \right] \right\} = \exp \left\{ -\alpha \left[Z_A - \frac{1}{2} \alpha Z'_B \Sigma (I + \alpha Z_C \Sigma)^{-1} Z_B \right] \right\} \frac{1}{\sqrt{|I + \alpha Z_C \Sigma|}}. \quad (\text{B.50})$$

Proof. When $Z_C = 0$, (B.50) gives the moment-generating function of the normal distribution. We can always assume $Z_C = 0$ by also assuming that x is a normal vector with mean 0 and covariance matrix $\Sigma(I + \alpha Z_C \Sigma)^{-1}$. ■

Lemma B.3 *Suppose that the $n \times n$ matrix Z_C is equal to $Z_{C1} Z'_{C2}$ for $n \times 1$ vectors (Z_{C1}, Z_{C2}) , and the symmetric $n \times n$ matrix Σ is positive definite. Then,*

$$|I + \alpha Z_C \Sigma| = 1 + \alpha Z'_{C1} \Sigma Z_{C2}. \quad (\text{B.51})$$

Proof. Since Σ is positive definite, it has a positive-definite square root. We denote that matrix by $\Sigma^{\frac{1}{2}}$ and its inverse by $\Sigma^{-\frac{1}{2}}$. We can write the determinant in (B.51) as

$$\begin{aligned} |I + \alpha Z_C \Sigma| &= \left| \left(\Sigma^{-\frac{1}{2}} + \alpha Z_C \Sigma^{\frac{1}{2}} \right) \Sigma^{\frac{1}{2}} \right| \\ &= \left| \Sigma^{\frac{1}{2}} \left(\Sigma^{-\frac{1}{2}} + \alpha Z_C \Sigma^{\frac{1}{2}} \right) \right| \\ &= \left| I + \alpha \Sigma^{\frac{1}{2}} Z_C \Sigma^{\frac{1}{2}} \right|, \end{aligned} \quad (\text{B.52})$$

where the second step follows because the determinant is commutative. We next compute

$$\Delta \equiv \left| \Sigma^{\frac{1}{2}} Z_C \Sigma^{\frac{1}{2}} \left(I + \alpha \Sigma^{\frac{1}{2}} Z_C \Sigma^{\frac{1}{2}} \right) \right|$$

in two different ways. First,

$$\begin{aligned} \Delta &= \left| \Sigma^{\frac{1}{2}} Z_C \Sigma^{\frac{1}{2}} \right| \left| I + \alpha \Sigma^{\frac{1}{2}} Z_C \Sigma^{\frac{1}{2}} \right| \\ &= \left| \Sigma^{\frac{1}{2}} Z_{C1} Z'_{C2} \Sigma^{\frac{1}{2}} \right| \left| I + \alpha \Sigma^{\frac{1}{2}} Z_C \Sigma^{\frac{1}{2}} \right| \\ &= \left| Z'_{C2} \Sigma^{\frac{1}{2}} \Sigma^{\frac{1}{2}} Z_{C1} \right| \left| I + \alpha \Sigma^{\frac{1}{2}} Z_C \Sigma^{\frac{1}{2}} \right| \\ &= Z'_{C2} \Sigma Z_{C1} \left| I + \alpha \Sigma^{\frac{1}{2}} Z_C \Sigma^{\frac{1}{2}} \right|, \end{aligned} \tag{B.53}$$

where the first step follows because the determinant of a product is the product of the determinants, and the third step because the determinant is commutative. Second,

$$\begin{aligned} \Delta &= \left| \Sigma^{\frac{1}{2}} Z_{C1} Z'_{C2} \Sigma^{\frac{1}{2}} \left(I + \alpha \Sigma^{\frac{1}{2}} Z_{C1} Z'_{C2} \Sigma^{\frac{1}{2}} \right) \right| \\ &= \left| Z'_{C2} \Sigma^{\frac{1}{2}} \left(I + \alpha \Sigma^{\frac{1}{2}} Z_{C1} Z'_{C2} \Sigma^{\frac{1}{2}} \right) \Sigma^{\frac{1}{2}} Z_{C1} \right| \\ &= \left| Z'_{C2} \Sigma Z_{C1} (1 + \alpha Z'_{C2} \Sigma Z_{C1}) \right| \\ &= Z'_{C2} \Sigma Z_{C1} (1 + \alpha Z'_{C2} \Sigma Z_{C1}). \end{aligned} \tag{B.54}$$

Comparing (B.53) to (B.54), and using (B.52), we find (B.51). ■

Proof of Proposition 7. We first derive a general expression for the expected utility of a fully cursed trader who receives no endowment shock. This derivation does not assume that all other traders are fully cursed, or that they have the same risk-aversion coefficient, or that $\sigma_\zeta^2 = 0$. We can write the expected utility of trader i in the ex-ante sense as

$$-\mathbb{E} \exp \{ -\alpha_i [x_i(d - p) + z_i d] \}. \tag{B.55}$$

Using the law of iterative expectations, and denoting by $I \equiv (\{s_j\}_{j=1,\dots,N}, s)$ the information set consisting of all the signals, we can write (B.55) as

$$\begin{aligned}
& -\mathbb{E}[\mathbb{E}(\exp\{-\alpha_i[x_i(d-p) + z_id]\} | I)] \\
& -\mathbb{E}\exp\left\{-\alpha_i\left[x_i(\mathbb{E}(d|I) - p) + z_i\mathbb{E}(d|I) - \frac{1}{2}\alpha_i(x_i + z_i)^2\text{Var}(d|I)\right]\right\} \\
& -\mathbb{E}\exp\left\{-\alpha_i\left[\frac{\mathbb{E}(d|I_{ic}) - p}{\alpha_i\text{Var}(d|I_{ic})}\left(\mathbb{E}(d|I) - p - \frac{1}{2}\frac{\mathbb{E}(d|I_{ic}) - p}{\text{Var}(d|I_{ic})}\text{Var}(d|I)\right) + z_ip\right]\right\} \\
& -\mathbb{E}\exp\left\{-\frac{\mathbb{E}(d|I_{ic}) - p}{\text{Var}(d|I_{ic})}\left(\mathbb{E}(d|I) - p - \frac{1}{2}\frac{\mathbb{E}(d|I_{ic}) - p}{\text{Var}(d|I_{ic})}\text{Var}(d|I)\right)\right\}
\end{aligned} \tag{B.56}$$

where the second step follows because of normality, the third from (8) and $\chi_i = 1$, and the fourth because $z_i = 0$. Using Lemma B.1 with $x = \epsilon$, $K = N + 1$ and $\{y_j\}_{j=1,\dots,N+1} = (\{\eta_j\}_{j=1,\dots,N}, \eta)$, we find

$$\begin{aligned}
\mathbb{E}(d|I) &= \bar{d} + \sum_{j=1}^N \frac{\tau_{\eta_j}}{\tau_\epsilon + \sum_{k=1}^N \tau_{\eta_k} + \tau_\theta} s_j + \frac{\tau_\theta}{\tau_\epsilon + \sum_{k=1}^N \tau_{\eta_k} + \tau_\theta} s \\
&= \bar{d} + \sum_{j=1}^N \frac{\tau_{\eta_j}}{\tau_\epsilon + N\tau_\eta + \tau_\theta} s_j + \frac{\tau_\theta}{\tau_\epsilon + N\tau_\eta + \tau_\theta} s,
\end{aligned} \tag{B.57}$$

$$\begin{aligned}
\text{Var}(d|I) &= \frac{\tau_\epsilon + \tau_\zeta + \sum_{j=1}^N \tau_{\eta_j} + \tau_\theta}{(\tau_\epsilon + \sum_{j=1}^N \tau_{\eta_j} + \tau_\theta)\tau_\zeta} \\
&= \frac{\tau_\epsilon + \tau_\zeta + N\tau_\eta + \tau_\theta}{(\tau_\epsilon + N\tau_\eta + \tau_\theta)\tau_\zeta}.
\end{aligned} \tag{B.58}$$

Substituting conditional means and variances from (B.11), (B.12), (B.57) and (B.58), we can write the expected utility (B.56) as

$$-\mathbb{E}\exp\left\{-\frac{1}{2}\frac{\tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)}\left(\sum_{j=1}^N a_{ij}s_j + b_is\right)\left(\sum_{j=1}^N \hat{a}_{ij}s_j + \hat{b}_is\right)\right\}, \tag{B.59}$$

where $(\{a_{ij}\}_{j=1,\dots,N}, b_i)$ are defined in (B.37)-(B.39), and

$$\hat{a}_{ij} \equiv \frac{2\tau_{\eta_j}}{\tau_\epsilon + N\tau_\eta + \tau_\theta} - 2A_j - \frac{(\tau_\epsilon + \tau_\zeta + N\tau_\eta + \tau_\theta)(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)} a_{ij} \quad \text{for } j = 1, \dots, N, \tag{B.60}$$

$$\hat{b}_i \equiv \frac{2\tau_\theta}{\tau_\epsilon + N\tau_\eta + \tau_\theta} - 2B - \frac{(\tau_\epsilon + \tau_\zeta + N\tau_\eta + \tau_\theta)(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)} b_i. \tag{B.61}$$

Using (1) and (2), we can write (B.59) as

$$-\mathbb{E} \exp \left\{ -\frac{1}{2} \frac{\tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} \left[\left(\sum_{j=1}^N a_{ij} + b_i \right) \epsilon + \sum_{j=1}^N a_{ij} \eta_j + b_i \theta \right] \left[\left(\sum_{j=1}^N \hat{a}_{ij} + \hat{b}_i \right) \epsilon + \sum_{j=1}^N \hat{a}_{ij} \eta_j + \hat{b}_i \theta \right] \right\}. \quad (\text{B.62})$$

To compute the expectation in (B.62), we use Lemma B.2, and set

$$\begin{aligned} Z_A &\equiv 0, \\ Z_B &\equiv 0, \\ Z_C &\equiv \frac{\tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{\alpha_i(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} v \hat{v}', \\ S_i &\equiv \text{Diag}(\sigma_\epsilon^2, \{\sigma_{\eta_j}^2\}_{j=1, \dots, N}, \sigma_\theta^2), \\ v &\equiv \left(\sum_{j=1}^N a_{ij} + b_i, \{a_{ij}\}_{j=1, \dots, N}, b_i \right)', \\ \hat{v} &\equiv \left(\sum_{j=1}^N \hat{a}_{ij} + \hat{b}_i, \{\hat{a}_{ij}\}_{j=1, \dots, N}, \hat{b}_i \right)'. \end{aligned}$$

Lemma B.2 implies that (B.62) is equal to

$$-\frac{1}{\sqrt{\left| I + \frac{\tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} v \hat{v}' \Sigma \right|}} = -\frac{1}{\sqrt{1 + \frac{\tau_\zeta(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)}{(\tau_\epsilon + \tau_\zeta + \tau_{\eta_i} + \tau_\theta)} v' \Sigma \hat{v}}}, \quad (\text{B.63})$$

where the second step follows from Lemma B.3.

We next use (B.63) to compute the expected utility of a fully cursed trader under the assumptions in the proposition. When $\alpha_i = \alpha$ for all i and $\sigma_\zeta^2 = 0$, $(\{a_{ij}\}_{j=1, \dots, N}, b_i)$ are given by (B.44)-(B.46). Moreover, substituting $(\{A_j\}_{j=1, \dots, N}, A, \{a_{ij}\}_{j=1, \dots, N}, b_i)$ from (B.42)-(B.46) into

(B.60) and (B.61), and using $\alpha_i = \alpha$ for all i and $\sigma_\zeta^2 = 0$, we find

$$\hat{a}_{ii} = \frac{[(N-1)(\tau_\epsilon + \tau_\theta) - N\tau_\eta + \tau_{\eta_i}]\tau_{\eta_i}}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)}, \quad (\text{B.64})$$

$$\hat{a}_{ij} = \frac{[(2N-1)(\tau_\epsilon + \tau_\theta) + \tau_{\eta_i}]\tau_{\eta_j}}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)} \quad \text{for } j \neq i, \quad (\text{B.65})$$

$$\hat{b}_i = \frac{[-(2N-1)\tau_\eta + \tau_{\eta_i}]\tau_\theta}{(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)}, \quad (\text{B.66})$$

$$\sum_{j=1}^N \hat{a}_{ij} + \hat{b}_i = \frac{[(2N-1)\tau_\eta - \tau_{\eta_i}]\tau_\epsilon}{(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)}. \quad (\text{B.67})$$

Substituting into (B.63), and using again $\sigma_\zeta^2 = 0$, we can write the term inside the squared root as

$$\begin{aligned} & 1 + \frac{(\tau_{\eta_i} - \tau_\eta)[(2N-1)\tau_\eta - \tau_{\eta_i}]\tau_\epsilon^2}{(\tau_\epsilon + \tau_\eta + \tau_\theta)^2(\tau_\epsilon + N\tau_\eta + \tau_\theta)}\sigma_\epsilon^2 \\ & + \frac{[(N-1)(\tau_\epsilon + \tau_\theta) + N\tau_\eta - \tau_{\eta_i}][(N-1)(\tau_\epsilon + \tau_\theta) - N\tau_\eta + \tau_{\eta_i}]\tau_{\eta_i}^2}{N^2(\tau_\epsilon + \tau_\eta + \tau_\theta)^2(\tau_\epsilon + N\tau_\eta + \tau_\theta)}\sigma_{\eta_i}^2 \\ & - \sum_{j \neq i} \frac{(\tau_\epsilon + \tau_{\eta_i} + \tau_\theta)[(2N-1)(\tau_\epsilon + \tau_\theta) + \tau_{\eta_i}]\tau_{\eta_j}^2}{N^2(\tau_\epsilon + \tau_\eta + \tau_\theta)^2(\tau_\epsilon + N\tau_\eta + \tau_\theta)}\sigma_{\eta_j}^2 + \frac{(\tau_\eta - \tau_{\eta_i})[-(2N-1)\tau_\eta + \tau_{\eta_i}]\tau_\theta^2}{(\tau_\epsilon + \tau_\eta + \tau_\theta)^2(\tau_\epsilon + N\tau_\eta + \tau_\theta)}\sigma_\theta^2. \end{aligned} \quad (\text{B.68})$$

Eq. (25) can be derived from (B.68) by following the same steps as when deriving (24) from (B.48). Trader i has higher expected utility than trader j if and only if the difference between the numerator inside the squared root in (25) and the corresponding term for j is positive. The difference is $\mathcal{Z}(\tau_{\eta_i} - \tau_{\eta_j})$, where

$$\mathcal{Z} \equiv N(\tau_\epsilon + \tau_\theta)^2 + (\tau_\epsilon + \tau_\theta)[2N(N+1)\tau_\eta - (N-2)(\tau_{\eta_i} + \tau_{\eta_j})] - (N\tau_\eta - \tau_{\eta_i} - \tau_{\eta_j})\tau_\eta. \quad (\text{B.69})$$

Since $\mathcal{Z}$ is linear in $\tau_{\eta_i} + \tau_{\eta_j} \in (0, N\tau_\eta)$, it is positive if this is the case at the boundaries $\tau_{\eta_i} + \tau_{\eta_j} = 0$ and $\tau_{\eta_i} + \tau_{\eta_j} = N\tau_\eta$. For $\tau_{\eta_i} + \tau_{\eta_j} = N\tau_\eta$,

$$\mathcal{Z} = N(\tau_\epsilon + \tau_\theta)^2 + N(N+4)(\tau_\epsilon + \tau_\theta)\tau_\eta > 0.$$

For $\tau_{\eta_i} + \tau_{\eta_j} = 0$,

$$\mathcal{Z} = N(\tau_\epsilon + \tau_\theta)^2 + 2N(N+1)(\tau_\epsilon + \tau_\theta)\tau_\eta - N\tau_\eta^2,$$

and is positive if (26) holds. Therefore, if (26) holds, trader i has higher expected utility than trader j if and only if $\tau_{\eta_i} > \tau_{\eta_j}$. If instead (26) does not hold, $\mathcal{Z} < 0$ for $\tau_{\eta_i} + \tau_{\eta_j} = 0$, and there exist $\tau_{\eta_i} > \tau_{\eta_j}$ such that trader i has lower expected utility than trader j . ■

Proof of Proposition 8. Setting $(\tau_{\eta_i}, A_i) = (\tau_\eta, A)$ in (B.16), we find $\tau_{\xi_i} = (N - 1)\tau_\eta$. Setting $(\chi_i, \alpha_i, \tau_{\eta_i}, \tau_{\xi_i}, A_i) = (\chi, \alpha, \tau_\eta, (N - 1)\tau_\eta, A)$ for all i in (11) and (12), we find (28) and (29), respectively. The comparative statics of (A, B) follow from (28) and (29).

Substituting p from (27) into (B.13), and using symmetry and $z_i = 0$, we can write the quantity that trader i trades in equilibrium as

$$x_i = \frac{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)}{\alpha(\tau_\zeta\{\tau_\epsilon + [1 + \chi(N - 1)]\tau_\eta + \tau_\theta\} + (\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta))} \left(\sum_{j=1}^N a_{ij}s_j + b_i s \right), \quad (\text{B.70})$$

where

$$a_{ii} \equiv \frac{\tau_\eta\{\tau_\epsilon + [1 + \chi(N - 1)]\tau_\eta + \tau_\theta\}}{(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)} - A, \quad (\text{B.71})$$

$$a_{ij} \equiv \frac{(1 - \chi)\tau_\eta}{\tau_\epsilon + N\tau_\eta + \tau_\theta} - A, \quad \text{for } j \neq i, \quad (\text{B.72})$$

$$b_i \equiv \frac{\tau_\theta\{\tau_\epsilon + [1 + \chi(N - 1)]\tau_\eta + \tau_\theta\}}{(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)} - B. \quad (\text{B.73})$$

Proceeding as in the proof of Proposition 6, we find

$$E(|x_i|) = \frac{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta)}{\alpha(\tau_\zeta\{\tau_\epsilon + [1 + \chi(N - 1)]\tau_\eta + \tau_\theta\} + (\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + N\tau_\eta + \tau_\theta))} \\ \times \sqrt{\frac{2}{\pi} \left[\left(\sum_{j=1}^N a_{ij} + b_i \right)^2 \sigma_\epsilon^2 + \sum_{j=1}^N a_{ij}^2 \sigma_{\eta_j}^2 + b_i^2 \sigma_\theta^2 \right]}. \quad (\text{B.74})$$

Substituting (A, B) from (28) and (29) into (B.71)-(B.73), we find

$$\begin{aligned} a_{ii} &= \frac{\chi(N-1)\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)}, \\ a_{ij} &= -\frac{\chi\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)}, \quad \text{for } j \neq i, \\ b_i &= 0, \\ \sum_{j=1}^N a_{ij} + b_i &= 0. \end{aligned}$$

Substituting into (B.74), we find (30). The comparative statics with respect to χ follow from (30). The comparative statics with respect to N also follow from (30) by writing the term multiplying the squared root as

$$\frac{\chi\tau_\zeta}{\alpha \left(\tau_\zeta \frac{\tau_\epsilon + [1 + \chi(N-1)]\tau_\eta + \tau_\theta}{\tau_\epsilon + N\tau_\eta + \tau_\theta} + \tau_\epsilon + \tau_\eta + \tau_\theta \right)}$$

and noting that

$$\frac{\tau_\epsilon + [1 + \chi(N-1)]\tau_\eta + \tau_\theta}{\tau_\epsilon + N\tau_\eta + \tau_\theta}$$

decreases in N . ■

Proof of Proposition 9. Setting $(\tau_{\eta_i}, A_i) = (\tau_{\eta_r}, A_r)$ for $i \in R$ and $(\tau_{\eta_i}, A_i) = (\tau_{\eta_c}, A_c)$ for $i \in C$ in (B.16), we find

$$\tau_{\xi_i} = \frac{[(N_r - 1)A_r + N_c A_c]^2 \tau_{\eta_r} \tau_{\eta_c}}{(N_r - 1)A_r^2 \tau_{\eta_c} + N_c A_c^2 \tau_{\eta_r}} \equiv \tau_\xi. \quad (\text{B.75})$$

for $i \in R$. We next set $(\chi_i, \alpha_i, \tau_{\eta_i}, \tau_{\xi_i}, A_i) = (0, \alpha_r, \tau_{\eta_r}, \tau_\xi, A_r)$ for $i \in R$ and $(\chi_i, \alpha_i, \tau_{\eta_i}, A_i) = (1, \alpha_c, \tau_{\eta_c}, A_c)$ for $i \in C$ in (11) and (12). Equation (11) written for a rational trader becomes

$$\frac{\tau_{\eta_r} - \tau_\xi \frac{A_r}{(N_r - 1)A_r + N_c A_c}}{\alpha_r(\tau_\epsilon + \tau_\zeta + \tau_{\eta_r} + \tau_\theta + \tau_\xi)} = A_r \left[\frac{N_r \left(\tau_\epsilon + \tau_{\eta_r} + \tau_\theta + \tau_\xi - \tau_\xi \frac{1}{(N_r - 1)A_r + N_c A_c} \right)}{\alpha_r(\tau_\epsilon + \tau_\zeta + \tau_{\eta_r} + \tau_\theta + \tau_\xi)} + \frac{N_c(\tau_\epsilon + \tau_{\eta_c} + \tau_\theta)}{\alpha_c(\tau_\epsilon + \tau_\zeta + \tau_{\eta_c} + \tau_\theta)} \right], \quad (\text{B.76})$$

and written for a fully cursed trader becomes

$$\frac{\tau_{\eta_c}}{\alpha_c(\tau_\epsilon + \tau_\zeta + \tau_{\eta_c} + \tau_\theta)} = A_c \left[\frac{N_r \left(\tau_\epsilon + \tau_{\eta_r} + \tau_\theta + \tau_\xi - \tau_\xi \frac{1}{(N_r - 1)A_r + N_c A_c} \right)}{\alpha_r(\tau_\epsilon + \tau_\zeta + \tau_{\eta_r} + \tau_\theta + \tau_\xi)} + \frac{N_c(\tau_\epsilon + \tau_{\eta_c} + \tau_\theta)}{\alpha_c(\tau_\epsilon + \tau_\zeta + \tau_{\eta_c} + \tau_\theta)} \right].$$

(B.77)

Equation (12) becomes

$$\begin{aligned} & \frac{N_r \tau_\theta}{\alpha_r(\tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta + \tau_\xi)} + \frac{N_c \tau_\theta}{\alpha_c(\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)} \\ &= B \left[\frac{N_r(\tau_\epsilon + \tau_{\eta r} + \tau_\theta + \tau_\xi)}{\alpha_r(\tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta + \tau_\xi)} + \frac{N_c(\tau_\epsilon + \tau_{\eta c} + \tau_\theta)}{\alpha_c(\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)} \right]. \end{aligned} \quad (\text{B.78})$$

Equations (B.76) and (B.77) form a system of two equations in the two unknowns (A_r, A_c) . We can reduce this system to one equation by setting $x \equiv \frac{A_r}{A_c}$. Equation (B.75) then becomes (35), and (B.77) and (B.78) yield (33) and (34), respectively. Moreover, dividing (32) by (33), we find

$$\begin{aligned} & \frac{\tau_{\eta r} - \tau_\xi \frac{x}{(N_r-1)x+N_c}}{\alpha_r(\tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta + \tau_\xi)} \frac{\alpha_c(\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)}{\tau_{\eta c}} = x \\ \Rightarrow x &= \frac{\alpha_c \left\{ \tau_{\eta r} - \frac{x[(N_r-1)x+N_c]\tau_{\eta r}\tau_{\eta c}}{(N_r-1)x^2\tau_{\eta c}+N_c\tau_{\eta r}} \right\} (\tau_\epsilon + \tau_\zeta + \tau_{\eta c} + \tau_\theta)}{\alpha_r \tau_{\eta c} \left\{ \tau_\epsilon + \tau_\zeta + \tau_{\eta r} + \tau_\theta + \frac{[(N_r-1)x+N_c]^2\tau_{\eta r}\tau_{\eta c}}{(N_r-1)x^2\tau_{\eta c}+N_c\tau_{\eta r}} \right\}}, \end{aligned} \quad (\text{B.79})$$

where the second step follows by (35). Equation (B.79) yields (36).

For $x \leq 0$, the left-hand side of (36) is non-positive and the right-hand side is positive. For $x \geq \frac{\tau_{\eta r}}{\tau_{\eta c}}$ the left-hand side of (36) is positive and the right-hand side is non-positive. Therefore, a solution of (36) must belong to $(0, \frac{\tau_{\eta r}}{\tau_{\eta c}})$. For $x \in (0, \frac{\tau_{\eta r}}{\tau_{\eta c}})$, the left-hand side of (36) is increasing in x and the right-hand side is decreasing in x (because the numerator is decreasing, the denominator is increasing, and both are positive). Since the left-hand side is zero at $x = 0$, and the right-hand side is zero at $x = \frac{\tau_{\eta r}}{\tau_{\eta c}}$, a solution of (36) exists and is unique. ■

Proof of Proposition 10. Because of symmetry, the coefficient γ_i is equal to a common value γ_r for all rational traders and to a common value γ_c for all fully cursed traders. Market clearing (5) implies that $N_r \gamma_r + N_c \gamma_c = 0$. Hence, to prove the proposition it suffices to show that $\gamma_c < 0$.

The coefficient γ_c is proportional to $\text{Cov}(x_i, p - \bar{d})$. Substituting p from (31) into (B.13), and setting $(\chi_i, \tau_{\eta_i}, z_i) = (1, \tau_{\eta c}, 0)$, we find that $\text{Cov}(x_i, p - \bar{d})$ has the same sign as

$$\text{Cov} \left(\bar{d} + \frac{\tau_{\eta c} s_i + \tau_\theta s}{\tau_\epsilon + \tau_{\eta c} + \tau_\theta} - p, p - \bar{d} \right) \quad (\text{B.80})$$

Using (1), (2) and (31), we find that $\text{Cov}(x_i, p - \bar{d})$ has the same sign as

$$\begin{aligned} & \left(\frac{\tau_{\eta c} + \tau_{\theta}}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - N_r A_r - N_c A_c - B \right) (N_r A_r + N_c A_c + B) \sigma_{\epsilon}^2 \\ & + \left(\frac{\tau_{\eta c}}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - N_c A_c \right) A_c \sigma_{\eta c}^2 - N_r A_r^2 \sigma_{\eta r}^2 + \left(\frac{\tau_{\theta}}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - B \right) B \sigma_{\theta}^2, \end{aligned} \quad (\text{B.81})$$

where $(\sigma_{\eta r}^2, \sigma_{\eta c}^2) \equiv (\frac{1}{\tau_{\eta r}}, \frac{1}{\tau_{\eta c}})$. To determine the sign of (B.81), we compute some of the terms in that equation.

Multiplying (B.76) by N_r , (B.77) by N_c , and adding the sum of the resulting equations to (B.78), we find

$$\begin{aligned} (N_r A_r + N_c A_c + B) \mathcal{D} &= \frac{N_r (\tau_{\eta r} + \tau_{\theta}) + N_r \tau_{\xi} \frac{(N_r - 1) A_r + N_c A_c}{(N_r - 1) A_r + N_c A_c}}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c (\tau_{\eta c} + \tau_{\theta})}{\alpha_c (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})} \\ &= \frac{N_r (\tau_{\eta r} + \tau_{\theta} + \tau_{\xi})}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c (\tau_{\eta c} + \tau_{\theta})}{\alpha_c (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})}, \end{aligned}$$

where

$$\mathcal{D} \equiv \frac{N_r (\tau_{\epsilon} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c (\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta})}{\alpha_c (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})}.$$

Therefore,

$$\begin{aligned} \frac{\tau_{\eta c} + \tau_{\theta}}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - N_r A_r - N_c A_c - B &= \frac{\tau_{\eta c} + \tau_{\theta}}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - \frac{\frac{N_r (\tau_{\eta r} + \tau_{\theta} + \tau_{\xi})}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c (\tau_{\eta c} + \tau_{\theta})}{\alpha_c (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})}}{\mathcal{D}} \\ &= \frac{\frac{N_r (\tau_{\eta c} + \tau_{\theta}) (\tau_{\epsilon} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - N_r (\tau_{\eta r} + \tau_{\theta} + \tau_{\xi})}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi}) \mathcal{D}} \\ &= \frac{N_r \tau_{\epsilon} (\tau_{\eta c} - \tau_{\eta r} - \tau_{\xi})}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi}) (\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}) \mathcal{D}}. \end{aligned} \quad (\text{B.82})$$

Multiplying (B.76) by $\frac{N_r A_r}{\tau_{\eta r}}$, (B.77) by $\frac{N_c A_c}{\tau_{\eta c}}$, and adding the resulting equations, we find

$$\begin{aligned} \left(\frac{N_r A_r^2}{\tau_{\eta r}} + \frac{N_c A_c^2}{\tau_{\eta c}} \right) \mathcal{D} &= \frac{N_r A_r + N_r \tau_{\xi} \frac{(N_r - 1) \frac{A_r^2}{\tau_{\eta r}} + \frac{N_c A_c^2}{\tau_{\eta c}}}{(N_r - 1) A_r + N_c A_c}}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c A_c}{\alpha_c (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})} \\ &= \frac{N_r A_r + N_r [(N_r - 1) A_r + N_c A_c]}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c A_c}{\alpha_c (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})} \\ &= \frac{N_r (N_r A_r + N_c A_c)}{\alpha_r (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c A_c}{\alpha_c (\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})}, \end{aligned}$$

where the second step follows from (B.75). Therefore,

$$\begin{aligned} \left(\frac{\tau_{\eta c}}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - N_c A_c \right) A_c \sigma_{\eta c}^2 - N_r A_r^2 \sigma_{\eta r}^2 &= \frac{A_c}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - \frac{\frac{N_r(N_r A_r + N_c A_c)}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c A_c}{\alpha_c(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})}}{\mathcal{D}} \\ &= \frac{\frac{N_r(\tau_{\epsilon} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi}) A_c}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - N_r(N_r A_r + N_c A_c)}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi}) \mathcal{D}}. \end{aligned} \quad (\text{B.83})$$

Using (34), we find

$$\begin{aligned} \frac{\tau_{\theta}}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - B &= \frac{\tau_{\theta}}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - \frac{\frac{N_r \tau_{\theta}}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})} + \frac{N_c \tau_{\theta}}{\alpha_c(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta c} + \tau_{\theta})}}{\mathcal{D}} \\ &= \frac{\frac{N_r \tau_{\theta}(\tau_{\epsilon} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - N_r \tau_{\theta}}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi}) \mathcal{D}} \\ &= \frac{N_r \tau_{\theta}(\tau_{\eta r} + \tau_{\xi} - \tau_{\eta c})}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})(\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}) \mathcal{D}}. \end{aligned} \quad (\text{B.84})$$

Equations (B.82), (B.83) and (B.84) imply that (B.81) is equal to

$$\begin{aligned} &\frac{N_r(\tau_{\eta c} - \tau_{\eta r} - \tau_{\xi})(N_r A_r + N_c A_c + B)}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})(\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}) \mathcal{D}} \\ &+ \frac{\frac{N_r(\tau_{\epsilon} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi}) A_c}{\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}} - N_r(N_r A_r + N_c A_c)}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi}) \mathcal{D}} + \frac{N_r(\tau_{\eta r} + \tau_{\xi} - \tau_{\eta c}) B}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})(\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}) \mathcal{D}} \\ &= \frac{N_r(\tau_{\epsilon} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})(A_c - N_r A_r - N_c A_c)}{\alpha_r(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta r} + \tau_{\theta} + \tau_{\xi})(\tau_{\epsilon} + \tau_{\eta c} + \tau_{\theta}) \mathcal{D}}. \end{aligned}$$

This is negative because $N_c \geq 1$, $A_r > 0$ and $A_c > 0$. ■

Proof of Proposition 11. Expected aggregate trading volume when all N traders are fully cursed is N times the expected volume that each trader generates, given by (23). To compute expected aggregate trading volume when one trader is rational and $N - 1$ traders are fully cursed, we start by computing the expected trading volume that one fully cursed trader generates. Substituting p from (31) into (B.13), setting $(\chi_i, \alpha_i, \tau_{\eta i}, z_i) = (1, \alpha, \tau_{\eta}, 0)$, and denoting the rational trader by i_r , we can write the quantity that trader $i \neq i_r$ trades in equilibrium as

$$x_i = \frac{\tau_{\zeta}(\tau_{\epsilon} + \tau_{\eta} + \tau_{\theta})}{\alpha(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta})} \left(\sum_{j=1}^N a_{ij} s_j + b_i s \right),$$

where

$$a_{ii} \equiv \frac{\tau_\eta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - A_c, \quad (\text{B.85})$$

$$a_{ii_r} \equiv -A_r, \quad (\text{B.86})$$

$$a_{ij} \equiv -A_c \quad \text{for } j \neq i, i_r, \quad (\text{B.87})$$

$$b_i \equiv \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - B. \quad (\text{B.88})$$

Proceeding as in the proof of Proposition 6, and using $\tau_{\eta_i} = \tau_\eta$ for all i , we find

$$E(|x_i|) = \frac{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)}{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)} \sqrt{\frac{2}{\pi} \left[\left(\sum_{j=1}^N a_{ij} + b_i \right)^2 \sigma_\epsilon^2 + \sum_{j=1}^N a_{ij}^2 \sigma_\eta^2 + b_i^2 \sigma_\theta^2 \right]}, \quad (\text{B.89})$$

where $\sigma_\eta^2 \equiv \frac{1}{\tau_\eta}$. Equations (B.85)-(B.88) imply that

$$\sum_{j=1}^N a_{ij} + b_i = \frac{\tau_\eta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - A_r - (N-1)A_c - B.$$

Using (B.82) and setting $\tau_{\eta r} = \tau_{\eta c} = \tau_\eta$, $N_r = 1$, $N_c = N-1$, and $\tau_\xi = (N-1)\tau_\eta$ (which is implied by (35) for $N_r = 1$ and $N_c = N-1$), we find

$$\sum_{j=1}^N a_{ij} + b_i = -\frac{(N-1)\tau_\epsilon \tau_\eta (\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)}{(\tau_\epsilon + \tau_\eta + \tau_\theta)\mathcal{G}}, \quad (\text{B.90})$$

where

$$\mathcal{G} \equiv (N-1)(\tau_\epsilon + \tau_\eta + \tau_\theta)(\tau_\epsilon + \tau_\zeta + N\tau_\eta + \tau_\theta) + (\tau_\epsilon + N\tau_\eta + \tau_\theta)(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta).$$

Using (B.84) and (B.88), and setting $\tau_{\eta r} = \tau_{\eta c} = \tau_\eta$, $N_r = 1$, $N_c = N-1$ and $\tau_\xi = (N-1)\tau_\eta$, we likewise find

$$b_i = \frac{(N-1)\tau_\theta \tau_\eta (\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)}{(\tau_\epsilon + \tau_\eta + \tau_\theta)\mathcal{G}}, \quad (\text{B.91})$$

Equations (B.85)-(B.87) imply that

$$\sum_{j=1}^N a_{ij}^2 = \left(\frac{\tau_\eta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - A_c \right)^2 + A_r^2 + (N-2)A_c^2.$$

To compute this quantity, we note that for $\tau_{\eta r} = \tau_{\eta c} = \tau_{\eta}$, $N_r = 1$, $N_c = N - 1$ and $\tau_{\xi} = (N - 1)\tau_{\eta}$, (36) implies that

$$x = \frac{\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta}}{2(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\theta}) + (N + 1)\tau_{\eta}},$$

and (32) and (33) become

$$A_r = \frac{\tau_{\eta} [2(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\theta}) + (N + 1)\tau_{\eta}]}{\mathcal{G}}, \quad (\text{B.92})$$

$$A_c = \frac{\tau_{\eta}(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta})}{\mathcal{G}}, \quad (\text{B.93})$$

respectively. Using (B.92) and (B.93), we find

$$a_{ii} = \frac{\tau_{\eta} [(N - 2)(\tau_{\epsilon} + \tau_{\eta} + \tau_{\theta})(\tau_{\epsilon} + \tau_{\zeta} + N\tau_{\eta} + \tau_{\theta}) + (N - 1)\tau_{\eta}(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta})]}{(\tau_{\epsilon} + \tau_{\eta} + \tau_{\theta})\mathcal{G}}, \quad (\text{B.94})$$

and

$$\begin{aligned} \sum_{j \neq i}^N a_{ij}^2 &= \frac{\tau_{\eta}}{\mathcal{G}} [(N - 1)(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta})^2 \\ &\quad + 2(N - 2)(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta})(\tau_{\epsilon} + \tau_{\zeta} + N\tau_{\eta} + \tau_{\theta}) + (N - 2)(\tau_{\epsilon} + \tau_{\zeta} + N\tau_{\eta} + \tau_{\theta})^2]. \end{aligned} \quad (\text{B.95})$$

Using (B.90), (B.91), (B.94) and (B.95), we can write (B.89) as

$$E(|x_i|) = \frac{\tau_{\zeta} \sqrt{2\tau_{\eta}(\tau_{\epsilon} + \tau_{\eta} + \tau_{\theta})\mathcal{N}_c}}{\alpha(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta})\mathcal{G}\sqrt{\pi}}, \quad (\text{B.96})$$

where

$$\begin{aligned} \mathcal{N}_c &\equiv (\tau_{\epsilon} + N\tau_{\eta} + \tau_{\theta})(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta}) [(N - 1)(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta}) + 2(N - 2)(\tau_{\epsilon} + \tau_{\zeta} + N\tau_{\eta} + \tau_{\theta})] \\ &\quad + (N - 2)(N - 1)(\tau_{\epsilon} + \tau_{\eta} + \tau_{\theta})(\tau_{\epsilon} + \tau_{\zeta} + N\tau_{\eta} + \tau_{\theta})^2. \end{aligned}$$

We next compute the expected trading volume that the rational trader i_r generates. The market-clearing equation (5) implies that

$$x_{i_r} = - \sum_{j \neq i_r} x_j = - \frac{\tau_{\zeta}(\tau_{\epsilon} + \tau_{\eta} + \tau_{\theta})}{\alpha(\tau_{\epsilon} + \tau_{\zeta} + \tau_{\eta} + \tau_{\theta})} \left(\sum_{k=1}^N \sum_{j \neq i_r} a_{jk} s_k + \sum_{j \neq i_r} b_j s \right),$$

and hence

$$E(|x_{i_r}|) = \frac{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)}{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)} \sqrt{\frac{2}{\pi} \left[\left(\sum_{k=1}^N \sum_{j \neq i_r} a_{jk} + \sum_{j \neq i_r} b_j \right)^2 \sigma_\epsilon^2 + \sum_{k=1}^N \left(\sum_{j \neq i_r} a_{jk} \right)^2 \sigma_{\eta_c}^2 + \left(\sum_{j \neq i_r} b_j \right)^2 \sigma_\theta^2 \right]}. \quad (\text{B.97})$$

Equations (B.85)-(B.88) imply that

$$\begin{aligned} \sum_{k=1}^N \sum_{j \neq i_r} a_{jk} + \sum_{j \neq i_r} b_j &= (N-1) \left(\frac{\tau_\eta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - (N-1)A_c - A_r - B \right) \\ &= -\frac{(N-1)^2 \tau_\epsilon \tau_\eta (\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)}{(\tau_\epsilon + \tau_\eta + \tau_\theta) \mathcal{G}}, \end{aligned} \quad (\text{B.98})$$

where the second step follows from (B.90). Equation (B.88) implies that

$$\begin{aligned} \sum_{j \neq i_r} b_j &= (N-1) \left(\frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - B \right) \\ &= \frac{(N-1)^2 \tau_\theta \tau_\eta (\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)}{(\tau_\epsilon + \tau_\eta + \tau_\theta) \mathcal{G}}, \end{aligned} \quad (\text{B.99})$$

where the second step follows from (B.91). Equations (B.86) and (B.87) imply that

$$\begin{aligned} \sum_{k=1}^N \left(\sum_{j \neq i_r} a_{jk} \right)^2 &= (N-1)^2 A_r^2 + (N-1) \left(\frac{\tau_\eta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - (N-1)A_c \right)^2 \\ &= \frac{(N-1) \tau_\eta^2 (\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)^2 \left[(N-1)(\tau_\theta + \tau_\eta + \tau_\theta)^2 + [\tau_\eta - (N-2)(\tau_\epsilon + \tau_\theta)]^2 \right]}{(\tau_\epsilon + \tau_\eta + \tau_\theta)^2 \mathcal{G}^2}, \end{aligned} \quad (\text{B.100})$$

where the second step follows from (B.92) and (B.93). Using (B.98), (B.99) and (B.100), we can write (B.97) as

$$E(|x_{i_r}|) = \frac{\tau_\zeta \sqrt{2(N-1) \tau_\eta (\tau_\epsilon + N \tau_\eta + \tau_\theta) \mathcal{N}_r}}{\alpha \mathcal{G} \sqrt{\pi}}, \quad (\text{B.101})$$

where

$$\mathcal{N}_r \equiv (N-1)^2 (\tau_\epsilon + \tau_\eta + \tau_\theta) - (N-2)(\tau_\epsilon + N \tau_\eta + \tau_\theta).$$

Combining (23) with (B.96) and (B.101), we find that expected aggregate trading volume is larger when one trader is rational and $N - 1$ traders are fully cursed than when all N traders are fully cursed if

$$\begin{aligned} N \frac{\sqrt{N-1}}{(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)\sqrt{N}} &< (N-1) \frac{\sqrt{(\tau_\epsilon + \tau_\eta + \tau_\theta)\mathcal{N}_c}}{(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)\mathcal{G}} + \frac{\sqrt{(N-1)(\tau_\epsilon + N\tau_\eta + \tau_\theta)\mathcal{N}_r}}{\mathcal{G}} \\ \Leftrightarrow \sqrt{N} &< \frac{\sqrt{(N-1)(\tau_\epsilon + \tau_\eta + \tau_\theta)\mathcal{N}_c}}{\mathcal{G}} + \frac{(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)\sqrt{(\tau_\epsilon + N\tau_\eta + \tau_\theta)\mathcal{N}_r}}{\mathcal{G}}. \end{aligned} \quad (\text{B.102})$$

Equation (B.102) holds under the sufficient condition

$$N < \frac{(N-1)(\tau_\epsilon + \tau_\eta + \tau_\theta)\mathcal{N}_c}{\mathcal{G}^2} + \frac{(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)^2(\tau_\epsilon + N\tau_\eta + \tau_\theta)\mathcal{N}_r}{\mathcal{G}^2}. \quad (\text{B.103})$$

Multiplying both sides by $\mathcal{G}^2$, using the definitions of $(\mathcal{G}, \mathcal{N}_c, \mathcal{N}_r)$, and rearranging, we can write (B.103) as (38).

When $\tau_\zeta = \infty$, (38) becomes

$$\frac{1}{N-1} \left(\frac{\tau_\epsilon + N\tau_\eta + \tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} \right)^2 + \left(\frac{2}{N-1} - 1 \right) \frac{\tau_\epsilon + N\tau_\eta + \tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} + 1 < 0. \quad (\text{B.104})$$

Setting $y \equiv \frac{\tau_\eta}{\tau_\epsilon + \tau_\theta}$, we can write (B.104) as

$$\begin{aligned} \frac{1}{N-1} \left(\frac{1+Ny}{1+y} \right)^2 - \frac{(N-3)(1+Ny)}{(N-1)(1+y)} + 1 &< 0 \\ 3 - (N^2 - 6N - 1)y + (4N - 1)y^2 &< 0. \end{aligned} \quad (\text{B.105})$$

The left-hand side of (B.105) converges to $-\infty$ when N goes to ∞ . Hence, (B.105) is satisfied for N large enough. ■

Proof of Proposition 12. To derive the results for the rational case, we use (10)-(13) and set $(\chi_i, \alpha_i, \tau_{\eta_i}, \tau_{z_i}, A_i, C_i) = (0, \alpha, \tau_\eta, \tau_z, A, C)$ for all i . Equations (10)-(13) yield

$$\tau_{\xi_i} = \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta} \equiv \tau_\xi \quad \text{for all } i, \quad (\text{B.106})$$

$$A = \frac{\tau_\eta + \tau_\xi}{N(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)}, \quad (\text{B.107})$$

$$B = \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi}, \quad (\text{B.108})$$

$$\frac{C}{A} = \alpha \frac{\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta + \tau_\xi}{\tau_\zeta\tau_\eta}, \quad (\text{B.109})$$

respectively. Substituting τ_ξ from (B.106) to (B.107)-(B.109), we find (40)-(42), respectively. Eq. (42) is cubic in $\frac{C}{A}$, and hence has at least one solution. Any of its solutions satisfies

$$\frac{C}{A}\tau_\zeta\tau_\eta - \alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta) > 0, \quad (\text{B.110})$$

and hence is positive. The derivative of the left-hand side of (42) with respect to $\frac{C}{A}$ is

$$2\frac{C}{A}\tau_\eta \left(\frac{C}{A}\tau_\zeta\tau_\eta - \alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta) \right) + \left(\tau_z + \frac{C^2}{A^2}\tau_\eta \right) \tau_\zeta\tau_\eta,$$

and is positive at any solution of (42) because of (B.110). Therefore, (42) has a unique solution.

To derive the results for the fully cursed case, we use (11)-(13) and set $(\chi_i, \alpha_i, \tau_{\eta_i}, \tau_{z_i}, A_i, C_i) = (1, \alpha, \tau_\eta, \tau_z, A, C)$ for all i . Equations (11)-(13) yield

$$\begin{aligned} A &= \frac{\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)}, \\ B &= \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta}, \\ C &= A\alpha \frac{\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta}{\tau_\zeta\tau_\eta}, \end{aligned}$$

respectively. The coefficients (A, B, C) coincide with those in (40)-(42) for $\tau_\zeta = 0$. ■

Proof of Proposition 13. To show the result for regression (21), we note that γ is proportional to

$$\text{Cov}(d - p, s) = (1 - NA - B)\sigma_\epsilon^2 - B\sigma_\theta^2,$$

where the equality follows from (1), (2) and (39). Substituting (A, B) from Proposition 12, we find that

$$\text{Cov}(d - p, s) = \left(1 - \frac{\tau_\eta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta} + \tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}} \right) \sigma_\epsilon^2 - \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}} \sigma_\theta^2 = 0$$

when all traders are rational, and

$$\text{Cov}(d - p, s) = \left(1 - \frac{\tau_\eta + \tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} \right) \sigma_\epsilon^2 - \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} \sigma_\theta^2 = 0$$

when they are fully cursed.

To show the result for regression (22), we likewise note that γ is proportional to

$$\begin{aligned}\text{Cov}(d - p, p - \bar{d}) &= (1 - NA - B)(NA + B)\sigma_\epsilon^2 - NA^2\sigma_\eta^2 - B^2\sigma_\theta^2 - NC^2\sigma_z^2 \\ &= (1 - NA - B)(NA + B)\sigma_\epsilon^2 - NA^2\left(\sigma_\eta^2 + \frac{C^2}{A^2}\sigma_z^2\right) - B^2\sigma_\theta^2,\end{aligned}$$

where $\sigma_z^2 \equiv \frac{1}{\tau_z}$. Substituting (A, B, C) from Proposition 12, we find that

$$\begin{aligned}\text{Cov}(d - p, p - \bar{d}) &= \frac{\tau_\eta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}}{\left(\tau_\epsilon + \tau_\eta + \tau_\theta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}\right)^2} - \frac{\left(\tau_\eta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}\right)^2 \left(\sigma_\eta^2 + \frac{C^2}{A^2}\sigma_z^2\right)}{N\left(\tau_\epsilon + \tau_\eta + \tau_\theta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}\right)^2} \\ &= \frac{\tau_\eta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}}{\left(\tau_\epsilon + \tau_\eta + \tau_\theta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}\right)^2} \left(1 - \frac{\left(\tau_\eta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}\right)\left(\tau_z + \frac{C^2}{A^2}\tau_\eta\right)}{N\tau_\eta\tau_z}\right) \\ &= -\frac{\left(\tau_\eta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}\right) \frac{C^2\tau_\eta}{NA^2\tau_z}}{\left(\tau_\epsilon + \tau_\eta + \tau_\theta + \frac{(N-1)\tau_\eta\tau_z}{\tau_z + \frac{C^2}{A^2}\tau_\eta}\right)^2} < 0\end{aligned}$$

when all traders are rational, and

$$\begin{aligned}\text{Cov}(d - p, p - \bar{d}) &= \frac{\tau_\eta}{(\tau_\epsilon + \tau_\eta + \tau_\theta)^2} - \frac{\tau_\eta^2 \left(\sigma_\eta^2 + \frac{C^2}{A^2}\sigma_z^2\right)}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)^2} \\ &= \frac{\tau_\eta}{(\tau_\epsilon + \tau_\eta + \tau_\theta)^2} \left(1 - \frac{\tau_\eta \left(\tau_z + \frac{C^2}{A^2}\tau_\eta\right)}{N\tau_\eta\tau_z}\right) \\ &= \frac{(N-1)\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)^2} \left(1 - \frac{\alpha^2(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)^2}{(N-1)\tau_\zeta^2\tau_\eta\tau_z}\right)\end{aligned}\tag{B.111}$$

when they are fully cursed. The last step in the derivation of (B.111) follows from (42). Equation (B.111) yields (43). ■

Proof of Proposition 14. We first determine expected trading volume when all traders are rational. When $(A_i, C_i) = (A, C)$ for all i , the signal $\epsilon + \xi_i$ defined by (9) takes the form

$$\epsilon + \xi_i = \frac{\sum_{j \neq i} s_j - \frac{C}{A} \sum_{j \neq i} z_j}{N-1}.\tag{B.112}$$

Substituting p from (39) into (B.13), and using symmetry, $\chi_i = 0$ and (B.112), we can write the quantity that trader i trades in equilibrium as

$$x_i = \frac{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)}{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta + \tau_\xi)} \left(\sum_{j=1}^N a_{ij}s_j + b_i s + \sum_{j=1}^N c_{ij}z_j \right), \quad (\text{B.113})$$

where

$$a_{ii} \equiv \frac{\tau_\eta}{\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi} - A, \quad (\text{B.114})$$

$$a_{ij} \equiv \frac{\tau_\xi}{(N-1)(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)} - A \quad \text{for } j \neq i, \quad (\text{B.115})$$

$$b_i \equiv \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi} - B, \quad (\text{B.116})$$

$$c_{ii} \equiv C - \frac{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta + \tau_\xi)}{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)}, \quad (\text{B.117})$$

$$c_{ij} \equiv C - \frac{C\tau_\xi}{(N-1)A(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)} \quad \text{for } j \neq i. \quad (\text{B.118})$$

Proceeding as in the proof of Proposition (6), we find

$$E(|x_i|) = \frac{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)}{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta + \tau_\xi)} \sqrt{\frac{2}{\pi} \left[\left(\sum_{j=1}^N a_{ij} + b_i \right)^2 \sigma_\epsilon^2 + \sum_{j=1}^N a_{ij}^2 \sigma_\eta^2 + b_i^2 \sigma_\theta^2 + \sum_{j=1}^N c_{ij}^2 \sigma_z^2 \right]}. \quad (\text{B.119})$$

Substituting (A, B, C) from (B.107)-(B.109) into (B.114)-(B.118), we find

$$\begin{aligned} a_{ii} &= \frac{(N-1)\tau_\eta - \tau_\xi}{N(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)}, \\ a_{ij} &= -\frac{(N-1)\tau_\eta - \tau_\xi}{N(N-1)(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)} \quad \text{for } j \neq i, \\ b_i &= 0, \\ c_{ii} &= -\frac{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta + \tau_\xi) [(N-1)\tau_\eta - \tau_\xi]}{N\tau_\zeta\tau_\eta(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)}, \\ c_{ij} &= \frac{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta + \tau_\xi) [(N-1)\tau_\eta - \tau_\xi]}{N(N-1)\tau_\zeta\tau_\eta(\tau_\epsilon + \tau_\eta + \tau_\theta + \tau_\xi)} \quad \text{for } j \neq i, \end{aligned}$$

$$\sum_{j=1}^N a_{ij} + b_i = 0.$$

Substituting into (B.119), we find

$$\begin{aligned}
E(|x_i|) &= \sqrt{\frac{2[(N-1)\tau_\eta - \tau_\xi]^2}{\pi N(N-1)\tau_\eta} \left(\frac{\tau_\zeta^2}{\alpha^2(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta + \tau_\xi)^2} + \frac{1}{\tau_\eta \tau_z} \right)} \\
&= \sqrt{\frac{2[(N-1)\tau_\eta - \tau_\xi]^2}{\pi N(N-1)\tau_\eta} \left(\frac{A^2}{C^2 \tau_\eta^2} + \frac{1}{\tau_\eta \tau_z} \right)} \\
&= \sqrt{\frac{2(N-1)^2 \tau_\eta^2 \left(1 - \frac{\tau_z}{\tau_z + \frac{C^2}{A^2} \tau_\eta} \right)^2}{\pi N(N-1)\tau_\eta} \left(\frac{A^2}{C^2 \tau_\eta^2} + \frac{1}{\tau_\eta \tau_z} \right)} \\
&= \sqrt{\frac{2(N-1) \frac{C^2}{A^2} \tau_\eta}{\pi N \tau_z \left(\tau_z + \frac{C^2}{A^2} \tau_\eta \right)}}, \tag{B.120}
\end{aligned}$$

where the second step follows from (B.109) and the third from (B.106).

Equation (B.120) implies that volume is increasing in N if $\frac{C}{A}$ is increasing in N . In the proof of Proposition 12 we show that the derivative of the left-hand side of (42) with respect to $\frac{C}{A}$ is positive at the solution $\frac{C}{A}$. Since the derivative with respect to N is negative, $\frac{C}{A}$ is increasing in N .

To show that volume is inverse hump-shaped in τ_η , we set $\omega \equiv \frac{C}{A} \sqrt{\tau_\eta}$ and write (42) as

$$(\tau_z + w^2) (\omega \tau_\zeta \sqrt{\tau_\eta} - \alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)) - \alpha(N-1)\tau_\eta \tau_z = 0 \tag{B.121}$$

and (B.120) as

$$E(|x_i|) = \sqrt{\frac{2(N-1)\omega^2}{\pi N \tau_z (\tau_z + \omega^2)}}. \tag{B.122}$$

Eq. (B.122) implies that the effects of τ_η on volume and ω have the same sign. The derivative of the left-hand side of (B.121) with respect to ω is equal to $\sqrt{\tau_\eta}$ times the same derivative with respect to $\frac{C}{A}$. Therefore, it is positive at the solution ω . The derivative with respect to τ_η is

$$(\tau_z + w^2) \left(\frac{\omega \tau_\zeta}{2\sqrt{\tau_\eta}} - \alpha \right) - \alpha(N-1)\tau_z,$$

and is equal to

$$\begin{aligned}
&\frac{1}{\tau_\eta} \left[(\tau_z + w^2) \left(\frac{1}{2} \omega \tau_\zeta \sqrt{\tau_\eta} - \alpha \tau_\eta \right) - \alpha(N-1)\tau_\eta \tau_z \right] \\
&= \frac{1}{\tau_\eta} \left[(\tau_z + w^2) \left(\frac{1}{2} \omega \tau_\zeta \sqrt{\tau_\eta} - \alpha \tau_\eta \right) - (\tau_z + w^2) (\omega \tau_\zeta \sqrt{\tau_\eta} - \alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)) \right]
\end{aligned}$$

at the solution w . It is negative if and only if

$$\omega > \frac{2\alpha(\tau_\epsilon + \tau_\zeta + \tau_\theta)}{\tau_\zeta \sqrt{\tau_\eta}}.$$

This condition is equivalent to the left-hand side of (B.121) being negative for $\omega = \frac{2\alpha(\tau_\epsilon + \tau_\zeta + \tau_\theta)}{\tau_\zeta \sqrt{\tau_\eta}}$.

We can write the latter condition as

$$[\tau_\zeta^2 \tau_\eta \tau_z + 4\alpha^2(\tau_\epsilon + \tau_\zeta + \tau_\theta)^2] (\tau_\epsilon + \tau_\zeta + \tau_\theta - \tau_\eta) - (N-1)\tau_\zeta^2 \tau_\eta^2 \tau_z < 0. \quad (\text{B.123})$$

The left-hand side of (B.123) is a quadratic function of τ_η that is positive for $\tau_\eta = 0$ and goes to $-\infty$ when τ_η goes to ∞ . Therefore, there exists a unique $\tau_\eta^* > 0$ such that (B.123) holds for $\tau_\eta > \tau_\eta^*$ and the opposite inequality holds for $\tau_\eta < \tau_\eta^*$. Volume and ω are thus decreasing in τ_η for $\tau_\eta < \tau_\eta^*$ and increasing in τ_η for $\tau_\eta > \tau_\eta^*$, i.e., are inverse hump-shaped in τ_η .

We next determine expected trading volume when all traders are fully cursed. Substituting p from (39) into (B.13), and using symmetry and $\chi_i = 1$, we can write the quantity that trader i trades in equilibrium as

$$x_i = \frac{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)}{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)} \left(\sum_{j=1}^N a_{ij} s_j + b_i s + \sum_{j=1}^N c_{ij} z_j \right), \quad (\text{B.124})$$

where

$$a_{ii} \equiv \frac{\tau_\eta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - A, \quad (\text{B.125})$$

$$a_{ij} \equiv -A \quad \text{for } j \neq i, \quad (\text{B.126})$$

$$b_i \equiv \frac{\tau_\theta}{\tau_\epsilon + \tau_\eta + \tau_\theta} - B, \quad (\text{B.127})$$

$$c_{ii} \equiv C - \frac{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)}{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)}, \quad (\text{B.128})$$

$$c_{ij} \equiv C \quad \text{for } j \neq i. \quad (\text{B.129})$$

Proceeding as in the proof of Proposition (6), we find

$$E(|x_i|) = \frac{\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)}{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)} \sqrt{\frac{2}{\pi} \left[\left(\sum_{j=1}^N a_{ij} + b_i \right)^2 \sigma_\epsilon^2 + \sum_{j=1}^N a_{ij}^2 \sigma_\eta^2 + b_i^2 \sigma_\theta^2 + \sum_{j=1}^N c_{ij}^2 \sigma_z^2 \right]}. \quad (\text{B.130})$$

Substituting (A, B, C) from (B.107)-(B.109) for $\tau_z = 0$ into (B.125)-(B.129), we find

$$\begin{aligned}
a_{ii} &= \frac{(N-1)\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)}, \\
a_{ij} &= -\frac{\tau_\eta}{N(\tau_\epsilon + \tau_\eta + \tau_\theta)} \quad \text{for } j \neq i, \\
b_i &= 0, \\
c_{ii} &= -\frac{(N-1)\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)}{N\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)}, \\
c_{ij} &= \frac{\alpha(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)}{N\tau_\zeta(\tau_\epsilon + \tau_\eta + \tau_\theta)} \quad \text{for } j \neq i, \\
\sum_{j=1}^N a_{ij} + b_i &= 0.
\end{aligned}$$

Substituting into (B.130), we find

$$E(|x_i|) = \sqrt{\frac{2(N-1)}{\pi N} \left(\frac{\tau_\zeta^2 \tau_\eta}{\alpha^2(\tau_\epsilon + \tau_\zeta + \tau_\eta + \tau_\theta)^2} + \frac{1}{\tau_z} \right)}. \quad (\text{B.131})$$

The square of the right-hand side of (B.131) is equal to its counterpart without endowment shocks (the square of the right-hand side of (23)) plus a constant. Therefore, (B.131) is increasing in N and is hump-shaped in τ_η . ■

Proof of Proposition 15. We first determine traders' demand functions assuming that the price takes the form (44). The information I_i of trader i consists of his private signal s_i , the public signal s , and the signal $\epsilon + \xi_i$ that is revealed from the price. Since all private signals enter the price with the same coefficient, (9) implies that

$$\epsilon + \xi_i = \frac{\sum_{j \neq i} s_j}{N-1} \Rightarrow \xi_i = \frac{\sum_{j \neq i} \eta_j}{N-1}. \quad (\text{B.132})$$

To compute the distribution of ϵ conditional on I_i , we use Lemma B.1 with $x = \epsilon$, $K = 3$, $\{y_j\}_{j=1,2,3} = (\eta_i, \eta, \xi_i)$, and trader i 's assessments of precision. Combining with (B.7) and (B.8), and setting $(\chi_i, I_{ir}) = (0, I_i)$ in (8), we can write the demand of trader i as

$$x_i = \frac{\bar{d} + \frac{\kappa\tau_\eta}{\tau_\epsilon + \kappa\tau_\eta + \tau_\theta + (N-1)\gamma\tau_\eta} s_i + \frac{\tau_\theta}{\tau_\epsilon + \kappa\tau_\eta + \tau_\theta + (N-1)\gamma\tau_\eta} s + \frac{(N-1)\gamma\tau_\eta}{\tau_\epsilon + \kappa\tau_\eta + \tau_\theta + (N-1)\gamma\tau_\eta} (\epsilon + \xi_i) - p}{\alpha \left(\frac{1}{\tau_\epsilon + \kappa\tau_\eta + \tau_\theta + (N-1)\gamma\tau_\eta} + \frac{1}{\tau_\zeta} \right)}. \quad (\text{B.133})$$

We next substitute (B.133) into the market-clearing condition (5), substituting also p from (44) and $\epsilon + \xi_i$ from (B.132). This yields an equation that is linear in $\left(\sum_{i=1}^N s_i, s\right)$. Identifying terms in $\sum_{i=1}^N s_i$ and s yields (45) and (46), respectively. The comparative statics of A and B follow from (45) and (46). ■

Proof of Proposition 16. Substituting p from (44) into (B.133) and using (45), (46) and (B.132), we can write the quantity that trader i trades in equilibrium as

$$x_i = \frac{\tau_\zeta}{\alpha [\tau_\epsilon + \tau_\zeta + [(N-1)\gamma + \kappa]\tau_\eta + \tau_\theta]} \sum_{j=1}^N a_{ij} s_j, \quad (\text{B.134})$$

where

$$a_{ii} \equiv \frac{N-1}{N}(\kappa - \gamma)\tau_\eta, \quad (\text{B.135})$$

$$a_{ij} \equiv -\frac{1}{N}(\kappa - \gamma)\tau_\eta \quad \text{for } j \neq i. \quad (\text{B.136})$$

Proceeding as in the proof of Proposition (6), we find

$$E(|x_i|) = \frac{\tau_\zeta}{\alpha [\tau_\epsilon + \tau_\zeta + [(N-1)\gamma + \kappa]\tau_\eta + \tau_\theta]} \sqrt{\frac{2}{\pi} \left[\left(\sum_{j=1}^N a_{ij} \right)^2 \sigma_\epsilon^2 + \sum_{j=1}^N a_{ij}^2 \sigma_\eta^2 \right]}. \quad (\text{B.137})$$

Substituting $\{a_{ij}\}_{j=1,\dots,N}$ from (B.135) and (B.136) into (B.137), we find (47). The asymptotic behavior of $E(|x_i|)$ and of aggregate volume $NE(|x_i|)$ follows from (B.137). ■

Proof of Proposition 17. The proposition follows by setting $\gamma = 0$ in (47) since full cursedness is equivalent to extreme dismissiveness. ■