

Quants, Strategic Speculation, and Financial Market Quality

George Malikov and Paolo Pasquariello^{*}

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Abstract

We study the effects of quantitative investing, an increasingly popular investment style, on financial market quality. Within a model of strategic speculation with two differentially informed traders, we define discretionary investing as fully strategic and quantitative investing as partially or fully committed to a backtested trading strategy. We show that growth in quantitative investing (modeled as greater backtest adherence) may have significant effects on financial market quality, generally worsening (improving) it when leading to less (more) aggressive trading than discretion — especially when endowed with less (more) precise information.

^{*}George Malikov is at the University of Western Ontario, Ivey Business School. Author's email: gmalikov@ivey.ca. Paolo Pasquariello is at the University of Michigan, Stephen M. Ross School of Business. Author's email: ppasquar@umich.edu. We thank Snehal Banerjee, Thomas Barkley (discussant), Walid Busaba, Craig Dunbar, Steven Foerster, David Miller, Greg Miller, Saurin Patel, Amiyatosh Purnanandam, Uday Rajan, Shyam Venkatesan, Junyuan Zou (discussant), and participants at the Tenth Erasmus Liquidity Conference, Cardiff Fintech Conference, Financial Management Association Annual Meeting, University of Western Ontario, and University of Michigan for their helpful comments.

1 Introduction

Over the last few decades, quantitative investing has become increasingly popular in financial markets. Quantitative investing takes many forms, from high frequency algorithmic market-making to fundamentally-oriented quantitative strategies. Of particular note is the rapid growth of quantitative (“quant”) investing within the active equity investment management sector. While such strategies were previously available primarily through hedge funds to select clients, they are now gaining wider prominence and are being offered to ordinary investors through traditional mutual funds and ETFs (see Abis (2022); Beggs and Hill-Kleespie (2025)).¹ In addition, greater data availability and higher computer processing capacity are leading to an institutional push to incorporate systematic approaches within the more traditional discretionary strategies.² Despite these trends, the potential effects of quant investing on the process of price formation in the affected financial markets are ex-ante unclear. Quantitative strategies are generally based on analytically-disciplined trading rules. Such trading discipline yields both benefits, via greater investment rigor and breadth of coverage, and drawbacks, via strategy-crowding and commitment that may be exploited by other market participants.³ The goal of this study is to develop a theoretical framework for exploring the strategic interaction between humans and machines in the financial markets and the implications of greater fund automation for their quality.

In brief, our model of price formation features both quantitative investors (“quants”) – who rely on historical data to maximize profits under the assumption that other market participants do not internalize their presence – as well as more traditional, “discretionary” investors – who trade strategically against those quants to potentially exploit their commitment. In this setting, we capture growth in quant investing as the greater reliance on quantitative strategies by a subset of market participants, as they transition from fully-strategic to fully-quantitative investing. Our key finding is that the effect of quantitative investing on financial market quality is dictated by the relative trading intensity of a fully-strategic versus a fully-quantitative strategy. A more-aggressive quant enhances financial market quality via greater information revelation and improved liquidity, while a less-aggressive quant mitigates both as the discretionary investors are able to exploit the quant’s commitment. Importantly, our analysis also shows that those effects take place even in the presence of

¹Additionally, the interaction between discretionary and quantitative investing in delegated portfolio management is studied in Harvey et al. (2017) and Grobys et al. (2022) for hedge funds and in Evans et al. (2023) for separately managed accounts.

²See, e.g., Lin (2019); Morgan Stanley Research (2017); Morgan Stanley Investment Management (2018).

³Liaudinskas (2023) proposes a form of discipline by algorithmic traders that stems from their insensitivity to the disposition effect. Crowding is exemplified by the “quant quake” of August 2007 (e.g., Khandani and Lo (2007); Wigglesworth (2017)). Exploitable commitment is highlighted in Zweig (2020).

low such commitment (i.e., for any deviation by the quant from fully-strategic trading). We believe these results shed a novel, important light on the externalities of increasingly sophisticated investment strategies for the functioning of financial markets.

Model summary. Our model structure is based on the notion that many fundamentally-oriented quantitative investment strategies are based on backtests. Backtesting conventionally refers to the development and validation of any trading strategy — from those relying on technical and regression analysis to others relying on the use of large amounts of information (“Big Data”) and sophisticated artificial intelligence and machine learning techniques — with historical data realized prior to its actual implementation in the marketplace (e.g., Becker and Reinganum (2017); Huang et al. (2024)). Thus, a defining characteristic of backtested strategies is their reliance on historical data to identify a signal which is predictive of future risk-adjusted returns. The investor then uses this estimation to translate a real-time signal into a trading rule. An attractive aspect of this approach is its inherent discipline: the trading rule is not as susceptible to human emotion due to its automated nature. However, this greater discipline comes at a cost. Precisely because the trading strategy relies on historical data, it cannot take into account the effect that the implementation of the strategy can have on other market participants. For example, if other fundamental investors expect the machines to receive a noisy signal, they may trade against them to take advantage of the potential mispricing. It is this inherent commitment of backtested strategies that we focus on as the primary differentiator between quantitative and discretionary investing.

Accordingly, the effects of quantitative investing on financial market quality can be twofold. On the one hand, incremental informed speculators are entering the market. On the other hand, those speculators adhere to quantitative strategies committed to a trading rule by definition. We build on the canonical strategic speculator framework of Kyle (1985) to jointly model the growth in the number of speculators in the financial markets as well as their potential pursuit of quantitative investing. First, we use Kyle’s economy with a single imperfectly informed speculator as the economy before quantitative investing: the “Training Economy.” In this baseline setting, we label the single speculator as the discretionary investor (“DI”), since his fully-strategic trading strategy is meant to resemble the trading strategies of the more traditional fundamental equity investment funds. Importantly, the Training Economy also serves as the backtesting environment for the quantitative investor (“QI”) — she uses the data generating process from this economy to build a profit-maximizing strategy, “the backtest,” under the assumption that the other market participants are not aware of her existence. This is the key assumption of the model, for it captures the notion of exploitable commitment inherent in quantitative strategies: by definition, the backtest

ignores the strategic response of the discretionary investor and the market maker to the trading strategy of the quant, since that strategy is trained in an environment where the quant herself was previously absent – as it would plausibly be for any aggregate incremental quant investing in the marketplace at any point in time.

Next, we introduce a second differentially informed speculator, the QI, to the market: the “Quantitative Economy.” The QI has a range of strategies available to her, from fully-strategic trading as in the Kyle framework, to partial or full reliance on the backtested strategy. The QI’s objective function is a weighted average of the fully-strategic approach and the backtest, with growth in quant parametrized as a greater weight placed on the latter. This modeling device has been extensively used in the literature on rational deviations from optimal speculation to capture central bank interventions in various financial markets (e.g., Bhattacharya and Weller (1997); Vitale (1999); Pedersen (2018); Pasquariello et al. (2020)) or speculative short-termism (e.g., Pasquariello and Vega (2009); Bhattacharyya and Nanda (2013); Pasquariello and Wang (2024)), among others. In our model, this stylized representation is meant to parsimoniously capture in reduced form unmodeled pecuniary and non-pecuniary benefits of committing, in full or in part, to quantitative trading strategies (e.g., greater fund flows or lower agency costs).

Finally, we also consider the limiting case in which the QI is fully strategic (as the DI): the “Strategic Economy.” This is the standard multi-speculator strategic trading setting akin to Foster and Viswanathan (1996). This allows us to extract exact theoretical implications of quantitative investing on market quality by comparing the equilibrium properties of the Quantitative Economy with full reliance on the backtest by the QI to those of the Strategic Economy. Otherwise, we investigate numerically the effects of partial automation, by increasing the reliance by the QI on the backtest in the Quantitative Economy.⁴

Main model predictions. Our primary finding is that the direction of the effect of greater automation by the quantitative investor on key dimensions of financial market quality (liquidity and informativeness) is determined by the sign of the wedge between the trading intensity of the fully-automated (i.e., fully reliant on the backtest) and the fully-discretionary QI. The sign of the wedge acts as a sufficient statistic for the net effect of the three primary parameters in the model: information precision of the DI, information precision of the QI, and the error correlation of their signals. A positive wedge – i.e., when the backtest is more aggressive than strategic trading – broadly improves market quality. Intuitively, greater automation

⁴The comparison of the equilibrium properties of economies with and without certain salient features of the financial markets to tease out their effects on equilibrium aggregates of interest is common in the literature on delegated portfolio management; for recent examples, see Basak and Pavlova (2013), Cong and Xu (2016), and Bhattacharya and O’Hara (2018), among others.

leads to greater expected trading volume by the quant, generally acts as a deterrent from more trading by the discretionary investor (as he becomes concerned about excess information slippage). This ultimately results in a net increase in the expected trading volume for the speculative sector as a whole. Since this net increase is driven by the trading behavior of a QI who adheres less and less to a profit-maximizing strategy, profits for the speculator sector decrease while price informativeness and market depth increase. However, a negative wedge between full automation and full discretion implies that the quant trades less aggressively with greater backtest adherence. Less aggressive trading creates opportunity for the discretionary investor to trade more aggressively at the expense of the quant. As such, the DI trades more in the presence of greater automation by the QI and makes greater profits, which more than offsets the declining profits for the quant. This ultimately results in lower trading volume and greater profits for the speculative sector as a whole. Market quality suffers as market depth and price informativeness fall.

We are able to theoretically characterize the determinants of the sign of the trading intensity wedge, which in turn directly maps to market quality outcomes. We first consider relatively uninformed discretionary investors trading against quants. When they disagree about asset fundamentals (i.e., when their signal errors are either uncorrelated or negatively correlated: “disagreement”), greater automation by the quant leads to improvements in market quality regardless of the quant’s signal precision. When they instead agree about asset fundamentals (i.e., when their signal errors are positively correlated: “agreement”), the effect of automation is ambiguous, although the probability of improvement in market quality increases in the quant’s signal precision. The presence of a quant with a significant information advantage trading against a relatively uninformed discretionary investor leads to definitive improvements in market quality.

Finally, we consider the case when a relatively informed discretionary investor trades against a quant. With agreement, the quant’s automation always hurts market quality since the DI is able to exploit the quant’s commitment and his information to his advantage. In the case of disagreement, the effect of quantitative investing is uncertain. However, the likelihood of deterioration in market quality is always rising in the quant’s information quality. In particular, the trading activity of highly informed quants trading against highly informed discretionary investors unambiguously hurts market quality since, yet again, the DI exploits the quant’s reliance on the backtest to his advantage.

Model interpretation of stylized facts. Our theoretical predictions provide a novel, intriguing interpretation for several key findings in the extant empirical literature on quant vs. discretionary investing. For instance, Abis (2022) finds that discretionary investors display

higher macro-timing and lower stock-picking ability than quants during recessions.⁵ To the extent that recessions coincide with disagreement, this result is consistent with relatively informed (uninformed) DIs betting against quants on market indices (individual stocks) and profiting (losing), ultimately negatively (positively) affecting aggregate (stock-specific) market quality.⁶

Beggs and Hill-Kleespie (2025) focus specifically on the market quality effects of quantitative investing and suggest that fire sales by quant funds cause greater market instability than fire sales by discretionary investors. To the extent that fire sales are caused by poor fund performance, one may conjecture that such funds possess signals with low information precision. Within our model, market quality is more likely to deteriorate when discretionary funds trade against relatively uninformed quant funds as opposed to quants trading against relatively uninformed DIs. Therefore, the likelihood of market instability is greater for trading initiated by relatively uninformed quant funds, which are the funds more likely to experience fire sales. While the link between the present framework and the existing empirical studies is not exact, our model can serve as a guide for future studies exploring the effects of quantitative investing on financial market quality.

Especially relevant to professional portfolio managers is the natural consequence of our model that quantitative strategies are more likely to be successful when their implementation positively affects market quality. Albeit stylized, backtesting in our model captures the dynamic notion of the quant’s reliance on historical data to build a profit-maximizing strategy. Ultimately, any backtested strategy has a greater chance of success when its trading wedge is positive. This is more likely to occur in the presence of speculative disagreement (e.g., during turbulent economic conditions), improving information quality for quants trading against relatively uninformed traditional investors (e.g., during technological advancements in opaque markets), or declining information quality for quants trading against relatively informed fundamental investors (e.g., when data is abundant in transparent markets). Hence, our model may provide guidance for identifying those market conditions that are more conducive to quantitative strategies.

Related literature. Overall, our results contribute to an important theoretical literature on price formation in the financial markets. Holden and Subrahmanyam (1992) show how aggressive competition among perfectly informed speculators may lead to speedy incorpora-

⁵However, Abis (2022) attributes this finding to an alternative theoretical mechanism based on differential rational inattention between quants and discretionary investors when learning about idiosyncratic versus systematic shocks.

⁶Relatedly, Dyer et al. (2025) demonstrate that quant funds underperform discretionary funds after the implementation of new accounting standards. The results can be mapped to our framework as a decline in quants’ signal quality, which may increase the likelihood of a decline in market quality and quant performance.

tion of information into prices (the “rat race”). Foster and Viswanathan (1996) demonstrate that under imperfect information and signals with sufficiently low correlation, the “rat race” may occur only initially, while less aggressive trading, i.e., a “waiting game,” may emerge in later rounds of trading. While our framework is static in nature, we capture both the “waiting game” and the “rat race” outcomes via the single-period trading intensity of the speculators in our game. Importantly, we allow for differential information quality, which interacts with signal correlation to dictate market quality outcomes.

Most literature on quantitative investing has focused on the effects of high frequency trading on market liquidity and price discovery. As pointed out by Kirilenko and Lo (2013), greater automation implies a key trade-off. On the one hand, algorithmic trading lacks human emotion, potentially leading to greater market stability. On the other hand, quantitative investing may be more highly correlated among funds, resulting in greater market instability. The theoretical literature exploring the interaction of quant and discretionary investing is nascent. To our knowledge, only Abis (2022) and Dugast and Foucault (2025) investigate this question. The former develops a theoretical framework for exploring the trading behavior of quantitative versus discretionary funds. Abis (2022) extends the mutual fund attention allocation model of Kacperczyk et al. (2016) to introduce quantitative investors as those who have unlimited learning capacity only in idiosyncratic shocks.⁷ The latter studies a single asset market, within which discretionary investors are assumed to have pre-determined information precision while quants are allowed to search for an optimal signal at a cost, in order to differentiate between lower information processing costs and greater data availability. Importantly, in both studies investors are competitive rather than strategic. We complement these approaches by allowing for strategic trading, a realistic feature of most financial markets, while abstracting from systematic versus idiosyncratic learning capacity or more advanced information production.

Lastly, several studies, including Khandani and Lo (2007), Khandani and Lo (2011), and Beggs and Hill-Kleespie (2025), have documented the fact that quantitative funds, whether hedge funds or mutual funds, tend to ignore the behavior of others, consistent with our model’s predictions, resulting in violent reversals in periods of unwinding. Many have shown that algorithmic trading, in particular high frequency trading, leads to improv-

⁷Relatedly, Davis (2025) shows that the presence of atomistic quantitative learners, defined as price-taking investors trading on the basis of canonical stochastic discount factor (SDF) models, may lead to higher CAPM alphas (as proxies for mispricing) in counterfactual experiments based on popular factor models in the literature. Both Colliard et al. (2026) and Dou et al. (2025) study equilibrium collusion when, respectively, market-makers or informed speculators rely on machine-learning algorithms to set prices or trade. The former incorporate machine learning by market-makers within an otherwise standard model of trading with asymmetric information based on Glosten and Milgrom (1985), while the latter introduce AI-powered speculators to the Kyle (1985) framework.

ing price efficiency and liquidity (e.g., Hendershott et al. (2011), Hendershott and Riordan (2013), Brogaard et al. (2014), Zhang (2018), and Chakrabarty et al. (2021)), although acquisition of new information may deteriorate (Weller (2018)).

2 Model

Our analysis considers two settings based on the Kyle (1985) framework: 1) the single-trader Training Economy, which is based on a single-period variant of the Kyle model, and 2) the multi-trader Quantitative Economy, which is a single-period version of Foster and Viswanathan (1996) with several key modifications discussed below. Both settings feature two assets: a risky asset and a risk-free asset with interest rate normalized to zero. The risky asset pays off a terminal value of $v \sim N(0, \tau_v^{-1})$ at the end of the period and has an endogenously determined price P . The model features a strategic trader (“DI” for discretionary investor, he) and a quantitative trader (“QI” or “quant” for quantitatively-capable investor, she), indexed by $i \in \{d, q\}$. Each trader i observes a private signal of the form:

$$s_i = v + e_i, \text{ where } e_i \sim N(0, \tau_i^{-1}), \quad (1)$$

and submits market order x_i . The Training Economy only includes the discretionary investor, while the Quantitative Economy includes both the QI and the DI. In both settings the DI is a standard strategic speculator, maximizing expected profits:

$$\mathbb{E}[x_d(v - P) | s_d]. \quad (2)$$

The quant, however, maximizes the following objective:

$$\mathbb{E}[\underbrace{-\gamma(x_q - x_b)^2}_{\text{backtest}} + \underbrace{(1 - \gamma)x_q(v - P)}_{\text{strategic speculation}} | s_q], \quad (3)$$

where $0 < \gamma \leq 1$ parametrizes the extent of reliance on the backtested strategy x_b . The backtested strategy, introduced in greater detail below, maximizes profits in the Training Economy under the assumption that the other market participants are not aware of the QI’s existence. As $\gamma \rightarrow 0$, the Quantitative Economy simplifies to a standard multi-speculator strategic trading benchmark: we term this limiting setting the Strategic Economy.

All economies feature noise traders, whose demands for the risky asset are exoge-

nously determined by $z \sim N(0, \tau_z^{-1})$, and a competitive risk-neutral market maker (“MM”), who observes aggregate order flow $\omega = x_d + x_q + z$ ($x_q = 0$ in the Training Economy) and sets the price to break even in expectation

$$P(\omega) = \mathbb{E}[v|\omega]. \quad (4)$$

We assume that v , z , e_i , where $i \in \{d, q\}$, are mutually independent, however, we allow for signal error covariance, $\mathbb{C}(e_d, e_q) = \sigma_e$. We restrict our attention to linear equilibria in which (i) the equilibrium trade by investor i is given by $x_i = \beta_i s_i$, and (ii) the market maker’s pricing rule is linear in the order flow: $P = \lambda\omega$. In what follows, $\phi_i = \tau_i/(\tau_v + \tau_i)$ is a measure of traders’ information quality, $\rho_e = \sigma_e\sqrt{\tau_d\tau_q}$ is the signal error correlation, and $\eta = \tau_v/\tau_z$ as a normalized measure of noise trading volatility.

2.1 Discussion of assumptions

Our goal is to study the implications of the growth in quantitative investing on financial market quality in a setting that deviates minimally from Kyle (1985). We take the view that traditional, non-quant, investors trade akin to the Kyle insider. The investor is strategic in that he accounts for the expected effect of his order on the price set by the market maker as well as the information revealed by his signal about the expected trading behavior of the quantitative investor. Within our framework, we model discretionary behavior as an investor’s ability to take into account the expected behavior of others in the market when developing a trading strategy. A quant, in contrast, lacks this ability either fully or partially.

Specifically, the quant investor develops a profit-maximizing trading rule under the assumption that both the discretionary investor and the market maker are unaware of her existence. This approach originates from the notion that many quantitative strategies are based on backtested signals, which by definition take as given the historical behavior of market participants in a past when those strategies were of course absent. In other words, when developing trading strategies based on historical market data, quant traders are not able to incorporate the effect that their *presence* may have had on the strategic trading behavior of other market participants present at the time.⁸ Even if the effects of other quantitative trading were present in historical data, any incremental trading due to new or modified strategies by incumbent or entrant quants would not be reflected in the backtest. As such, our model captures parsimoniously the notion that at any point in time there would always be at least some quants whose strategies are in aggregate only partially accounted for

⁸This concept is known within the macroeconomics literature as the “Lucas Critique” (Lucas (1976))

by the rest of the market, hence based on past backtesting that did not fully include them.

We model the potentially exploitable commitment of the quantitative investor in a reduced form. Eq. (3) is based on the observation that a quant’s welfare is at least partially determined by her adherence to a backtested, potentially well-known, trading approach (x_b). The degree of adherence, or “automation,” is parametrized by γ . As we discuss further next, such behavior may be explained by marketing reasons, and the related greater investing discipline and transparency. For example, quantitative fund strategies are less-likely to be affected by human emotion, and the associated discipline may appeal to investors thereby generating greater fund flows. Furthermore, the adherence to a particular well-known strategy may reduce the moral hazard issues associated with delegated portfolio management.

It is important to emphasize that human judgment continues to play an important role in quantitative strategies. From the choice of investment strategy to its real-world implementation, human decisions are at the core of launching and maintaining the operations of quant funds. Quants may very well be strategic in their trading via, e.g., “feeler orders” to test market liquidity, scaling and turning strategies on and off depending on market conditions, and attending industry conferences to interact with other quant fund managers to understand the behavior of others. We model this “discretionary” aspect of quantitative investing in a reduced form via a positive loading $1 - \gamma$ of the strategy on the traditional profit maximization objective of the Kyle insider.

An immediate consequence of Eq. (3) is that the quant is not maximizing her profits. As also noted in the Introduction, this modeling approach is common in the literature on rational deviations from purely speculative motives (e.g., Vitale (1999); Bhattacharyya and Nanda (2013); Pedersen (2018)). Implicit in this assumption are certain unmodeled gains that may arise due to the pursuit of a quantitative versus a discretionary strategy. For example, the lower reliance on human judgment may lower the risk of moral hazard, thereby reducing agency frictions. Furthermore, adherence to a very specific strategy may cater to a particular set of investors, thereby attracting greater fund flows. Lastly, quantitative strategies may have a greater breadth due to their reliance on computing power, thereby potentially allocating to a much higher number of securities. The resulting benefits to diversification, although absent from the model, may also be captured by the backtested trading strategy.

Exogenous parameterizations of γ in Eq. (3) also capture in reduced form the average reliance on quantitative strategies among professional investors as it is observed in the marketplace. Such reliance is often overt and its potential benefits are often openly publicized, e.g., in funds’ own marketing materials (Abis (2022) and Beggs and Hill-Kleespie

(2025) provide numerous examples of such disclosures) — consistent with the assumption, conventional in the aforementioned literature, that quant investors’ exogenous adherence coefficient γ is known to all market participants. In addition, if rational (as in our setting), all market participants would always be able to correctly infer any ex-ante optimal γ selected by quant investors, i.e., even if it was not otherwise known to them. Accordingly, Eq. (3) allows us to capture those unmodeled incentives to commit (in full or in part) to such a strategy in a parsimonious and analytically convenient fashion.⁹

Besides strategic considerations, quantitative and discretionary investors plausibly rely on information of varying quality and correlation. Smart-beta funds may rely exclusively on historical accounting and market data, while sophisticated hedge funds may incorporate alternative data sources for developing precise financial forecasts. Similarly, discretionary funds may rely solely on sell-side ratings and projections, or develop their own financial forecasts, interact with corporate management teams to extract greater information from historical trends, and incorporate alternative data into their financial models. Furthermore, the reliance on historical data for projections may work well during stable economic conditions but become unreliable during periods of elevated economic uncertainty. We capture such considerations by allowing for both differential information quality (i.e., $\phi_d, \phi_q \in (0, 1]$) and signal error correlation (i.e., $\rho_e \in [-1, 1]$).

Finally, while *prima facie* static, the Training and Quantitative Economies allow us to introduce the notion of quantitative investing as a backtested strategy based on the “past” Training Economy and to differentiate between the effects of incremental informed speculation and adherence to quantitative strategies in the “subsequent” Quantitative Economy. As such, this setting naturally and parsimoniously captures the dynamic notion of a quantitative investor developing a backtested trading strategy — i.e., one assessed from historical data prior to her entering the market, when her presence could not have been accounted for by all other market participants.

3 Analysis

In what follows we first introduce the quant’s backtest derived from the Training Economy. We then explore theoretically the effects of quantitative investing in two settings: (1) the discretionary investor has perfect information: $\phi_d = 1$, and (2) the quant has perfect in-

⁹Allowing for multiple, possibly heterogeneously informed speculators (e.g., Foster and Viswanathan (1996); Pasquariello and Vega (2007); Pasquariello and Vega (2009)) and / or quantitative investors would considerably complicate the analysis that follows without materially affecting its main insights.

formation: $\phi_q = 1$. In both settings we identify the implications of quantitative investing by comparing the Strategic Equilibrium ($\gamma = 0$, i.e., in its absence) to the Quantitative Equilibrium ($\gamma = 1$, i.e., in its full presence). Finally, we explore numerically the market quality implications of intermediate adherence to the backtest ($0 < \gamma < 1$, i.e., increasing automation) with imperfect information and error correlation for both traders.

3.1 The Training Economy and the Quant's Backtest

The Training Economy is one in which a single informed speculator (DI) trades strategically to minimize information slippage and maximize profits. This is the traditional Kyle (1985) framework, with the sole difference that the informed speculator observes a noisy signal $s_d = v + e_d$ about the risky asset payoff. The DI maximizes the following objective

$$\mathbb{E}[x_{d,TE}(v - P_{TE}(x_{d,TE} + z)) | s_d] = x_{d,TE}\mathbb{E}[v | s_d] - \lambda_{TE}x_{d,TE}^2, \quad (5)$$

where the price is based on the above conjecture for the market maker's pricing rule. This leads to the following optimal strategy

$$x_{d,TE} = \frac{1}{2\lambda_{TE}}\mathbb{E}[v | s_d] = \frac{1}{2\lambda_{TE}}\phi_d s_d \equiv \beta_{d,TE}s_d. \quad (6)$$

The market maker solves Eq. (4) with $\omega = x_{d,TE} + z$,

$$\lambda_{TE} = \frac{\mathbb{C}(v, \omega)}{\mathbb{V}(\omega)} = \frac{\beta_{d,TE}}{\beta_{d,TE}^2/\phi_d + \eta}, \quad (7)$$

resulting in linear demand, $x_{d,TE} = \beta_{d,TE}s_d$, and price, $P_{TE} = \lambda_{TE}\omega$, functions. Importantly, as described below, the quant is absent by definition from this market, but can observe its realizations in a repeated games sense and, with a sufficiently long dataset, can back out the DI's demand function and the MM's pricing rule. The QI can then develop a profit maximizing strategy under the assumption that the DI and the MM are not aware of her existence by maximizing

$$\mathbb{E}[x_b(v - P_{TE}(x_{d,TE} + z + x_b)) | s_q] = x_b(\mathbb{E}[v | s_q] - \lambda_{TE}\mathbb{E}[x_{d,TE} | s_q]) - \lambda_{TE}x_b^2, \quad (8)$$

which, since $\mathbb{E}[x_{d,TE} | s_q] = \beta_{d,TE}\mathbb{E}[s_d | s_q] = \beta_{d,TE}(\phi_q + \phi_q\tau_v\sigma_e)s_q$, implies that

$$x_b = \frac{\phi_q - \lambda_{TE}\beta_{d,TE}(\phi_q + \phi_q\tau_v\sigma_e)}{2\lambda_{TE}}s_q \equiv \beta_b s_q. \quad (9)$$

Solving the above system of equations for $\{\beta_{d,TE}, \lambda_{TE}\}$ and the backtested strategy, gives us the following result.

Proposition 1. *With a single informed speculator, there exists a unique, linear equilibrium with $x_{d,TE} = \beta_{d,TE}s_d$ and $P_{TE} = \lambda_{TE}\omega$ where*

$$\beta_{d,TE} = \sqrt{\phi_d \eta} \text{ and } \lambda_{TE} = \frac{1}{2} \sqrt{\frac{\phi_d}{\eta}}. \quad (10)$$

Moreover, there exists a unique, linear profit-maximizing strategy for the quant, $x_b = \beta_b s_q$, under the assumption that the DI and MM are not aware of her existence, where

$$\beta_b = \frac{\phi_q}{2} \sqrt{\frac{\eta}{\phi_d}} (2 - \phi_d \sigma_e \tau_v - \phi_d), \quad (11)$$

and expected profits π_b , given by,

$$\pi_b = \mathbb{E}[x_b(v - P_{TE})] = \frac{\phi_q}{8} \sqrt{\frac{\eta}{\phi_d}} \tau_v (\phi_d \sigma_e \tau_v + \phi_d - 2)^2, \quad (12)$$

are positive as long as the backtested trading intensity is non-zero, i.e., $\sigma_e \neq \tau_v^{-1} + 2\tau_d^{-1}$.

As canonical in Kyle (1985) settings, the DI is more aggressive in trading on his signal with more noise trading, a more precise signal, and a greater expected payoff. The MM sets prices such that the expected profits from providing liquidity to the noise traders exactly offset the expected losses from trading against the DI. Therefore, equilibrium price impact, as measured by $\lambda_{TE} = \frac{\sqrt{\phi_d}}{2\sqrt{\eta}}$, is increasing in signal quality and is decreasing in the relative amount of noise trading. Both are driven by the market maker's reaction to adverse selection: the more precise the DI's information or the greater the likelihood of informed trading, the more sensitive is the price to order flow.

Similar to the DI's trading strategy, the QI's backtest trades more aggressively with a more precise signal, more noise trading, and a greater expected payoff. For negative and sufficiently low positive error covariance (i.e., when $\sigma_e < \tau_v^{-1} + 2\tau_d^{-1}$), the quant always buys more shares with greater expected payoff as she's less concerned about moving the price in the same direction as the DI. However, with high error covariance (i.e., when $\sigma_e > \tau_v^{-1} + 2\tau_d^{-1}$), the QI may trade against the DI since she becomes concerned about excess information slippage. Accordingly, the backtested strategy depends not only on the quant's signal precision and level of noise trading, but also on the DI's signal precision and the error covariance.

A defining characteristic of a backtested strategy is its reliance on historical data to

identify a signal, which is predictive of future risk-adjusted returns. The quant relies on the strategy to map a real-time signal to a trading rule, which is implemented in the financial markets. By relying on historical data to generate a signal, the quant cannot know how other market participants would have reacted in the past to her presence in the market. Even if similar strategies already existed in the market during the backtest, the quant's strategy would likely be incremental, implying that the backtest cannot fully capture the strategic behavior of other market participants by definition.

In our model, we focus on this willful yet potentially exploitable commitment to a backtested trading rule, as the primary friction associated with quantitative strategies. In particular, the objective function of Eq. (3) implies that the QI, albeit endowed with a private signal, builds her trading strategy as one based at least partly on the Training Economy in which other market participants are not aware of her existence. One can think of the Training Economy as years of past trading data used as the backtest into the quant's trading approach: from this data, the quant backs out the trading rule of the DI and the pricing strategy of the MM.

Specifically, the DI's trading strategy and a simple manipulation of the MM's pricing rule, Eq. (10), imply that:

$$P_{TE} = \frac{\phi_d}{2}v + \frac{\phi_d}{2}e_d + \frac{1}{2}\sqrt{\frac{\phi_d}{\eta}}z. \quad (13)$$

Let's assume that the Training Economy plays out over many periods, e.g., days, $t = 1, \dots, T$ and that in each day t the following data is recorded: $\{P_{TE,t}, \omega_t, v_t\}$, i.e., that the QI is able to observe historical prices, trading volume, and fundamentals. The quant can then take this data and run the following ordinary least squares regressions:

$$P_{TE,t} = a + b\omega_t + \varepsilon_t \text{ and } P_{TE,t} = c + dv_t + \epsilon_t. \quad (14)$$

By construction, $\varepsilon_t = 0 \perp \omega$ and $\epsilon_t = \frac{\phi_d}{2}e_d + \frac{1}{2}\sqrt{\frac{\phi_d}{\eta}}z \perp v$ implying that the QI obtains unbiased estimates for $a = c = 0$, $b = \frac{1}{2}\sqrt{\frac{\phi_d}{\eta}}$ and $d = \frac{\phi_d}{2}$. Assuming the QI has a sufficiently long data sample, she infers both the DI's signal precision ϕ_d and the normalized amount of noise trading η from the data. Together, these parameters allow her to identify the MM's pricing rule and the DI's trading strategy: we assume that the data sample is sufficiently long such that she obtains highly accurate estimates. This, in turn, allows her to construct an optimal, profit-maximizing strategy *under the assumption that the DI and MM are not aware of her existence*. As highlighted in Eq. (8), the QI's commitment to the backtest is

captured by her reliance on the MM's pricing function $P_{TE}(\omega)$ and the DI's demand $x_{d,TE}(s_d)$ from the Training Economy. Intuitively, the QI assumes that the MM treats her order flow as noise trading and the DI does not internalize the QI's presence.

3.2 Quantitative Economy

The Quantitative Economy introduces a second investor, the quant, who relies partially or fully on the backtested strategy x_b described in Section 3.1 above. The quant maximizes:

$$\mathbb{E}[-\gamma(x_q - x_b)^2 + (1 - \gamma)x_q(v - \lambda_\gamma(x_q + \beta_d s_d + z)) | s_q] \quad (15)$$

$$= -\gamma x_b^2 + x_q(2\gamma x_b + (1 - \gamma)(\mathbb{E}[v | s_q] - \lambda_\gamma \beta_d \mathbb{E}[s_d | s_q])) - x_q^2(\gamma + (1 - \gamma)\lambda_\gamma). \quad (16)$$

This implies that the quant's optimal trading strategy is given by

$$x_q = \frac{2\gamma x_b + (1 - \gamma)(\mathbb{E}[v | s_q] - \lambda_\gamma \beta_d \mathbb{E}[s_d | s_q])}{2(\gamma + (1 - \gamma)\lambda_\gamma)} \quad (17)$$

$$= \frac{2\gamma \beta_b + (1 - \gamma)\phi_q(1 - \lambda_\gamma \beta_d(1 + \sigma_e \tau_v))}{2(\gamma + (1 - \gamma)\lambda_\gamma)} s_q \equiv \beta_{q,\gamma} s_q. \quad (18)$$

Importantly, the setting allows other market participants to internalize the presence and the investment strategy of the quant. The discretionary investor now maximizes

$$\mathbb{E}[x_d(v - \lambda_\gamma(x_d + \beta_{q,\gamma} s_q + z)) | s_d] = x_d(\mathbb{E}[v | s_d] - \lambda_\gamma \beta_{q,\gamma} \mathbb{E}[s_q | s_d]) - \lambda_\gamma x_d^2, \quad (19)$$

resulting in an optimal demand of

$$x_d = \frac{\mathbb{E}[v | s_d] - \lambda_\gamma \beta_{q,\gamma} \mathbb{E}[s_q | s_d]}{2\lambda_\gamma} = \frac{\phi_d(1 - \lambda_\gamma \beta_{q,\gamma}(1 + \sigma_e \tau_v))}{2\lambda_\gamma} s_d \equiv \beta_d s_d. \quad (20)$$

The market maker's price impact function λ_γ is indexed by the level of the quant's automation γ , since he now also takes into account the quant's trading behavior:

$$\lambda_\gamma = \frac{\mathbb{C}(v, \omega)}{\mathbb{V}(\omega)} = \frac{\beta_d + \beta_{q,\gamma}}{(\beta_d + \beta_{q,\gamma})^2 + \beta_d^2(\phi_d^{-1} - 1) + \beta_{q,\gamma}^2(\phi_q^{-1} - 1) + 2\beta_d \beta_{q,\gamma} \sigma_e \tau_v + \eta}. \quad (21)$$

Note that the quant's trading intensity can be rewritten as

$$\beta_{q,\gamma} = \frac{\gamma}{\gamma + (1 - \gamma)\lambda_\gamma} \beta_b + \frac{(1 - \gamma)\lambda_\gamma}{\gamma + (1 - \gamma)\lambda_\gamma} \frac{\phi_q(1 - \lambda_\gamma \beta_d(1 + \sigma_e \tau_v))}{2\lambda_\gamma}, \quad (22)$$

emphasizing that a quant's trading strategy is an (endogenous) weighted average of the backtest β_b and the fully-strategic approach. As $\gamma \rightarrow 0$, the quant's limiting behavior becomes that of a strategic investor. If $\gamma = 1$ the quant relies exclusively on the backtest. Finally, for intermediate values of γ , the quant's trading strategy puts a percentage $w_b = \gamma/(\gamma + (1 - \gamma)\lambda_\gamma)$ on the backtest and $1 - w_b$ on profit maximization, under the assumption that other market participants internalize the level of automation γ .

To highlight the intuition of our model, we first focus on two theoretical benchmarks: (1) a perfectly-informed discretionary investor ($\phi_d = 1$), and (2) a perfectly-informed quant ($\phi_q = 1$); with fully-strategic or fully-quantitative behavior by the QI (i.e., $\gamma \in \{0, 1\}$).

3.2.1 Perfectly-informed DI

The first benchmark case assumes that the DI has perfect information ($\phi_d = 1$), hence that the quant has inferior information. This assumption is motivated by the observation that traditional fundamental investors may have superior access to fundamental information via corporate management meetings, industry and market expertise, and deep-dive fundamental analysis. Quants, on the other hand, may look at rough proxies for fundamental value, such as historical multiples or price trends, and bet that on average, across a large sample of securities, such proxies are indicative of future payoffs.¹⁰ Examples of such quant funds would be smart-beta exchange traded funds and statistical arbitrage strategies nested within hedge funds. The discretionary investor's optimization simplifies to:

$$x_d = \frac{1 - \lambda_\gamma \beta_{q,\gamma}}{2\lambda_\gamma} s_d \equiv \beta_{d,\gamma} s_d, \quad (23)$$

where $\gamma \in \{0, 1\}$. In the Strategic Equilibrium ($\gamma = 0$), the QI's behavior becomes fully-strategic:

$$x_q = \frac{\phi_q (1 - \lambda_\gamma \beta_{d,\gamma})}{2\lambda_\gamma} s_q \equiv \beta_{q,0} s_q, \quad (24)$$

while in the Quantitative Equilibrium with full-automation ($\gamma = 1$), she trades based on the backtest:

$$x_q = \beta_b s_q \equiv \beta_{q,1} s_q. \quad (25)$$

¹⁰ Accordingly, Abis (2022) finds that quant funds hold on average 37% more stocks than discretionary funds.

In both settings the market maker sets the price according to

$$\lambda_\gamma = \frac{\mathbb{C}(v, \omega)}{\mathbb{V}(\omega)} = \frac{\beta_{d,\gamma} + \beta_{q,\gamma}}{(\beta_{d,\gamma} + \beta_{q,\gamma})^2 + \beta_{q,\gamma}^2 (\phi_q^{-1} - 1) + \eta}. \quad (26)$$

Solving for the Strategic $\{\beta_{d,0}, \beta_{q,0}, \lambda_0\}$ and Quantitative $\{\beta_{d,1}, \beta_{q,1}, \lambda_1\}$ equilibria leads to the following result.

Proposition 2. *When the DI has perfect information, there exists a unique linear equilibrium in the Strategic Economy, where*

$$\beta_{d,0} = (2 - \phi_q) \sqrt{\frac{\eta}{(\phi_q - 3)\phi_q + 4}}, \beta_{q,0} = \phi_q \sqrt{\frac{\eta}{(\phi_q - 3)\phi_q + 4}}, \text{ and } \lambda_0 = \frac{\sqrt{\frac{(\phi_q - 3)\phi_q + 4}{\eta}}}{4 - \phi_q}, \quad (27)$$

and the Quantitative Economy, where

$$\beta_{d,1} = \frac{1}{4} \left(\sqrt{\eta(\phi_q(4 - 3\phi_q) + 16)} - \sqrt{\eta}\phi_q \right), \beta_{q,1} = \frac{\sqrt{\eta}\phi_q}{2}, \text{ and } \lambda_1 = \frac{2}{\sqrt{\eta(\phi_q(4 - 3\phi_q) + 16)}}. \quad (28)$$

Quantitative investing causes the QI to trade less-aggressively, $\beta_{q,1} < \beta_{q,0}$, leading to lower profits, $\pi_{q,1} < \pi_{q,0}$, which incentivizes the DI to trade more aggressively, $\beta_{d,1} > \beta_{d,0}$, and earn greater profits, $\pi_{d,1} > \pi_{d,0}$. Price informativeness decreases, $PI_1 < PI_0$, and price impact increases, $\lambda_1 > \lambda_0$, due to quantitative investing.

If the DI is perfectly informed, the QI's trading intensity is lower in the quantitative equilibrium than in the Strategic Equilibrium. Intuitively, the quant develops the backtested rule under the assumption that the market maker and the strategic speculator are not aware of her existence. For a perfectly-informed DI, this implies that the quant is facing the highest price impact set by the market maker since the risk of adverse selection is greatest in the Training Economy with a perfectly-informed trader. Therefore, the backtest is forced to be less aggressive to avoid excess information revelation. Conversely, in the Strategic Equilibrium, the standard competitive effects kick in: the traders trade more aggressively due to competition and the market maker takes into account their more aggressive trading as well as their signal precisions.

Since the potential profit pool is fixed by the level of noise trading volatility, the DI internalizes a lower trading intensity by the quant, allowing him to trade more aggressively and so generate greater profits at the QI's expense. The market maker internalizes this more-aggressive trading and increases the price impact, which also lowers price informativeness. Overall, market quality is negatively affected by quantitative investing in the presence of

perfectly-informed DIs. However, as described in the following Corollary, the magnitude of the effect is in part determined by the informational advantage of the DI.

Corollary 1. *QI's (DI's) trading intensity and profits increase (decrease) in the quant's signal precision across both equilibria but do so at a lower rate in the Quantitative Equilibrium. Price informativeness increases in the quant's signal precision across both equilibria but does so at lower rate in the Quantitative Equilibrium. Price impact is U-shaped for both equilibria but decreases at a higher (lower) rate for $\phi_q < \underline{\phi}_q$, decreases (increases) for $\underline{\phi}_q < \phi_q < \bar{\phi}_q$, and increases at a higher (lower) rate for the Strategic (Quantitative) Equilibrium.*

The effects of quantitative investing on financial market quality are amplified as the QI becomes more informed, as illustrated in Fig. 1. A more precise signal allows the QI to be more aggressive in both equilibria. However, this effect is greater in the Strategic Equilibrium since in the Quantitative Equilibrium, the backtest incorporates a higher price impact. In response, the DI becomes less aggressive in ϕ_q , which occurs at a faster rate in the Strategic Equilibrium. Since the quant's limiting trading intensity and profits as $\phi_q \rightarrow 0$ in both equilibria are zero, the effects of moving from the Strategic Equilibrium to the Quantitative Equilibrium are lowest for less-precise quants. Therefore, price impact rises and price informativeness falls the least as $\phi_q \rightarrow 0$. Conversely, for more precise quants, the trading intensity effects and, therefore, price informativeness and impact effects are more significant. Nevertheless, and importantly, while the effects of the change from strategic to quantitative investing are amplified with more-precise quants, price informativeness increases in the signal precision and market depth improves for sufficiently precise quants for both the quantitative and strategic equilibria.

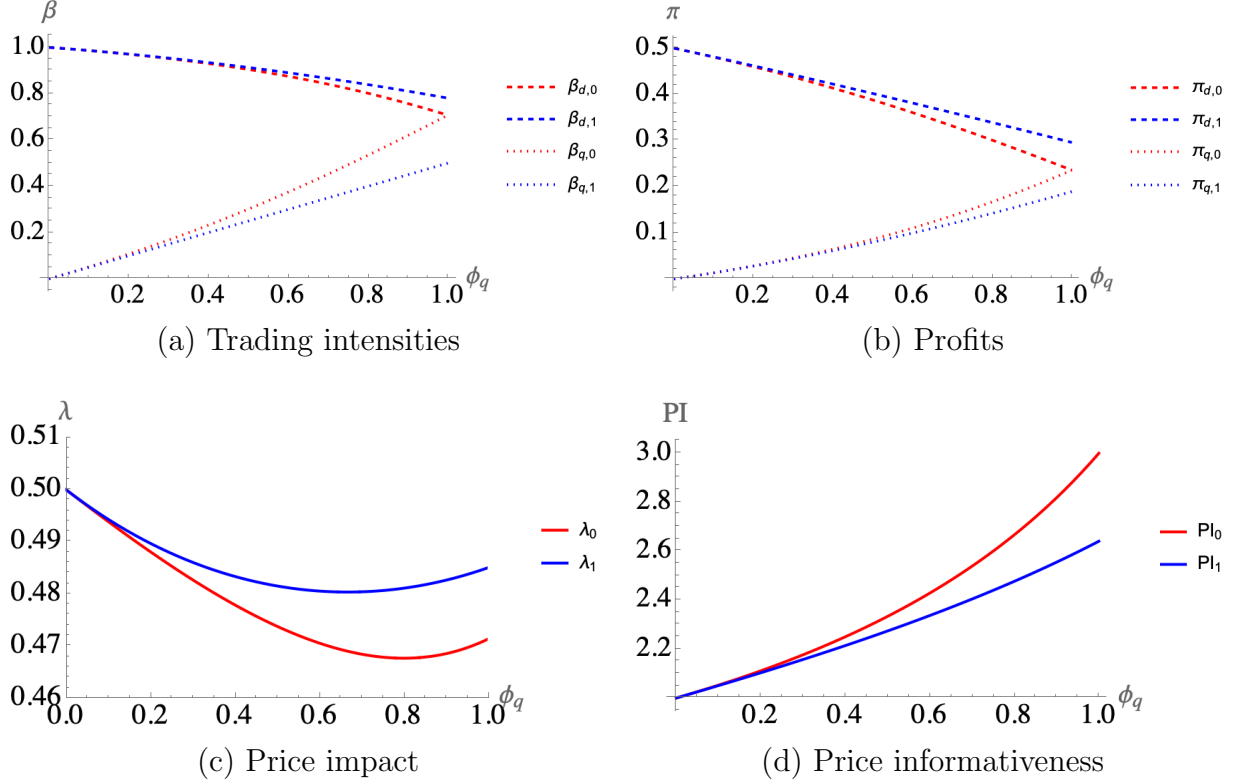
3.2.2 Perfectly-informed QI

The second benchmark case assumes the QI has perfect information ($\phi_q = 1$), hence the DI has inferior information. Unlike for the first benchmark, we now assume that quants have superior access to information processing – for example, hedge funds that rely on credit card transaction data to accurately estimate retailers' revenues or utilize airfare pricing datasets to forecast airline profitability – and use this superior information as inputs into their backtested strategies.¹¹

¹¹See, e.g., Froot et al. (2017), Zhu (2019), Katona et al. (2025) for examples of alternative data being used by investment managers.

Figure 1: Trading strategies, profits, price impact and informativeness versus signal precision.

The figure plots trading strategies, profits, price impact and informativeness under the fully-strategic and fully-automated equilibria. Panel (a) plots the discretionary (dashed) and quantitative (dotted) equilibrium trading intensities as a function of ϕ_d for fully-strategic ($\gamma = 0$, red) and fully-automated ($\gamma = 1$, blue) equilibria. Panel (b) does the same profits. Panel (c) plots the equilibrium price impact. Panel (d) plots price informativeness. Parameters are set to $\tau_v = \eta = 1$.



The discretionary investor's optimization is now:

$$x_d = \frac{\phi_d(1 - \lambda_\gamma \beta_{q,\gamma})}{2\lambda_\gamma} s_d \equiv \beta_{d,\gamma} s_d. \quad (29)$$

where $\gamma \in \{0, 1\}$. In the Strategic Equilibrium ($\gamma = 0$), the QI's behavior becomes fully-strategic,

$$x_q = \frac{1 - \lambda_\gamma \beta_{d,\gamma}}{2\lambda_\gamma} s_q \equiv \beta_{q,0} s_q, \quad (30)$$

while in the Quantitative Equilibrium with full-automation ($\gamma = 1$), she trades based on the

backtest,

$$x_q = \beta_b s_q \equiv \beta_{q,1} s_q. \quad (31)$$

In both settings the market maker sets the price according to

$$\lambda_\gamma = \frac{\mathbb{C}(v, \omega)}{\mathbb{V}(\omega)} = \frac{\beta_{d,\gamma} + \beta_{q,\gamma}}{(\beta_{d,\gamma} + \beta_{q,\gamma})^2 + (\phi_d^{-1} - 1) \beta_{d,\gamma}^2 + \eta}. \quad (32)$$

Solving for the Strategic $\{\beta_{d,0}, \beta_{q,0}, \lambda_0\}$ and Quantitative $\{\beta_{d,1}, \beta_{q,1}, \lambda_1\}$ equilibria leads to the following result.

Proposition 3. *When the QI has perfect information, there exists a unique linear equilibrium in the Strategic Economy, where*

$$\beta_{d,0} = \phi_d \sqrt{\frac{\eta}{(\phi_d - 3)\phi_d + 4}}, \beta_{q,0} = (2 - \phi_d) \sqrt{\frac{\eta}{(\phi_d - 3)\phi_d + 4}}, \text{ and } \lambda_0 = \frac{\sqrt{(\phi_d - 3)\phi_d + 4}}{(4 - \phi_d)\sqrt{\eta}}, \quad (33)$$

and the Quantitative Economy, where

$$\begin{aligned} \beta_{d,1} &= \frac{1}{4} \sqrt{\frac{\eta}{\phi_d}} \left(\sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} - (\phi_d - 2)^2 \right), \beta_{q,1} = \sqrt{\frac{\eta}{\phi_d}} \left(1 - \frac{\phi_d}{2} \right), \\ \text{and } \lambda_1 &= \sqrt{\frac{\phi_d}{\eta}} \frac{2\phi_d}{\sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} - 2(\phi_d - 2)(\phi_d - 1)}. \end{aligned} \quad (34)$$

For $\phi_d < (>) \phi_d^* = (7 - \sqrt{33})/2$, quantitative investing causes the QI to trade more (less) aggressively, $\beta_{q,1} > (<) \beta_{q,0}$, which causes the DI to trade less (more) aggressively, $\beta_{d,1} < (>) \beta_{d,0}$, and earn lower (greater) profits, $\pi_{d,1} < (>) \pi_{d,0}$. Price informativeness increases (decreases), $PI_1 > (<) PI_0$, and price impact decreases (increases), $\lambda_1 < (>) \lambda_0$ due to quantitative investing.

Proposition 3 argues that in the presence of a perfectly-informed QI, the effects of quantitative investing on market quality crucially depend on the information quality of the DI. This is in stark contrast to Proposition 2, whereby quantitative investing unambiguously worsened market quality in the presence of a perfectly-informed DI. Specifically, the effect of quantitative investing on market quality in Proposition 3 depends on whether adherence to the backtest causes the QI to trade more or less aggressively relative to the strategic setting. The intuition for this result is as follows.

First, consider the change in the QI's trading intensity as a function of ϕ_d , as we

transition from the Strategic to the Quantitative Equilibrium. For sufficiently uninformed DIs, as $\phi_d \rightarrow 0$, both $\beta_{d,TE}$ and λ_{TE} approach zero in the Training Economy, as can be seen from Proposition 1. This implies that the backtested strategy is extremely aggressive and becomes infinite in the limit. In the Quantitative Equilibrium, this aggressive trading is internalized by the market maker, which allows him to lower price impact since order flow becomes (almost) perfectly revealing of the fundamental value, as also reflected in the QI's profits, which approach zero. Conversely, as $\phi_d \rightarrow 0$, the Strategic Equilibrium begins to resemble the single-speculator version of the Kyle model, as the DI reduces his trading intensity to zero. Therefore, the trading intensity is finite for the QI in this setting, and is below her trading intensity in the Quantitative Equilibrium, $\beta_{q,1} > \beta_{q,0}$. As ϕ_d increases, the backtested strategy faces increasing price impact, causing it to be less aggressive. In the limit, as $\phi_d \rightarrow 1$, the strategic trading intensity of the QI exceeds that of the backtest, $\beta_{q,1} < \beta_{q,0}$: the lower price impact set by the market maker in response to competition allows the QI to trade more aggressively in the Strategic Equilibrium. Accordingly, there exists a ϕ_d^* below which the backtest is more aggressive than the strategic trading approach, and above which it is less aggressive. This finding is highlighted by the intersection of the blue and red dotted lines in panel (a) of Fig. 2 – we refer to the signed vertical distance between the blue and the red dotted lines, $\beta_{q,1} - \beta_{q,0}$, as the *quant's trading wedge*.

The sign of the trading wedge is the key determinant of market quality outcomes due to quantitative investing for the following reasons. First, note that the expected profit pool for the informed traders is fixed by the level of noise trading volatility. Second, the backtest is suboptimal from a profit-maximization perspective, yet it also reveals information about the fundamental value to the market maker who is aware of the QI's trading intensity and the precision of her signal. Third, the DI is also aware of the QI's trading intensity and takes it as given in his optimization. Therefore, if quantitative trading intensity is lower than strategic trading intensity – i.e., if the quant's trading wedge is negative – the DI can extract higher profits from the market by trading more aggressively than in the Strategic Equilibrium. Conversely, if the automated strategy is more aggressive – i.e., if the quant's trading wedge is positive – the DI is forced to reduce his trading intensity, which results in lower profits. Both of these patterns are highlighted by the single-crossing property of the dashed red and blue lines in panels (a) and (b) of Fig. 2.

Importantly, if the QI's trading wedge is positive, the net effect of the QI's increased trading intensity and the DI's decreased trading intensity is an improvement in market quality as price impact falls and prices become more informative. When the QI's trading intensity increases above the strategic level, the level of competition in the market implicitly

increases as well. Conversely, when the wedge is negative, the DI is able to strategically trade less aggressively, which reduces competition in the market and further mitigates information revelation, hence ultimately yielding lower market depth and less price informativeness. As summarized in the following Corollary, these effects vary in the DI's signal precision.

Corollary 2. *QI's (DI's) trading intensity decreases (increases) in the DI's signal precision across both equilibria but does so at a higher rate in the Quantitative Equilibrium. The DI's profits increase in his signal precision and do so at a higher rate in the Quantitative Equilibrium. For the QI's profits, there exists a $\hat{\phi}_d < \phi_d^*$ such that for $\phi_d < \hat{\phi}_d$ and $\phi_d > \phi_d^*$, quantitative investing leads to lower profits for the QI, while for $\hat{\phi}_d < \phi_d < \phi_d^*$ quantitative investing results in greater profits. Price impact is U-shaped (increasing) in the DI's signal quality for the Strategic (Quantitative) Equilibrium, intersecting at ϕ_d^* . For $\phi_d < \phi_d^+$, price impact is increasing in the Quantitative Equilibrium and decreasing in the Strategic Equilibrium. For $\phi_d > \phi_d^+$ price impact is increasing in both equilibria, but at a higher rate in the Quantitative Economy. Price informativeness is increasing (U-shaped) in the Strategic (Quantitative) Equilibrium, also intersecting at ϕ_d^* . For $\phi_d < (>) \phi_d^*$, quantitative investing leads to more (less) informative prices. For $\phi_d < \bar{\phi}_d$, price informativeness is decreasing in the Quantitative Equilibrium and increasing in the Strategic Equilibrium. For $\phi_d > \bar{\phi}_d$ price informativeness is increasing in both equilibria, but at a higher rate in the Quantitative Economy.*

As the information advantage of the QI increases, i.e., as ϕ_d falls and approaches zero, the positive effects of quantitative investing are amplified. Specifically, rapidly increasing quantitative trading intensity leads to excess information revelation, allowing the market maker to lower price impact (to zero in the limit) and price informativeness increases (and prices become perfectly-informative in the limit). Conversely, in the Strategic Equilibrium, reduction in ϕ_d causes the MM to increase price impact as she becomes increasingly concerned about adverse selection risk. Therefore, $\lambda_1 - \lambda_0$ and $PI_1 - PI_0$ decrease and increase, respectively, as ϕ_d approaches 0.

Interestingly, there is a region, $\hat{\phi}_d < \phi_d < \phi_d^*$, within which the Quantitative Equilibrium generates greater profits for the QI than the Strategic Equilibrium – as highlighted by the two points of intersection between the dotted blue and red lines of panel (b) in Fig. 2. This increase in profits for the QI is accompanied by more informative prices and greater market liquidity. While this result may appear counter-intuitive – as the quant is by definition not maximizing profits – it stems from her ex-ante commitment to a trading strategy. Specifically, in our setting, quantitative investing takes the form of Stackelberg competition: the Quantitative Equilibrium is sequential since the QI commits to a trading strategy prior

to the DI forming his trading strategy or the MM setting his pricing rule. In the parameter region highlighted above, such commitment leads to greater profits.¹²

As the information advantage of the QI decreases, i.e., as ϕ_d exceeds ϕ_d^* and approaches 1, the negative effects of quantitative investing are first amplified and then dampened. Specifically, for $\phi_d^* < \phi_d < \phi_d^+$, price impact is increasing in the Quantitative Equilibrium but decreasing in the Strategic Equilibrium. In this region, the Strategic Equilibrium benefits from the increased competition driven by the greater signal precision of the DI. However, in the Quantitative Equilibrium, the DI is better able to exploit the quant’s commitment, leading to increasing price impact and less-informative prices. However, as $\phi_d \rightarrow 1$, both equilibria experience increasing price impact in tandem with more informative prices due to the more-precise signal of the strategic investor.

3.3 Generalized Model

The analysis in Section 3.2 is based upon strict restrictions on the parameters controlling the precision of the private signals endowed to the DI and QI ($\phi_d = 1$ or $\phi_q = 1$) as well as QI’s commitment to a backtested strategy ($\gamma = 1$ or $\gamma = 0$). In this section, we investigate a generalized version of our model in which we do not restrict the DI or QI to perfect information (i.e., $\phi_d < 1$ or $\phi_q < 1$), allow for signal error correlation between informed traders (i.e., $\sigma_e \neq 0$), and consider partial automation by the QI (i.e., $0 < \gamma < 1$). We do so via numerical analysis of the model’s equilibrium for a large number of parameter draws, as well as of several subsets of interest, since its comparative statics with respect to γ in closed form are analytically unfeasible; details of this investigation are in Tables 1 and 2 (and the accompanying Section A.4 of the Appendix), as well as Fig. 3.

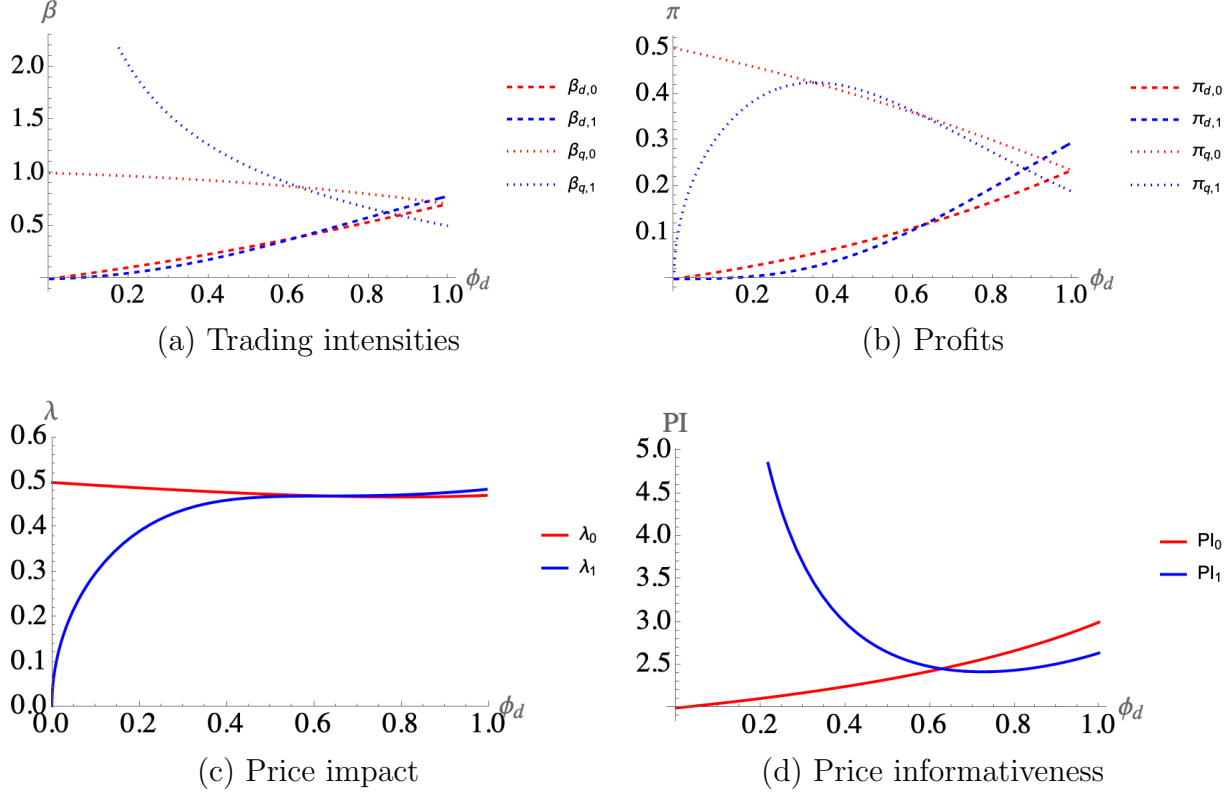
Intermediate backtest adherence is important since quantitative funds are ultimately deployed by humans, and inherent in this is a certain level of discretion. Humans may choose to strategically scale, turn off, and alter their investment strategies, even if such strategies full rely on backtested analysis. In addition, greater γ can be mapped to the aforementioned observed growth in quantitative investing, as the former implies a growing presence of the latter in the market. Lastly, differential signal precision for the QI and the DI further allows us to explore the effects of both superior and inferior information for the quant, especially when perfect information is not attainable for either investor.

Consistent with the intuition from our theoretical findings, our numerical analy-

¹²See also Bernhardt and Boulatov (2023) for a discussion of the value of commitment (specifically, by a trader to the market maker) in a Kyle setting.

Figure 2: Trading strategies, profits, price impact and informativeness versus signal precision.

The figure plots trading strategies, profits, price impact and informativeness under the fully-strategic and fully-automated equilibria. Panel (a) plots the discretionary (dashed) and quantitative (dotted) equilibrium trading intensities as a function of ϕ_d for fully-strategic ($\gamma = 0$, red) and fully-automated ($\gamma = 1$, blue) equilibria. Panel (b) does the same for profits. Panel (c) plots the equilibrium price impact. Panel (d) plots price informativeness. Parameters are set to $\tau_v = \eta = 1$.



sis shows that the effects of quantitative investing on financial market quality depend on whether the quant's trading wedge, $|\beta_{q,1}| - |\beta_{q,0}|$, is positive or negative.¹³ Since the quant's strategy is (loosely, i.e., Eq. (22)) a weighted average between the Strategic and Quantitative Equilibrium, growth in automation (γ) leads to more (less) aggressive trading by the QI if $|\beta_{q,1}| > (<) |\beta_{q,0}|$. The change in trading behavior due to greater automation is internalized by the discretionary investor and the market maker and ultimately determines the effects of quantitative investing on financial market quality. Since the fully-automated quant is by definition not maximizing profits, to the extent that this sub-optimality is accompanied by less aggressive trading, the DI has the opportunity to exploit the greater resulting mispricing

¹³Note that, unlike the theoretical benchmarks with perfect information, trading intensities can be negative with signal error correlation, hence it is more precise to compare absolute values.

to his advantage by trading more aggressively without positive implications to market quality. If, however, greater automation leads to greater trading intensity by the quant, the DI is mostly unable to exploit this to his advantage as he is concerned about excess information leakage. The net effect in the latter scenario is an improvement in market quality.

3.3.1 Theory and Numerical Analysis

In Proposition 4 below, we solve for the equilibrium of the Generalized Model, one in which we allow for imperfectly informed investors ($\phi_d < 1$ or $\phi_q < 1$), correlated signal errors ($\sigma_e \neq 0$), as well as partial reliance on the backtested trading strategy ($0 < \gamma < 1$).

Proposition 4. *There exists a linear equilibrium when automation is partial ($0 < \gamma < 1$) and a unique linear equilibrium when automation is binary ($\gamma \in \{0, 1\}$). The corresponding equilibrium trading intensities and price impact $\{\beta_{d,\gamma}, \beta_{q,\gamma}, \lambda_\gamma\}$ are those solving a (quartic and quadratic, respectively) polynomial from a system of three equations: Eq. (173) to (175); see Section A.4 of the Appendix.*

As noted in Proposition 4, we are able to demonstrate uniqueness of the equilibrium for binary automation but only its existence for intermediate reliance on the backtest. Furthermore, while equilibrium market depth and price informativeness can be derived in closed form from Proposition 4, their relevant comparative statics are analytically unfeasible. Accordingly, we confirm that uniqueness and assess those comparative statics via the numerical analysis of a large number of random draws of the parameters controlling for the model's information environment. Results of these simulations are reported in Tables 1 and 2 and summarized in Conclusion 1.

We also relax the binary automation of Proposition 3 by considering those comparative statics of interest with respect to intermediate γ coefficients for three specific subsets of model parameters, in Fig. 3. Specifically, in Fig. 3, the quant's trading wedge is either negative ($\phi_d = 1$), zero ($\phi_d = \phi_d^* = (7 - \sqrt{33})/2 \approx 0.6277$), or positive ($\phi_d = 0.45$), while the remaining parameters are the same as in Fig. 2, but, crucially, we allow for intermediate automation ($0 < \gamma < 1$).

Conclusion 1. *The effect of greater automation γ by the QI on financial market quality depends on whether the fully-automated QI trades more than the fully-strategic QI. If the fully-automated QI trades more ($|\beta_{q,1}| > |\beta_{q,0}|$), market quality broadly improves as market depth and price informativeness increase in γ . Furthermore, the speculator sector as a whole trades more, profits are mostly lower, and the effects on the DI's trading and profits can be*

increasing, decreasing, or U-shaped in γ , while the QI always trades more and her profits are increasing, decreasing or hump-shaped in γ . If the fully-automated quant trades less ($|\beta_{q,1}| < |\beta_{q,0}|$), market quality deteriorates via lower market depth and less informative prices. The speculator sector as a whole trades less and makes greater profits as the DI trades more aggressively and earns greater profits, while the QI trades less and earns lower profits.

Conclusion 1, contains the main result of the paper: the effects of quantitative investing on market quality depend upon the relative intensity of automated versus strategic trading. To illustrate its intuition, consider the two theoretical benchmarks highlighted in Section 3.2 (Propositions 2 and 3). The case of a perfectly-informed DI (in Section 3.2.1) is one in which the trading wedge is always negative, regardless of the QI's signal precision. In this setting, market quality always deteriorates in the presence of quantitative investing, the more so when the quant's trading wedge becomes more negative. In the case of a perfectly-informed QI (in Section 3.2.2), the implications of quant investing for market quality are determined by the sign of the trading wedge: a negative (positive) wedge leads to worse (better) market quality.

Further insights come from Fig. 3, which extends the above analysis to allow for intermediate automation. Recall that the QI is perfectly informed, hence the sign of her trading wedge is determined by the DI's signal precision: the wedge is decreasing in ϕ_d and is exactly zero when $\phi_d = \phi_d^* \approx 0.6277$. As shown in panel (c), a greater γ increases (decreases) the quant's trading intensity if the trading wedge is positive (negative), ultimately resulting in greater (lower) profits in panel (d). The discretionary investor internalizes this change in behavior and trades less (more) aggressively in panel (a), resulting in lower (greater) profits in panel (b). Finally, the greater (lower) quantitative trading intensity leads to a more (less) liquid market and more (less) informative price in panels (e) and (f) respectively.

Relatedly, another takeaway from the theoretical exercise in Section 3.2 is that the magnitude and sign of the wedge are determined by the signal precision of the imperfectly informed investor. As their information precision increases (decreases), so does the correlation of their signals, which in turn decreases (increases) the quant's trading wedge. Intuitively, strategic trading intensity is not as sensitive to the increased signal correlation as the backtest's. For both, an increase in signal correlation has the effect of greater competition since both traders are more likely to trade in the same direction. However, the effect of increasing competition in the Strategic Economy is dampened by the market maker's ensuing greater liquidity provision (in the form of lower price impact). Conversely, the backtested strategy, by definition, does not anticipate this decline in price impact, resulting in a greater re-

	Incr. (1)	Decr. (2)	Hump (3)	U (4)	SE>QE (5)	IE<SE (6)	IE>QE (7)	% Sim. (8)
All	43.7	44.6	0.0	11.6	46.8	49.0	45.2	100.0
$ \beta_{q,1} > \beta_{q,0} $	74.3	5.7	0.0	20.0	9.2	12.9	6.6	57.0
$ \beta_{q,1} \leq \beta_{q,0} $	3.2	96.3	0.0	0.5	96.6	96.7	96.4	43.0

(a) Market depth

	Incr. (1)	Decr. (2)	Hump (3)	U (4)	SE>QE (5)	IE<SE (6)	IE>QE (7)	% Sim. (8)
All	57.0	43.0	0.0	0.0	43.0	43.0	43.0	100.0
$ \beta_{q,1} > \beta_{q,0} $	100.0	0.0	0.0	0.0	0.0	0.0	0.0	57.0
$ \beta_{q,1} \leq \beta_{q,0} $	0.0	100.0	0.0	0.0	100.0	100.0	100.0	43.0

(b) Price informativeness

	Incr. (1)	Decr. (2)	Hump (3)	U (4)	SE>QE (5)	IE<SE (6)	IE>QE (7)	% Sim. (8)
All	57.7	42.1	0.0	0.2	42.2	42.3	42.1	100.0
$ \beta_{q,1} > \beta_{q,0} $	99.1	0.6	0.0	0.4	0.7	0.8	0.6	57.0
$ \beta_{q,1} \leq \beta_{q,0} $	2.8	97.2	0.0	0.0	97.2	97.2	97.2	43.0

(c) Trading volume: aggregate

	Incr. (1)	Decr. (2)	Hump (3)	U (4)	SE>QE (5)	IE<SE (6)	IE>QE (7)	% Sim. (8)
All	44.6	43.7	11.6	0.0	53.2	51.0	54.8	100.0
$ \beta_{q,1} > \beta_{q,0} $	5.7	74.3	20.0	0.0	90.8	87.1	93.4	57.0
$ \beta_{q,1} \leq \beta_{q,0} $	96.3	3.2	0.5	0.0	3.4	3.3	3.6	43.0

(d) Profits: aggregate

Table 1: Simulation Results – Market Aggregates

We use 1,000,000 parameter draws: $\rho_e \sim U(-1, 1)$, $\phi_d \sim U(0, 1)$, $\phi_q \sim U(0, 1)$, $\eta \sim U(0, 2)$, $\tau_v^{-1} = 1$. “SE” is the Strategic Equilibrium ($\gamma = 0$), “QE” is the Quantitative Equilibrium ($\gamma = 1$), and “IE” is the Interior Equilibrium ($0 < \gamma < 1$). For the IE, we evaluate market quality for 99 values of γ from 1% to 99% at 1% increments. Numbers represent the percent of simulations such that the condition in the header is satisfied (Cols. 1–5) or the average fraction of γ ’s across all simulations such that the condition is satisfied (Cols. 6–7). The first four columns document the shape of the market quality measure in the IE for increasing γ .

	Incr. (1)	Decr. (2)	Hump (3)	U (4)	SE>QE (5)	IE<SE (6)	IE>QE (7)	% Sim. (8)
All	59.0	24.9	0.0	16.1	31.2	34.2	26.6	100.0
$ \beta_{q,1} > \beta_{q,0} $	28.1	43.6	0.0	28.2	54.8	60.0	46.8	57.0
$ \beta_{q,1} \leq \beta_{q,0} $	99.9	0.0	0.0	0.0	0.0	0.0	0.0	43.0

(a) Trading volume: DI

	Incr. (1)	Decr. (2)	Hump (3)	U (4)	SE>QE (5)	IE<SE (6)	IE>QE (7)	% Sim. (8)
All	57.0	43.0	0.0	0.0	43.0	43.0	43.0	100.0
$ \beta_{q,1} > \beta_{q,0} $	100.0	0.0	0.0	0.0	0.0	0.0	0.0	57.0
$ \beta_{q,1} \leq \beta_{q,0} $	0.0	100.0	0.0	0.0	100.0	100.0	100.0	43.0

(b) Trading volume: QI

	Incr. (1)	Decr. (2)	Hump (3)	U (4)	SE>QE (5)	IE<SE (6)	IE>QE (7)	% Sim. (8)
All	57.2	32.7	0.0	10.1	37.7	39.3	34.1	100.0
$ \beta_{q,1} > \beta_{q,0} $	26.9	55.3	0.0	17.8	64.0	66.8	57.7	57.0
$ \beta_{q,1} \leq \beta_{q,0} $	97.2	2.8	0.0	0.0	2.8	2.8	2.8	43.0

(c) Expected profits: DI

	Incr. (1)	Decr. (2)	Hump (3)	U (4)	SE>QE (5)	IE<SE (6)	IE>QE (7)	% Sim. (8)
All	13.0	62.6	24.4	0.0	81.1	76.3	85.3	100.0
$ \beta_{q,1} > \beta_{q,0} $	22.8	34.4	42.7	0.0	66.9	58.5	74.3	57.0
$ \beta_{q,1} \leq \beta_{q,0} $	0.0	100.0	0.0	0.0	100.0	100.0	100.0	43.0

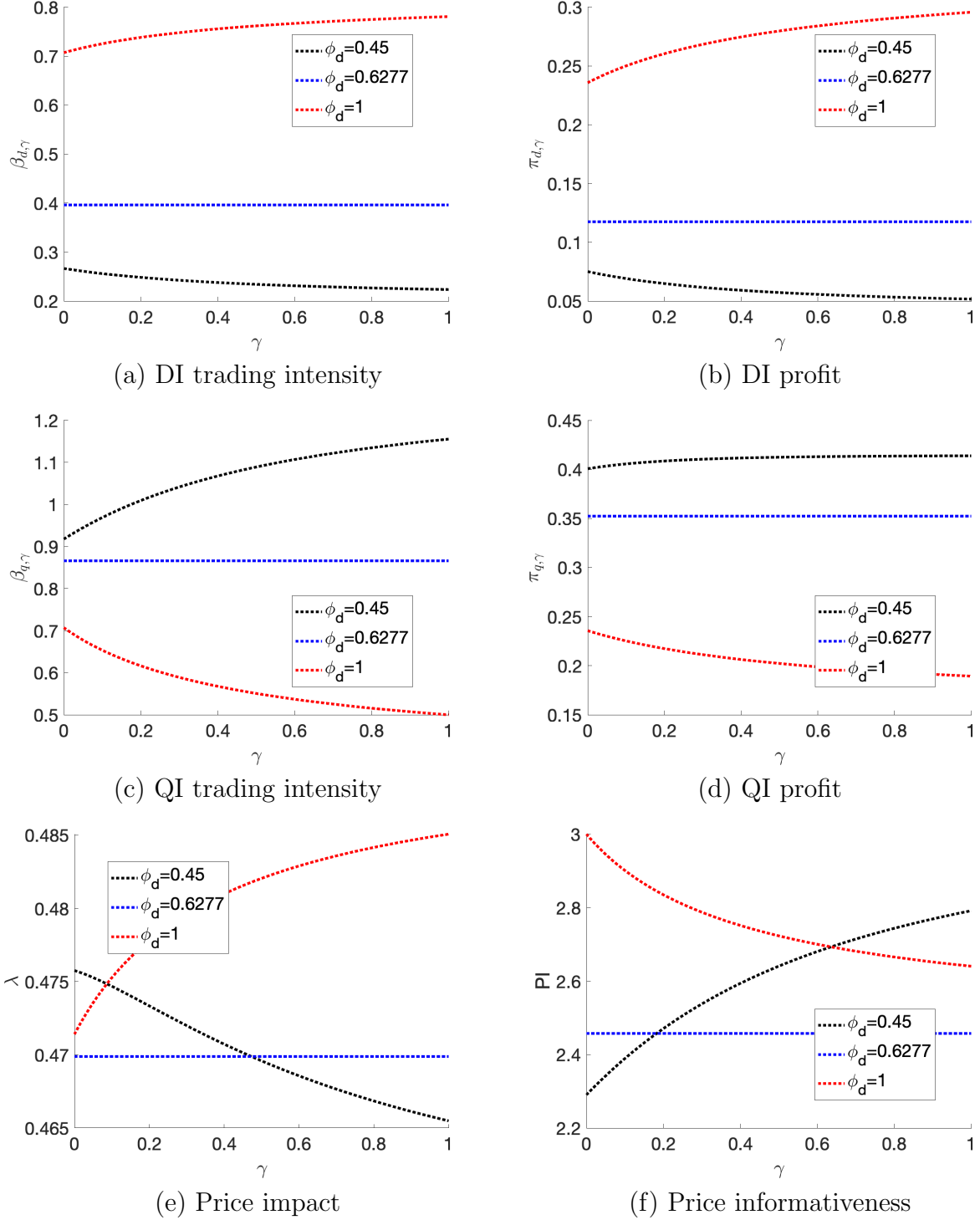
(d) Expected profits: QI

Table 2: Simulation Results – Breakdown by Trader

We use 1,000,000 parameter draws: $\rho_e \sim U(-1, 1)$, $\phi_d \sim U(0, 1)$, $\phi_q \sim U(0, 1)$, $\eta \sim U(0, 2)$, $\tau_v^{-1} = 1$. “SE” is the Strategic Equilibrium ($\gamma = 0$), “QE” is the Quantitative Equilibrium ($\gamma = 1$), and “IE” is the Interior Equilibrium ($0 < \gamma < 1$). For the IE, we evaluate market quality for 99 values of γ from 1% to 99% at 1% increments. Numbers represent the percent of simulations such that the condition in the header is satisfied (Cols. 1–5) or the average fraction of γ ’s across all simulations such that the condition is satisfied (Cols. 6–7). The first four columns document the shape of the market quality measure in the IE for increasing γ .

Figure 3: Trading strategies, profits, price impact and informativeness versus automation.

The figure plots trading strategies, profits, price impact and informativeness as a function of automation γ for various levels of signal precision for the DI, $\phi_d \in [0.45, 0.6277, 1]$. Panel (a) plots the discretionary equilibrium trading intensity as a function of γ . Panel (b) does the same for profits. Panel (c) plots the quantitative equilibrium trading intensity as a function of γ . Panel (d) does the same profits. Panel (e) plots the equilibrium price impact. Panel (f) plots price informativeness. Other parameters are set to $\phi_q = \tau_v = \eta = 1$.



sponse to competition. Accordingly, the quant's trading wedge falls when signal correlation is greater.

In the Generalized Model, trader signal correlation is determined by the net effect of (ϕ_d, ϕ_q, ρ_e) since

$$\rho_{s_d, s_q} = \sqrt{\phi_d \phi_q} + \rho_e \sqrt{(1 - \phi_d)(1 - \phi_q)}, \quad (35)$$

and, therefore, the sign of the quant's trading wedge stems from this triplet. Importantly, the sign of $(|\beta_{q,1}| - |\beta_{q,0}|)$ is a sufficient statistic for market quality outcomes. The relationship between the quantitative and strategic trading intensity of the QI is summarized in the following result.

Lemma 1. *For a fixed (ϕ_d, ϕ_q) , the QI's trading wedge, $|\beta_{q,1}| - |\beta_{q,0}|$, is either 1) positive $\forall \rho_e \in [-1, 1]$; 2) negative $\forall \rho_e \in [-1, 1]$; or 3) decreasing in ρ_e and positive $\forall \rho_e \in [-1, \rho_e^*)$ and negative for $\forall \rho_e \in (\rho_e^*, 1]$ for $\rho_e^* \in (-1, 1)$.*

The key takeaway from Lemma 1 is that for any information quality pair (ϕ_d, ϕ_q) , we can find a breakeven signal error correlation parameter ρ_e^* such that for any $\rho_e < \rho_e^*$, the trading wedge is positive, and, consequently, quantitative investing improves market quality. Therefore, since $\rho_e \in [0, 1]$, if (ϕ_d, ϕ_q) is such that 1) $\rho_e^* \leq -1$, the trading wedge is never positive, 2) $\rho_e^* \geq 1$, the trading wedge is always positive, and 3) $\rho_e^* \in (0, 1)$, the trading wedge is positive for $\rho_e \in [-1, \rho_e^*)$. In addition, a higher ρ_e^* implies a greater likelihood of a positive trading wedge, which in turn corresponds to a higher probability of improvement to market quality due to quantitative investing. We rely on this logic to provide a classification of the parameter space via the contour plot of Fig. 4. Specifically, for each pair of signal precision parameters (ϕ_d, ϕ_q) , we plot the maximum correlation level ρ_e^* for all values below which the fully-automated quant trades more than the fully-discretionary quant. Bright yellow regions correspond to information precision pairs for which market quality always improves. Dark red regions reflect information precision pairs for which market quality always deteriorates. Finally, for pairs located in the intermediate region the effect is not definite, yet higher breakeven correlation levels imply a greater likelihood of market quality improvement.

As apparent from Fig. 4, when trading against relatively uninformed discretionary investors (i.e., for ϕ_d below ≈ 0.52), the likelihood of market quality improvement due to quant investing is increasing in the quant's signal precision. In particular, as we demonstrate in Section A.5 of the Appendix, if $\phi_q > 3\phi_d$, the trading wedge is always positive, implying that market quality always improves due to quantitative investing – consistent with Proposition 3. Conversely, if trading against relatively informed DIs (i.e., for ϕ_d above ≈ 0.52),

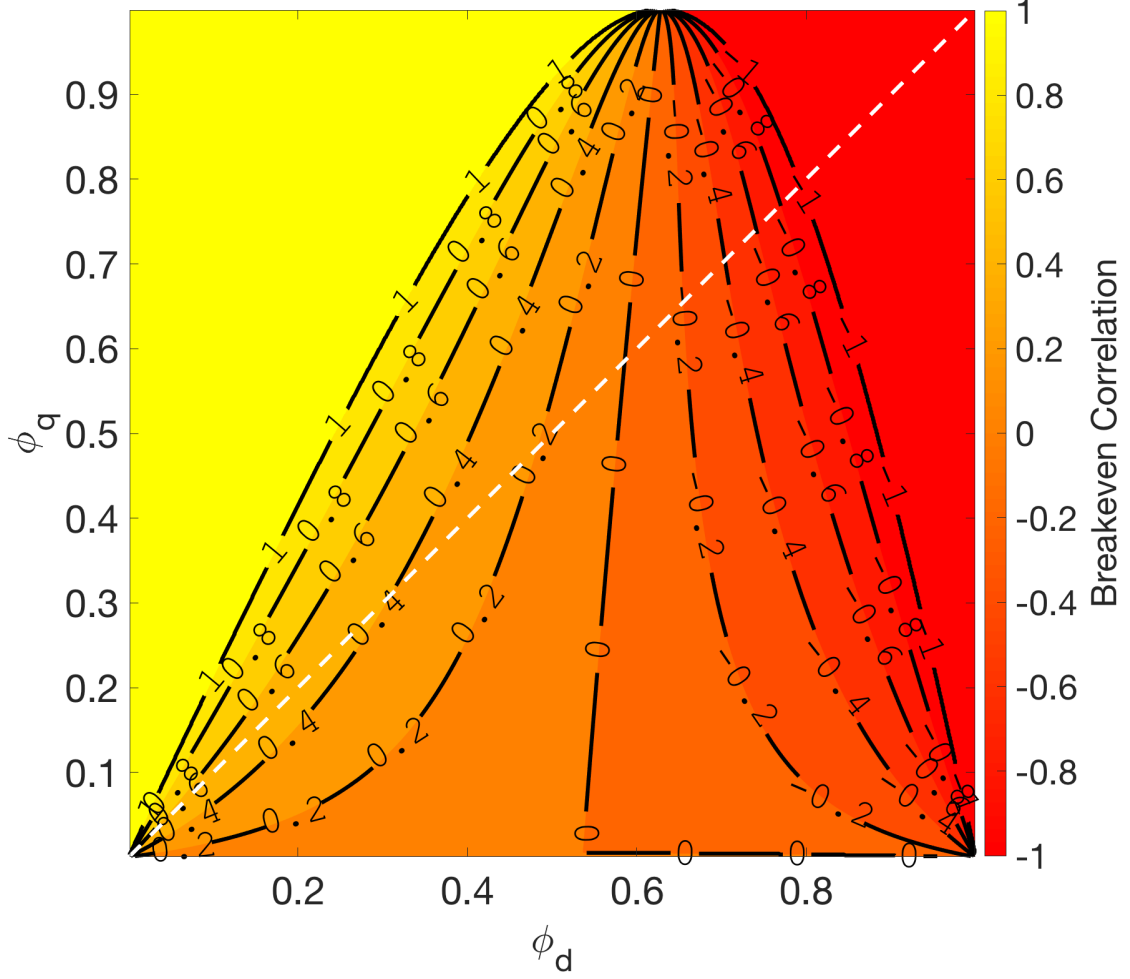


Figure 4: Breakeven Correlation for the Quant's Trading Wedge

The contour plot displays the maximum signal correlation levels such that the fully discretionary quant ($\beta_{q,0}$) trades less than the fully automated quant ($\beta_{q,1}$) for varying levels of signal precision for the DI and QI. The white dotted line corresponds to equal signal precision for the DI and QI, with the region above implying an informational advantage for the quant, and the region below implying an informational advantage for the discretionary investor.

the likelihood of market quality improvement is declining in the quant’s signal precision. Highly informed DIs (e.g., $\phi_d \geq 0.8$) trading against highly informed quants (e.g., $\phi_q \geq 0.8$) unambiguously leads to deterioration in market quality. Similarly, DIs with nearly perfect information (i.e., $\phi_d \approx 1$) cause market quality declines with near certainty regardless of the quant’s signal precision – consistent with Proposition 2.

If we assume that the DI’s information quality is ex ante uniformly distributed (i.e., $\phi_d \sim U(0, 1)$), a more subtle outcome of Fig. 4 is that a higher ϕ_q is more likely to result in improvements in market quality. Conversely, for any fixed information precision for the quant, the likelihood of improvement in market quality is decreasing in ϕ_d . These insights are consistent with the evidence in Beggs and Hill-Kleespie (2025) that mutual fund fire sales have greater price impact for quant vs. discretionary funds. To the extent that fire sales are more likely for funds with less precise information, our model suggests that lower information precision is more likely to have adverse effects on market quality for quants as opposed to discretionary funds.

Tables 1 and 2 establish that the sign of the quant’s trading wedge dictates market quality outcomes. A positive wedge results in always increasing price informativeness and mostly increasing market depth in the level of automation γ by the quant. These overall improvements in market quality are driven by greater expected trading volume for the quant, mostly lower volume for the DI, and mostly greater volume for the speculator sector as a whole. The effects on the quant’s profits are ambiguous, while the DI and the speculator sector as a whole mostly earn declining profits. Greater automation, which results in more aggressive trading by the quantitative investor, has a positive impact on financial market quality.

In cases where the quant’s trading wedge is negative, market quality generally deteriorates as the lower trading intensity allows the DI to benefit at the expense of the QI. The simulation highlights that market depth mostly and price informativeness always decrease with greater automation by the quant. This is driven by lower trading volume for the quant, greater trading volume for the DI, and lower trading volume for the speculator sector as a whole. Concurrently, profits for the quant unambiguously fall, while profits for the discretionary investor and the speculator sector as a whole mostly increase with greater automation. The DI is able to exploit the quant’s greater commitment to the backtest, which ignores the DI’s strategic response to its presence in the market. Overall, greater automation by the quant, which results in less aggressive trading, leads to a deterioration in market quality.

An important takeaway from the simulation above is that the backtest is more likely

to perform well when the quant’s trading wedge is positive. Although greater reliance on the backtest implies greater deviation from a profit-maximizing strategy, a positive trading wedge leads to greater profits for the fully-automated quant (QE>SE) in roughly one-third of the simulations in Tables 1 and 2. Furthermore, the profit pattern is either increasing or hump-shaped in roughly two-thirds of those simulations, suggesting that either full automation or an intermediate level of automation can lead to greater profits for the quant relative to the discretionary strategy. This is in stark contrast to the outcomes of a negative trading wedge, whereby the quant’s profits always fall with greater automation, while the DI benefits at her expense. Therefore, conditions under which the trading wedge is positive are also conditions under which the corresponding backtested strategies are more likely to be successful.

3.3.2 Empirical implications

Our theory may provide guidance for future empirical research on the effects of quantitative investing on financial market quality, instruct policy makers on the effects of quant investing on financial stability, and direct portfolio managers to market environments ripe for quantitative strategies. We summarize those key, novel insights below.

First, our theory highlights the differential market externalities of quantitative investing when trading against relatively uninformed vs. relatively informed discretionary investors. In particular, our model suggests that quants are more likely to improve market quality when trading against uninformed vs. informed DIs, a prediction that can be tested both in the time-series and the cross-section. Our model further suggests that error correlation ρ_e — a measure of disagreement in financial markets — is an important determinant of these effects. This relationship could be investigated in relation with macroeconomic cycles: To the extent that recessions correspond to periods of disagreement (i.e., $\rho_e < 0$), our model predicts that quantitative investors are more likely to ameliorate market quality (i.e., the trading wedge is more likely to be positive). In addition, when trading against relatively uninformed discretionary investors in periods of disagreement, quantitative investing unambiguously improves market quality, while only highly-informed DIs can realistically worsen it. The latter observation is consistent with the evidence in Abis (2022) who finds that quants are better stock-pickers and worse market-timers than traditional investors during recessions.

From a policy perspective, our analysis highlights some conditions under which quantitative investing can have detrimental effects on financial markets. Sophisticated discretionary investors are more likely to take advantage of quant funds by exploiting their

reliance on the backtested strategy. Stable and expansionary periods with low disagreement are also environments when quant investing is more likely to negatively affect market quality. Finally, our analysis also suggests that uninformed quant funds are more prone to exploitation. The latter observation is of particular concern given the proliferation of index funds, many of which (especially the most basic broad-market value-weighted funds) can be viewed as quantitative funds with low signal precision.

Finally, from an investment management perspective, our model highlights conditions under which quantitative investment strategies based on backtests are more likely to be successful. Although the backtested strategy is highly stylized in our framework, it captures the key dimension of using historical data to develop a profit-maximizing trading rule. The conditions for a positive trading wedge for the quant are precisely the conditions for the backtested strategy to more likely perform well. Specifically, as suggested by the determinants of the quant’s trading wedge, markets with high disagreement are generally more likely to be conducive to backtested strategies. Furthermore, the information quality of traditional investors is important. To the extent that the market is saturated by relatively uninformed investors, the bar for a successful quant strategy is lower, and the likelihood of its success rises in the precision of the quant’s information. Conversely, if the market is populated by relatively informed investors, the bar for success is higher, and its probability of success is falling in the quant’s signal precision.

4 Conclusion

Quantitative investment strategies are playing an increasingly important role in financial markets. What was previously available primarily via hedge funds to a select clientele is now widely accessible to households via mutual funds and smart-beta ETFs. The effects of such growth in quantitative investing on the quality of price formation in financial markets are not immediate. Quantitative trading is inherently disciplined by backtesting, hence may not fully incorporate the strategic trading behavior of other market participants. We develop a model of strategic speculation that captures the potentially exploitable commitment of quantitative funds through their reliance on a backtested trading strategy – i.e., one assuming by definition that other market participants are unaware of the quant’s existence.

We formally show that the growth in quantitative investing may have disparate effects on financial market quality. If greater adherence to backtesting results in greater trading intensity for the quant, market quality improves as the strategic market participants are unable to take advantage of the quant’s commitment. Conversely, if greater automation

leads to less trading by the quant, the fully-strategic speculators may take advantage of the quant's commitment, leading to worse market quality. Importantly, many of these effects depend on potentially observable fund characteristics, such as the relative precision and correlation of the information of discretionary and quant investors.

Our analysis provides a novel theoretical framework to guide future empirical investigations of the implications of the growth in quantitative investing — and its strategic interactions with more traditional investment styles — for the process of price formation in financial markets. In particular, our model emphasizes the importance of relative signal precision and signal correlation among discretionary and quantitative investors when assessing the effects of quantitative investing on market quality. For example, smart-beta ETFs are generally deemed to be less informed than proprietary quant traders, and the correlation of their trading strategies may change over time – with materially different implications for the liquidity and informativeness of the affected markets. Future research bringing our model to the data has the potential to shed light on the empirical effects of quantitative investing on the functioning of modern financial markets.

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A Proofs

For all proofs we assume that $\phi_d \in (0, 1]$ and $\phi_q \in (0, 1]$ and for the perfect-information benchmarks either $\phi_d = 1$ or $\phi_q = 1$. Further, if necessary, we refer to Sturm's theorem to demonstrate the number of real roots for a function $f(\phi)$ for $\phi \in (0, 1]$. The theorem relies on the Sturm sequence of a univariate polynomial: $f_0, f_1, \dots$, such that $f_0 = f, f_1 = f', \dots, f_{i+1} = -\text{rem}(f_{i-1}, f_i), \dots$, where the latter refers to the remainder of the Euclidian division of f_{i-1} by f_i and the length of the sequence is at most the degree of $f(\phi)$. For any χ , the number of sign changes, $S(\chi)$, associated with the Sturm sequence, is the number of times adjacent terms (ignoring zeros) f_j, f_{j+1} change signs. The theorem states that the number of distinct real roots in the interval $(a, b]$ is equal to $S(a) - S(b)$.

In many of the proofs to follow, we rely on the following logic and structure. We need to demonstrate how the following expression compares to zero:

$$f(\phi) + g(\phi)\sqrt{h(\phi)} \gtrless 0, \quad (36)$$

where $\phi \in (0, 1]$. We rely on Sturm's theorem, or more basic techniques for lower-degree polynomials, to first demonstrate how $f(\phi)$ and $g(\phi)$ compare to zero for $\phi \in (0, 1]$. The proof then follows from the following cases:

- $f(\phi) > 0, g(\phi) > 0 \Rightarrow f(\phi) + g(\phi)\sqrt{h(\phi)} > 0$
- $f(\phi) > 0, g(\phi) < 0 \Rightarrow f(\phi) + g(\phi)\sqrt{h(\phi)} > 0 \Leftrightarrow f(\phi)^2 > g(\phi)^2 h(\phi)$
- $f(\phi) < 0, g(\phi) > 0 \Rightarrow f(\phi) + g(\phi)\sqrt{h(\phi)} > 0 \Leftrightarrow f(\phi)^2 < g(\phi)^2 h(\phi)$
- $f(\phi) < 0, g(\phi) < 0 \Rightarrow f(\phi) + g(\phi)\sqrt{h(\phi)} < 0$

We present the proofs with some abuse of notation, i.e., reusing function names and labels for critical values. Finally, when taking derivatives with respect to ϕ_i where $i \in \{d, q\}$ we assume that τ_v does not change, i.e., that improvements in information quality are driven by a more precise signal τ_i . The latter assumption is also reflected in the simulation, in which we hold fixed τ_v .

A.1 Proof of Proposition 1

The solutions $\{\beta_{d,TE}, \lambda_{TE}\}$ follow from solving the system of equations:

$$\beta_{d,TE} = \frac{1}{2\lambda_{TE}}\phi_d \quad (37)$$

$$\lambda_{TE} = \frac{\beta_{d,TE}}{\beta_{d,TE}^2/\phi_d + \eta}. \quad (38)$$

There are two sets of solutions, but we limit our solution to $\lambda_{TE} > 0$ to satisfy the investor's second order condition. This yields

$$\beta_{d,TE} = \sqrt{\phi_d\eta} \text{ and } \lambda_{TE} = \frac{1}{2}\sqrt{\frac{\phi_d}{\eta}}. \quad (39)$$

Substituting the above into Eq. 9, the expression for β_b ,

$$\beta_b = \frac{\phi_q - \lambda_{TE}\beta_{d,TE}(\phi_q + \phi_q\tau_v\sigma_e)}{2\lambda_{TE}} \quad (40)$$

$$= \frac{1}{2}\phi_q\sqrt{\frac{\eta}{\phi_d}}(2 - \phi_d\sigma_e\tau_v - \phi_d). \quad (41)$$

Note that expected backtested profits are

$$\pi_b = \mathbb{E}[x_b(v - P_{TE})] = \frac{\phi_q}{8}\sqrt{\frac{\eta}{\phi_d}}(\tau_v^{-1}(2 - \phi_q) - \phi_q\tau_q^{-1})(\phi_d\sigma_e\tau_v + \phi_d - 2)^2 \quad (42)$$

$$= \frac{\phi_q}{8}\sqrt{\frac{\eta}{\phi_d}}\tau_v(\phi_d\sigma_e\tau_v + \phi_d - 2)^2, \quad (43)$$

which are positive as long as $\phi_d\sigma_e\tau_v + \phi_d - 2 \neq 0 \Leftrightarrow \sigma_e \neq \tau_v^{-1} + 2\tau_d^{-1}$.

□

A.2 Proof of Proposition 2

The solutions for $\{\beta_{d,\gamma}, \beta_{q,\gamma}, \lambda_\gamma\}$ follow from the following system of equations:

$$\lambda_\gamma = \frac{\beta_{d,\gamma} + \beta_{q,\gamma}}{(\beta_{d,\gamma} + \beta_{q,\gamma})^2 + \left(\frac{1}{\phi_q} - 1\right)\beta_{q,\gamma}^2 + \eta} \quad (44)$$

$$\beta_{q,\gamma} = \frac{\gamma}{\gamma + (1 - \gamma)\lambda_\gamma}\beta_b + \frac{(1 - \gamma)\lambda_\gamma}{\gamma + (1 - \gamma)\lambda_\gamma}\frac{\phi_q(1 - \lambda_\gamma\beta_{d,\gamma})}{2\lambda_\gamma} \quad (45)$$

$$\beta_{d,\gamma} = \frac{1 - \lambda_\gamma\beta_{q,\gamma}}{2\lambda_\gamma}. \quad (46)$$

For $\gamma = 0$, the set of solutions that satisfy the traders' second order condition are

$$\beta_{d,0} = (2 - \phi_q) \sqrt{\frac{\eta}{(\phi_q - 3)\phi_q + 4}} \quad (47)$$

$$\beta_{q,0} = \phi_q \sqrt{\frac{\eta}{(\phi_q - 3)\phi_q + 4}} \quad (48)$$

$$\lambda_0 = \frac{1}{4 - \phi_q} \sqrt{\frac{(\phi_q - 3)\phi_q + 4}{\eta}}. \quad (49)$$

For $\gamma = 1$, the set of solutions are

$$\beta_{d,1} = \frac{1}{4} \left(\sqrt{\eta(\phi_q(4 - 3\phi_q) + 16)} - \sqrt{\eta}\phi_q \right) \quad (50)$$

$$\beta_{q,1} = \frac{\sqrt{\eta}\phi_q}{2} \quad (51)$$

$$\lambda_1 = \frac{2}{\sqrt{\eta(\phi_q(4 - 3\phi_q) + 16)}}. \quad (52)$$

In what follows, note that both sets of solutions are positive.

Quant's trading intensity. We can characterize the change in trading intensity for the quant as follows:

$$\beta_{q,1} - \beta_{q,0} < 0 \Leftrightarrow \beta_{q,1}^2 - \beta_{q,0}^2 < 0 \Leftrightarrow \frac{\eta(\phi_q - 3)\phi_q^3}{4(\phi_q^2 - 3\phi_q + 4)} < 0, \quad (53)$$

where the final inequality always holds. Therefore the quant's trading intensity in the Strategic Equilibrium is always greater than in the Quantitative Equilibrium. Further, $\lim_{\phi_q \rightarrow 0^+} \beta_{q,0}(\phi_q) = \lim_{\phi_q \rightarrow 0^+} \beta_{q,1}(\phi_q) = 0$, $\beta_{q,1}(1) = \sqrt{\eta}/2 < \beta_{q,0}(1) = \sqrt{\eta}/2$. Finally,

$$\beta'_{q,0}/\beta'_{q,1} = \frac{8 - 3\phi_q}{((\phi_q - 3)\phi_q + 4)^{3/2}} > 1 \Leftrightarrow -\phi_q^5 + 9\phi_q^4 - 39\phi_q^3 + 99\phi_q^2 - 147\phi_q + 96 > 0, \quad (54)$$

where the final inequality holds over the interval by Sturm's theorem (3 sign variations and positive values at each of 0 and 1). Taken together, $\beta_{q,0}$ is always greater than $\beta_{q,1}$ and always grows at a faster rate over ϕ_q .

Discretionary trading intensity. First, note that $\lim_{\phi_q \rightarrow 0^+} \beta_{d,0}(\phi_q) = \lim_{\phi_q \rightarrow 0^+} \beta_{d,1}(\phi_q) = \sqrt{\eta}$

and $\beta_{d,0}(1) = \sqrt{\eta/2} < \beta_{d,1}(1) = \frac{1}{4}(\sqrt{17} - 1)\sqrt{\eta} < \lim_{\phi_q \rightarrow 0^+} \beta_{d,0}(\phi_q) = \lim_{\phi_q \rightarrow 0^+} \beta_{d,1}(\phi_q)$. Next,

$$\beta_{d,1} - \beta_{d,0} > 0 \Leftrightarrow \beta_{d,1}^2 - \beta_{d,0}^2 > 0 \quad (55)$$

$$\Leftrightarrow -\phi_q^3 + 5\phi_q^2 - 10\phi_q + \sqrt{-3\phi_q^2 + 4\phi_q + 16}(-\phi_q^2 + 3\phi_q - 4) + 16 > 0 \quad (56)$$

$$\Leftrightarrow 4(\phi_q - 3)\phi_q^2(\phi_q^3 - 5\phi_q^2 + 11\phi_q - 11) > 0 \Leftrightarrow \phi_q^3 - 5\phi_q^2 + 11\phi_q - 11 < 0, \quad (57)$$

where the latter inequality holds on the interval because the function is negative for $\phi_q = 0$ and $\phi_q = 1$ and always increasing. Next we consider the rate of change:

$$\beta'_{d,0}/\beta'_{d,1} = \frac{2(\phi_q + 2)\sqrt{\phi_q(4 - 3\phi_q) + 16}}{((\phi_q - 3)\phi_q + 4)^{3/2}(\sqrt{\phi_q(4 - 3\phi_q) + 16} + 3\phi_q - 2)} > 1 \Leftrightarrow \quad (58)$$

$$4(\phi_q + 2)^2(\phi_q(4 - 3\phi_q) + 16) > ((\phi_q - 3)\phi_q + 4)^3 \left(\sqrt{\phi_q(4 - 3\phi_q) + 16} + 3\phi_q - 2 \right)^2 \quad (59)$$

$$\Leftrightarrow -3\phi_q^8 + 31\phi_q^7 - 163\phi_q^6 + 543\phi_q^5 - 1260\phi_q^4 + 2030\phi_q^3 - 2288\phi_q^2 + 1856\phi_q - 512 \quad (60)$$

$$+ \sqrt{-3\phi_q^2 + 4\phi_q + 16}(-3\phi_q^7 + 29\phi_q^6 - 135\phi_q^5 + 375\phi_q^4 - 666\phi_q^3 + 744\phi_q^2 - 480\phi_q + 128) > 0 \quad (61)$$

$$\equiv f(\phi_q) + g(\phi_q)\sqrt{h(\phi_q)} > 0. \quad (62)$$

Note that $f(0) < 0$, $f(1) > 0$, as well as that the function has a single zero on in the interval at $\underline{\phi} \approx 0.447$. Further, $g(0) > 0$, $g(1) < 0$ and the function has a single zero on the interval at $\bar{\phi} = 2/3$. Finally,

$$f(\phi_q)^2 - g(\phi_q)^2 h(\phi_q) = 9\phi_q^{14} - 186\phi_q^{13} + 1861\phi_q^{12} - 11856\phi_q^{11} + 53403\phi_q^{10} - 178737\phi_q^9 \quad (63)$$

$$+ 454615\phi_q^8 - 881633\phi_q^7 + 1281068\phi_q^6 - 1321096\phi_q^5 + 815217\phi_q^4 \quad (64)$$

$$- 40784\phi_q^3 - 440064\phi_q^2 + 382976\phi_q - 101376. \quad (65)$$

The function above has a single zero on the interval (confirmed by Sturm's theorem, 8 sign variations at 0, 7 at 1, $\check{\phi} \approx 0.510$), is negative for $\phi_d = 0$, positive for $\phi_d = 1$. After considering the various cases specified in the beginning of the Appendix, it follows that $\beta'_{d,0}/\beta'_{d,1} > 1$.

Discretionary profits. First, note that by Eq. (193) with $\phi_q = 1$

$$\pi_{d,0}/\pi_{d,1} = \frac{8(\phi_q - 2)^2}{(4 - \phi_q)(\phi_q - \sqrt{-3\phi_q^2 + 4\phi_q + 16})^2} \sqrt{\frac{-3\phi_q^2 + 4\phi_q + 16}{\phi_q^2 - 3\phi_q + 4}} < 1 \quad (66)$$

$$\Leftrightarrow \phi_q^8 - 11\phi_q^7 + 18\phi_q^6 + 150\phi_q^5 - 584\phi_q^4 + 320\phi_q^3 + 1408\phi_q^2 - 2048\phi_q + \quad (67)$$

$$\sqrt{-3\phi_q^2 + 4\phi_q + 16}(-\phi_q^7 + 13\phi_q^6 - 58\phi_q^5 + 80\phi_q^4 + 128\phi_q^3 - 512\phi_q^2 + 512\phi_q) < 0 \quad (68)$$

$$\Leftrightarrow 4(\phi_q - 3)\phi_q^3(\phi_q^{12} - 23\phi_q^{11} + 206\phi_q^{10} - 838\phi_q^9 + 869\phi_q^8 + 5117\phi_q^7 - 18248\phi_q^6 \quad (69)$$

$$+ 7952\phi_q^5 + 61312\phi_q^4 - 107008\phi_q^3 - 16384\phi_q^2 + 184320\phi_q - 131072) > 0, \quad (70)$$

where we verify that $\phi_q^8 - 11\phi_q^7 + 18\phi_q^6 + 150\phi_q^5 - 584\phi_q^4 + 320\phi_q^3 + 1408\phi_q^2 - 2048\phi_q < 0$, $-\phi_q^7 + 13\phi_q^6 - 58\phi_q^5 + 80\phi_q^4 + 128\phi_q^3 - 512\phi_q^2 + 512\phi_q > 0$, and the latter inequality holds in the interval – all by applying Sturm's theorem and evaluating the functions at the endpoints of the interval (hence the final equivalence is satisfied). Next

$$\pi'_{d,0} = \frac{\sqrt{\eta}(\phi_q - 2)(\phi_q(3\phi_q - 10) + 24)}{2(\phi_q - 4)^2((\phi_q - 3)\phi_q + 4)^{3/2}} < 0 \quad (71)$$

$$\pi'_{d,1} = \frac{\sqrt{\eta}(-3\phi_q^3 + 6\phi_q^2 + 4\phi_q - 16 + \sqrt{\phi_q(4 - 3\phi_q) + 16}(-3\phi_q^2 + 4\phi_q + 16))}{4(\phi_q(3\phi_q - 4) - 16)\sqrt{\phi_q(4 - 3\phi_q) + 16}} < 0, \quad (72)$$

where the latter inequality holds because the denominator is negative ($3\phi_q^2 - 4\phi_q - 16 < 0$) and the sign on the numerator is positive if

$$(-3\phi_q^3 + 6\phi_q^2 + 4\phi_q - 16)^2 - (\phi_q(4 - 3\phi_q) + 16)(-3\phi_q^2 + 4\phi_q + 16)^2 < 0, \quad (73)$$

which by Sturm's theorem (3 sign variation at each end) and endpoint values holds on the interval (note that $-3\phi_q^3 + 6\phi_q^2 + 4\phi_q - 16 < 0$ on the interval). Finally, note that

$$\lim_{\phi_q \rightarrow 0^+} \pi_{d,0}(\phi_q) = \lim_{\phi_q \rightarrow 0^+} \pi_{d,1}(\phi_q) = \sqrt{\eta}/2 > \pi_{d,1}(1) = \frac{1}{68}(9\sqrt{17} - 17)\sqrt{\eta} > \pi_{d,0}(1) = \frac{\sqrt{\eta}}{3\sqrt{2}}.$$

Quantitative profits. First, note that by Eq. (193) with $\phi_q = 1$

$$\pi_{q,0}/\pi_{q,1} = \frac{4}{(4 - \phi_q)(\sqrt{-3\phi_q^2 + 4\phi_q + 16} + \phi_q - 2)} \sqrt{\frac{-3\phi_q^2 + 4\phi_q + 16}{\phi_q^2 - 3\phi_q + 4}} > 1 \quad (74)$$

$$\Leftrightarrow \phi_q^6 - 11\phi_q^5 + 34\phi_q^4 + 30\phi_q^3 - 400\phi_q^2 + 832\phi_q - 512 \quad (75)$$

$$+ \sqrt{-3\phi_q^2 + 4\phi_q + 16} (-\phi_q^5 + 13\phi_q^4 - 66\phi_q^3 + 168\phi_q^2 - 224\phi_q + 128) > 0 \quad (76)$$

$$\Leftrightarrow 4(\phi_q - 3)\phi_q^2(\phi_q^9 - 23\phi_q^8 + 226\phi_q^7 - 1230\phi_q^6 + 3961\phi_q^5 \quad (77)$$

$$- 7147\phi_q^4 + 4560\phi_q^3 + 7424\phi_q^2 - 16384\phi_q + 9216) < 0, \quad (78)$$

where we verify that $\phi_q^6 - 11\phi_q^5 + 34\phi_q^4 + 30\phi_q^3 - 400\phi_q^2 + 832\phi_q - 512 < 0$, $-\phi_q^5 + 13\phi_q^4 - 66\phi_q^3 + 168\phi_q^2 - 224\phi_q + 128 > 0$, and the latter inequality holds in the interval – all by applying Sturm's theorem and evaluating the functions at the endpoints of the interval. Next, note that

$$\pi'_{q,0} = \frac{\sqrt{\eta}(2\phi_q^3 - 3\phi_q^2 - 12\phi_q + 32)}{2(\phi_q - 4)^2((\phi_q - 3)\phi_q + 4)^{3/2}} > 0, \quad (79)$$

$$\pi'_{q,1} = \frac{\sqrt{\eta}(9\phi_q^4 - 24\phi_q^3 - 80\phi_q^2 + 128\phi_q + 256 + \sqrt{\phi_q(4 - 3\phi_q) + 16}(-3\phi_q^3 + 6\phi_q^2 + 28\phi_q - 32))}{4(\phi_q(4 - 3\phi_q) + 16)^2} > 0 \quad (80)$$

$$\Leftrightarrow 108\phi_q^8 - 576\phi_q^7 - 1260\phi_q^6 + 8832\phi_q^5 + 6064\phi_q^4 - 48192\phi_q^3 - 20736\phi_q^2 + 90112\phi_q + 49152 > 0 \quad (81)$$

$$\Leftrightarrow 4(3\phi_q^2 - 4\phi_q - 16)(9\phi_q^6 - 36\phi_q^5 - 105\phi_q^4 + 404\phi_q^3 + 484\phi_q^2 - 1216\phi_q - 768) > 0, \quad (82)$$

where the inequalities follow from $2\phi_q^3 - 3\phi_q^2 - 12\phi_q + 32 > 0$, $9\phi_q^4 - 24\phi_q^3 - 80\phi_q^2 + 128\phi_q + 256 > 0$, $-3\phi_q^3 + 6\phi_q^2 + 28\phi_q - 32 < 0$, $3\phi_q^2 - 4\phi_q - 16 < 0$. The final term in parenthesis is negative by Sturm's theorem – 3 sign variations and negative at each of the endpoints. Finally, $\lim_{\phi_q \rightarrow 0^+} \pi_{q,0}(\phi_q) = \lim_{\phi_q \rightarrow 0^+} \pi_{q,1}(\phi_q) = 0 < \pi_{q,1}(1) = \frac{1}{68}(17 - \sqrt{17})\sqrt{\eta} < \pi_{q,0}(1) = \frac{\sqrt{\eta}}{3\sqrt{2}}$.

Price impact. First note that,

$$\lambda_1^2 - \lambda_0^2 = \frac{(3 - \phi_q)\phi_q^2(3\phi_q - 4)}{\eta(\phi_q - 4)^2(3\phi_q^2 - 4\phi_q - 16)}, \quad (83)$$

where both the numerator and denominator are negative in the region, implying that $\lambda_1 > \lambda_0$.

Next, note that

$$\lambda'_0(\phi_d) = \frac{5\phi_q - 4}{2(\phi_q - 4)^2 \sqrt{\eta((\phi_q - 3)\phi_q + 4)}}, \quad (84)$$

implying that λ_0 decreases for $\phi_q < 0.8 \equiv \bar{\phi}_q$ and increases for $\phi_q > \bar{\phi}_q$. Additionally,

$$\lambda'_1(\phi_d) = \frac{\eta(6\phi_q - 4)}{(\eta(\phi_q(4 - 3\phi_q) + 16))^{3/2}}, \quad (85)$$

implying that λ_1 decreases for $\phi_q < 2/3 \equiv \underline{\phi}_q$ and increases for $\phi_q > \underline{\phi}_q$. Next,

$$(\lambda'_0)^2 - (\lambda'_1)^2 \quad (86)$$

$$= \frac{819\phi_q^8 - 6708\phi_q^7 + 22576\phi_q^6 - 80192\phi_q^5 + 319232\phi_q^4 - 688128\phi_q^3 + 626688\phi_q^2 - 196608\phi_q}{4\eta(\phi_q - 4)^4 (\phi_q^2 - 3\phi_q + 4) (3\phi_q^2 - 4\phi_q - 16)^3}, \quad (87)$$

where the denominator is negative on the interval, implying that the sign on the expression is dictated by the sign on $819\phi_q^8 - 6708\phi_q^7 + 22576\phi_q^6 - 80192\phi_q^5 + 319232\phi_q^4 - 688128\phi_q^3 + 626688\phi_q^2 - 196608\phi_q$, which is negative at $\phi_q = 0$ and $\phi_q = 1$, and has two zeros on the interval, verified by Sturm's theorem (5 sign variations at 0 and 3 at 1), approximately $\phi_q \approx 0.754$, $\phi_q \approx 0.916$. Therefore, for $\phi_q < 0.754$ and $\phi_q > 0.916$ $|\lambda'_0| > |\lambda'_1|$, for $0.754 < \phi_q < 0.916$ $|\lambda'_0| < |\lambda'_1|$.

Together with the signs on derivatives, for $\phi_q < 2/3$, λ_0 decreases more steeply than λ_1 , for $2/3 < \phi_q < 0.8$, λ_0 decreases and λ_1 increases, for $0.8 < \phi_q < 0.916$, λ_1 increases more steeply than λ_0 , and for $\phi_q > 0.916$ λ_0 increases more steeply than λ_1 . Finally, $\lim_{\phi_q \rightarrow 0^+} \lambda_0(\phi_q) = \lim_{\phi_q \rightarrow 0^+} \lambda_1(\phi_q) = \frac{1}{2\sqrt{\eta}} > \lambda_1(1) = \frac{2}{\sqrt{17}\sqrt{\eta}} > \lambda_0(1) = \frac{1}{3}\sqrt{\frac{2}{\eta}}$.

Price informativeness. First, using Eq. (191) for a perfectly-informed DI, and taking the derivative with respect to ϕ_q implies that that price informativeness is increasing for both equilibria:

$$PI'_0 = \frac{2}{(\phi_q - 2)^2} > 0 \quad (88)$$

$$PI'_1 = \frac{(\phi_q + 8) \left(\left(\sqrt{\phi_q(4 - 3\phi_q) + 16} - \phi_q + 2 \right) \phi_q + 8 \right)}{2\sqrt{\phi_q(4 - 3\phi_q) + 16} (-\phi_q^2 + \phi_q + 4)^2} > 0. \quad (89)$$

Furthermore,

$$PI'_0 - PI'_1 = \frac{\phi_q^5 + 2\phi_q^4 - 44\phi_q^3 + 56\phi_q^2 + 160\phi_q - 256 + \sqrt{-3\phi_q^2 + 4\phi_q + 16} (3\phi_q^4 - 12\phi_q^3 + 64)}{2(\phi_q - 2)^2 \sqrt{-3\phi_q^2 + 4\phi_q + 16} (\phi_q^2 - \phi_q - 4)^2}, \quad (90)$$

where, since the denominator is positive, $3\phi_q^4 - 12\phi_q^3 + 64 > 0$, $\phi_q^5 + 2\phi_q^4 - 44\phi_q^3 + 56\phi_q^2 + 160\phi_q - 256 < 0$ on the interval, the expression is positive if

$$(\phi_q^5 + 2\phi_q^4 - 44\phi_q^3 + 56\phi_q^2 + 160\phi_q - 256)^2 - (-3\phi_q^2 + 4\phi_q + 16) (3\phi_q^4 - 12\phi_q^3 + 64)^2 < 0 \quad (91)$$

$$\Leftrightarrow 4\phi_q (\phi_q^2 - \phi_q - 4)^2 (7\phi_q^5 - 48\phi_q^4 + 76\phi_q^3 - 112\phi_q^2 + 912\phi_q - 1536) < 0 \quad (92)$$

$$\Leftrightarrow 7\phi_q^5 - 48\phi_q^4 + 76\phi_q^3 - 112\phi_q^2 + 912\phi_q - 1536 < 0. \quad (93)$$

The latter inequality always holds because the expression is negative at the endpoints and there are no roots in the interval as verified by Sturm's theorem (3 sign variations at both 0 and 1). Therefore $PI'_1 < PI'_0$, and it is immediate that $\lim_{\phi_q \rightarrow 0^+} PI_1(\phi_q) = \lim_{\phi_q \rightarrow 0^+} PI_0(\phi_q) = 2$, and $PI_0(1) = 3 > PI_1(1) = \frac{1}{8}(\sqrt{17} + 17)$. $\square$

A.3 Proof of Proposition 3

The solutions for $\{\beta_{d,\gamma}, \beta_{q,\gamma}, \lambda_\gamma\}$ follow from the following system of equations:

$$\lambda_\gamma = \frac{\beta_{d,\gamma} + \beta_{q,\gamma}}{\left(\frac{1}{\phi_d} - 1\right) \beta_{d,\gamma}^2 + (\beta_{d,\gamma} + \beta_{q,\gamma})^2 + \eta} \quad (94)$$

$$\beta_{q,\gamma} = \frac{\gamma}{\gamma + (1 - \gamma)\lambda_\gamma} \beta_b + \frac{(1 - \gamma)\lambda_\gamma}{\gamma + (1 - \gamma)\lambda_\gamma} \frac{1 - \lambda_\gamma \beta_{d,\gamma}}{2\lambda_\gamma} \quad (95)$$

$$\beta_{d,\gamma} = \frac{\phi_d(1 - \lambda_\gamma \beta_{q,\gamma})}{2\lambda_\gamma}. \quad (96)$$

For $\gamma = 0$, the set of solutions that satisfy the traders' second order condition are

$$\beta_{d,0} = \phi_d \sqrt{\frac{\eta}{(\phi_d - 3)\phi_d + 4}} \quad (97)$$

$$\beta_{q,0} = (2 - \phi_d) \sqrt{\frac{\eta}{(\phi_d - 3)\phi_d + 4}} \quad (98)$$

$$\lambda_0 = \frac{1}{4 - \phi_d} \sqrt{\frac{(\phi_d - 3)\phi_d + 4}{\eta}}. \quad (99)$$

For $\gamma = 1$, the set of solutions are

$$\beta_{d,1} = \frac{1}{4} \sqrt{\frac{\eta}{\phi_d}} \left(\sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16 - \phi_d^2 + 4\phi_d - 4} \right) \quad (100)$$

$$\beta_{q,1} = \sqrt{\frac{\eta}{\phi_d}} \left(1 - \frac{\phi_d}{2} \right) \quad (101)$$

$$\lambda_1 = \sqrt{\frac{\phi_d}{\eta}} \frac{2\phi_d}{\sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16 - 2\phi_d^2 + 6\phi_d - 4}}. \quad (102)$$

In what follows, note that both sets of solutions are positive.

Quant's trading intensity. We can characterize the change in trading intensity for the quant as follows:

$$\beta_{q,1} - \beta_{q,0} > 0 \Leftrightarrow \beta_{q,1}^2 - \beta_{q,0}^2 > 0 \Leftrightarrow \frac{\eta(\phi_d^4 - 11\phi_d^3 + 36\phi_d^2 - 44\phi_d + 16)}{4\phi_d(\phi_d^2 - 3\phi_d + 4)} \equiv g(\phi_d) > 0 \quad (103)$$

Note that:

$$\phi_d^4 - 11\phi_d^3 + 36\phi_d^2 - 44\phi_d + 16 = (\phi_d - 2)^2 (\phi_d^2 - 7\phi_d + 4) \equiv f(\phi_d), \quad (104)$$

implying that the only zero for $\phi_d \in (0, 1]$ is $\phi_d^* = \frac{1}{2}(7 - \sqrt{33})$. Further, note that $\eta/(4\phi_d(\phi_d^2 - 3\phi_d + 4)) > 0$, $f(0) > 0$, $f(1) < 0$, which, together, implies that for $\phi_d < (>) \phi_d^*$ the trading intensity of the QI is greater in the Quantitative (Strategic) Equilibrium. Next,

$$\beta'_{q,1} = -\frac{(\phi_d + 2) \sqrt{\eta\phi_d}}{4\phi_d^2} < 0 \quad (105)$$

$$\beta'_{q,0} = -\frac{\sqrt{\eta}(\phi_d + 2)}{2((\phi_d - 3)\phi_d + 4)^{3/2}} < 0, \quad (106)$$

which implies that QI's trading intensity decreases for both equilibria. Finally, note that

$$\lim_{\phi_d \rightarrow 0^+} \beta_{q,0}(\phi_d) = \sqrt{\eta} < \lim_{\phi_d \rightarrow 0^+} \beta_{q,1}(\phi_d) = \infty, \beta_{q,0}(1) = \sqrt{\eta/2} > \beta_{q,0}(1) = \sqrt{\eta}/2.$$

Discretionary trading intensity. We can characterize the change in trading intensity for the DI as follows:

$$\beta_{d,1} - \beta_{d,0} > 0 \Leftrightarrow \beta_{d,1}^2 - \beta_{d,0}^2 > 0 \quad (107)$$

$$\Leftrightarrow \phi_d^4 - 7\phi_d^3 + 28\phi_d^2 - 28\phi_d + 16 + \sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} (-\phi_d^2 + 3\phi_d - 4) > 0 \quad (108)$$

$$\equiv f(\phi_d) + g(\phi_d)\sqrt{h(\phi_d)} > 0, \quad (109)$$

where the latter equivalence follows from simplifying for terms that are positive over the interval. Note that $g(\phi_d)$ is negative on the interval and $f(\phi_d)$ is positive on the interval (verified by Sturm's theorem). Hence, the expression above is equal to zero on the interval if:

$$-16\phi_d^3(\phi_d^2 - 7\phi_d + 4) = 0, \quad (110)$$

which holds exactly for $\phi_d = \phi_d^*$, i.e., $\beta_{d,0}(\phi_d^*) = \beta_{d,1}(\phi_d^*)$. It follows that the DI's trading intensity is greater (lower) in the Quantitative Equilibrium when $\phi_d > (<) \phi_d^*$

Furthermore, note that in the Strategic Equilibrium

$$\beta'_{d,0}(\phi_d) = \frac{\sqrt{\eta}(8 - 3\phi_d)}{2(\phi_d^2 - 3\phi_d + 4)^{3/2}}, \quad (111)$$

which is greater than zero for $\phi_d \in (0, 1]$. In the Quantitative Equilibrium, first define $h(\phi_d) \equiv \phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16$ so that

$$\beta_{d,1} = \frac{\sqrt{\eta}}{4} \frac{\sqrt{h(\phi_d)} - (\phi_d - 2)^2}{\sqrt{\phi_d}}, \quad (112)$$

which implies that the sign of the derivative is determined by

$$\beta'_{d,1}(\phi_d) \propto \sqrt{\phi_d} \left(\frac{1}{2\sqrt{h(\phi_d)}} h'(\phi_d) - 2(\phi_d - 2) \right) - \frac{1}{2\sqrt{\phi_d}} \left(\sqrt{h(\phi_d)} - (\phi_d - 2)^2 \right) \quad (113)$$

$$\propto \phi_d \left(h'(\phi_d) - 4(\phi_d - 2)\sqrt{h(\phi_d)} \right) - \left(h(\phi_d) - (\phi_d - 2)^2\sqrt{h(\phi_d)} \right) \quad (114)$$

$$\propto 3\phi_d^4 - 16\phi_d^3 + 40\phi_d^2 - 16 - \sqrt{h(\phi_d)}(\phi_d - 2)(3\phi_d + 2). \quad (115)$$

The above function is zero when

$$\phi_d^2(3\phi_d^4 + 8\phi_d^3 - 72\phi_d^2 + 32\phi_d + 48) = 0, \quad (116)$$

which does not hold for $\phi_d \in (0, 1]$. Note that $\beta'_{d,1}(1) > 0$, implying that $\beta'_{d,1}(\phi_d) > 0$ for $\phi_d \in (0, 1]$. Finally, $\lim_{\phi_d \rightarrow 0^+} \beta_{d,0}(\phi_d) = \lim_{\phi_d \rightarrow 0^+} \beta_{d,1}(\phi_d) = 0$, $\beta_{d,1}(1) = \sqrt{\eta/2} > \beta_{d,0}(1) = \frac{1}{4}(\sqrt{17} - 1)\sqrt{\eta}$.

Discretionary profits. First, note that by Eq. (193) with $\phi_q = 1$, profits, scaled by τ_v , are given by

$$\pi_d = \beta_d(1 - \lambda\beta_q) - \phi_d^{-1}\lambda\beta_d^2 \quad (117)$$

Note that

$$\pi_{d,0} - \pi_{d,1} > 0 \Leftrightarrow \pi_{d,0}^2 / \pi_{d,1}^2 > 1. \quad (118)$$

We evaluate the latter ratio and compare the numerator and denominator, which results in the following necessary and sufficient condition:

$$\phi_d^{12} - 27\phi_d^{11} + 348\phi_d^{10} - 2768\phi_d^9 + 14848\phi_d^8 - 55848\phi_d^7 + 149504\phi_d^6 - 285408\phi_d^5 \quad (119)$$

$$+ 384896\phi_d^4 - 359424\phi_d^3 + 224256\phi_d^2 - 86016\phi_d + 16384 \quad (120)$$

$$+ (-\phi_d^{10} + 23\phi_d^9 - 244\phi_d^8 + 1548\phi_d^7 - 6400\phi_d^6 + 17872\phi_d^5 - 33952\phi_d^4 \quad (121)$$

$$+ 43264\phi_d^3 - 35584\phi_d^2 + 17408\phi_d - 4096)\sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} \quad (122)$$

$$\equiv f(\phi_d) + g(\phi_d)\sqrt{h(\phi_d)} < 0. \quad (123)$$

A necessary condition for the expression above to be zero is:

$$f(\phi_d)^2 - g(\phi_d)^2 h(\phi_d) = -16(\phi_d - 2)^2 \phi_d^5 (\phi_d^2 - 7\phi_d + 4) \quad (124)$$

$$(\phi_d^{10} - 20\phi_d^9 + 188\phi_d^8 - 1100\phi_d^7 + 4316\phi_d^6 - 11568\phi_d^5 + 21168\phi_d^4 - 25152\phi_d^3 \quad (125)$$

$$+ 17664\phi_d^2 - 6144\phi_d + 4096) = 0. \quad (126)$$

On the interval, as confirmed by Sturm's theorem for the 10th-degree polynomial (strictly positive), the only zero is $\phi_d = \phi_d^*$. We confirm that $f(\phi_d^*) + g(\phi_d^*)\sqrt{h(\phi_d^*)} = 0$, $f(\phi_d) > 0$, $g(\phi_d) < 0$ on the interval. It follows that for $\phi_d < (>) \phi_d^*$, DI's profits in the Strategic (Quantitative) Equilibrium are greater.

For the Quantitative Equilibrium, taking the derivative with respect to ϕ_d , implies that the derivative is positive if and only if:

$$v(\phi_d) = 9\phi_d^8 - 110\phi_d^7 + 660\phi_d^6 - 2008\phi_d^5 + 3024\phi_d^4 - 1312\phi_d^3 - 1088\phi_d^2 + 1408\phi_d - 512 \quad (127)$$

$$+ \sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} (-9\phi_d^6 + 74\phi_d^5 - 256\phi_d^4 + 384\phi_d^3 - 48\phi_d^2 - 224\phi_d + 128) \quad (128)$$

$$> 0. \quad (129)$$

Note that $v(0) = 0$ and $v(1) > 0$. Further, a necessary condition for $v(\phi_d)$ to be zero is:

$$\begin{aligned} & (\phi_d^8 - 110\phi_d^7 + 660\phi_d^6 - 2008\phi_d^5 + 3024\phi_d^4 - 1312\phi_d^3 - 1088\phi_d^2 + 1408\phi_d - 512)^2 \\ &= (\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16) (-9\phi_d^6 + 74\phi_d^5 - 256\phi_d^4 + 384\phi_d^3 - 48\phi_d^2 - 224\phi_d + 128)^2 \\ &\Leftrightarrow 45\phi_d^7 - 280\phi_d^6 + 540\phi_d^5 + 496\phi_d^4 - 2448\phi_d^3 + 1536\phi_d^2 + 832\phi_d - 1280 = 0. \end{aligned}$$

We confirm that the latter function has no zeros in the interval by Sturm's theorem (specifically three sign variations for each side of the interval). Therefore, π_d is increasing in the interval.

For the Strategic Equilibrium:

$$\pi_d' = \frac{\sqrt{\eta} (\phi_d (\phi_d (2\phi_d - 3) - 12) + 32)}{2 (\phi_d - 4)^2 ((\phi_d - 3) \phi_d + 4)^{3/2}}, \quad (130)$$

which is positive if and only if

$$p(\phi_d) \equiv 2\phi_d^3 - 3\phi_d^2 - 12\phi_d + 32 > 0. \quad (131)$$

Note that $p(0) = 32 > p(1) = 19 > 0$ and $p'(\phi_d)$ is negative on the interval, which implies that π_d is increasing. Finally, $\lim_{\phi_d \rightarrow 0^+} \pi_{d,0}(0) = 0$, $\lim_{\phi_d \rightarrow 0^+} \pi_{d,1}(0) = 0$, $\pi_{d,0}(1) = \frac{\sqrt{\eta}}{3\sqrt{2}} < \pi_{d,1}(1) = \frac{1}{68} (9\sqrt{17} - 17) \sqrt{\eta}$, and $\pi_{d,0}(\phi^*) = \pi_{d,1}(\phi^*)$.

Quantitative profits. First, note that by Eq. (193) with $\phi_q = 1$, profits, scaled by τ_v , are given by

$$\pi_q = \beta_q (1 - \lambda \beta_d) - \lambda \beta_q^2 \quad (132)$$

Note that

$$\pi_{d,0} - \pi_{d,1} > 0 \Leftrightarrow \pi_{d,0}^2 / \pi_{d,1}^2 > 1. \quad (133)$$

We evaluate the latter ratio and compare the numerator and denominator, which results in the following necessary and sufficient condition:

$$- \phi_d^8 + 19\phi_d^7 - 164\phi_d^6 + 856\phi_d^5 - 2736\phi_d^4 + 5392\phi_d^3 - 5952\phi_d^2 + 3584\phi_d - 1024 \quad (134)$$

$$+ (\phi_d^6 - 15\phi_d^5 + 92\phi_d^4 - 332\phi_d^3 + 656\phi_d^2 - 640\phi_d + 256) \sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} \quad (135)$$

$$\equiv f(\phi_d) + g(\phi_d)\sqrt{h(\phi_d)} < 0. \quad (136)$$

A necessary condition for the expression above to be zero is:

$$f(\phi_d)^2 - g(\phi_d)^2 h(\phi_d) = -16\phi_d^3 (\phi_d^2 - 7\phi_d + 4) \quad (137)$$

$$(\phi_d^8 - 20\phi_d^7 + 172\phi_d^6 - 864\phi_d^5 + 2736\phi_d^4 - 5504\phi_d^3 + 7168\phi_d^2 - 4864\phi_d + 1024) \quad (138)$$

There are two zeros on the interval: $\phi_d = \phi_d^*$ and $\phi_d \approx 0.350 \equiv \hat{\phi}_d$. We confirm that $f(\phi_d) + g(\phi_d)\sqrt{h(\phi_d)}$ equals zero at ϕ_d^* and $\hat{\phi}_d$, $f(\phi_d) < 0$, $g(\phi_d) > 0$ on the interval. It follows that for $\phi_d < \hat{\phi}_d$, $\pi_{d,0} > \pi_{d,1}$, for $\hat{\phi}_d < \phi_d < \phi_d^*$, $\pi_{d,0} < \pi_{d,1}$, and for $\phi_d > \phi_d^*$, $\pi_{d,0} > \pi_{d,1}$.

For the Quantitative Equilibrium, the derivative of profits is positive if and only if:

$$w(\phi_d) = -9\phi_d^8 + 110\phi_d^7 - 668\phi_d^6 + 2008\phi_d^5 - 2704\phi_d^4 + 800\phi_d^3 + 1472\phi_d^2 - 1408\phi_d \quad (139)$$

$$+ \sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} (9\phi_d^6 - 74\phi_d^5 + 272\phi_d^4 - 336\phi_d^3 - 48\phi_d^2 + 224\phi_d - 128) \quad (140)$$

$$> 0. \quad (141)$$

Note that $w(0) = 0$ and $w(1) < 0$. Further, note that $w(\phi_d) = 0$ if and only if

$$(-9\phi_d^8 + 110\phi_d^7 - 668\phi_d^6 + 2008\phi_d^5 - 2704\phi_d^4 + 800\phi_d^3 + 1472\phi_d^2 - 1408\phi_d)^2 \quad (142)$$

$$= (\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16) (9\phi_d^6 - 74\phi_d^5 + 272\phi_d^4 - 336\phi_d^3 - 48\phi_d^2 + 224\phi_d - 128)^2 \quad (143)$$

$$\Leftrightarrow -144\phi_d^{11} + 2048\phi_d^{10} - 15424\phi_d^9 + 67840\phi_d^8 - 192000\phi_d^7 + 196608\phi_d^6 + 329728\phi_d^5 \quad (144)$$

$$- 761856\phi_d^4 + 225280\phi_d^3 + 262144\phi_d^2 - 278528\phi_d + 65536 = 0. \quad (145)$$

By Sturm's theorem, the last equality has a single root on the interval (5 sign variations at 0 and 4 sign variations at 1), which we numerically evaluate to be approximately $\check{\phi}_d \approx 0.353$. Therefore, $\pi'_{q,1}(\phi_d) > 0$ for $\phi_d < \check{\phi}_d$ and $\pi'_{q,1}(\phi_d) < 0$ for $\phi_d > \check{\phi}_d$.

For the Strategic Equilibrium:

$$\pi'_q = \frac{\sqrt{\eta}(\phi_d - 2)(\phi_d(3\phi_d - 10) + 24)}{2(\phi_d - 4)^2((\phi_d - 3)\phi_d + 4)^{3/2}}, \quad (146)$$

which is negative on the interval because $\phi_d - 2 < 0$ and $\phi_d(3\phi_d - 10) + 24 > 0$. Finally, $\lim_{\phi_d \rightarrow 0^+} \pi_{q,1}(\phi_d) = 0 < \pi_{q,1}(1) = \frac{1}{68}(17 - \sqrt{17})\sqrt{\eta} < \pi_{q,0}(1) = \frac{\sqrt{\eta}}{3\sqrt{2}} < \lim_{\phi_d \rightarrow 0^+} \pi_{q,0}(\phi_d) = \sqrt{\eta}/2$.

Price impact. Price impact in the Strategic Equilibrium is U-shaped in ϕ_d :

$$\lambda'_0(\phi_d) = \frac{5\phi_d - 4}{2\eta(\phi_d - 4)^2 \sqrt{\frac{\phi_d^2 - 3\phi_d + 4}{\eta}}}, \quad (147)$$

which implies that that price impact decreases for $\phi_d < 0.8 \equiv \phi_d^+$ and increases for $\phi_d > \phi_d^+$. The price impact for the Quantitative Equilibrium is always increasing in ϕ_d for the following reasons. Label $j(\phi_d) \equiv 2\phi_d^2 - 6\phi_d + 4$. Since $\lambda_1(\phi_d) > 0$, the sign of the derivative is determined by:

$$\lambda'_1(\phi_d) > 0 \Leftrightarrow (\lambda_1(\phi_d)^2)' > 0 \Leftrightarrow \left(\frac{\phi_d^3}{h(\phi_d) + j(\phi_d)^2 - 2j(\phi_d)\sqrt{h(\phi_d)}} \right)' > 0 \quad (148)$$

$$\Leftrightarrow \frac{(2\phi_d^4 + 6\phi_d^3 - 12\phi_d^2)\sqrt{h(\phi_d)} - \phi_d^6 + 40\phi_d^4 - 64\phi_d^3 + 48\phi_d^2}{\sqrt{h(\phi_d)}(\sqrt{h(\phi_d)} - 2\phi_d^2 + 6\phi_d - 4)^3} > 0. \quad (149)$$

Note that for $\phi_d \in (0, 1]$:

$$2\phi_d^4 + 6\phi_d^3 - 12\phi_d^2 < 0 \quad (150)$$

$$-\phi_d^6 + 40\phi_d^4 - 64\phi_d^3 + 48\phi_d^2 > 0 \quad (151)$$

$$-2\phi_d^2 + 6\phi_d - 4 < 0, \quad (152)$$

implying that for the numerator to be positive, it must be the case that

$$(-\phi_d^6 + 40\phi_d^4 - 64\phi_d^3 + 48\phi_d^2)^2 - (2\phi_d^4 + 6\phi_d^3 - 12\phi_d^2)^2 h(\phi_d) > 0, \quad (153)$$

which implies that

$$(2 - \phi_d) \phi_d^5 (3\phi_d^6 - 2\phi_d^5 + 32\phi_d^4 + 720\phi_d^3 + 48\phi_d^2 - 928\phi_d + 384) > 0, \quad (154)$$

which holds on the interval by Sturm's theorem (as the latter terms has 2 sign changes and positive values at each endpoint) . Next, note that the denominator is positive if and only if

$$h(\phi_d) - (2\phi_d^2 - 6\phi_d + 4)^2 = -\phi_d (3\phi_d^3 - 16\phi_d^2 + 12\phi_d - 16) > 0, \quad (155)$$

which also holds on the interval by Sturm's theorem (as the latter term has two signs changes and is negative at each endpoint). Taken together, $\lambda_1'(\phi_d) > 0$ for $\phi_d \in (0, 1]$. In addition, note that the two price impact functions intersect at a single point on the interval for the following reasons.

$$\lambda_1 - \lambda_0 = 0 \Leftrightarrow 1/\lambda_1 \sqrt{\phi_d/\eta} = 1/\lambda_0 \sqrt{\phi_d/\eta} \Leftrightarrow 1/(\lambda_1^2(\phi_d/\eta)) - 1/(\lambda_0^2(\phi_d/\eta)) = \quad (156)$$

$$\Leftrightarrow \frac{5\phi_d^6 - 51\phi_d^5 + 240\phi_d^4 - 548\phi_d^3 + 640\phi_d^2 - 416\phi_d + 128 +}{4\phi_d^2(\phi_d^2 - 3\phi_d + 4)} \quad (157)$$

$$\frac{\sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16}(-4\phi_d^4 + 24\phi_d^3 - 60\phi_d^2 + 72\phi_d - 32)}{4\phi_d^2(\phi_d^2 - 3\phi_d + 4)} \quad (158)$$

$$\equiv \frac{j(\phi_d) + k(\phi_d)\sqrt{l(\phi_d)}}{4\phi_d^2(\phi_d^2 - 3\phi_d + 4)} = 0. \quad (159)$$

Necessary and sufficient conditions for the above to equal zero are

$$j(\phi_d)^2 - k(\phi_d)^2 l(\phi_d) = \quad (160)$$

$$(\phi_d - 2)^2 \phi_d^2 (\phi_d^2 - 7\phi_d + 4) (9\phi_d^6 - 91\phi_d^5 + 444\phi_d^4 - 1308\phi_d^3 + 1776\phi_d^2 - 1088\phi_d + 256) = 0, \quad (161)$$

and $j(\phi_d) > 0, k(\phi_d) < 0$ or $j(\phi_d) < 0, k(\phi_d) > 0$, which for $\phi_d \in (0, 1]$ only holds when $\phi_d = \phi_d^*$ (although by Sturm's theorem the latter term has a single zero on the interval – 4 (3) sign variations at 0 (1) and positive (negative), $\check{\phi}_d \approx 0.975$ – both $j(\check{\phi}_d) < 0, k(\check{\phi}_d) < 0$. Finally, note that $\lim_{\phi_d \rightarrow 0^+} \lambda_1(\phi_d) = 0 < \lambda_0(1) = \frac{\sqrt{2}}{3\sqrt{\eta}} < \lambda_1(1) = \frac{2}{\sqrt{17}\sqrt{\eta}} < \lim_{\phi_d \rightarrow 0^+} \lambda_0(\phi_d) = 1/(2\sqrt{\eta})$.

We can now fully characterize the behavior of the two price impact functions: 1) for $0 < \phi_d < 0.8$ λ_0 is decreasing, λ_1 is increasing, with a single point of intersection at ϕ_d^* . 2) for $\phi_d > 0.8$, both λ_0 and λ_1 are increasing, but λ_1 is increasing at a faster rate.

Price informativeness. Eq. (191) for a perfectly-informed quant simplifies to

$$\mathbb{V}(v|P)^{-1} = 1 + \frac{(\beta_q + \beta_d)^2}{\beta_d^2 (\phi_d^{-1} - 1) + \eta} \equiv PI(\phi_d), \quad (162)$$

where the expression is scaled by τ_v^{-1} . For the full-discretionary equilibrium, price informativeness can be written as

$$PI_0(\phi_d) = \frac{\phi_d - 4}{\phi_d - 2}, \quad (163)$$

which is increasing in ϕ_d :

$$PI'_0(\phi_d) = \frac{2}{(\phi_d - 2)^2} > 0. \quad (164)$$

For the fully-automated equilibrium, price informativeness is:

$$PI_1(\phi_d) = \frac{\phi_d^2 + 4 + \sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16}}{8\phi_d} + \frac{\phi_d + 2}{4 - 2\phi_d}, \quad (165)$$

the sign of the derivative on which is determined by the sign on

$$(\phi_d - 2)^5 (\phi_d + 2) + \sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} (\phi_d^4 - 4\phi_d^3 + 16\phi_d^2 + 16\phi_d - 16) \quad (166)$$

$$\equiv r(\phi_d) + \sqrt{h(\phi_d)}q(\phi_d) \quad (167)$$

We only consider the interval $\phi_d \in (0, 1]$. First, note that $r(\phi_d) < 0$ and $r'(\phi_d) > 0$, which also implies that $r(\phi_d)^2$ is decreasing on the interval. Second, note that $q(\phi_d)$ is increasing on the interval because 1) $q'(\phi_d)$ is a cubic with $0 < q'(0) < q'(1)$, 2) $q''(\phi_d) > 0$ for all ϕ_d . Since $q(0) < 0$ and $q(1) > 0$, there exists a single $\underline{\phi}_d (\approx 0.643)$, such that $q(\phi_d) < 0$ for $\phi_d < \underline{\phi}_d$ and $q(\phi_d) > 0$ for $\phi_d > \underline{\phi}_d$. Therefore, for $\phi_d < \bar{\phi}_d$, $PI'_1(\phi_d) < 0$. For $\phi_d > \bar{\phi}_d$, the derivative is positive if

$$\begin{aligned} h(\phi_d)q(\phi_d)^2 - r(\phi_d)^2 &= (\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16) (\phi_d^4 - 4\phi_d^3 + 16\phi_d^2 + 16\phi_d - 16)^2 \\ &\quad - (2 - \phi_d)^{10} (\phi_d + 2)^2 > 0. \end{aligned} \quad (168)$$

The expression above is equal to zero at $\phi_d \approx 0.725 \equiv \bar{\phi}_d$. Note that $h(\phi_d)$ is U-shaped because $h'(\phi_d)$ is a cubic, $h'(0) < 0$, $h'(1) > 0$ and $h''(\phi_d) > 0$. The bottom of the function is at $\phi_d \approx 0.458 < \bar{\phi}_d$. This implies that for $\phi_d > \bar{\phi}_d$, $h(\phi_d)q(\phi_d)^2$ is increasing, while $r(\phi_d)^2$, implying that the derivative remains positive. Taken together, $PI'_0(\phi_d) < 0$ for $\phi_d < \bar{\phi}_d$ and

$PI'_0(\phi_d) > 0$ for $\phi_d > \bar{\phi}_d$

Note that $\lim_{\phi_d \rightarrow 0^+} PI_0(\phi_d) = 2$, $\lim_{\phi_d \rightarrow 0^+} PI_1(\phi_d) = +\infty$, $PI_0(1) = 3$, $PI_1(1) \approx 2.64$, and $PI_0(\phi_d^*) = PI_1(\phi_d^*)$. Therefore for $\phi_d < (>) \phi_d^*$, price informativeness is greater (less) in the Quantitative (Strategic) Equilibrium.

Finally, we show that the point of intersection is unique on the interval by noting that:

$$PI_0 - PI_1 = 0 \Leftrightarrow PI_0^2 - PI_1^2 = 0 \quad (169)$$

$$\Leftrightarrow \phi_d^5 - 10\phi_d^4 + 160\phi_d^2 + 16\phi_d - 32 + \sqrt{\phi_d^4 - 8\phi_d^3 + 40\phi_d^2 - 32\phi_d + 16} (\phi_d^3 - 6\phi_d^2 - 4\phi_d - 8) \quad (170)$$

$$\equiv f(\phi_d) + g(\phi_d)\sqrt{h(\phi_d)} = 0. \quad (171)$$

Note that $g(\phi_d)$ is negative on the interval, $f(\phi_d)$ is negative for $\phi_d < \check{\phi}_d \approx 0.402$ and positive for $\phi_d > \check{\phi}_d$. A necessary condition is for the equality

$$-64\phi_d^2 (\phi_d^2 - 7\phi_d + 4) (\phi_d^2 - 6\phi_d - 8) (\phi_d^2 - 3\phi_d - 6) = 0, \quad (172)$$

with the only zero on the interval: $\phi_d = \phi_d^* > \check{\phi}_d$, which also satisfies the necessary condition that $g(\phi_d)$ is negative and $f(\phi_d)$ is positive. Hence the intersection is unique on the interval at ϕ_d^* $\square$

A.4 Generalized Model Solution

The solution for $\{\beta_{d,\gamma}, \beta_{q,\gamma}, \lambda_\gamma\}$ follows from the following system of equations:

$$\lambda_\gamma = \frac{\beta_{d,\gamma} + \beta_{q,\gamma}}{\left(\frac{1}{\phi_d} - 1\right) \beta_{d,\gamma}^2 + 2\sigma_e \tau_v \beta_{d,\gamma} \beta_{q,\gamma} + (\beta_{d,\gamma} + \beta_{q,\gamma})^2 + \left(\frac{1}{\phi_q} - 1\right) \beta_{q,\gamma}^2 + \eta} \quad (173)$$

$$\beta_{q,\gamma} = \frac{\gamma}{\gamma + (1 - \gamma)\lambda_\gamma} \beta_b + \frac{(1 - \gamma)\lambda_\gamma}{\gamma + (1 - \gamma)\lambda_\gamma} \frac{\phi_q(1 - \lambda_\gamma \beta_{d,\gamma})}{2\lambda_\gamma} \quad (174)$$

$$\beta_{d,\gamma} = \frac{\phi_d(1 - \beta_{q,\gamma}\lambda_\gamma(1 + \sigma_e \tau_v))}{2\lambda_\gamma}, \quad (175)$$

where

$$\beta_b = \frac{\phi_q}{2} \sqrt{\frac{\eta}{\phi_d}} (2 - \phi_d \sigma_e \tau_v - \phi_d). \quad (176)$$

Strategic Equilibrium For $\gamma = 0$, the set of solutions that satisfy the traders' second order

condition are:

$$\beta_{d,0} = \beta_{q,0}k \quad (177)$$

$$\beta_{q,0} = \frac{\phi_q (\phi_d \sigma_e \tau_v + \phi_d - 2) (\phi_d \phi_q (\sigma_e \tau_v + 1)^2 - 4) \sqrt{\eta}}{\sqrt{(\phi_d \phi_q (\sigma_e \tau_v + 1)^2 - 4)^2 (\phi_d (\phi_q (\sigma_e \tau_v + 1) (\sigma_e \tau_v (\phi_d + \phi_q) + \phi_d + \phi_q - 8) + 4) + 4\phi_q)}} \quad (178)$$

$$\lambda_0 = \sqrt{\frac{\phi_d (\phi_q (\sigma_e \tau_v + 1) (\sigma_e \tau_v (\phi_d + \phi_q) + \phi_d + \phi_q - 8) + 4) + 4\phi_q}{\eta (\phi_d \phi_q (\sigma_e \tau_v + 1)^2 - 4)^2}}, \quad (179)$$

where

$$k = \frac{\phi_d (\sigma_e \phi_q \tau_v + \phi_q - 2)}{\phi_q (\phi_d \sigma_e \tau_v + \phi_d - 2)} \quad (180)$$

Quantitative Equilibrium For $\gamma = 1$, the set of solutions are

$$\beta_{d,1} = \frac{\sqrt{\phi_q (\beta_b^2 (\phi_d (\phi_q (\sigma_e \tau_v + 1) (\phi_d \sigma_e \tau_v + \phi_d - 8) + 4) + 4\phi_q) + 4\eta \phi_d \phi_q)} + \phi_q \beta_b (\phi_d \sigma_e \tau_v + \phi_d - 2)}{2\phi_q} \quad (181)$$

$$\beta_{q,1} = \beta_b = \frac{\phi_q}{2} \sqrt{\frac{\eta}{\phi_d}} (2 - \phi_d \sigma_e \tau_v - \phi_d) \quad (182)$$

$$\lambda_1 = \frac{\phi_d \phi_q}{\sqrt{\phi_q (\beta_b^2 (\phi_d (\phi_q (\sigma_e \tau_v + 1) (\phi_d \sigma_e \tau_v + \phi_d - 8) + 4) + 4\phi_q) + 4\eta \phi_d \phi_q)} + 2\phi_q \beta_b (\phi_d \sigma_e \tau_v + \phi_d - 1)} \quad (183)$$

Interior Equilibrium The system of equations is solved as follows. First, we solve for λ_γ in both Eq. (174) and (175) and set the results equal to derive the relationship between $\beta_{d,\gamma}$ and $\beta_{q,\gamma}$

$$\beta_{d,\gamma} = \frac{-\phi_d \beta_{q,\gamma} (-2\gamma \beta_b - 2\gamma \beta_b \sigma_e \tau_v - 2\gamma + \gamma \sigma_e \phi_q \tau_v - \phi_q (\sigma_e \tau_v + 1) + \gamma \phi_q + 2) - (\phi_d \beta_{q,\gamma}^2 (2\gamma + 2\gamma \sigma_e \tau_v))}{4\gamma \beta_{q,\gamma} - 4\gamma \beta_b - (\gamma - 1) \phi_q (\phi_d \sigma_e \tau_v + \phi_d - 2)} \quad (184)$$

$$\equiv \frac{a\beta_{q,\gamma}^2 + b\beta_{q,\gamma}}{c\beta_{q,\gamma} + d}. \quad (185)$$

Next, we solve for $1/\lambda_\gamma$ in both Eq. (175) and (173), set the results equal, substitute Eq.

(184), to arrive at:

$$\begin{aligned}
& -\eta\phi_q(4\gamma\beta_b + (\gamma - 1)\phi_q(\phi_d\sigma_e\tau_v + \phi_d - 2))^2 \\
& + 8\gamma\eta\phi_q\beta_{q,\gamma}(4\gamma\beta_b + (\gamma - 1)\phi_q(\phi_d\sigma_e\tau_v + \phi_d - 2)) \\
& + \beta_{q,\gamma}^2 \left(4\gamma^2\beta_b^2(3\phi_d\phi_q(\sigma_e\tau_v + 1)^2 - 4) + 2(\gamma - 1)\gamma\beta_b\phi_d\phi_q(\sigma_e\tau_v + 1)(\phi_q(\sigma_e\tau_v + 1)(\phi_d\sigma_e\tau_v + \phi_d - 4) + 4) \right. \\
& \left. + \phi_q((\gamma - 1)^2(\phi_d(\phi_q(\sigma_e\tau_v + 1)(\sigma_e\tau_v(\phi_d + \phi_q) + \phi_d + \phi_q - 8) + 4) + 4\phi_q) - 16\gamma^2\eta) \right) \\
& - 2\gamma\beta_{q,\gamma}^3(4\gamma\beta_b(3\phi_d\phi_q(\sigma_e\tau_v + 1)^2 - 4) + (\gamma - 1)\phi_d\phi_q(\sigma_e\tau_v + 1)(\phi_q(\sigma_e\tau_v + 1)(\phi_d\sigma_e\tau_v + \phi_d - 4) + 4)) \\
& + 4\gamma^2\beta_{q,\gamma}^4(3\phi_d\phi_q(\sigma_e\tau_v + 1)^2 - 4) = 0,
\end{aligned} \tag{186}$$

which is quartic in $\beta_{q,\gamma}$, has a closed-form solution, and has a maximum of four roots. We use Eq. (184) to solve for $\beta_{d,\gamma}$ and, finally, Eq. (173) to solve for λ_γ .

A.4.1 Closed Form for Market Quality Measures

The simulation uses the following measures for market quality and trader behavior.

Price Informativeness Variance conditional on prices in the 2-trader economy is given by:

$$\mathbb{V}(v|P) = \mathbb{V}(v|\lambda(\beta_q s_q + \beta_d s_d + z)) = \mathbb{V}(v|\lambda((\beta_q + \beta_d)v + \beta_q e_q + \beta_d e_d + z)) \tag{187}$$

$$= \tau_v^{-1} - \frac{\lambda^2(\beta_q + \beta_d)^2\tau_v^{-2}}{\lambda^2((\beta_q + \beta_d)^2\tau_v^{-1} + \beta_q^2\tau_q^{-1} + \beta_d^2\tau_d^{-1} + 2\beta_d\beta_q\sigma_e + \tau_z^{-1})} \tag{188}$$

$$= \tau_v^{-1} \frac{\beta_q^2\tau_q^{-1} + \beta_d^2\tau_d^{-1} + 2\beta_d\beta_q\sigma_e + \tau_z^{-1}}{(\beta_q + \beta_d)^2\tau_v^{-1} + \beta_q^2\tau_q^{-1} + \beta_d^2\tau_d^{-1} + 2\beta_d\beta_q\sigma_e + \tau_z^{-1}} \tag{189}$$

$$= \tau_v^{-1} \frac{\beta_q^2(\phi_q^{-1} - 1) + \beta_d^2(\phi_d^{-1} - 1) + 2\beta_d\beta_q\sigma_e\tau_v + \eta}{(\beta_q + \beta_d)^2 + \beta_q^2(\phi_q^{-1} - 1) + \beta_d^2(\phi_d^{-1} - 1) + 2\beta_d\beta_q\sigma_e\tau_v + \eta}, \tag{190}$$

which implies that price informativeness is equal to:

$$\mathbb{V}(v|P)^{-1} = \tau_v \frac{(\beta_q + \beta_d)^2 + \beta_q^2(\phi_q^{-1} - 1) + \beta_d^2(\phi_d^{-1} - 1) + 2\beta_d\beta_q\sigma_e\tau_v + \eta}{\beta_q^2(\phi_q^{-1} - 1) + \beta_d^2(\phi_d^{-1} - 1) + 2\beta_d\beta_q\sigma_e\tau_v + \eta} \equiv PI(\phi), \tag{191}$$

Speculator Profits Expected profits of trader i where $i \in \{d, q\}$ are equal to:

$$\mathbb{E}[\pi_{ij}] = \mathbb{E}[x_{ij}(v - P)] = \mathbb{E}[(\beta_{i,\gamma}s_i)(v - \lambda_\gamma\omega)] \tag{192}$$

$$= \beta_{i,\gamma}(1 - \lambda_\gamma\beta_{d,\gamma} - \lambda_\gamma\beta_{q,\gamma})\tau_v^{-1} - \lambda_\gamma\beta_{i,\gamma}^2\tau_i^{-1} - \lambda_\gamma\beta_{d,\gamma}\beta_{q,\gamma}\sigma_e, \tag{193}$$

which implies that aggregate speculative profits are equal to

$$\mathbb{E}[\pi_{d,\gamma} + \pi_{q,\gamma}] = \mathbb{E}[\pi_{d,\gamma}] + \mathbb{E}[\pi_{q,\gamma}] \quad (194)$$

$$= (\beta_{d,\gamma} + \beta_{q,\gamma})(1 - \lambda_\gamma \beta_{d,\gamma} - \lambda_\gamma \beta_{q,\gamma}) \tau_v^{-1} - \lambda_\gamma (\beta_{d,\gamma}^2 \tau_d^{-1} + \beta_{q,\gamma}^2 \tau_q^{-1}) - 2\lambda_\gamma \beta_{d,\gamma} \beta_{q,\gamma} \sigma_e. \quad (195)$$

Expected Trading Volume We are after $\mathbb{E}[|x_{d,\gamma} + x_{q,\gamma}|]$, which is the expected value of the absolute value of a normal random variable. Otherwise known as the “folded normal distribution,” given a normally distributed random variable $X \sim N(\mu, \sigma^2)$, the expected value of $|X|$ is given by:

$$\mathbb{E}[|X|] = \sigma \sqrt{\frac{2}{\pi}} \exp\left(-\frac{\mu^2}{2\sigma^2}\right) + \mu \left(1 - 2\Phi\left(-\frac{\mu}{\sigma}\right)\right) \quad (196)$$

where Φ is the standard normal cumulative distribution function. It follows that

$$x_{d,\gamma} + x_{q,\gamma} \sim N\left(\underbrace{0}_{\equiv \mu_{x_{d,\gamma} + x_{q,\gamma}}}, \underbrace{(\beta_{d,\gamma} + \beta_{q,\gamma})^2 \tau_v^{-1} + \beta_{d,\gamma}^2 \tau_d^{-1} + \beta_{q,\gamma}^2 \tau_q^{-1} + 2\beta_{d,\gamma} \beta_{q,\gamma} \sigma_e}_{\equiv \sigma_{x_{d,\gamma} + x_{q,\gamma}}^2}\right) \quad (197)$$

Substituting into equation 196

$$\mathbb{E}[|x_{d,\gamma} + x_{q,\gamma}|] = \sigma_{x_{d,\gamma} + x_{q,\gamma}} \sqrt{\frac{2}{\pi}}.$$

By the same logic, for trader $i \in \{d, q\}$

$$x_{i,\gamma} \sim N\left(\underbrace{0}_{\equiv \mu_{x_{i,\gamma}}}, \underbrace{\beta_{i,\gamma}^2 (\tau_v^{-1} + \tau_i^{-1})}_{\equiv \sigma_{x_{i,\gamma}}^2}\right), \quad (198)$$

which implies that

$$\mathbb{E}[|x_{i,\gamma}|] = \sigma_{x_{i,\gamma}} \sqrt{\frac{2}{\pi}}$$

A.5 Breakeven Correlation

We compare the absolute trading intensity of the QI in the Quantitative Equilibrium to the Strategic Equilibrium:

$$|\beta_{q,1}| > |\beta_{q,0}| \Leftrightarrow \beta_{q,1}^2 > \beta_{q,0}^2 \Leftrightarrow \beta_b^2 / \beta_{q,0}^2 > 1 \Leftrightarrow \quad (199)$$

$$\frac{1}{4}\phi_q(\sigma_e\tau_v + 1)(\sigma_e\tau_v(\phi_d + \phi_q) + \phi_d + \phi_q - 8) + \frac{\phi_q}{\phi_d} > 0 \quad (200)$$

$$\Leftrightarrow \sigma_e^2 \left(\frac{1}{4}\phi_d\phi_q\tau_v^2 + \frac{1}{4}\phi_q^2\tau_v^2 \right) + \sigma_e \left(\frac{1}{2}\phi_d\phi_q\tau_v + \frac{1}{2}\phi_q^2\tau_v - 2\phi_q\tau_v \right) + \frac{\phi_d\phi_q}{4} + \frac{\phi_q}{\phi_d} + \frac{\phi_q^2}{4} - 2\phi_q > 0 \quad (201)$$

$$\equiv f(\sigma_e) > 0. \quad (202)$$

The quadratic in σ_e has two solutions:

$$\sigma_e^* = \frac{4 - \phi_d - \phi_q - 2\sqrt{3 - \frac{\phi_q}{\phi_d}}}{\tau_v(\phi_d + \phi_q)}, \sigma_e^* = \frac{4 - \phi_d - \phi_q + 2\sqrt{3 - \frac{\phi_q}{\phi_d}}}{\tau_v(\phi_d + \phi_q)}. \quad (203)$$

Note that since $\rho_e = \sigma_e\sqrt{\tau_d\tau_q}$ and τ_d, τ_q, τ_v are assumed to be constant in estimating the breakeven correlation, $f(\sigma_e)$ can be rewritten as $g(\rho_e)$. Therefore, the sign of the trading wedge will be determined by the solution to $g(\rho_e) = 0$, which is $\rho_e^* = \sigma_e^*\sqrt{\tau_d\tau_q}$:

$$\rho_{e,\pm}^* = \sqrt{\frac{\phi_d\phi_q}{(1-\phi_d)(1-\phi_q)}} \frac{4 - \phi_d - \phi_q \pm 2\sqrt{3 - \frac{\phi_q}{\phi_d}}}{\phi_d + \phi_q}. \quad (204)$$

Since $g(\rho_e)$ is an upward parabola and $\rho_e \in [-1, 1]$, the inequality above holds for the following conditions:

1. $\forall \rho_e \in [-1, 1]$ if $\phi_q > 3\phi_d$ or $\rho_{e,-}^* > 1$ or $\rho_{e,+}^* < -1$
2. $\forall \rho_e \in [\rho_{e,+}^*, 1]$ if $\rho_{e,-}^* \leq -1$ and $\rho_{e,+}^* \in (0, 1)$
3. $\forall \rho_e \in [-1, \rho_{e,-}^*]$ if $\rho_{e,+}^* \geq 1$ and $\rho_{e,-}^* \in (0, 1)$
4. $\forall \rho_e \in [0, \rho_{e,-}^*] \cup [\rho_{e,+}^*, 1]$ if $\rho_{e,-}^* \in (0, 1)$ and $\rho_{e,+}^* \in (0, 1)$
5. Never holds if $\rho_{e,-}^* < -1$ and $\rho_{e,+}^* > 1$

Given the range of $\phi_d \in (0, 1]$ and $\phi_q \in (0, 1]$, a numerical analysis demonstrates that only conditions 1, 3, and 5 are possible.