The Transparency-Revenue Conundrum in Social Trading: Implications for Platforms and Investors

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Abstract

Social trading – an emerging paradigm in the spirit of the sharing economy – enables a trader to share her trading wisdom with other investors. A special type of social trading is copy trading, where less experienced investors (followers) are allowed to copy the trades of experts (traders) in real-time after paying a fee. Such a copy trading mechanism often runs into a transparency-revenue conundrum. On the one hand, social trading platforms need to release traders' trades as transparently as possible to allow followers to evaluate traders. On the other hand, complete transparency may undercut the platform's revenue since followers could free ride. That is, followers could manually copy the delayed trades of a trader to circumvent paying following fees.

This study addresses this simple, but fundamental problem by determining the optimal policy for releasing trade information. Of key interest here is the real time value of trade information. We measure this real time value using the concept of profit-gap, i.e., the would-be profit difference between the real time and a delayed execution of a trade. Our data shows that profit-gap increases with delay in a concave manner. To provide empirical evidence of the conundrum, we explore how the amount following is affected by delay and users' evaluation activity on the trader (measured by the number of views received by the trader's profile page). Surprisingly, when the number of views is high, a larger delay is associated with a lower amount following. A large delay handicaps the ability of potential followers to evaluate the trader, thus reducing the amount that would potentially have followed the trader. This potential loss is higher when the number of views is higher. On the other hand, a larger delay discourages existing followers to free ride and hence protects the existing amount following a trader.

We propose the notion – money-at-risk – to quantify the possible loss of existing followers (amount following) as a result of releasing delayed trades. The tradeoff between transparency and money-at-risk is cast as an optimization problem that attempts to maximize information transparency while respecting a money-at-risk constraint. Three information release policies are compared: (1) Uniform Release Policy, (2) Customized Money-at-Risk Release Policy, and (3) Customized Indifference Policy. We demonstrate the performance of the above policies using data from a leading social trading platform operating in the Foreign Exchange market. We also study a Stochastic control formulation that directly optimizes platform revenue. The control is the delay that is calculated as a function of the current amount of money following a trader and the number of views received by the trader's profile page. Besides, the calculated revenue can be incorporated into the ranking algorithm to provide a systematic way to infuse the platform's goals into the ranking the traders.

Keywords: *Fintech*; *Social Trading*; *Information Value*; *Information Release Policy*

1 Introduction

The emergence of new financial technologies (Fintech) has helped bridge the digital divide of financial services, especially in terms of access to financial advising and wealth management services. Among them is social trading, through which a retail investor can manage her wealth (no matter how small it is) by directly following other traders' financial advice (Eldridge 2017). These traders often share their opinions (aka financial advice) on financial markets through specialized social media platforms (e. g., StockTwits and Seeking Alpha), where traders can make friends, post their opinions, and directly communicate with other investors (Doering et al. 2015). Investors can then use such financial advice to make trading decisions.

Recently there emerges a more disruptive type of social trading platforms, represented by eToro, Zulutrade and Collective2. They go beyond merely providing a platform for traders to share their trading opinions, they even allow investors to observe and follow the actual trading (*action*) of peer traders on stocks, currencies, and cryptocurrencies (Pelster and Hofmann 2017). And we focus on these newer types of social trading services.

These social trading platforms have gained growing popularity as evidenced by receiving multiple rounds of venture capital funding (Reuters 2018) and the growing pool of traders on these platforms with over 13.9 million online retail traders as of 2018 (BusinessWire 2017), (BrokerNotes 2018). eToro alone has attracted over 9 million active users in 2018, mostly small retail investors, who are allowed to open an account with as little as 200 USD [1]. The demand for social trading services is projected to explode in the future (Empire 2017), covering 37% of the population of investors by 2021 (eToro 2017). Most of these social trading platforms are regulated. For example, the Financial Conduct Authority (FCA) in 2015 stipulated a rule that all traders in social trading need to comply with the MiFID II ruling to qualify as investment managers [2]. A handful of these platforms are allowed to operate in the U.S. market to serve U.S. residents, including Collective2, Peertrade and Zulutrade's Forex and FXCM markets [3].

Of central interest to us is the social trading feature called *copy trading*. This feature enables investors to replicate – in real-time and in their own accounts – the actual trades of other investors. An investor is allowed to follow other traders for a fee and have the platform automatically execute the trades of other traders on her own account in a real time manner. There are several key advantages of such a copy trading mechanism, compared to other wealth management services: 1) More transparency since investors will observe every single trade of a trader [4]; 2) higher-level of control since the execution is done in the investor's own account[5]; 3) more reasonable fee (compared to funds), typically zero management fee and 20 percent when there is a gain (https://www.zulutrade.com/trader-

[1] https://bitcoinist.com/9-million-traders-flocked-etoros-social-trading-platform/

[2] The key regulations on social trading include 1) No hedging of trades - a trader cannot have a trade in the same instrument open in two opposite directions (Buy and Sell simultaneously); and 2) First In First Out (FIFO) trades rule - when a trader has multiple trades open of the same pair in the same direction, they must however be closed in the order they are opened, https://financefeeds.com/mifid-ii-entering-age-completely-self-directed-traders-final-nail-goes-copy-trading-coffin/.

[3] https://socialtradingguru.com/social-trading-for-us-residents

[4] For example, although institutional money managers with $100 million or more in qualifying assets are required to file quarterly an SEC Form 13F detailing their investment holdings, investors do not know exactly when the fund manager bought and sold a commodity in the portfolio.

[5] In institutional markets, investors have less flexibility over their portfolios; for example, less control over timing the recognition of gains and no way to customize the specific set of commodities in the portfolio.

guide)[6], and 4) preventing potential manipulation that may occur in the financial advising industry, where financial advisors may strategically distort their recommendations by "speaking in two tongues", for example, issuing overly positive recommendations but less optimistic forecasts (Malmendier and Shanthikumar 2014). Under copy trading, it is hard for traders to "speak in two tongues" since their real investment actions are observed and copied. Top social trading networks (platforms) that enable copy trading include eToro, ZuluTrade, Ayondo, Tradeo, etc. For example, eToro launched this feature in 2007 for followers to replicate traders' trades (Kortekaas 2013). According to eToro, among its 300 billion U.S. dollars worth of trades, two-thirds were executed through copy trading (Brand 2017).

We seek to devise a proper information revelation mechanism to optimize information transparency in social trading. Improving information transparency has been one of the key drivers underlying the current wave of financial technology innovations (Lee and Shin 2018). Compared with traditional fund management, social trading platforms provide much higher information transparency by sharing not only aggregated metrics but detailed trade-level information among traders. Many social trading platforms have gone to the extreme of publicizing all the trades of each trader (Glaser and Risius 2018). This complete information transparency policy is one of the main drivers behind the explosive growth of the user base in social trading (Röder and Walter 2017).

Information transparency in trading involves two aspects: (1) what information should be disclosed (e.g., detailed versus aggregate trading performance), and (2) when information should be disclosed (e.g., immediate versus delayed). Timing the release of information is particularly relevant in social trading since trading information quickly loses value in a fast-paced financial market. A trend in the social trading industry is to release as much information to investors as possible (e.g. eToro and Zulutade have started releasing each trade transacted by each trader including the securities bought or sold, time and

[6] It is reported that investors earned an average of 4.67% on mutual funds over the last 20 years, which is even 3.52% less than the average SP 500 index return; mutual funds provided an average return of 6.92% over the last 5 years, around 3% less than the SP 500 index over the same period (Kim 2017). As Warren Buffett described about fund managers: "Professionals in other fields, like dentists, bring a lot to the layman, but people get nothing for their money from professional money managers." The fund industry is overdue for change. The fee war is just part of the problem; price-conscious investors also want more transparency around how they pay for advice (Kapadia 2018).

price of the transaction etc.)[7], and as such there is typically no ambiguity with regard to decision 1 in social trading. Our study thus focuses on decision 2, *when* to release information.

Specifically, concerning the decision of when to release information, in copy trading, timing the release of information is crucial. Potential investors have to rely on the information the platforms provide to evaluate traders in order to choose a subset of traders to follow. Information becomes less transparent if it is released with longer delay. On the other hand, releasing trade information with very little or no delay can also cause problems. Copy trading is not free for followers: the platform functions as an online broker and, in addition to a brokerage fee, it also charges followers a fee to follow the trades of traders in real-time. Traders receive a commission calculated as a fraction of the follower fees generated from their trades. Followers will not pay to follow if detailed trade information is already released for free in real-time. Thus, traders will lose paid followers and consequently, will lose the incentive to participate in the platform. Therefore, a fundamental decision for a copy trading platform is to choose the right level of information transparency with regard to the timing of releasing trade information.

At one extreme, some social trading platforms have allowed complete information transparency by releasing real-time trading information of traders to the public.[8] However, complete information transparency invokes the opportunistic behavior of investors, since they no longer have to pay to follow traders and can get the real-time information for free. At the other extreme, social trading platforms may choose to delay information release indefinitely. This, of course, renders such information unusable. Most social trading platforms, however, seek a balance between complete information transparency and complete hiding by adding some time delay to release detailed, trade-level information.

We therefore focus on the decision of determining the optimal time to release detailed

[7]Concerning the decision of what information to release, most platforms release full information. By providing the detailed trade-level information, the platform protects itself by delegating the responsibility of evaluating traders to followers, thereby reducing the probability of followers making biased decisions acting on aggregated performance indicators (e.g. monthly returns). However, because releasing detailed information could increase the information processing burden of investors, detailed information is usually made available on-demand (e.g., by clicking on a link), while only summarized information is made visible by default.

[8]ZuluTrade initially experimented with this policy around 2013, but later, moved to the policy of releasing trade information with some delay.

trading information. While releasing such valuable trade information is important, displaying this information with a large time delay may defeat its purpose. A large delay makes it difficult for potential followers to evaluate traders thoroughly. Traders may trade with different strategies on different securities and they often need to adjust their trading strategies based upon the changing market conditions. Potential followers would only be able to evaluate the on-going strategies if the trades are released without too much delay.

At the high level, we answer the simple but fundamental question: is copy trading worthwhile for followers? In other words, *how valuable is it for followers to know (in real-time) the trades of traders, given that they must pay a fee to receive this information*? This is a fundamental question all copy trading platforms need to answer before designing an optimal information revelation policy.

The answer to this question is vital for several reasons. First, the copy trading platforms will collapse if followers do not see the real-time value in their service. Thus, the answer will help followers decide when it is valuable to follow in real-time and when it is not. Second, answering the above question is key for the platform to best monetize the dissemination of its financial advice. Third, it helps platforms determine the right magnitude of delay to add before releasing trade information to the public for free, while preventing arbitrage opportunities and at the same time guaranteeing information transparency. For example, ZuluTrade releases traders' trades after 30 minutes to allow potential followers to evaluate different traders before following them. Lastly, the answer offers cues for the platform to personalize the delay (and, possibly the following fee) for each trader, based on the characteristics of the trader and the market conditions associated with the investment product.

Thus, in this study, we specifically investigate the following three research questions.

- How does the level of information transparency (as measured by delay) affect the profit of a trade?
- How is the amount following a trader affected by information transparency?
- How should the platform design an information revelation policy?

Empirically, we examine the copy trading phenomenon implemented by ZuluTrade, a leading social trading platform that mainly operates in the Foreign Exchange market. It mainly deals with day trading, and thus the time to open and close a trade within a market is important. ZuluTrade provides two types of accounts: trader and follower. A follower can "follow" one or more traders. Trades from trader accounts will be copied in real-time and automatically executed in a follower's own accounts. The platform functions as an online broker and charges followers a fee (per trade with some rate) to follow the trades of a trader. While traders themselves also pay a commission to the platform to execute their trades, they receive a kickback bonus (usually settled on a monthly basis) that is calculated based upon the amount of money that follows their trades. The platform operates as a two-sided market, where more followers will motivate more traders to join and vice versa. Followers pay to copy real-time trades; however, these trades are available for free after some time of delay (for example, 30 minutes during our study period). Thus, investors can free ride if they are willing to accept the time delay introduced by the platform.

The data we obtained consists of individual traders' trades executed on ZuluTrade, for the Foreign Exchange (Forex, or currency trading) market. Our interest is to quantify the information value of knowing these trades in real-time. We define *profit-gap*, as the difference between the real-time profit of a trade and the simulated profit (calculated using historical Forex spot price data) of the trade, but executed with some open delay and/or some close delay. We use the data to examine how delay affects the profit-gap, after controlling for various factors related to the trader and other market conditions. Next, from the data, we present empirical evidence to demonstrate the platform's dilemma: Lowering the delay increases transparency (that could potentially increase future revenue) but risks losing the amount of money following (and hence hurts the platform's current revenue).

We then formulate and solve several optimization problems that address the platform's transparency-revenue conundrum. First, we examine the current approach adopted by Zulutrade and study how it can be improved. Currently ZuluTrade seeks to maximize transparency while holding the Money-at-Risk at or below an acceptable level, where Money-at-Risk measures the vulnerability of the platform's current revenue as a function of the delay and the fees the platform charges followers to receive information on a trader's trades in real-time. We study an improved information release policy that is trader specific and demonstrate that it can substantially increase transparency (reduce delay) while maintaining the Money-at-Risk at a level equal to ZuluTrade's current release policy.

We further study – using a Stochastic Optimal Control formulation of the problem – how the information release policy can be chosen to optimize revenue. That is, rather than indirectly addressing the problem by maximizing transparency subject to given (exogenously chosen) Money-at-Risk, we set up a model to directly maximize platform revenue. The Stochastic Control problem is solved to yield a feedback control (i.e., delay) that is based on the current amount following a trader and the current attention being received by the trader from potential followers (measured by the trader's profile page views). The calculated revenue can be incorporated into the ranking algorithm to provide a systematic way to infuse the platform's goals into the ranking of the traders. In so doing, this study also helps followers to determine whether it is worthwhile to follow a specific trader in real-time.

The rest of this paper is organized as follows. We next provide a review of related work. In Section 3, we introduce the data and the operations of the platform. In Section 4 we study the data to provide the empirical basis for the optimization models in Section 5 and Section 6. In Section 7, we provide a discussion and conclude the study.

2 Literature Review

In this section, we briefly summarize the literature on social trading. The first stream of literature studies investment decisions made by individuals as a result of their social interactions. Ammann and Schaub (2016) investigate the role of social interaction in investment decisions by mining trader posts and other communications. They find that traders with superior performance are more likely to discuss their investment strategies. Heimer (2016) focuses on a phenomenon called the *disposition effect*. This anomaly, discovered in behavioral finance, uncovers the tendency of investors selling too early in the up market, while holding too long in a down market. Disposition effect is found to be magnified when investors receive advice from their friends.

The second related stream of literature studies the phenomenon of copy trading. Doering et al. (2015) describe how copy trading platforms are organized and discuss the basic mechanics behind the relationship between signal provider (portfolio manager) and signal followers (investors). They find that signal providers typically engage in active trading rather than buy-and-hold strategies, which result in non-normal return distribution. Lee and Ma (2015) propose a system identifying traders with good and consistent performance to answer the question "whom to follow". Oehler et al. (2016) show that, on average, traders on wikifolios (a copy trading platform) do not outperform the market on average but the best performing traders earn significant short-term excess returns.

Within this literature on social trading, several studies analyzed the trading behavior and performance of traders in copy trading. Pan et al. (2012) study the role of social mechanisms in a financial system and find that social trades outperform individual trades. Röder and Walter (2017) discover that traders who communicate actively with investors attract significantly more attention, and visibility of their trading portfolios boosts investments. Breitmayer et al. (2017) investigate the trading patterns of traders who received social recognition for their investment advice. They show that confirmatory social recognition leads to increased trading activity. Pelster and Hofmann (2017) study the relationship between providing financial advice and the disposition effect. They find that leading traders are more susceptible to the disposition effect than traders without followers.

The third stream of relevant literature is on information transparency with regard to what information and how much information to release in financial services. For example, in crowdfunding, platforms need to decide what level of borrower information to release to help these lenders evaluate a loan. Crowdfunding studies find that what information (explicit or implicit) to release strongly influence the overall market efficiency and the lenders' decisions to participate (Herzenstein et al. 2011, Mäschle 2012). Zhou et al. (2018) build a structural model to uncover how lenders' behaviors are affected by an exogenous information-disclosure policy change. They show that displaying extra information leads to a higher browsing propensity and helps lenders to make sound investment decisions.

The fourth stream of related literature is on the value of information for devising trading strategies. Mutual funds are mandated to disclose their portfolio holdings to investors periodically, e.g. quarterly. Some investors might mimic the trading strategy from the released portfolio, called copycat funds in finance. Verbeek and Wang (2013) indicate that free-riding on disclosed fund holdings is an attractive strategy and suggest that mutual funds may suffer from such information disclosure regulations. The timeliness of portfolio holdings disclosure has been of interest among regulators, academics and practitioners since the Investment Company Act of 1940. The Securities Exchange

Commission (SEC) has been trying to strike a balance (a uniform delay across all mutual funds) between investors' interest in timely disclosure and the potential costs associated with revealing the strategies of investment managers (Hee Choi and Chhabria 2012). The information required to be released in mutual funds is the portfolio holdings, not the exact time when the mutual fund manager bought and sold the portfolio holdings. In this study, our data comes from a social trading platform focusing on day trading and the platform does releases the time traders execute a trade.

Different from the prior research that studies the social trading phenomenon mainly from a social or behavioral perspective, our study is more normative. We address the fundamental mechanism design problem in copy trading to determine the right level of information to release to the public. Specifically, the main goal of this study is to measure the economic value of paying for, and obtaining, real-time trade information on a copy trading platform, and to address how to choose the optimal level of transparency for copy trading platforms. None of the prior research has considered this perspective.

3 Data and Platform Operations

In this section, we first introduce the data and then describe the operations of the social trading platform we consider.

3.1 Data

Our data comes from ZuluTrade, one of the largest copy trading platforms in the world. The platform allows followers to auto-copy Forex trades made by financial experts (traders). Each trader owns a public profile page, which reveals information on her past trading performance tracing back to the first day the trader joined the platform. ZuluTrade releases various performance metrics including the total profit of all the trades a trader has executed via the platform, the best and the worst realized profit of the trade among all her trades, the percentage of winning trades, the number of followers following the trader, the total amount of money following the trader, the number of weeks the trader has been trading on the platform, the number of views the trader's profile has received, etc. Importantly, ZuluTrade also releases on-going trades (trades have been opened but not closed yet) for free after adding some time delay to the public. Figure 1 provides a screen shot of a trader's profile page.

We obtained individual trading information of 15,352 traders during a 17 month period from August 2016 to December 2017. The data is at the most granular trade

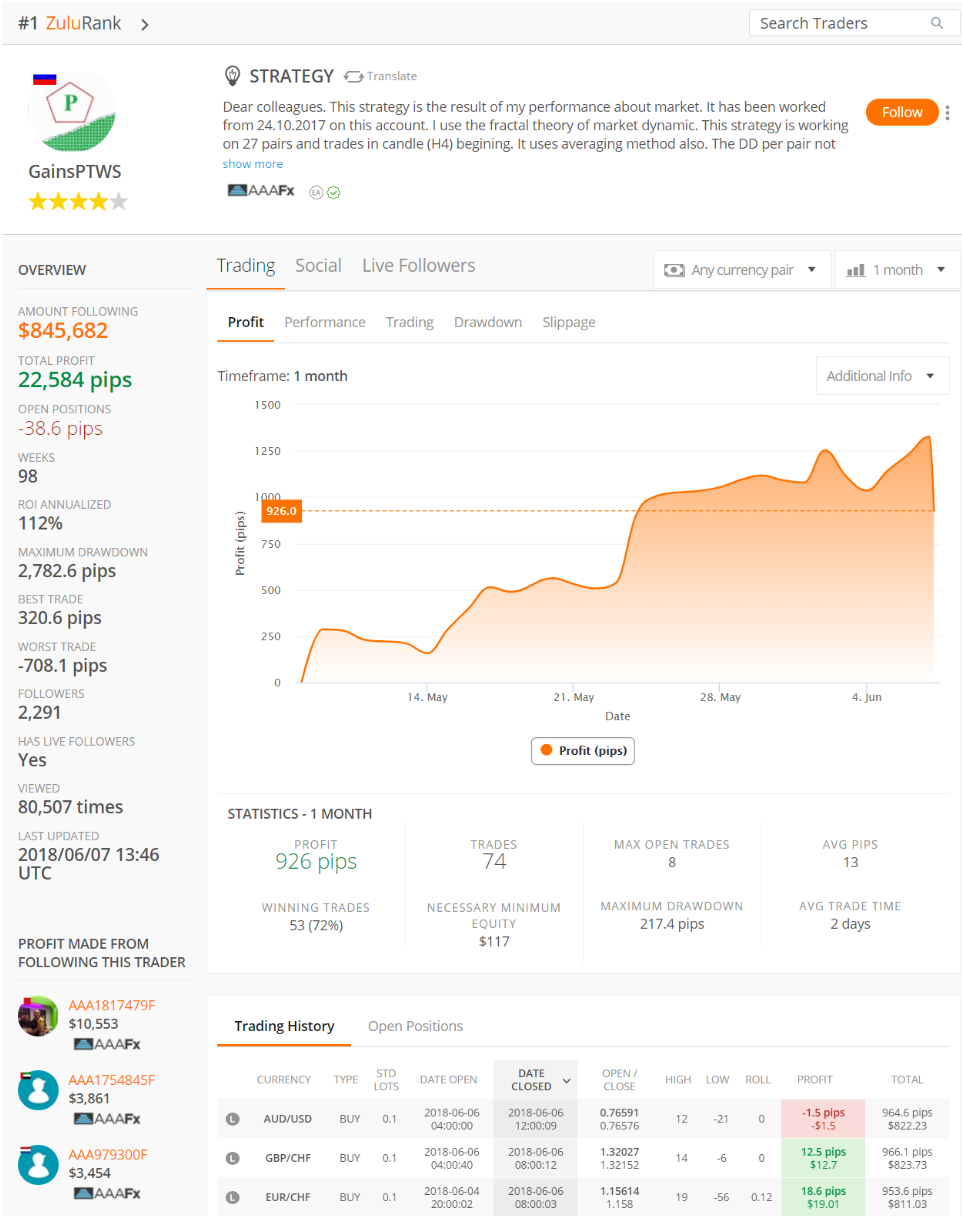

Figure 1: Snapshot of a Trader's Profile Page

level possible for each trader. The detailed trade information includes the currency (e.g. EUR/USD), type (buy or sell), standard lot size, date open, date close, open price (the spot price at the time when the trade was opened), close price (the spot price at the time when the trade was closed), profit, the highest potential profit during the holding period of the trade, the lowest potential profit (max drawdown) during the holding period of the trade, etc. We focus on the intra-day trades since the Forex market is volatile and more than half trades are open and closed within the same day. The Forex market provides an ideal market (environment) to study the time value of trade information since the profit of a trade is very sensitive to the magnitude of delay. In this study, we focus on the five largest currency markets – EUR/USD, GBP/USD, GBP/JPY, USD/JPY, and USD/CAD – that together account for more than 60% of all the trades on this platform. Table 1 presents the proportions of the five currencies among all the intra-day trades.

Table 1: Relative Proportions of Five Currencies

Currency	Frequency	Percent
EUR/USD	585,939	37.83%
GBP/JPY	226,230	14.61%
GBP/USD	385,702	24.90%
USD/CAD	126,421	8.16%
USD/JPY	224,461	14.49%
Total	1,548,753	100%

The second dataset we obtain is the historical spot prices for these five currency markets from the Dukascopy Historical Data Feed. We use this data set to calculate the hypothetical profit (loss) of a trade, which we will elaborate in the next section.

3.2 ZuluTrade Operations

On the ZuluTrade platform, once a follower clicks to "follow" a trader, the trades of this trader are automatically copied and executed in this follower's account. The platform charges followers commission (following fee): 2 pips for a complete open-close trade per standard lot size [9] This commission is already factored in the buy and sell price. Followers can choose how to *copy* traders' trades. For example, followers can choose a fraction $\gamma \in [0, 1]$ for each trader; only a γ fraction of the trader's trade amount will be executed in the copied trade. The copying trades will automatically be executed in real-time in the follower's account. Followers who do not follow a trader cannot receive this trader's trade information in real-time. However, the platform releases this trade information with some delay on the trader's profile page for the public to see, and for free.

The platform shares revenue with traders: 0.5 pip for each standard lot executed in a

[9] In the Forex market, the standard lot size is $100,000$. A pip is the smallest price move that a given exchange allows. Major currency pairs are priced to four decimal places; the smallest change is that of the last decimal point. For example, for the currency EUR/USD, 1 pip is equivalent to $0.0001. Therefore, for a trade of size $100,000, the platform charges followers $20 as commission.

follower account (that is $5 for a trade of $100,000). During our study period, the trader's compensation is calculated on a monthly calendar basis, but a trader is compensated only if the profit earned in the trader's account for that month is positive. Traders either get fully compensated or zero for their trades in the month.

4 Empirical Investigations

In this section, we first describe how we measure the hypothetical profit (loss) of executing a trade after some time delay is added to the original, real-time trade. We then explore what factors influence the profit-gap, especially how magnitude of delay impacts the profit-gap. Finally, we study what drives the amount of money following a trader and empirically demonstrate the platform's dilemma concerning delay.

4.1 Simulating Delayed Trades

Let us assume that a trader opens a particular trade at time t_1 and closes this trade at time t_2; the difference $(t_2 - t_1)$, is called *holding time*. Such trade level data is directly observed in this study. Also observed is the profit or loss associated with the trade. Now, consider a hypothetical trade that is the same as the above trade (the same currency, type, and standard lot size) but the open time and close time are, respectively, $t_1 + \delta_1$, and $t_2 + \delta_2$. Here, δ_1 and δ_2 denote the open delay and close delay respectively. We can recover the profit (loss) of this delayed trade using the historical spot prices in the currency market traded at time $t_1 + \delta_1$, and $t_2 + \delta_2$. We vary the values for open and close delay at different levels: 0, 5, 15, 30, 60, 90, and 120 minutes [10]. When $\delta_1 = \delta_2 = 0$, it represents a real-time trade. The open and close delay are chosen such that the simulated close time is later than the simulated open time. Thus, we simulate a maximum of 48 distinct hypothetical trades corresponding to each original (or real-time) trade in the data sample. Figure 2 depicts how we generate the hypothetical trade after considering time delay.

For each simulated trade, we calculate the profit-gap as the real-time profit minus the simulated profit. The profit-gap directly measures the economic value of acting upon real-time information, relative to acting upon delayed information. The higher the profit-gap value, the more worthwhile for followers to follow the real-time trade (with fees). We would like to mention that the profit-gap value can be negative for some trades, meaning the delayed trades may even earn higher profit than the real-time trades. However, we

[10] A delayed trade of more than 2 hours is hardly worth considering in the volatile Forex market.

believe that a good trader is able to time the market (when to enter and exit the market). Delaying the trade would then lower the value of her original trade.

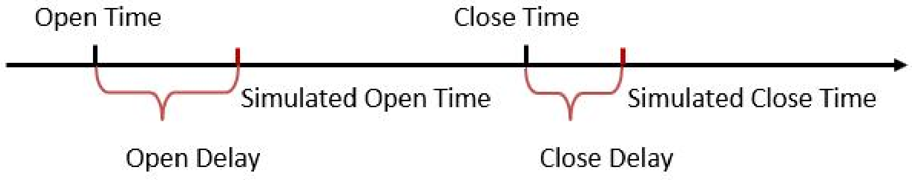

Figure 2: Illustration of Generating Hypothetical Trade

4.2 What drives profit-gap

We next investigate how different factors affect the value of following the trade in real-time. To this end, we specifically explore how the magnitude of delay influences the profit-gap.

We use i to index a trade, j to index a trader, m to index a currency market, and t to index each 15-minute time period across the 17 months [11]. The dependent variable is $ProfitGap_{i,j,t}$. The explanatory variables of interest are $OpenDelay_{i,j,t}$, $CloseDelay_{i,j,t}$, and $Followers_{i,j,t}$. The variable $OpenDelay_{i,j,t}$ ($CloseDelay_{i,j,t}$) is the open (close) delay added for trade i, executed by trader j at time period t. The variable $Followers_{i,j,t}$ represents the total number of followers following trader j at time t [12]. The econometric model we consider is specified as follows:

$$ProfitGap_{i,j,t} = \beta_1 OpenDelay_{i,j,t} + \beta_2 (OpenDelay_{i,j,t})^2 + \beta_3 CloseDelay_{i,j,t} + \beta_4 (CloseDelay_{i,j,t})^2 + \beta_5 Followers_{i,j,t} + X_{i,j,t} + Trader_j + Currency_m + Time_t + \varepsilon_{i,j,t} \quad (1)$$

In equation (1), $Trader_j$ is the trader-level fixed effects, $Currency_m$ is the currency (market) specific fixed effects([13], and $Time_t$ is the time-specific fixed effects capturing the market status corresponding to a specific time period. The term $X_{i,j,t}$ represents a vector of control variables, including the standard lot size of trade i ($StandardLots_{i,j,t}$), the highest potential profit (measured in pips) during the holding time of trade i by trader

[11] We use a relatively short time window of 15 minutes because of the high volatility of the Forex market.

[12] In the regression model, we take the logarithm of the followers to account for skewness in this variable.

[13] For notation simplification, we suppressed m from the subscription of all the other variables.

j at time t ($HighestProfit_{i,j,t}$), the lowest potential profit (worst drawdown) during the holding time of trade i by trader j at time t ($WorstDrawdown_{i,j,t}$), the holding time of trade i by trader j at time t ($HoldingTime_{i,j,t}$), the total profit (with unit dollars) of trader j by time t ($Profit_{i,j,t}$), the total profit (with unit pips) of trader j by time t ($Profitpips_{i,j,t}$), the highest profit of a trade among all the trades of trader j until time t ($BestTrade_{i,j,t}$), the lowest profit of a trade among all the trades of trader j until time t ($WorstTrade_{i,j,t}$), the number of trades of trader j by time t ($Trades_{i,j,t}$), the annual return of investment of trader j by time t ($ROI_{i,j,t}$), the percentage of trades with positive profits among all the trades of trader j by time t ($WinRatio_{i,j,t}$), the number of weeks trader j has been traded on the platform by time t ($Age_{i,j,t}$), the rank of trader j at time t ($Rank_{i,j,t}$), the average profit of trader j by time t ($AvgTrade_{i,j,t}$), the maximum number of open trades trader j has been held by time t ($MaxOpenTrade_{i,j,t}$), the minimum capital required to trade all the trades from trader j in a follower's account at time t ($MinEquity_{i,j,t}$), the profit of open (unrealized) positions of trader j at time t ($OpenPosition_{i,j,t}$), the number of views trader j's profile page has received by time t ($View_{i,j,t}$), and the indicator whether there are followers following trader j at time t ($DummyFollower_{i,j,t}$). Table 2 tabbulates the summary statistics of profit-gap, open delay, close delay, etc.

To test potential existence of multicollinearity, we calculate the variance inflation factors (VIF) and find that they are well below the acceptable threshold (10), indicating the absence of multicollinearity. We use the White test to check for heteroscedasticity, and the result (the chi-square value is 1,467,927 with p-value less than 0.001) shows significant heteroscedasticity in the error term. We therefore control for it using robust standard errors.

We simulate hypothetical trades with different magnitudes of delay. Please note that the volume of our hypothetical trades are minuscule relative to the gigantic Forex market. It is unlikely that any trade in our data would be subject to instant market impact (slippage) [14]. Therefore, we assume exogeneity of the variable $OpenDelay$ and $CloseDelay$. Potential endogeneity might arise in variable $Followers_{i,j,t}$. For example, it can be argued that higher profit-gap may likely be the cause why followers follow the trader, i.e.

[14] For example, the daily trading volume of Forex market is on average 1.8 trillion in January 2018. The maximum amount of money following a trader in our data is 3 million dollars.

Table 2: Summary Statistics of Data

Variable	Obs	Mean	Std. Dev.	Median	Min	Max
$ProfitGap$	48,125,024	0.69	19.79	0.30	-1,002.20	1,031.90
$OpenDelay$	48,125,024	31.30	37.15	15	0	120
$CloseDelay$	48,125,024	42.22	42.89	30	0	120
$Followers$	48,125,024	9.22	59.14	0	0	2,589
$StandardLots$	48,125,024	3.75	86.63	0.06	0.01	1e5
$HighestProfit$	48,125,024	18.79	24.35	11	0	881
$WorstDrawdown$	48,125,024	-19.66	22.56	-12	-1,351	0
$HoldingTime$	48,125,024	190.74	250.64	95.35	1	1,440
$Profit$	48,125,024	144.95	21,221.78	1.35	-1.77e6	1.28e7
$Profitpips$	48,125,024	5.38	31.32	6.10	-655.60	772.40
$AvgTrade$	48,125,024	5.30	72.04	1.00	-10,611.30	4,898
$MaxOpenTrade$	48,125,024	45.94	49.99	30	0	428
$Rank$	48,125,024	9,826.72	12,034.6	2,598	1	32,001
$Trades$	48,125,024	1,888.94	2,353.35	911	0	14,676
Age	48,125,024	39.45	49.71	23	0	478
$Amount$	48,125,024	10,308.21	63,718.35	0	0	3,267,296
$BestTrade$	48,125,024	508.49	1,360.10	200	-499.60	69,938.40
$WorstTrade$	48,125,024	-785.72	8,291.01	-371	-1,807,046	0
$WinRatio$	48,125,024	65.45	22.57	68	0	100
ROI	48,125,024	392.28	3,261.81	32	-11,963	84,266.6
$MinEquity$	48,125,024	1,866.37	2,050.23	1,064	0	9,955.44
$OpenPosition$	48,125,024	-1,529.13	11,028.39	0.00	-1,486,899	622,768.30
$View$	48,125,024	8,912.46	30,339.39	1,834	0	2,258,260
$DummyFollower$	48,125,024	0.08	0.27	0	0	1

simultaneity may occur.

To account for potential endogeneity, we use the two-stage least squares (2SLS) regression with instrument variables (IV). We construct two IVs for variable $Followers_{i,j,t}$. The first IV (IV1) uses the amount following other traders of the same followers. Specifically, IV1 is the Hausman type of instrument, constructed as the total number of followers (from the set of followers following the focal trader) following other traders (but excluding the focal trader) at time t. Variable IV1 is correlated with $Followers_{i,j,t}$ because it is constructed from the same set of followers; but it should not directly influence the focal trader's performance (the dependent variable $ProfitGap$) because of the exclusion of the focal trader from the construction of IV1. Another IV (IV2) is the average rank of other traders who are followed by the same set of followers at time t. The rank of a trader is displayed by ZuluTrade. Likewise, the average rank of other traders should be correlated with the number of followers because this is a metric followers care about when deciding whether to follow a trader; but rank does not directly influence the focal trader's performance because it is constructed from the other traders (Rossi 2014).

To validate our IVs, we perform a Hausman test, where under the null hypothesis the specified endogenous regressors can actually be treated as exogenous. We have chi-square value 1190.6 with p-value < 0.001, indicating the preference of IV based estimation. The IVs should further satisfy two prerequisites: the relevance assumption and the exogeneity assumption (Green 2007). The relevance assumption requires that the IVs should be correlated with the endogenous variables and that this correlation should not be weak. The F-statistics for the endogenous variable (followers) is 46,145 (p-value $= 0.000$). The other condition, exogeneity, requires that instruments excluded from the structural equation must be uncorrelated with the structural errors, which is typically done using a test of over-identifying restrictions via Hansen's J statistic (Hansen 1982). The Hansen J statistic is 2.642 with p-value $= 0.1041$, indicating that we do not reject the null hypothesis that the instruments are exogenous and excludable.

Table 3 presents the estimation results corresponding to the econometric model in equation (1). Larger magnitudes of open and close delay increase the profit-gap, indicating that it is more valuable for investors to follow in real-time if the platform releases a trader's trade with longer delay. From Table 3, we see that the coefficients of the squared delay terms are significantly negative. Thus, the profit-gap increases with delay in a concave manner. Holding everything else equal, the marginal effect of delay on the profit-gap decreases with larger delay magnitude. As the platform adds larger magnitude of delay, the impact on profit-gap decreases. Besides, the profit-gap increases with larger number of followers following a trader. The profit-gap is heterogeneous across different currency markets, and it varies as the level of market volatility varies in different markets.

Table 3: The Impact of Delay on the Profit-Gap

Dependent Variable: $ProfitGap$	
VARIABLES	Coefficients
$OpenDelay$	0.016***(0.000)
$(OpenDelay)^2$	-0.0009***(0.000)
$CloseDelay$	0.017***(0.000)
$(CloseDelay)^2$	-0.0007***(0.000)
$Followers$	0.154***(0.001)
Control Variables	Yes
Currency-level FE	Yes
Trader-level FE	Yes
Time-level FE	Yes
Observations	48,125,024
R-squared	0.128

Note. The robust standard error is reported in parenthesis.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

4.3 Transparency-revenue Conundrum

To investigate what drives the amount following a trader, we estimate the regression model as specified in equation (2). The dependent variable is the amount following trade i from trader j at time t. The variables of interests are the number of (cumulative) views of trader j received by time t ($View_{i,j,t}$), the profit-gap (with 30-minute open delay and zero close delay as implemented by ZuluTrade) of trade i from trader j at time t ($ProfitGap_{i,j,t}$), and the interaction term of view and profit-gap. The number of views captures the potential number of interested users that the trader might be able to convert into followers. From the results with respect to equation (1), we know that larger magnitude of delay is associated with higher profit-gap. The profit-gap measures the information transparency level. $X_{i,j,t}$ represents the set of control variables as specified in equation (1). We take logarithms of amount and view. We also control for the trader-level and time-level fixed effects.

$$\begin{aligned} Amount_{i,j,t} = \theta_1 View_{i,j,t} + \theta_2 ProfitGap_{i,j,t} + \theta_3 View_{i,j,t} * ProfitGap_{i,j,t} + X_{i,j,t} \\ + Trader_j + Time_t + \varepsilon_{i,j,t} \end{aligned} \tag{2}$$

The variance inflation factors are all well below 10, indicating absence of multi-collinearity. We control for heteroscedasticity using robust standard errors. Both variables $View$ and $ProfitGap$ might be subject to endogeneity. For example, it can be argued that a trader's profile attracts more views because the trader has higher amount of money following her; followers choose to follow a trader because it is worthwhile to follow her in real time (higher profit-gap), i.e. simultaneity may occur. Hence, we construct instrument variables for both variables. The IV we construct for $ProfitGap_{i,j,t}$ is the holding time of trade i. The profit-gap is sensitive to the holding time of the trade, but a follower's decision regarding whether to follow a trader or not does not directly rely on the holding time of the trade.

We construct two IVs for variable $View_{i,j,t}$. The first IV (IV1) uses sum of the number of views of the other traders followed by the same set of followers following the focal trader j. Specifically, IV1 is the Hausman type of instrument, constructed as the total number of views (from the set of followers following the focal trader) following other traders (but excluding the focal trader) at time t. Variable IV1 is expected to correlate with $View_{i,j,t}$ because it is constructed from the same set of followers; but it should not be systematically correlated with the focal trader's performance (the dependent variable $Amount_{i,j,t}$) because the focal trader is excluded from the construction of IV1. The other IV (IV2) is the average rank of other traders who are followed by the same set of followers at time t. The rank of a trader is displayed by ZuluTrade; traders with higher ranks are listed at more prominent positions, attracting more views. Likewise, the average rank of other traders should be correlated with the views because this is a metric followers care about when deciding whether to follow a trader; but rank does not directly influence the focal trader's views because it is constructed on the other traders (Rossi 2014).

The Hausman test statistics is 864.6 with p-value < 0.001, indicating the preference of IV based estimation. The F-statistics for the three variables ($ProfitGap$, $View$, and the interaction term) are 8,144.60 (p-value < 0.01), 2,246.30 (p-value < 0.01), and 17,621.87 (p-value < 0.01) respectively, pointing to strong IVs. The Hansen J statistic is $\chi^2_{(1)} = 1.647$ with p-value $= 0.199$, satisfying exogeneity condition.

Table 4: The Driving Forces of the Amount Following a Trader

Dependent Variable: *Amount*	
VARIABLES	Coefficients
View	3.281*** (0.055)
ProfitGap	0.289*** (0.095)
View*ProfitGap	-0.031*** (0.01)
Rank	-0.003*** (0.000)
AgeLog	-4.055*** (0.081)
BestTrade	0.001** (0.000)
WorstTrade	-0.001*** (0.000)
WinRatio	0.052*** (0.002)
ROI	0.001*** (0.000)
Trades	-0.002*** (0.000)
AvgTrade	0.001*** (0.000)
MinEquity	-0.001*** (0.000)
StandardLots	0.002 (0.000)
HighestProfit	-0.005*** (0.001)
WorstDrawdown	-0.005*** (0.002)
Profit	0.001 (0.001)
MaxOpenTrade	-0.008*** (0.001)
Profitpips	0.003*** (0.001)
OpenPosition	0.001*** (0.000)
Trader-level FE	Yes
Time-level FE	Yes
Observations	730,812
R-squared	0.912

Note. The standard error is reported in parenthesis.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

The results in Table 4 show that both coefficients of view and profit-gap are significant and positive. Interestingly, the interaction term of the two is negative, implying that view and profit-gap weaken each other. The marginal effect of profit-gap on the amount is $(0.289 - 0.031 \times View)$. When the number of views of a trader attracted is low, higher profit-gap is associated with higher amount following the trader. However, when the number of views is large, higher profit-gap results in lower amount following the trader. In other words, in the case when a large number of potential followers are interested in a trader, low transparency would make it more difficult for potential followers to evaluate the trader's ability and thus reduces the chance of converting them into followers. The marginal effect of view on the amount is $(3.281 - 0.031 \times ProfitGap)$ and can be interpreted in a similar manner. Taken together, this negative interaction presents the empirical evidence that the platform faces the trader-off between increasing transparency (to facilitate performance evaluation for interested investors and help traders convert those potential followers) and reducing transparency (to prevent free-riding). Having demonstrated the tradeoff, we next devise various information release policies.

5 Optimizing Information Release

In this section, we develop and compare several information release policies that handle the transparency-revenue tradeoff in different ways. Central to the manner in which the tradeoff is handled, is the notion of Money-at-Risk, a concept we operationalize later in this section. This concept was introduced to us during our interactions with the ZuluTrade management team. It is important to mention that the policies we study in this section (including the current release policy employed by ZuluTrade), do not explicitly optimize the revenue of the platform. Rather, these policies can be expected to indirectly impact the revenue in a desirable manner. Direct revenue optimization policies are introduced in the next section.

Conceptually, the platform would like to maximize the transparency of each trade in order for potential followers to evaluate traders, without endangering its revenue collected from commissions and follower fees. Thus, the platform needs to strike a fine balance between transparency and its revenue objectives. Transparency is maximized when a trader's trades are released to the public without any delay. However, such a (complete) transparency policy runs the risk that followers might manually copy the trades of a trader and execute them elsewhere without paying follower fees. This suggests the notion of *Money-at-Risk*, defined as the expected loss in the amount following a trader for a given delay and follower fee. To put it simply, Money-at-Risk (MaR) measures the risk of losing the amount following a trader. Mathematically, the Money-at-Risk for a trader is the amount following the trader (a_i) multiplied by the probability that the profit-gap of the trades associated with this trader is less than the follower fee (c) or,

$$a_i P_i\{x_i(\delta) \leq c\},$$

where $x_i(\delta)$ is the random variable representing the profit-gap of the trades associated with a trader. From the platform's perspective, an important goal is to limit the total Money-at-Risk across all the traders, namely, $\sum_{i=1}^{A} a_i P_i\{x_i(\delta) \leq c\}$, where A [15] is the total number of traders.

We first introduce a theoretical model to capture how the profit-gap of a trade evolves as a function of the delay. This model will be proven useful in the analysis of the information release policies that are studied in this section.

5.1 Profit-Gap Model

Based on the empirical findings in Table 1, the mean profit-gap was observed to be a concave increasing function of the delay. This finding suggests the following stochastic process to model the profit-gap of a trade ($x_i(t)$) after introducing a delay of t from the point in time when the real-time trade was executed by trader i.

$$dx_i(t) = \frac{\alpha_i}{2\sqrt{t}}dt + \sigma_i dz(t),$$

where the parameters α_i and σ_i are trader specific.

The above model (VABM) is a *variant* of an Arithmetic Brownian Motion (ABM), where the drift term is inversely proportional to the square root of time (t). This model can be solved to show that the value of $x_i(t)$ is Normally distributed with a mean of $\alpha_i\sqrt{t}$ and a variance of $\sigma_i^2 t$. The mean $\alpha_i\sqrt{t}$, reflects the concave, increasing relationship with delay.

We apply Maximum Likelihood Estimation (MLE) to estimate the parameters for the profit-gap of a trader ($\hat{\alpha}_i$ and $\hat{\sigma}_i$ for trader i). The VABM model fits the data better

[15] More precisely, we should interpret A as the total number of trader *accounts*. For convenience, however, we will use the term trader to mean trader account. These two terms differ in practice, but inconsequential to our mdoel.

than two alternative models: (1) a model with no drift term, or Brownian Motion (BM), and (2) a model with a linear drift term, or Arithmetic Brownian Motion (ABM). The average Bayesian Information Criterion (BIC) values for a sample of of 1,000 traders are: VABM (85,200), ABM (86,600) and BM (87,600), showing that VABM has the best fit among the three models. This finding shows that, generally speaking, the profit-gap of a trade evolves with delay with a positive and concave drift, not just as white noise or with linear drift. However, there are indeed some traders with negative drift and some others with zero drift.

For any given trader and delay δ , we can use the above VABM process to find the probability that the profit-gap associated with the trades of the trader is less than the following fee c. This probability is calculated as the cumulative distribution function of the normal distribution with mean $\hat{\alpha}_i\sqrt{\delta_i}$ and variance $\hat{\sigma}_i^2\delta_i$, $F_i(c|\delta_i)$, where $c = 1$, $\hat{\alpha}_i$ and $\hat{\sigma}_i$ are the VABM parameters for trader i. Figure 3 illustrates how the probability changes with delay for a representative trader with id 102885. We see that the fitted probability $\hat{F}_i(c|\delta_i)$ decreases with δ_i in a convex manner. This convex property is seen to hold for most traders.

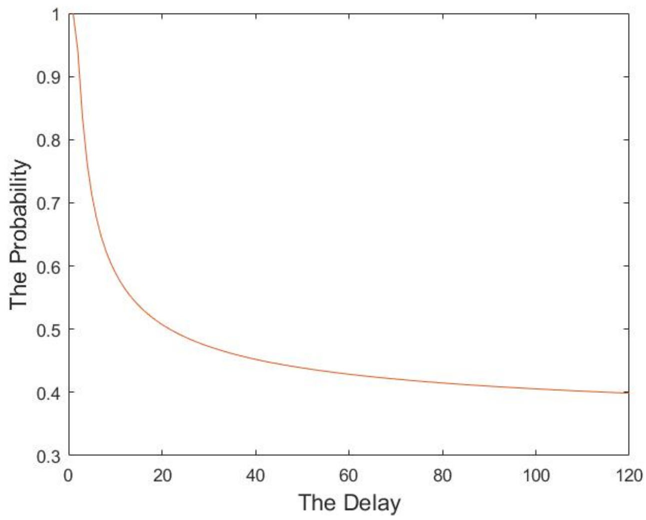

Figure 3: The fitted probability with delay for trader 102885

5.2 Comparison of Different Release Policies

We first propose an indifference information release policy that maximizes trade transparency while ensuring that the release of trade information is such that the expected profit-gap for a trader is exactly equal to the following fee. This policy is based on the premise that, on average, there will be no loss of commission revenue because the release of trade information is such that a *risk neutral* follower will be indifferent between following in real time (with a fee) and executing the same trade with delay (for free). Next, we propose two policies that consider the profit-gap distribution to decide on the delay, rather than basing this decision on the mean of this distribution. The first is a *uniform* release policy where all trades are publicly posted for everyone to see with a delay of δ. The second policy is a *customized money-at-risk* release policy where the information release policy (i.e., delay, δ_i) depends on the characteristics of trader i. The uniform policy is, of course, a subset of the customized money-at-risk release policy.

5.2.1 Customized Indifference Policy

In this policy, a trader's trades are released with a delay such that the expected profit-gap equals the difference in commission fees between real-time and delayed trades.

Let $F_i(x|\delta_i)$ ($f_i(x|\delta_i)$) denote the cumulative probability density (probability density function) for the profit-gap (x) associated with trader i when the trades of this trader are released with a delay of δ_i. Because the profit-gap could be negative, we allow the support of the profit-gap distribution to be $x \in$ [-∞, $+\infty$]. Then, the customized indifference delay would be given by the value of δ_i such that

$$\int_{-\infty}^{+\infty} x f_i(x) dx = c,$$

where c is the fee paid to follow the trades of a trader.

5.2.2 Customized Money-at-Risk Policy

In this policy, each trader (or specifically, each trader's *account*) can be customized with a different release delay, δ_i. The optimization problem can be stated as below.

$$\begin{aligned} \underset{\delta_i, i \in \{1,2,\ldots,A\}}{\text{Minimize}} \quad & \sum_{i=1}^{A} v_i \delta_i \\ \text{subject to} \quad & \sum_{i=1}^{A} a_i F_i(c|\delta_i) \leq \eta \end{aligned}$$

In the above specification, δ_i is the decision variable, A is the total number of traders, a_i is the amount of money following trader i, v_i is the number of views received by trader i in a period, $F_i(c|\delta_i)$ is the probability the profit-gap less than the following fee c given delay δ_i, and η is maximum money-at-risk (the platform can tolerate). Intuitively, the platform should release a trader's trades with less delay if the trader receives more views, to help the trader convert more potential followers.

In the above problem, the objective function is a measure of trade *opacity*; thus we wish to minimize this measure. Our data tracks the number of potential followers viewing a trader. We denote the total number of page views per period as (v_i). These page views are a direct measure of potential followers evaluating the trader. The constraint in the above problem represents the Money-at-Risk (MaR). When the probability that the profit-gap for a trader is below the follower fee $(F_i(c|\delta_i))$, investors who follow the trader could switch from following in real-time to free-riding with some delay (δ_i). This probability is a measure of the vulnerability of losing the commissions the platform receives from the followers of a particular trader. The Money-at-Risk captures this vulnerability, and is calculated as the probability $F_i(c|\delta_i)$ multiplied by the amount following.

The probability $F_i(c|\delta_i)$ decreases with δ_i. At the extreme, if $\delta_i = 0$, the real-time profit and the delayed profit are the same; hence, the profit-gap is zero. Thus, the probability that the profit-gap is less than c is 1. As the delay increases, the delayed profit reduces (while the real time profit stays the same); hence the profit-gap increases. Thus, $F_i^{'}(c|\delta_i) < 0$. Based on our regression results (see Table 3), we would expect the profit-gap to exhibit diminishing returns with respect to delay, implying that the profit-gap can be expected to be a concave function of the delay. Thus, we can expect that the cumulative density F to be convex with respect to the delay, i.e., $F_i^{''}(c|\delta_i) > 0$, a property that is also supported in data.

The function $F_i(c|\delta_i)$ is trader specific and embeds in its knowledge of how proficient the trader is at spotting short-lived opportunities in the market. For the same delay (say δ_1), if $F_i(c|\delta_1) < F_j(c|\delta_1)$, it implies that trader $i's$ trades carry more information value, or equivalently, for the same delay, these trades are more worthwhile to follow in real time. Thus, they can be released earlier to serve the goal of increasing transparency. However, relative to trader i, trader $j's$ trades need more protection (from the perspective of information value), and need to be released later.

To solve the above problem, it is sufficient to note that it is a convex optimization problem. This is because the objective function is linear in the decision variables while the constraint is jointly convex in the decision variables. In the constraint, it is easy to see that the decision variables do not interact with one another and the data supports the property that the cumulative density associated with trader i, $F_i(c|\delta_i)$, is convex in δ_i.

5.2.3 Uniform Policy

$$\begin{aligned} \underset{\delta}{\text{Minimize}} \quad & \sum_{i=1}^{A} v_i \delta \\ \text{subject to} \quad & \sum_{i=1}^{A} a_i F_i(c|\delta) \leq \eta \end{aligned}$$

As before, the objective function is a measure of trade *opacity*; thus we wish to minimize this measure. The constraint is also conceptually similar. The uniform policy is a special case of the customized money-at-risk policy where all trader's trades are released with the same time delay (δ).

5.2.4 Numerical Illustration

We randomly choose ten traders to illustrate how the different release policies work. The amount of money following each trader (a_i) is $[2800, 400, 126, 773, 150, 58, 324, 650, 58, 200]$. The average views per period (day) for each trader (v_i) is $[1, 1, 1, 2, 3, 3, 3, 3, 5, 8]$. We take the following fee as $c = 1$ (with unit pips). For each trader, we first estimate the parameters α_i and σ_i using the data and obtain the cumulative probability function $F_i(c|\delta_i)$.

Given different values of the maximum money-at-risk (η), we can calculate the optimal opacity and draw the Pareto curve associated with the uniform policy as shown in Figure 4 (a). The uniform 30-minute delay policy (marked as point U_1) adopted by the ZuluTrade platform corresponds to a money-at-risk of 1694.8 and an opacity measure of 900. Given the same money-at-risk value, the optimal opacity is only 460.9 under the customized money-at-risk release policy (marked as point C_1). The optimal delay for each trader is $[91.2, 31.7, 24.5, 32.9, 3.3, 4.6, 28.7, 19.1, 3.3, 8]$. As can be seen from the data, the first three traders have the same number of views ($v_1 = v_2 = v_3 = 1$), but the amounts of money following these traders are different. It is better to use a longer delay for a trader with a higher amount of money following. This is done to protect the revenue earned from the current followers of such traders. We can see that $a_1 > a_2 > a_3$ results in $\delta_1^* > \delta_2^* > \delta_3^*$. Conversely, everything else held constant, for a trader with a higher number of views, it is better to use a shorter delay.

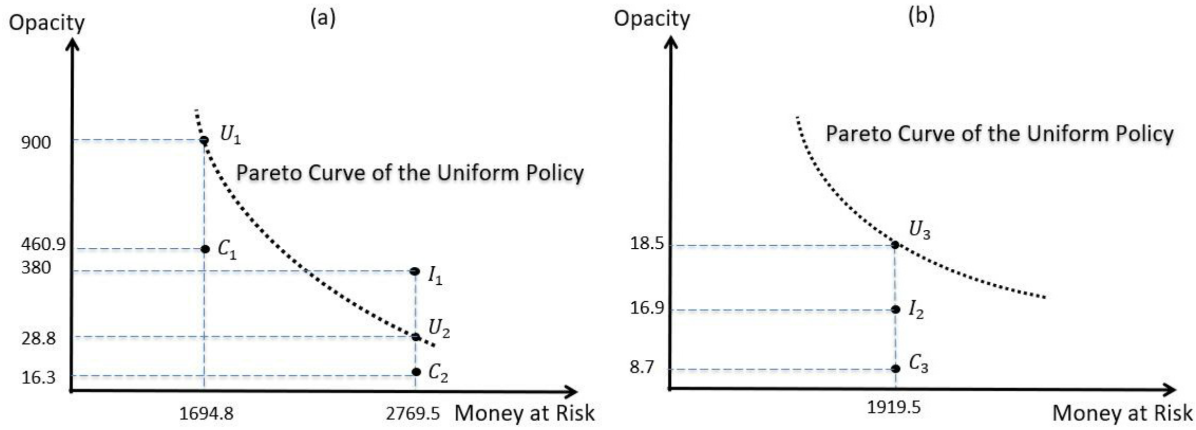

Figure 4: The Comparison of Different Release Policies

In Figure 4 (a), point I_1 represents the customized indifference policy with a money-at-risk value of 2769.5 and an opacity of 380. The delay added for each trader's trades is $[0.4, 26.6, 1.9, 47.4, 2.1, 4.4, 11.3, 0.4, 1.6, 24.2]$. Given the same level of money-at-risk, the optimal opacity is 28.8 under the uniform policy with 1 minute delay (point U_2), and 16.3 under the customized money-at-risk policy (point C_2). The optimal delay for each trader is $[4.5, 1.8, 0.5, 1.3, 0.2, 0, 1.1, 1, 0, 0]$.

In Figure 4 (a), we can see that the uniform release policy performs better than the customized indifference policy in terms of opacity given the same level of maximum money-at-risk. However, these two policies do not have a strict ordering in terms of their opacity values for the same money-at-risk. For example, as illustrated in Figure 4 (b), for different set of traders, the customized indifference policy (point I_2) can perform better than the uniform policy (point U_3). Point C_3 represents the customized money-at-risk policy.

It is not surprising that the customized money-at-risk release policy always dominates the uniform release policy, since the uniform policy is a subset of customized money-at-risk policy. However, the customized money-at-risk policy can significantly outperform the uniform policy given the same money-at-risk.

6 Revenue Optimization

So far, we have considered information release policies that attempted to strike a balance between information transparency (represented as views-weighted delay) and revenue (represented as Money-at-Risk). Our optimization formulations for these policies, however, do not directly consider platform revenue as the objective to optimize. We next present a stochastic control model to directly optimize platform revenue. This model is developed at the trader level, i.e., for every trader, depending on the trader's parameters, we implement the feedback control $\delta(a(t), v(t))$, representing the delay introduced for a particular trader when the current amount following is $a(t)$ and the number of accumulated views is $v(t)$. Because we pose an infinite horizon model, we do not need to explicitly consider time (t) in the choice of the control, although the variables a and v are, of course, functions of time.

The objective of the platform would be to maximize its revenue – from commissions and following fees – that is generated from the amount following a trader, $a(t)$. The revenue per unit time (or the revenue *rate*) earned by the platform can be expected to increase with the amount. Thus, we model the revenue rate as k times $a(t)$, where k is a trader specific constant that could be chosen based upon the frequency of trades executed by the trader. As mentioned above, there are two state variables that drive the feedback control, $a(t)$ and $v(t)$. We accordingly propose two stochastic differential models for the evolution over time of both state variables.

The amount following the trader is modeled using a stochastic differential equation whose drift term is a function of the control $\delta(a(t), v(t))$ and the views $v(t)$, as $g(\delta(a(t), v(t)), v(t))$. This is consistent with our understanding of the forces that drive the amount following a trader. For any given trader, we expect that the number of views generates an inflow into the set of current followers. However, this inflow is throttled if the opacity increases, i.e., the recent investment activities of the trader are not visible to potential followers. On the other hand, increasing transparency runs the risk of losing current followers. The noise term is modeled as $\sigma_a dZ(t)$, where σ_a is the volatility coefficient and $dZ(t)$ is the increment of the Wiener process following $\mathcal{N}(0,\, dt)$. Following convention in control theory, we suppress the time argument and write the state equation for the amount as below.

$$da(t) = g(\delta, v)dt + \sigma_a dZ(t)$$

Since ZuluTade uses a one-size-fits-all uniform release policy ($\delta = 30$ minutes), the impact of the control on the change in the amount following a trader cannot be empirically observed. However, concerning the impact of delay, we expect that the inflow of new followers to be a function of the delay whereas the outflow of current followers to depend on the square root of delay. The influence of the delay on the inflow is based on the assumption that new followers cannot evaluate a trader's current trades if the delay is large. On the other hand, the outflow should depend on the *square root* of delay, rather than directly on the delay. This is because the square root of delay is proportional to the profit-gap (as we show in Section 5.1), a quantity that ultimately controls a follower's decision to pay the follower fee and execute the real-time trade, or execute the delayed trade released by the platform for free.

We therefore propose that the drift term (or the mean change in the amount following a trader) to be given by

$$g(\delta, v) = \left(-\alpha v \sqrt{\frac{a}{c+\delta}} + \gamma \sqrt{v} \frac{a}{c+\delta} \right)$$

We expect $\alpha, \gamma > 0$. The first term in the expression for $g(\delta, v)$ represents the *outflow* in the amount; increasing δ reduces the outflow since it protects the current amount of money following the trader. We take the square root of delay because profit gap, rather than delay, can be expected to influence the outflow. The outflow should increase with the amount, but do so in a diminishing manner: As the amount following a trader increases, it could slow down the increase in the outflow. Finally, the outflow can be expected to increase with the number of views. This can be understood as a learning effect. The exit decision of a follower depends on a comparison between the profit gap (a stochastic quantity) and the following fee (a deterministic quantity). Thus before leaving a trader, a follower would likely need to learn how the profit gap for the trader compares with the following fee. To capture this learning effect, we use the number of views v to represent the amount of learning that has occurred for the trader.

The second term in the drift is the inflow in the amount following a trader. This term captures the effect that a higher delay makes it harder (for followers) to evaluate a trader; this effect is aggravated if the number of views and the amount is also high. The amount following a trader should influence the level of interest for the trader: a higher amount means that the trader can be expected to attract more attention from potential followers. Similarly, the number of views should also generate more interests in the trader's profile page. However, the amount effect can be expected to be stronger – hence, the square root operator is applied to the views but the amount effect is linear.

The views received by the trader is modeled as another stochastic differential equation whose drift term is a function of the amount following and the current number of views, $h(a, v)$. The noise term is modeled as $\sigma_v dW(t)$, where σ_v is the volatility coefficient and $dW(t)$ is the increment of the Wiener process. Thus we have,

$$dv(t) = h(a, v)dt + \sigma_v dW(t)$$

Conspicuously absent in the above relationship is the impact of the control variable (delay). However, this is expected. While the ability of potential followers to evaluate a trader depends on the delay, we do not expect the control to affect the evaluation *interest* (or views) from potential followers. Because we do not expect the control (delay) to affect the change in views in a direct manner, we look for empirical support for the function $h(a, v)$. Turning to the data, it is natural to expect that a higher amount following (number of views) generates more interest. In Table 5, we find empirical support for a relatively simple form for the *change* in the number of views: $\Delta v(t) = v(t+1) - v(t) = c_3 a(t) + c_4 v(t)$, by running the regression in equation (3). Therefore, empirical evidence allows us to propose $h(a, v) = pa + qv$.

$$\Delta View_{j,t} = \theta_1 Amount_{j,t} + \theta_2 View_{j,t} + X_{j,t} + Trader_j + Time_t + \epsilon_{j,t} \tag{3}$$

Table 5: Impact of Amount and Views on the Change in Views

Dependent Variable: $\Delta View$	
VARIABLES	Coefficients
Amount	0.003***(0.0003)
View	0.005***(0.0006)
Control Variables	Yes
Trader-level FE	Yes
Time-level FE	Yes
Observations	181,666
R-squared	0.020

Note. The standard error is reported in parenthesis.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

6.1 Stochastic Control Model

Based on the above discussion, we present the revenue optimization problem for the platform as the following stochastic control model, after suppressing all implicit time arguments.

$$\begin{aligned}
\max_{\delta} \quad & \mathbb{E}\left[\int_0^T kae^{-\rho t}dt\right] \\
\text{subject to} \quad & da = \left(-\alpha v\sqrt{\frac{a}{\delta_0+\delta}} + \gamma\sqrt{v}\frac{a}{\delta_0+\delta}\right)dt + \sigma_a dZ \\
& dv = (pa + qv)dt + \sigma_v dW
\end{aligned} \tag{4}$$

where δ is the control parameter, a is the amount of money following a trader at time t, v is the number of views at time t, and ρ is the discount factor.

6.1.1 Solution

To solve the stochastic optimal control problem, the optimal control δ should satisfy the following Hamilton-Jacobi-Bellman (HJB) equation for the value function V.

$$\begin{aligned}
\rho V(a,v,t) = \max_{\delta}\{ka + V_a\left(-\alpha v\sqrt{\frac{a}{\delta_0+\delta}} + \gamma\sqrt{v}\frac{a}{\delta_0+\delta}\right) + V_v(pa+qv) + V_t \\
+\frac{1}{2}V_{aa}\sigma_a^2 + \frac{1}{2}V_{vv}\sigma_v^2\}
\end{aligned} \tag{5}$$

Using the above equation, a point-wise optimization problem can be solved as below.

The optimal solution is *bang-bang*, implying that the trades of a trader should either be released with minimum possible delay (δ_0) or the highest delay that is reasonable. In this context, we can set δ_0 to be a small value (say a few seconds) to represent the minimum possible delay that can be implemented given information technology constraints. Concerning the maximum delay, we can set this value to a relatively large value, e.g., 120 minutes. A transaction released beyond 120 minutes would likely be independent of the original real-time transaction and increasing the delay further would not make sense. The above values of minimum possible delay and maximum delay are illustrative, and could change with the platform's technology and the market. Note that, the optimal delay changes dynamically in the life of a trader, depending on the current values of the state variables associated with the trader (amount and number of views).

To prove the optimal policy structure, let $g(\delta)$ denote the terms involving the control variable in the HJB as shown below.

$$g(\delta) = -\alpha v\sqrt{\frac{a}{\delta_0+\delta}} + \gamma\sqrt{v}\frac{a}{\delta_0+\delta}$$

The first order condition yields

$$g'(\delta) = \frac{\sqrt{av}}{2(\delta_0+\delta)^{\frac{3}{2}}}\left(\alpha\sqrt{v} - \frac{2\gamma\sqrt{a}}{\sqrt{\delta_0+\delta}}\right)$$

The optimal solution is a corner solution as shown below.

- If $g'(0) \geq 0$, then $g(\delta)$ increases in δ. Hence, the maximum delay should be chosen. Thus, $\delta^\star = \delta_m$, where $(\delta_0 + \delta_m)$ represents the maximum delay.
- When $g'(0) < 0$, then the optimal solution is either $\delta^\star = 0$ or $\delta^\star = \delta_m$. This can be seen by setting $g'(\delta) = 0$. Solving for $\delta = \delta_1$ yields a minimum because $g''(\delta_1) > 0$. The value of δ_1 is unique because once $g'(\delta) > 0$, it stays positive. Hence, the optimal solution can be found by evaluating the value of the function $g(\delta)$ at the two extreme points $(0,\delta_m)$ and choosing the higher of the two values.

While the above bang-bang policy does not easily lend itself to an analytical solution for the value function, a numerical value of the optimal discounted revenue for a trader can be obtained for given values of a and v and the other trader specific parameters. Currently, ZuluTrade provides a ranking of traders, whose ranking algorithm is not made public. However, this ranking can be assumed to be based on trader characteristics such as profit, risk, and so on, that signal the quality of the trader to potential followers. It could also be based on factors that are in the interest of the platform, such as the amount following. The numerical value of the optimal revenue can be incorporated into the current ranking algorithm to provide a systematic way to infuse the economic goals of the platform into the ranking of traders.

To illustrate the impact of the optimal policy on the platform's goal, we compare, for a hypothetical trader, the current policy (30 minute delay) and the bang-bang policy. Figure 5 show how the amount evolves over time under the 30-minute policy and the bang-bang policy. We see that the bang-bang policy outperforms the 30-minute policy in terms of the amount of money. We also compare the value function (objective function in equation (4)) by numerically calculating the integral. The value function is 1.11 under the 30-minute policy and 1.18 under the bang-bang policy.

7 Conclusion

We studied information release strategies in social trading using data from ZuluTrade that primarily engages in the Foreign Exchange (currency trading) market. The data

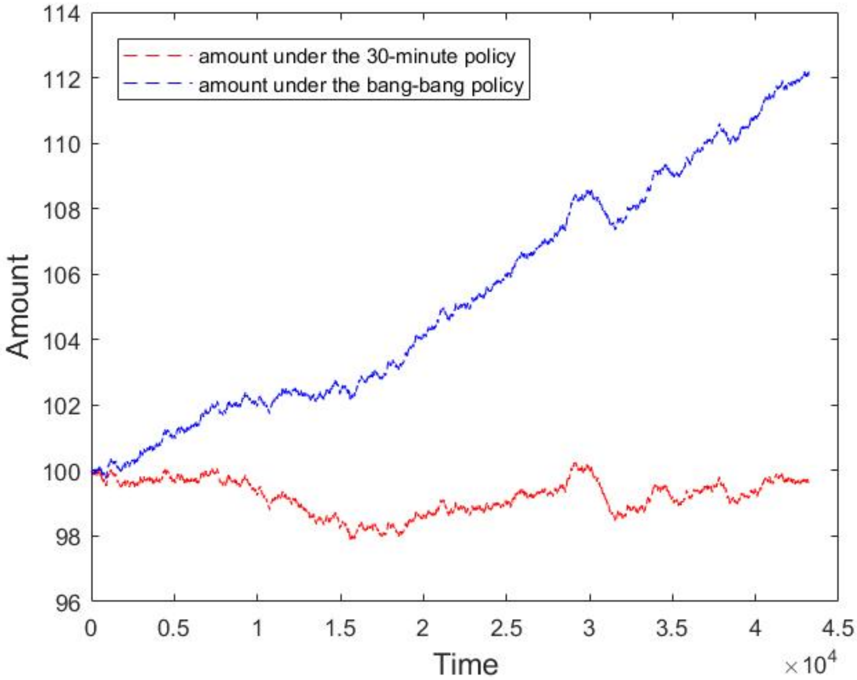

Figure 5: The Comparison between 30-minute and the bang-bang policy

Notes: $\alpha = 0.000001$, $\gamma = 0.000001$, $p = 0.000015$, $q = 0.00001$, $\sigma_a = 0.01$, $\sigma_v = 0.01$, $\rho = 0.000000093$, $k = 2.6e - 7$, $T = 43200$, $dt = 1$, $a(0) = 100$, and $v(0) = 20$.

tracks 15,352 traders, copied by 15,492 followers across five major currencies. Our main interest was to determine the optimal information release policy for the platform. Towards this goal, we estimate the hypothetical profit earned by a trade if it was executed with some delay (i.e., a virtual, *simulated* trade constructed by adding some time delays to the open and close time of the original trade). To estimate the profit earned by a simulated trade, we used historical spot price data of the currency being traded. Having estimated the profit earned from the simulated trade, we developed a measure called *profit-gap*, defined as the real-time profit minus the simulated profit. We estimated various econometric models to unravel the drivers of the profit-gap, the amount of money following a trader, and the number of views received by the trader. Using the empirical evidence gathered from the ZuluTrade platform, the study devised different ways for the platform to address the transparency-revenue dilemma, both implicitly (by maximizing transparency while respecting a Money-at-Risk constraint) and explicitly (by directly optimizing the revenue generated from commissions and follower fees).

The key contribution of our proposed approach was in its ability to address the problem at the level of the trader, or at an even more granular level, such as a trader-currency combination. This is in sharp contrast to the current approach of the platform that adopts a simple, one-size-fits-all policy that chooses the same level of delay for all trades occurring on the platform. Like the platform, our focus was on the use of delay as a control variable, while holding the follower fee at a fixed level. A natural extension would be to consider both the delay and the follower fee as control variables that are trader specific. The inclusion of customized follower fees would provide a finer degree of control for the platform: Rather than running the risk of losing existing followers, the platform could offer a lower follower fee to maintain the existing set of followers associated with a trader. The platform could also consider offering a menu of options for followers, each with a given level of delay and an associated follower fee. The current options offered by the platform lie at the two extremes: zero delay and a follower fee versus a 30-minute delay and zero follower fee.

While the focus of our study was on the goals of the platform, our study can also help followers answer the question whether they are paying too much for financial advice. To illustrate, consider a follower that faces an uncertain profit-gap (x) that is Normally distributed as $N(\alpha\sqrt{\delta}, \sigma^2\delta)$. A natural question is: is paying a follower fee of c (per trade) justified? As a simple answer, a comparison could be made between the expected profit-gap ($\alpha\sqrt{\delta}$) and the following fee c: If $\alpha\sqrt{\delta} > c$, then real-time following is worthwhile.

At a broader level, our study is one of the first of its kind to explore the value of information in a real-world setting. The context in this study, namely the Forex market, provided us with an ideal testbed to study information value measured by the profit impact of delaying a trader's trades. This is because the Forex market is very speculative and volatile, and the impact of a small delay on the profit of a trade can be significant. In other markets, e.g., the traditional stock market where the fundamentals do not change rapidly, the impact of a small delay on profit may be too small to measure. Thus, to study the impact of delay in the stock market, it will be necessary to simulate much larger delays. The problem with introducing large delays, of course, is that exogenous events that occur during the delay period could affect the profit-gap. Even so, the problem of following in real-time versus doing so with delay is a prevalent phenomenon, not unique to the Forex market.

In this study, we discussed the question of *how* to follow (i.e., real-time versus delay) and the platform should manage delay in a way to maximize its revenue from commissions and following fees. Future work could explore the additional question of *whom* to follow. That is, it is possible that a trader-currency may not be worthwhile to follow at all, whether in real-time or with delay. Together, the joint decision of whom to follow, and if so, how to follow, is what must eventually be addressed for a more comprehensive study of the problem.

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Appendix

Table 6: VIF Values of Equation (2)

Variable	VIF	1/VIF
$View$	4.18	0.24
$Profitpips$	4.18	0.24
$AgeLog$	3.25	0.31
$HighestProfit$	3.13	0.32
$AvgTrade$	2.14	0.47
$WorstDrawdown$	2.08	0.48
$Trades$	2.08	0.48
$WorstTrade$	1.96	0.51
$MaxOpenTrade$	1.94	0.52
$MinEquity$	1.67	0.60
$BestTrade$	1.51	0.66
$WinRatio$	1.37	0.73
$ProfitGap$	1.16	0.86
ROI	1.13	0.89
$OpenPosition$	1.11	0.90
$Rank$	1.09	0.92
$StandardLots$	1.01	0.99
$Profit$	1.01	0.99