Essays in Behavioral and Computational Finance

Thesis submitted for the degree of
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by

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To my family and friends

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Abstract

This thesis consists of two essays on behavioral finance and financial market microstructure with computational approaches.

Chapter 2 investigates the effects of steroid hormones and trader composition on financial markets in a mathematical model. We focus on the composition of traders in financial markets, namely, female traders and male traders, as risk preferences change in different ways with the mediation of steroid hormones. Firstly, we examine the effects of testosterone on financial risk preferences and market stability in the model. The results from simulation show that the effects of a more balanced gender composition are more nuanced. An increase in the proportion of female traders may actually increase the volatility of returns; however, the chances of extreme events are reduced. Secondly, we analyze the effects of cortisol on traders' risk preference and market behavior in our model with traders' risk preferences influenced by market uncertainty via the mediation of cortisol. Results from our model show that concerns about heightened market uncertainty mitigate traders' excessive risk-taking behaviors and performance of traders is largely affected by market sentiment. In the third part of Chapter 2, we examine the overall effect of testosterone and cortisol on market behavior with traders having heterogeneous behavioral and physiological responses to trading outcomes and market uncertainty. Results from simulation show that male-dominated market is less volatile as the effect of concerns about market uncertainty outweighs the effect of trading outcomes on traders' behavior.

Chapter 3 examines the impact of two different types of information on high frequency market microstructure. We present a dynamic trading game in the limit order market with computerized traders and human traders trading in one risky asset, where traders might have lags in observing the contemporaneous fundamental value and the order book status. Optimal strategies and market characteristics are determined through a unique numerical technique. Our results show that these two types of information have different values for traders with information on contemporaneous fundamental value being more valuable than the information on contemporaneous limit order book status.

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Declaration

I declare that chapter 2: "The Role of Hormones in Financial Markets" is a joint work with Dr. Subir Bose and Dr. Daniel Ladley, University of Leicester. An early version of the first part of this chapter has been uploaded to the 2016 University of Leicester Discussion Paper Series in Economics and on the SSRN (Bose, Ladley, and Li, 2016). The author names are listed alphabetically. The first part of Chapter 2 also received media coverage including *The Times* and BBC World Business Report and has been presented at the 21st CEF conference 2015 (Taipei) and 7th IFABS conference 2015 (Hangzhou) with the title "The Effects of Hormones on Financial Market Stability", 4th ISCEF conference 2016 (Paris) and 3rd Young Finance Scholars' conference 2016 (University of Sussex, Brighton) with the title of "The Role of Hormones in Financial Markets". Chapter 3 is a joint work with Dr. Subir Bose and Dr. Daniel Ladley.

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Chapter 1

Introduction

In financial markets, stock prices fluctuate dramatically compared to indicators of fundamentals. Among the explanations proposed by researchers, there is one associated with the phenomenon of time-varying risk preferences among the traders. Some traders might exert a larger impact on market price and drive trends over short periods. The idea is that traders could become less risk-averse, presenting excessive risk-taking behaviors given successful trading outcomes. The role of hormones in financial risk preferences has attracted considerable attention over the last decade. In previous studies, steroid hormones, such as testosterone and cortisol, have been shown to affect risk preferences in traders (e.g., Coates and Herbert, 2008; Kandasamy et al., 2014; Cueva et al., 2015). Furthermore, levels of testosterone and cortisol have been shown to be influenced by trading outcomes and market uncertainty respectively, male traders being more sensitive to both effects than females. As the trading floors are overwhelmingly dominated by men (e.g., Coates, 2012), these effects could have significant impact on markets. However, it is difficult to generalize the effects of steroid hormones on the market as a whole, as most studies only look at small groups of traders. This thesis adds to the debate by exploring how the fluctuations in steroid hormones might affect traders and the overall financial market in a mathematical model. As these hormonal influences are complex and tend to affect different types of behavior under different market conditions differently, we study the influence of testosterone and cortisol separately in Part I and Part II of Chapter 2. We then consider the interaction of these hormonal influences and study the overall impact in the third part of Chapter 2.

The first part of Chapter 2 looks into the effects of testosterone and trader composition on financial markets in a mathematical model of traders trading in a financial market with the levels of testosterone affecting traders' decisions. The level of risk aversion decreases in response to successful trading outcomes and increases in response to losses. Particularly, there are systematic differences between male and female traders with male traders being more sensitive to gains and losses. The results of our model show that increasing the proportion of female traders might not reduce the volatility on a day-to-day basis, but at the same time it can reduce the occurrence of the most extreme crashes. Our results also show that male traders on average earn less than females, but the best performing individuals are likely to be male due to the greater variation of males' risk-taking behaviors. Part II of Chapter 2 examines effects of cortisol on traders' risk preference and market behavior. Results of our model show that in the market with neutral market sentiment male traders could stabilize the market as their trading behaviors are more moderated due to concerns about heightened market uncertainty. The third part of Chapter 2 explores the overall effects of steroid hormones on traders' behavior and the financial market where traders are heterogeneous in behavioral and physiological responses to market information. In our model, traders have time-varying risk preferences which are affected by their levels of testosterone and levels of cortisol with male traders having greater responses to both trading outcomes and market movements. The results of our model show that the concerns about market uncertainty exert a greater effect on traders' risk preferences than the impact of trading outcomes. The market dominated by male traders is less volatile than the market with balanced gender composition while volatility itself reverts back to a normal level after periods of fluctuations.

Chapter 3 sheds light on the value of two different types of information in a high frequency market microstructure setting. With the advent of high frequency trading technology, price adjustment and information transmission in financial markets have become extremely fast-paced. In this chapter, we study a dynamic trading game between computerized traders and human traders in the limit order market, where optimal strategies of traders are determined through a unique numerical technique. Our results show that these two types of information create different values for traders. The information on contemporaneous fundamental value is more valuable than the information on contemporaneous limit order book status. Information on contemporaneous order book status is valuable for human traders, reducing their trading costs and risks.

Chapter 2

The Role of Hormones in Financial Markets

Abstract

Steroid hormones, such as testosterone and cortisol, have been shown to affect risk preferences in humans with high levels of testosterone or low levels of cortisol leading to excessive risk-taking. Hormone levels, in turn, are affected by trading outcomes, market uncertainty and gender- males are more sensitive to stimuli than females. We investigate the effects of hormones on market behavior and trader performance in a mathematical model. Results from our model show that an increase in the proportion of female traders does not necessarily make markets less volatile; however, it reduces the occurrence of market crashes under certain market conditions. Male traders on average under-perform females, although the best performing individuals are more likely to be male.

2.1 Introduction

In the past decade, there has been considerable discussions in the media on excessive risk-taking in financial markets. In particular, 'reckless' risk-taking by traders was, at least partly, blamed for the turmoils and crashes observed in recent years.[1] Importantly, it was also argued that traders in the financial markets are 'too male' both in terms of their numbers as well as in the excessively masculine culture of trading floors (e.g., Coates, 2012; Eckel and Fullbrunn, 2015). Consequently, there have been arguments from academics (e.g., Coates et al., 2010), the popular press (e.g., Belsky, 2012; Leslie, 2012) and policy makers (e.g., Lagarde, 2013) that a more balanced gender ratio would reduce volatility and help stabilize the markets. Our objective in this chapter is to study exactly this issue: to examine how a change in the gender balance of traders affects their performance and the stability of financial markets.

Physiological studies have shown that steroid hormones, for example testosterone, affect risk preference in humans. High levels of testosterone have been shown to be associated with greater, even excessive, amounts of risky behavior (e.g., Apicella et al., 2008; Garbarino et al., 2011) and asset market bubbles (e.g., Nadler et al., 2015), while cortisol has been shown to affect risk preference and to predict market instability (e.g., Cueva et al., 2015). Chronic elevations in circulating cortisol would increase risk aversion of individuals (e.g., Kandasamy et al., 2014), while elevated cortisol can have a number of effects on emotions, cognition and behavioral responses to stress (e.g., de Kloet, 2000). Moreover, there are feedback effects: while hormones affect behavior, outcomes resulting from such behavior and the market uncertainty in turn may affect hormone levels. In the case of testosterone, levels increase (decrease) in response to success (failure). It has also been demonstrated that there are systematic differences between males and females in this regard: men tend to have higher levels of testosterone as well as experience greater fluctuations in their levels than women (e.g., Kivilighan et al., 2005). Gains and losses from financial trading have been shown, in laboratory experiments as well as through the analysis of real traders, to lead to greater variance in male testosterone levels and risk preferences than that observed in females (e.g., Dreber and Hoffman, 2010). Meanwhile, the extents to which levels of cortisol response to market uncertainty are different between male and female traders, with levels of cortisol in men being more sensitive compared to women (e.g., Kirschbaum et al., 1992; Kivlighan et al., 2005).

It is this greater sensitivity to gains and losses that has led to some policy makers, academics and the popular press to call for a reduction in the proportion of male

[1] See for example Adams (2011), Belsky (2012), Foroohar (2013).

traders in financial markets in order to enhance stability. While it is clear that the behavior of *individual* male traders is generally more volatile than that of female traders, it is not immediately clear that a decrease in the proportion of male traders would necessarily make *markets* less volatile. Returns from trading, particularly at short time horizons, are to a large extent affected by trends and dynamics resulting from the trading behavior of others. It is these effects that proponents of the above policy wish to dampen through changing the gender ratio. However, levels of cortisol in male traders increase more under stressed market conditions than that of female traders which would have diminished effects on price movement due to the increased risk aversions. There are situations when males' greater sensitivity might trigger excessive risk-taking behaviors, while concerns over market uncertainty might reduce more of male traders' risk-taking behaviors. Moreover, price movements often arise from the interactions of many trading strategies, together with the arrival of information, such that it is not possible to deduce a straightforward relationship between market volatility and the proportions of male and female traders. Our key finding is that an increase in the proportion of female traders might make markets more volatile. However, this finding is with respect to the standard measure of volatility as used in academia and industry; in the popular press the word 'volatility' is often associated with instability. In that regard we find the opposite: a decrease in the proportion of male traders does make the occurrences of *extreme events* less likely.

To analyze the effects of hormones, we consider a simple trading model in the tradition of De Long et al. (1990b). In our model, informed and positive feedback investors trade over multiple periods in a risky and a riskless asset. Traders have time-varying risk preferences that affect their choice of portfolio compositions. There has been much work examining the form of utility functions (e.g., Kahneman and Tversky, 1982; Spiegel and Subrahmanyam, 1992; Vayanos, 2001) and the degree of risk aversion of individuals (e.g., Longstaff and Wang, 2012; Chabakauri, 2013; Bhamra and Uppal, 2014); these studies, however, assume that choices are made over time based on fixed risk preferences. As argued above, risk preferences not only differ across individuals but also vary over time for a given individual in response to outcomes from individuals' actions. Traders who make profits become less risk-averse, whereas those who make losses become more so. Meanwhile, higher (lower) market uncertainty would increase (decrease) traders' risk aversions. We incorporate these effects in our model by allowing a trader's risk preference parameter to vary in response to the results of recent trades as well as market uncertainty. Each trader chooses a portfolio in every period to maximize expected utility from wealth with the optimal choices depending on the trader's risk preference. When the realized return from the chosen portfolio is higher (lower) than the expected return, the risk aversion parameter for the next period decreases (increases) given the impact of testosterone. The effect is that success results in an increase in appetite for risk-taking whereas failure lowers it. On the other hand, traders become more risk averse under stressed market conditions and less risk-averse in stable markets. A crucial issue is not just that risk preferences change but that this variation is *systematically* different between males and females. To incorporate this we allow the *extent* of the effect to vary between traders.

The results of our model show that an increase in the proportion of female traders increases the volatility of returns. The presence of a larger fraction of male traders however increases the chances of extreme events. We also find that while female traders have higher *average* earnings than male traders, the best and the worst performing traders are more likely to be men. This finding indicates the difficulty of changing the gender balance of the trading population in a culture that only rewards star traders.

The rest of the chapter is organized as follows. Section 2.2 briefly reviews the relevant literature on asset pricing methods and the role of hormones in mediating financial behaviors and risk preferences. Section 2.3 sets out our model incorporating heterogeneous beliefs. Section 2.4 presents details on the impact of testosterone and discusses the results. Section 2.5 examines the effects of cortisol and discusses the results. Section 2.6 presents analysis on the combined impact of testosterone and cortisol in financial markets and discusses the results.

2.2 Related Literature

This chapter is related to the literature concerning physiological effects on economic behavior. Research in this area has examined the links between hormones, financial risk preferences, traders' performance and market uncertainty (e.g., Dreber and Hoffman, 2007; Garbarino et al., 2011). Apicella et al. (2008) and Coates and Page (2009) investigate associations between circulatory testosterone levels and financial risk preferences. These studies look at diverse experimental settings and find that increases in testosterone lead to greater optimism and risk-taking. Moreover, trading results (monetary rewards) of individuals are seen to affect their circulatory testosterone levels with high performance linked to higher levels of testosterone (e.g., Apicella et al., 2014). Coates and Herbert (2008) examine the relation between levels of testosterone and trading performance using a sample of male traders. They find that the traders in their sample achieved better results on those days when the trader's testosterone level was higher than the trader's median level over the period. Significantly, when considering the above relationship, male and female traders differed substantially in the variation of testosterone levels after winning (losing), affecting their subsequent risk-taking and thus the resulting trading outcomes (e.g., Kivilighan et al., 2005; Dreber and Hoffman, 2010). In general, levels of testosterone in males seem to be more responsive to winning and losing than in females. This has been argued to be due to the differences in the brain physiology and the early exposures to testosterone (e.g., Cronqvist et al., 2015). While the above papers study behavior of traders, we investigate the effects on the overall market outcomes.

The associations between levels of testosterone and social behaviors in humans have been examined by a large number of studies in the biology literature. One key finding is the positive relationship between rewards (or punishment) and post-competition testosterone levels (Mazur and Booth, 1998; Van Honk et al., 2004; Schultheiss et al., 2005). These studies find that increased testosterone levels are associated with rewards and decreased levels are associated with punishments. Buser (2011) explores the biological and hormonal determinants of social preferences by regressing the choices in social preference games on prenatal testosterone exposures (finger length index ratio 2D:4D), and current exposures to progesterone and oxytocin. The study finds a negative effect of prenatal testosterone levels on giving rates in trust, ultimatum and public good games.

In addition, results of Coates and Herbert (2008) also show that levels of cortisol in male traders are positively related to market uncertainty. The authors find that as market volatility rose over an 8-day period mean daily cortisol levels in traders increased by 68%. In addition to the above relationship, degrees of such physiological response to market uncertainty are different between male and female traders although there is no difference between males and females in daily cortisol levels (e.g., Van Honk et al., 2003). Levels of cortisol in men are shown to experience greater reactions to uncertainty and stress than that of women (e.g., Kivlighan et al., 2005). Kirschbaum et al. (1992) look at gender differences in cortisol responses to psychological stress in a sample of 153 participants. The authors find that both men and women showed elevated levels of cortisol under psychological stress with cortisol responses in men being 1.5 to 2 fold higher than that of women.

Moreover, levels of cortisol are related to financial risk preferences of individuals. Van Honk et al. (2003) look at the cortisol levels of people playing the Iowa Gambling Task Game. The authors find a significant negative correlation between levels of cortisol and choice of risky desks, where individuals with low cortisol levels chose more of those high variance and low expected return desks. Kandasamy et al. (2014) investigate the correlation between cortisol and risk-taking of participants through computerized trading tasks with a double-blind, placebo-controlled dosing experiment. The authors test the effect of administered cortisol on risk preferences of participants and find that chronic elevations in levels of cortisol would promote risk aversions. Particularly, individuals' levels of cortisol were raised pharmaceutically by 68% to replicate the changes in cortisol levels observed in the study of Coates and Herbert (2008). Results from their study show that in response to the sustained increase in cortisol risk aversions of participants rose by 44%.

Whilst not focusing on hormones, Cueva and Rustichini (2015) consider the role of gender in markets. These authors run market experiments on small groups of single and mixed sex participants in an open plan setting, and find that the mixed sex markets demonstrated better stability. They explain this finding as being driven by low cognitive ability traders being more cautious in mixed gender environments. It is not clear, however, in a real financial market, in which the majority of participants have high cognitive ability, and are trading against individuals not in the same room if these findings will hold.

This study is also related to the literature on traders with wrong beliefs (sometimes called irrational traders in the literature). Friedman (1953) argued that such traders cannot influence long-run asset prices because they consistently lose money. This argument was further elaborated on by Muth (1961), Fama (1965) and Lucas (1972), and was used in studies on market efficiency in the presence of noise traders (e.g., Kyle, 1985; De Long et al., 1990a; Campbell and Kyle, 1993; Guo and Ou-Yang, 2015). However, De Long et al. (1990b) demonstrate that traders with wrong beliefs may survive under certain market conditions, while Saacke (2002) and Kogan et al. (2006) show that irrational traders can affect prices and persist for long periods in markets. Such effects have also been shown in models such as Brock and Hommes (1998) where the interaction of trading strategies results in persistent and substantial deviations from the fundamental value. In financial markets, discrepancies in traders' opinions on asset price often come from differences in information as well as investors' interpretations of market data. Some studies examine the impact of individual optimism and different investor sentiments on financial decision making under uncertainty (e.g., Shiller, 2000; Nofsinger, 2005). In our model, we consider traders with different degrees of optimism or pessimism on market outlook, either as a reaction to the stream of market news, or as an estimation of future economic outlook.

2.3 The Model

The model is constructed in the spirit of De Long et al. (1990b), based on the framework of Brock and Hommes (1998). Consider a market populated by two types of traders, informed and positive feedback (denoted by $h \in \{I, PF\}$), where informed traders know the underlying dividend process. The market allows the trade of a risky asset and a risk-free asset. Denote by p_t the ex-dividend price per share of the risky asset at time t and y_t the stochastic dividend distributed in period t. Traders may choose to invest in the risk-free asset with a gross return R or to borrow at the same rate, $R \geq 1$.

Let w_t denote the trader's wealth at time t and Q_t the number of shares of the risky asset purchased or shorted at time t. Wealth of agents evolves according to

$$w_{t+1} = Rw_t + (p_{t+1} + y_{t+1} - Rp_t)Q_t \tag{2.1}$$

In period t, each type of traders has an expectation of the excess return per share of the risky asset for the coming period, $E_{h,t}[p_{t+1} + y_{t+1} - Rp_t]$. Expectations are conditional expectation but for notational simplicity we henceforth refer to them as expectations.

Let $a_{h,t}$ denote the level of risk aversion of agent-type h at time t. Traders are myopic mean-variance maximizers who choose the optimal quantity $Q_{h,t}$ to solve

$$\max_{Q_{h,t}}\{E_{h,t}[w_{t+1}] - \frac{1}{2}a_{h,t}Var_{h,t}[w_{t+1}]\} \tag{2.2}$$

subject to Equation (2.1). In our study, traders have time-varying risk preferences. $E_{h,t}[.]$ and $Var_{h,t}[.]$ are the subjective conditional expectation and conditional variance respectively given their beliefs. The conditional variance of wealth w_{t+1} is

$$Var_{h,t}[w_{t+1}] = Q_{h,t}^2 Var_{h,t}[p_{t+1} + y_{t+1} - Rp_t] \tag{2.3}$$

where the conditional variance of excess returns is assumed to be fixed over time and normalized to $Var_{h,t} = Var$ for all traders.[2] The optimal quantity for trader-type h is the following[3]

$$Q_{h,t} = \frac{E_{h,t}[p_{t+1} + y_{t+1} - Rp_t]}{a_{h,t}Var} \tag{2.4}$$

Let n_h represent the proportion of trader-type h in the market ($\sum n_h = 1$) and Q_{st} the supply of shares per investor. Equilibrium of demand and supply in the market leads to

$$\sum n_h Q_{h,t} = Q_{st} \tag{2.5}$$

When there is only one type of trader in the market, market equilibrium indicates

$$E_{h,t}[p_{t+1} + y_{t+1}] - Rp_t = a_{h,t}VarQ_{st} \tag{2.6}$$

In the special case of zero supply of outside shares, the required expected return

[2] Allowing this figure to vary between trader types does not qualitatively affect the results.

[3] Short selling is permitted ($Q_{h,t} < 0$).

becomes

$$E_t[p^*_{t+1} + y_{t+1}] = Rp^*_t \tag{2.7}$$

where p^*_t is the fundamental value (i.e., present value of future dividends) of the risky asset at time t and $E_t[p^*_{t+1} + y_{t+1}]$ represents the expectation of the fundamental value and dividend conditional on the information set of past prices and dividends.[4]

In each period, the risky asset distributes a stochastic dividend. The dividend follows an i.i.d. process with mean value $\bar{y}$ and

$$y_t = \bar{y} + \varepsilon_t \tag{2.8}$$

the noise component $\{\varepsilon_t\}$ is an i.i.d. stochastic process with mean 0. Innovations of dividends are independent across periods. For this process the best estimate of the future dividend is the mean $\bar{y}$.[5]

Informed traders estimate the gross return per share according to

$$E_{I,t}[p_{t+1} + y_{t+1}] = E_t[p^*_{t+1} + y_{t+1}] \tag{2.9}$$

where $E_t[p^*_{t+1} + y_{t+1}]$ is the common expectation of the fundamental and dividend.

Informed traders believe that the price of the risky asset is determined by its fundamental value, the discounted value of future dividends. They are informed of the underlying dividend processes but not the dividend in any future period.

The second type of trader, positive feedback traders, attempt to profit by exploiting market trends. Positive feedback traders estimate the capital gain by the use of an exponentially weighted moving average of previous returns

$$E_{PF,t}[\frac{p_{t+1} - p_t}{p_t}] = c(\frac{p_t - p_{t-1}}{p_{t-1}}) + (1-c)E_{PF,t-1}[\frac{p_t - p_{t-1}}{p_{t-1}}] \tag{2.10}$$

where c is the weight on the most recent percentage observation, $0 < c < 1$. The expected dividend yield is estimated in the same way,

$$E_{PF,t}[\frac{y_{t+1}}{p_t}] = g(\frac{y_t}{p_{t-1}}) + (1-g)E_{PF,t-1}[\frac{y_t}{p_{t-1}}], 0 < g < 1 \tag{2.11}$$

where g is the weight on the most recent dividend yield. Positive feedback traders rely on only past prices and dividends in making their trading decisions.

Trade therefore happens between those two types of traders when there are disagreements on the asset value and price movements. In every period, the asset price is then determined endogenously by demand and supply.

[4] In the case of positive supply, risk-averse traders require a positive risk premium to hold the risky asset.

[5] Our results are robust to alternative dividend processes, see Section 2.4.6.

2.4 Part I: Testosterone and Financial Markets

In this section, we incorporate the effect of testosterone on traders' risk preferences into the traditional framework set out in Section 2.3 and present the results from the analysis.

2.4.1 Performance Feedback and Risk Aversion

In each period, traders calculate their demand based on their levels of risk aversion, conditional expectations and conditional variance of future excess returns per share (as described in Section 2.3). The results of trading are determined by actual excess return per share, denoted by $\Delta r_t = p_t + y_t - Rp_{t-1}$. A trader's level of satisfaction given the outcome of trade is calculated as

$$Z_{h,t} = \frac{\Delta r_t}{E_{h,t-1}[p_t + y_t - Rp_{t-1}]} - 1 \tag{2.12}$$

We define a positive (negative) outcome as the occasion when the realized profit is greater (lower) than the expected excess return per share, $Z_{h,t} > 0$ ($Z_{h,t} < 0$).[6]

Within each type of trading strategies (denoted by j) we consider two sub-groups of traders, namely female traders (F) and male traders (M). Each trader type has a function $F^j_{h,t}$, which reflects the change in levels of testosterone in response to trading outcomes. While the exact shape of the relationships between outcomes, testosterone levels and risk aversion are not known research has demonstrated several key features. Positive (negative) outcomes result in increased (decreased) testosterone levels and decreased (increased) risk aversion (Mazur and Booth, 1998; Coates and Herbert, 2008). Further testosterone levels are persistent over time and saturate (e.g., Van Honk et al., 2004; Sapienza et al., 2009). A number of functional forms would describe such a relationship. We adopt one such function $F^j_{h,t}(Z_{h,t})$ which models the change in testosterone levels in response to stimulus and has an increasing and asymptotically bounded form

$$F^j_{h,t} = \kappa^j \arctan(Z_{h,t}), \kappa^j > 0 \tag{2.13}$$

[6] Other forms for the identification of positive and negative outcomes were also considered as the true functional form of humans' responses to trading performance is only known approximately. One such alternative measure is $Z_{h,t} = \frac{\Delta r_t}{E_{h,t-1}[p_t+y_t-Rp_{t-1}]}$, in which a positive outcome happens when traders correctly estimate the sign of the excess return. As long as they make profits, both greater than expected and smaller than expected profits are deemed as positive outcomes. For the case in which agents expect the risky asset to have a positive excess return per share ($E_{h,t-1}[p_t + y_t - Rp_{t-1}] > 0$), they enjoy a positive outcome for all $\Delta r_t > 0$, even if the achieved return per share is positive but lower than expected ($0 < \Delta r_t < E_{h,t-1}[p_t+y_t-Rp_{t-1}]$). With this alternative measure of positive outcomes, results are qualitatively similar to those with Equation (2.12).

where κ^j measures the degree of testosterone fluctuations of sub-group j. The function $F^j_{h,t}$ is centered around 0 with range $(-\frac{2}{\pi}\kappa^j, \frac{2}{\pi}\kappa^j)$. Traders having positive outcomes ($Z_{h,t} > 0$) have their levels of testosterone rise correspondingly ($F^j_{h,t} > 0$), while negative outcomes ($Z_{h,t} < 0$) lead to declining levels of testosterone ($F^j_{h,t} < 0$). Heterogeneity between female and male traders in our model lies in the degree of hormonal responses to trading outcomes: testosterone levels in males being highly responsive to trading outcomes compared to females, $\kappa^M > \kappa^F$ (see for example Kivilighan et al., 2005; Cueva et al., 2015). We model informed traders as having fixed risk aversion while positive feedback traders have heterogeneously time-varying risk preferences. This clarifies the mechanism driving our findings.[7] However, results are qualitatively similar when we allow for both informed traders and positive feedback traders having heterogeneous time-varying risk preferences.

Based on the changes in testosterone levels, traders' risk aversion varies according to the following function

$$a^j_{h,t} = a^j_{h,t-1}(1 - F^j_{h,t}) \tag{2.14}$$

where elevated testosterone levels ($F^j_{h,t} > 0$) decrease traders' levels of risk aversion thereafter ($a^j_{h,t} < a^j_{h,t-1}$).[8] Traders that achieved good trading outcomes become less risk-averse in the subsequent trading period due to their elevated testosterone levels.

Both informed traders and positive feedback traders estimate future price movements and make trading decisions according to their beliefs. The price of the risky asset is determined by the collective demand and supply in the market. Actual excess returns per share from the risky asset come from both price movements and dividends. It is the divergence between actual returns and previous estimations of it that causes fluctuations of testosterone levels, affecting agents' risk preferences and therefore their trading decisions. Here we consider two groups within the population of positive feedback traders which respond differently to gains and losses. Given the same trading outcome, male positive feedback traders experience greater elevations (drops) in levels of testosterone and thus their risk aversion decreases (increases) more than that of female positive feedback traders.

The inclusion of endogenous time-varying risk aversion makes the model analytically intractable. As a result the behavior of the model and the effect of the composition of traders on this behaviors are analyzed numerically.

[7] As the informed traders rely more on their information of the fundamental value, they may be considered less responsive to periodical returns and have a fixed level of risk preference over the finite period of trading.

[8] In order to avoid negative risk aversions, in Section 2.4.2 we choose the parameter values of κ^j that ensure both $-1 < F^j_{h,t} < 1$ and the risk aversions $a^j_{h,t} > 0$ across all periods of trading.

2.4.2 Parametrization

At each time step, the risky asset distributes a stochastic dividend with mean $\bar{y} = 1$ and a noise component ε_t uniformly distributed on the interval $[-1, 1]$. The gross risk-free return is $R = 1.01$. The fundamental value of the risky asset at the beginning of the first period is $p^* = 100$.[9] The conditional variance of excess returns per share Var, is equal to 1.

In each period, informed traders estimate the fundamental value of the risky asset as the present value of its discounted future dividends. In determining their beliefs about future returns positive feedback traders set the weight on the most recent observation as $c = 0.2$, while the weight on most recent dividend yield is $g = 0.5$.[10]

The degrees of testosterone fluctuations for female traders and male traders, κ^F and κ^M, are 0.001 and 0.003 respectively. These values of κ^F and κ^M mean that traders' levels of risk aversions range between 0 and 12. Results are qualitatively similar for other values of κ^F and κ^M, as long as $\kappa^F < \kappa^M$.

The total number of time steps per simulated time series is $T = 1000$. The evolution of the market price is path dependent as the trading decisions of each trader in each time step affect market prices, trader's payoffs and thus trading decisions in future periods. For each parameter combination 1000 repetitions were conducted (i.e., runs, denoted by N), with different random draws from the dividend process. To maintain comparability between parameter combinations, the same 1000 dividend paths are used in each case. The parameters for the numerical analysis are presented in Table 2.1.

2.4.3 Market Stability

In this section we show how traders with testosterone mediated risk preferences affect overall market stability.

We consider two ratios of male and female positive feedback traders: 95% male to 5% female and 50% male to 50% female. The composition of 95% male to 5% female is close to the observed real world composition of trading floors.[11] The composition of 50% male to 50% female is representative of the approximate distribution in the general population and is in line with opinions in the mainstream media, which argue this ratio would stabilize markets.[12] In the following discussion we refer to

[9] These parameters satisfy the no-bubble condition $p^* = \frac{\bar{y}}{R-1}$. See Brock and Hommes (1998) for a detailed analysis of the no-bubble condition.

[10] We tested different values of c and g and our results are robust for $0 < c < 0.7$ and $0 < g < 1$. For $c \geq 0.7$, the prices become too volatile. The use of the exponentially weighted moving average avoids the highly unstable prices.

[11] This low participation rate of female traders is highlighted by Coates (2012), however, exact figures for this ratio are difficult to obtain.

[12] See for instance "Too much testosterone, too much confidence" in Leslie (2012).

Table 2.1: Baseline Parametrization

Parameter	Meaning	Value
$\bar{y}$	Mean dividend	1
ε_t	Noise component	$U(-1,1)$
R	Risk-free return	1.01
p^*	Initial fundamental value	100
Var	Conditional variance of excess return	1
c	Weight on most recent percentage price change	0.2
g	Weight on most recent dividend yield	0.5
κ^F	Degree of testosterone fluctuation for female traders	0.001
κ^M	Degree of testosterone fluctuation for male traders	0.003
T	Number of time steps	1000
N	Number of runs	1000

the first as the real composition and the second as the balanced composition.

Table 2.2 reports results examining market stability (see also in Figure 2.1). The volatility of returns under the realistic market composition is significantly lower than under the balanced population (Sign test, Male:Female 95:5 vs. 50:50, $z = -31.5912$, $p = 0.000$).[13] There is no statistically significant difference between the data sets of the skewness of returns under the realistic composition and the balanced composition (Sign test, Male:Female 95:5 vs. 50:50, $z = -0.0316$, $p = 0.9748$). Based on the results of volatility in our model, increasing the proportion of female traders does not reduce volatility. This is due to the interactions between traders' profits and their hormonal responses. We can view the distribution of results as a range of possible outcomes for a trader entering the market. If a trader is successful, correctly identifying profitable trades, their risk aversion will go down and they will take on larger positions. They will then have a larger effect on market prices and potentially drive trends. If, however, a trader is unsuccessful and loses money, they will become more risk-averse and take smaller positions. Return volatility is driven by differences in opinion between traders. In the former scenario traders take larger positions and so drive higher volatility. It is the latter scenario, however, that occurs more frequently as, on average, positive feedback traders are outperformed by informed traders. The greater testosterone fluctuations of male traders increase

[13]Results of pairwise Sign tests (analogue of paired t-test) are presented as volatility data are non-normal and the paired differences are not symmetric.

the scale of this effect. As a male trader loses money they become more risk-averse than a female trader in the same position and so have a diminished effect on asset returns. As a result a greater proportion of male traders in the market reduces overall volatility.[14]

Table 2.2: Moments of Returns

Market Measure	Male:Female 50 : 50	Male:Female 95 : 5	Male:Female 50 : 50 vs. Male:Female 95 : 5 (p-value)
Volatility (%)	0.2345	0.1746	0.0000
	(0.0114)	(0.0124)	
Skewness	0.0054	0.0049	0.9748
	(0.0715)	(0.0774)	
Kurtosis	2.4071	2.5502	0.0000
	(0.1024)	(0.1230)	

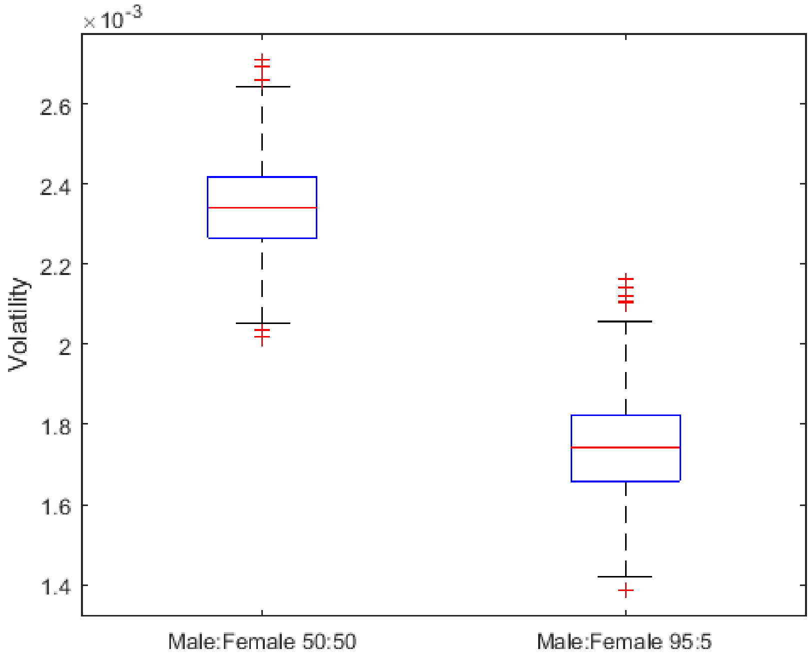
Note: Results for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

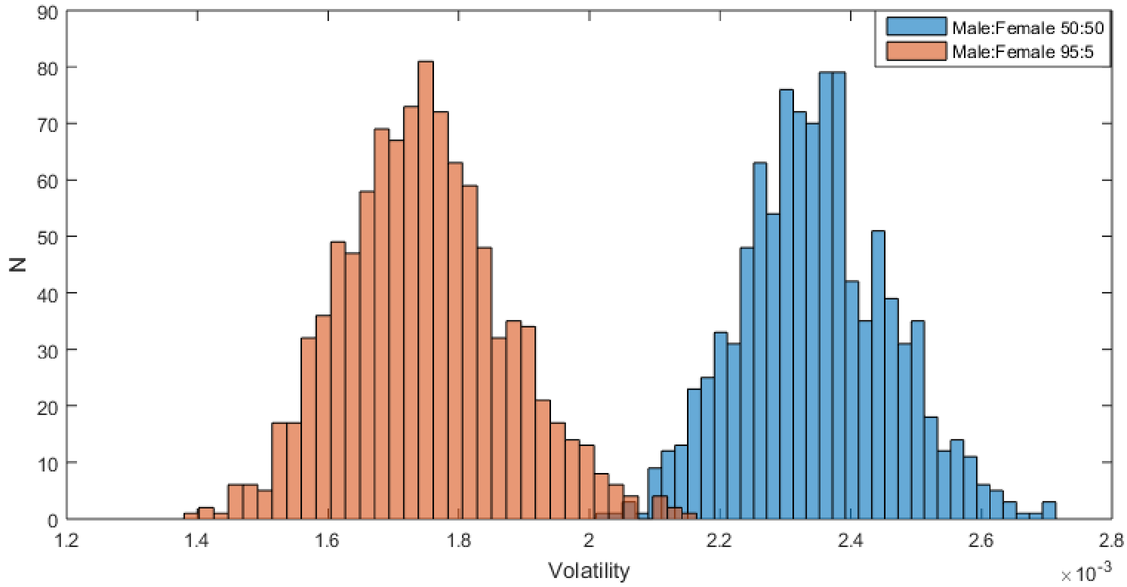
While showing a lower average volatility, markets with a realistic composition exhibit higher kurtosis and so are more prone to extreme price changes (Sign test, Male:Female 95:5 vs. 50:50, $z = 31.5912$, $p = 0.000$).[15] At the same time these markets also have a larger dispersion of volatility (Brown-Forsythe test, F statistic$=$ 5.996, $p = 0.014$), indicating lower stability and more periods of high volatility, than those under a balanced composition. Extreme volatility typically occurs when the positive feedback traders correctly pick a trend and make a profit. The profit leads to higher testosterone levels and so greater risk-taking. As a result the positive feedback traders are able to build and continue a bubble. The larger proportion of male traders exacerbates this effect resulting in larger bubbles and therefore greater volatility. At some point, however, this bubble will burst as informed traders drive the price back towards the fundamental value. While in the majority of cases the

[14] This mechanism still holds if both informed and positive feedback traders are split into male and female. The increase in demand from the male informed traders, pushes prices back towards the fundamental, further reducing volatility.

[15] In both cases we do not observe excess kurtosis. This, however, is driven by the choice of the i.i.d. dividend process. If instead the process were AR(1) then the same qualitative results are obtained but with the addition of excess kurtosis (see Section 2.4.6). We focus here on the i.i.d. case as it is the most parsimonious.

Figure 2.1: Box Plot and Histogram- Volatility





Note: Volatility figures for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. For the box plot, each box represents the volatility of returns in the market given the specified trader composition. The tops and bottoms of each box are the 25th and 75th percentiles of the samples with the central mark representing median and the whisker length specified as 1.5 times the interquartile range. Each simulation was a run for 1000 time steps, which generates one volatility. Volatility data are collected over 1000 runs. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

positive feedback traders can not establish trends, when they do that results in higher volatility with more male traders.[16]

The results on volatility and kurtosis have substantial implications for the debate concerning financial market stability. Increasing the proportion of female traders in the market might have mixed results - an increase in daily volatility coupled with a decreased frequency of extreme events. From a regulatory point of view the second of these concerns will be generally dominant arguing for efforts to rebalance the population of traders. However, our results show that this may be 'politically' difficult. The regulators may face potential criticism as making this change may increase daily volatility. Many observers, including the popular press and financial commentators, use volatility as a proxy for risk, including the risk of catastrophic events. While our results show that the change would indeed be beneficial in terms of reducing the risk of catastrophic events, the regulator may struggle to make this point. In particular the main benefit, the decreased frequency of rare extreme events would, by definition, be hard to observe and therefore use as a justification.

2.4.4 Trader Performance

In this section we examine the relative performance of male traders and female traders. Since gender affects risk aversion, it is natural to examine whether male positive feedback traders outperform female traders or vice versa. Trading outcomes across men and women have been investigated by Barber and Odean (2001) who examine common stock investments of over 35,000 households. By partitioning the data set into accounts traded by men or women, the authors find that performance of women is superior to that of men. The relative performance of traders working for financial firms with respect to their gender, however, has received little attention.

Table 2.3 reports the periodical profits of informed traders in the market with half informed traders and half positive feedback traders. Two sets of values are presented with the first set representing the balanced male/female composition while the second set corresponds to the real life composition of 95% male to 5% female. Informed traders make positive payoffs on average, however, the size of their payoffs is affected by the male/female proportions within the group of positive feedback traders.

The profits earned by informed traders decrease when the proportion of male traders in the market is increased (Sign test, Male: Female 50:50 vs. 95:5, $z = 31.5912$, $p = 0.000$). As explained in Section 2.4.3, price volatility decreases in

[16] Robustness checks show increased dispersion of volatility if the fraction of informed traders is higher than 40% ($n_I > 0.4$). For $n_I \leq 0.4$, higher proportions of male traders could reduce both average volatility and the dispersion of volatility due to the greater losses generated by male traders.

Table 2.3: Normalized Profits

	Informed Traders	Male	Female	p-value		
	I	II	III	I vs. II	I vs. III	II vs. III
Male:Female 50:50						
Normalized profits	0.197	-0.203	-0.192	0.000	0.000	0.000
	(0.028)	(0.029)	(0.027)			
Dispersion	1.111	1.174	1.078	0.000	0.000	0.000
	(0.036)	(0.044)	(0.032)			
Skewness	0.960	-1.172	-0.826	0.000	0.000	0.000
	(0.169)	(0.232)	(0.131)			
Male:Female 95:5						
Normalized profits	0.176	-0.177	-0.164	0.000	0.000	0.000
	(0.028)	(0.028)	(0.026)			
Dispersion	1.129	1.138	1.036	0.000	0.000	0.000
	(0.044)	(0.045)	(0.032)			
Skewness	1.166	-1.195	-0.826	0.000	0.000	0.000
	(0.247)	(0.256)	(0.149)			
Male:Female 50:50 vs. Male:Female 95:5 (p-value)						
Normalized profits	0.000	0.000	0.000			
Dispersion	0.000	0.000	0.000			
Skewness	0.000	0.000	0.072			

Note: Results for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Normalized profits are volume weighted profits per period. Each simulation was a run for 1000 time steps. Profits, dispersion and skewness are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

the proportion of male positive feedback traders due to increased risk aversions. As the positive feedback traders trade less the price of the risky asset becomes largely driven by informed traders and so becomes closer to the fundamental values. As a result there is little disagreement in the market and so little trade. With fewer positive feedback traders in the market, the total amount of wealth that transfers from positive feedback traders to the informed traders decreases. In effect the larger fraction of male traders inadvertently makes the market more informationally efficient.

In order to assess the relative performance of male and female traders, we compare the volume weighted profit per period. This measure describes the average gains or losses on every share traded by the male and female traders. Using this measure removes any across run and time effect on the payoffs due to different trading quantities, leaving only the gender effect. We term this measure normalized profits. The results in Table 2.3 show that male positive feedback traders achieve both inferior payoffs and larger dispersion of the normalized profits compared to female positive feedback traders. This is the case regardless of the relative proportions of male and female traders within the population. Additionally the distribution of normalized profits for male positive feedback traders is more heavily negatively skewed, exhibiting a much longer tail of losses compared to that of female positive feedback traders. As such male traders have inferior performance on average and more often make the biggest losses.

While male traders underperform female traders on average their payoffs are also more dispersed than that of female traders. In order to analyze the profits and losses separately, the distributions of payoffs are partitioned by sign. Table 2.4 presents these statistics. The results for profitable periods reveal an important difference. Male traders earn more than female traders on average when profits are made and their payoffs display significantly larger dispersion and higher positive skewness than those of female traders (e.g., Sign test, positive profits male vs. female, $z = 8.5698$, $p = 0.000$; Sign test, Dispersion male vs. female, $z = 31.5912$, $p = 0.000$). The best-performing male traders earn more than the top-ranking female traders. The maximum amount of normalized profits earned by the male positive feedback traders is significantly higher than the maximum amount earned by female positive feedback traders (Sign test, male vs. female, $z = 31.5912$, $p = 0.000$).

Table 2.4 also shows that among those periods when positive feedback traders make profits, female traders outperform male traders more frequently. However, when male traders make higher profits than females, they outperform female traders by a large amount. This is why the average profit of male traders is greater than that of female traders. Rather than skills it is the excessive risk-taking behavior that makes the best performing traders more likely being male.

Table 2.4: Profits – Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Male:Female 50:50			
Positive profits	0.629	0.627	0.000
	(0.025)	(0.022)	
Dispersion	0.660	0.586	0.000
	(0.043)	(0.027)	
Skewness	1.790	1.285	0.000
	(0.225)	(0.139)	
Outperforming	42%	58%	0.000
	(0.035)	(0.035)	
Positive return periods	453	453	
	(14.637)	(14.637)	
Male:Female 95:5			
Positive profits	0.615	0.612	0.000
	(0.025)	(0.022)	
Dispersion	0.654	0.579	0.000
	(0.043)	(0.028)	
Skewness	1.843	1.334	0.000
	(0.235)	(0.147)	
Outperforming	41%	59%	0.000
	(0.035)	(0.035)	
Positive return periods	459	459	
	(14.682)	(14.682)	

Note: Results for market with 50% informed traders to 50% positive feedback traders. Profits analyzed here are positive normalized profits generated by male positive feedback traders and female positive feedback traders. Normalized profits are volume weighted profits per period. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Outperforming is the fraction of periods that the given gender outperforms the other gender. Each simulation was a run for 1000 time steps. Positive profit measures are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

These findings have concerning implications for financial firms, regulators and those wishing to change the gender balance in the financial markets. Even though male traders may underperform female traders and make profits less often, reward schemes in financial firms may still select towards large groups of male traders. Financial bonus schemes typically reward the best performers and often lead to large numbers of other traders being fired, potentially even those making small profits. It is important to note that the better performing male traders in these experiments were not more skilled, rather they were lucky. They made larger profits through riding their luck - decreasing their risk aversion, and increasing their investment, in response to profits. The better performing female traders are less susceptible to these effects and so make extreme profits less frequently, even though they also lose money less often. As such testosterone effects may explain why financial markets are dominated by men. Trying to rebalance the population of traders to better match that of the population as a whole may require a complete change in how financial firms reward their staff. A movement away from large bonus' for the best performers to a system that better rewards consistent profits.

2.4.5 Strategy

Our analysis of market stability has so far focused on the role of gender; the distribution of informed to positive feedback traders, however, may also have an effect. There is some disagreement with regard to the proportion of traders who use technical rules. It has been estimated to be as high as 90% by Allen and Taylor (1990) and Taylor and Allen (1992). Lewellen et al. (1980) place the figure between 27% and 38% while Hoffmann and Shefrin (2014) suggest 32%. Much of this disagreement seems to stem from the degree of usage of technical approaches with some traders using them as part, rather than all, of their strategy. In this chapter we base our analysis on the survey results of Menkhoff and Taylor (2007) who find that in most cases the weight given to technical trading is between 30% and 70%. In Table 2.5, we report results for two strategy mixes (the gender mix is held constant at the real composition of 95% male and 5% female). The first set represents a market with 50% informed to 50% positive feedback traders, and the second for a market with 70% informed to 30% positive feedback traders.

The results in Table 2.5 show that positive feedback traders are capable of destabilizing the market. The larger the proportion of these traders, the higher the volatility and the kurtosis of returns.[17] Volatility of returns in a market with 70% informed traders to 30% positive feedback traders is significantly lower than the scenario with

[17]This result was tested under different fractions of male and female traders and was found to hold across all compositions.

Table 2.5: Moments of Returns

Measure	Informed:Positive Feedback		p-value
	50 : 50	70 : 30	50 : 50 vs. 70 : 30
Volatility (%)	0.175	0.075	0.000
	(0.012)	(0.005)	
Kurtosis	2.550	2.487	0.000
	(0.123)	(0.113)	

Note: Results for market with 95% male to 5% female traders within the group of positive feedback traders. Informed:Positive Feedback is the proportion of informed traders to positive feedback traders in the market. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

50% informed traders to 50% positive feedback traders. Positive feedback traders add volatility to the market price while informed traders arbitrage mispricings bringing prices closer to the fundamental price and reducing volatility. The more informed traders there are in the market, the greater is this effect and the closer is the price of the risky asset to its fundamental value.

This stabilizing effect of informed traders is consistent with the literature on the effect of heterogeneous beliefs in financial markets. Friedman (1953) and Campbell and Kyle (1993) show that traders who know better the value of the asset make positive profits and so eventually force the irrational traders out of market. In contrast, De Long et al. (1990b) demonstrate that traders with wrong beliefs are able to increase volatility sufficiently that informed traders are unable to drive them out of the market and so some irrational traders persist in equilibrium. In our model, positive feedback traders lose money in the long-run; however, their trading behaviors impact asset returns while they have wealth available to do so. In the real world, where new traders are continually arriving at the market as they are hired by firms or start brokerage accounts, this implies that these traders will continue to add volatility to returns.

2.4.6 Extension with Different Stochastic Processes

In the description below, we check the robustness of results to different dividend processes.

We first consider a first order autoregressive process, AR(1),

$$y_t = b + \rho y_{t-1} + \varepsilon_t \tag{2.15}$$

where the white noise ε_t has a mean of zero. This specification addresses the possibility that market information is correlated across periods, and dividends depend linearly on past values. In order to compare with the first stochastic process, the means of dividends are set to be equal, $\frac{b}{1-\rho} = \bar{y}$, with parameters $b = 0.639$, $\rho = 0.361$.

Consistent with Section 2.4.3, results show that volatility decreases in the male proportion of positive feedback traders, holding the proportion of informed to positive feedback traders fixed (see Table 2.6). Returns are more stable with an increased proportion of informed traders relative to positive feedback traders (see Table 2.7). The relative performance of traders is in line with that of Section 2.4.4 (see Table 2.8 and Table 2.9). Informed traders make positive profits both in terms of average periodical profits and cumulative profits over the 1000 periods of trading. Male positive feedback traders perform worse than female positive feedback traders on average, while the group of positive feedback traders makes losses on average. Conditional on positive returns, male positive feedback traders earn higher volume weighted profits than females. Different from our main results, the greater dispersion of volatility due to a larger male proportion of positive feedback traders does not persist with AR(1) type dividends (no statistically significant difference in variance of volatility, Brown-Forsythe test, $p = 0.1565$). In addition, the level of volatility is significantly higher than that of our baseline economy (with dividend $y_t = \bar{y} + \varepsilon_t$), even though the two sets of stochastic dividends themselves have the same level of dispersion (e.g., Sign test for levels of volatility with Male: Female 95:5, AR(1) vs. IID, $z = 31.5912$, $p = 0.000$).

Table 2.6: Moments of Returns

Market Measure	Male:Female 50 : 50	Male:Female 95 : 5	Male:Female 50 : 50 vs. Male:Female 95 : 5 (p-value)
Volatility (%)	0.627	0.563	0.000
	(0.024)	(0.023)	
Kurtosis	3.024	3.038	0.000
	(0.229)	(0.233)	

Note: Results for market with 50% informed traders to 50% positive feedback traders with AR(1) dividend process. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $b = 0.639$, $\rho = 0.361$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

Table 2.7: Moments of Returns

Measure	Informed:Positive Feedback		p-value
	50 : 50	70 : 30	50 : 50 vs. 70 : 30
Volatility (%)	0.563	0.455	0.000
	(0.023)	(0.016)	
Kurtosis	3.038	3.008	0.000
	(0.233)	(0.225)	

Note: Results for market with 95% male to 5% female traders within the group of positive feedback traders with AR(1) dividend process. Informed:Positive Feedback is the proportion of informed traders to positive feedback traders in the market. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $b = 0.639$, $\rho = 0.361$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

The next stochastic dividend process is a two-state Ornstein-Uhlenbeck (OU) process, where the dividend y_t is generated from the following stochastic process

$$y_t = e^{-\lambda^\omega \Delta t} y_{t-1} + \mu^\omega (1 - e^{-\lambda^\omega \Delta t}) + \sigma \sqrt{\frac{1 - e^{-2\lambda^\omega \Delta t}}{2\lambda^\omega}} \varepsilon_t \tag{2.16}$$

ε_t is a Wiener process and $\sigma > 0$. The state of the economy is represented by ω, where $\omega \in \{high, low\}$, with mean values of dividends $\mu^{high} > \mu^{low}$, and λ^ω is the speed of mean reversion, $0 < \lambda^{high} < \lambda^{low}$. The Ornstein-Uhlenbeck process is a modified random walk, in which the process tends to revert back to its long term mean. The mean is higher during expansions and lower in contractions. This two-state process is adopted to capture the boom and bust of an economy. The state switching mechanism is controlled by an unobservable state variable that follows a Markov chain permitting multiple structural changes with unknown timing of state switching. In reality, economic conditions change over time and switching of states could be in line with business cycles or caused by short-term dynamics in the market. The Markov switching model used here captures the exogenous changes to the economy.

Parameters for this model are $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\varepsilon_t \sim N(0,1)$. Tables 2.10, 2.11, 2.12, and 2.13 present results on market stability and traders' performance with a narrow distance between boom and bust (state means $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$), while Tables 2.14, 2.15, 2.16, and 2.17

Table 2.8: Normalized Profits

	Informed Traders	Male	Female	p-value		
	I	II	III	I vs. II	I vs. III	II vs. III
Male:Female 50:50						
Normalized profits	0.190	-0.196	-0.186	0.000	0.000	0.000
	(0.042)	(0.044)	(0.041)			
Dispersion	1.553	1.628	1.512	0.000	0.000	0.000
	(0.084)	(0.099)	(0.075)			
Skewness	1.000	-1.183	-0.885	0.000	0.000	0.000
	(0.514)	(0.641)	(0.436)			
Male:Female 95:5						
Normalized profits	0.171	-0.172	-0.159	0.000	0.000	0.000
	(0.042)	(0.042)	(0.040)			
Dispersion	1.574	1.585	1.462	0.000	0.000	0.000
	(0.097)	(0.100)	(0.075)			
Skewness	1.153	-1.178	-0.855	0.000	0.000	0.000
	(0.662)	(0.679)	(0.464)			
Male:Female 50:50 vs. Male:Female 95:5 (p-value)						
Normalized profits	0.000	0.000	0.000			
Dispersion	0.000	0.000	0.000			
Skewness	0.000	0.000	0.000			

Note: Results for market with 50% informed traders to 50% positive feedback traders with AR(1) dividend process. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Normalized profits are volume weighted profits per period. Profits, dispersion and skewness are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $b = 0.639$, $\rho = 0.361$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

Table 2.9: Profits –Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Male:Female 50:50			
Positive profits	0.824	0.822	0.000
	(0.045)	(0.041)	
Dispersion	1.106	1.011	0.000
	(0.118)	(0.087)	
Skewness	3.008	2.536	0.000
	(0.744)	(0.542)	
Outperforming	42%	58%	0.000
	(0.035)	(0.035)	
Positive return periods	460	460	
	(14.159)	(14.159)	
Male:Female 95:5			
Positive profits	0.806	0.802	0.000
	(0.044)	(0.040)	
Dispersion	1.089	0.992	0.000
	(0.118)	(0.087)	
Skewness	3.056	2.567	0.000
	(0.764)	(0.558)	
Outperforming	42%	58%	0.000
	(0.035)	(0.035)	
Positive return periods	465	465	
	(14.078)	(14.078)	

Note: Results for market with 50% informed traders to 50% positive feedback traders with AR(1) dividend process. Profits analyzed here are positive normalized profits generated by male positive feedback traders and female positive feedback traders. Normalized profits are volume weighted profits per period. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Outperforming is the fraction of periods that the given gender outperforms the other gender. Each simulation was a run for 1000 time steps. Positive profit measures are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. p-values from pairwise Sign tests. Parameters: $b = 0.639$, $\rho = 0.361$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

describe results for a larger difference in means ($\mu^{high} = 1.3452$, $\mu^{low} = 0.7$).[18]

Table 2.10: Moments of Returns

Market Measure	Male:Female 50 : 50	Male:Female 95 : 5	Male:Female 50 : 50 vs. Male:Female 95 : 5 (p-value)
Volatility (%)	0.753	0.688	0.000
	(0.070)	(0.069)	
Kurtosis	10.397	12.345	0.000
	(2.928)	(3.450)	

Note: Results for market with 50% informed traders to 50% positive feedback traders with two-state Ornstein-Uhlenbeck dividend process. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

Table 2.11: Moments of Returns

Measure	Informed:Positive Feedback		p-value
	50 : 50	70 : 30	50 : 50 vs. 70 : 30
Volatility (%)	0.688	0.581	0.000
	(0.069)	(0.066)	
Kurtosis	12.345	17.503	0.000
	(3.450)	(4.667)	

Note: Results for market with 95% male to 5% female traders within the group of positive feedback traders with two-state Ornstein-Uhlenbeck dividend process. Informed:Positive Feedback is the proportion of informed traders to positive feedback traders in the market. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

With the two-state Ornstein-Uhlenbeck dividend process, results are qualitatively similar to our baseline model. Specifically, informed traders still make positive profits over time. Meanwhile, return volatility decreases in the male proportion of

[18] In order to compare with the other two dividend processes, these two pair of state means together with the speeds of mean revision parameters in the OU process are set to match the average and dispersion of the dividend paths from the other two processes. We tested different pairs of state means and the values of other parameters in the OU model satisfying the conditions and results are qualitatively similar for other paired values.

Table 2.12: Normalized Profits

	Informed Traders	Male	Female	p-value		
	I	II	III	I vs. II	I vs. III	II vs. III
Male:Female 50:50						
Normalized profits	0.213	-0.219	-0.207	0.000	0.000	0.000
	(0.047)	(0.049)	(0.046)			
Dispersion	1.802	1.890	1.755	0.000	0.000	0.000
	(0.132)	(0.158)	(0.118)			
Skewness	1.188	-1.378	-1.069	0.000	0.000	0.000
	(0.895)	(1.058)	(0.796)			
Male:Female 95:5						
Normalized profits	0.190	-0.191	-0.177	0.000	0.000	0.000
	(0.047)	(0.048)	(0.045)			
Dispersion	1.828	1.841	1.698	0.000	0.000	0.000
	(0.156)	(0.159)	(0.118)			
Skewness	1.346	-1.372	-1.040	0.000	0.000	0.000
	(1.085)	(1.108)	(0.835)			
Male:Female 50:50 vs. Male:Female 95:5 (p-value)						
Normalized profits	0.000	0.000	0.000			
Dispersion	0.000	0.000	0.000			
Skewness	0.000	0.000	0.000			

Note: Results for market with 50% informed traders to 50% positive feedback traders with two-state Ornstein-Uhlenbeck dividend process. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Normalized profits are volume weighted profits per period. Each simulation was a run for 1000 time steps. Profits, dispersion and skewness are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

Table 2.13: Profits –Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Male:Female 50:50			
Positive profits	0.920	0.916	0.000
	(0.058)	(0.054)	
Dispersion	1.308	1.200	0.000
	(0.166)	(0.124)	
Skewness	3.450	3.006	0.000
	(1.055)	(0.849)	
Outperforming	42%	58%	0.000
	(0.035)	(0.035)	
Positive return periods	460	460	
	(14.455)	(14.455)	
Male:Female 95:5			
Positive profits	0.899	0.894	0.000
	(0.058)	(0.054)	
Dispersion	1.288	1.178	0.000
	(0.166)	(0.123)	
Skewness	3.494	3.038	0.000
	(1.073)	(0.863)	
Outperforming	41%	59%	0.000
	(0.035)	(0.035)	
Positive return periods	466	466	
	(14.300)	(14.300)	

Note: Results for market with 50% informed traders to 50% positive feedback traders with two-state Ornstein-Uhlenbeck dividend process. Profits analyzed here are positive normalized profits generated by male positive feedback traders and female positive feedback traders. Normalized profits are volume weighted profits per period. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Outperforming is the fraction of periods that the given gender outperforms the other gender. Each simulation was a run for 1000 time steps. Positive profit measures are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

Table 2.14: Moments of Returns

Market Measure	Male:Female 50 : 50	Male:Female 95 : 5	Male:Female 50 : 50 vs. Male:Female 95 : 5 (p-value)
Volatility (%)	2.452	2.359	0.000
	(0.530)	(0.516)	
Kurtosis	101.742	104.901	0.000
	(46.942)	(50.732)	

Note: Results for market with 50% informed traders to 50% positive feedback traders with two-state Ornstein-Uhlenbeck dividend process. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.3452$, $\mu^{low} = 0.7$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

Table 2.15: Moments of Returns

Measure	Informed:Positive Feedback		p-value
	50 : 50	70 : 30	50 : 50 vs. 70 : 30
Volatility (%)	2.359	2.203	0.000
	(0.516)	(0.492)	
Kurtosis	104.901	110.439	0.000
	(50.732)	(58.053)	

Note: Results for market with 95% male to 5% female traders within the group of positive feedback traders with two-state Ornstein-Uhlenbeck dividend process. Informed:Positive Feedback is the proportion of informed traders to positive feedback traders in the market. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.3452$, $\mu^{low} = 0.7$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

Table 2.16: Normalized Profits

	Informed Traders	Male	Female	p-value		
	I	II	III	I vs. II	I vs. III	II vs. III
Male:Female 50:50						
Normalized profits	0.362	-0.373	-0.352	0.000	0.000	0.000
	(0.151)	(0.158)	(0.146)			
Dispersion	4.412	4.579	4.315	0.000	0.000	0.000
	(1.951)	(2.137)	(1.847)			
Skewness	9.696	-9.790	-9.624	0.000	0.000	0.000
	(6.273)	(6.342)	(6.267)			
Male:Female 95:5						
Normalized profits	0.322	-0.323	-0.298	0.000	0.000	0.000
	(0.153)	(0.154)	(0.142)			
Dispersion	4.419	4.440	4.165	0.000	0.000	0.000
	(2.079)	(2.099)	(1.798)			
Skewness	9.801	-9.808	-9.666	0.000	0.000	0.000
	(6.441)	(6.451)	(6.360)			
Male:Female 50:50 vs. Male:Female 95:5 (p-value)						
Normalized profits	0.000	0.000	0.000			
Dispersion	0.029	0.000	0.000			
Skewness	0.000	0.000	0.000			

Note: Results for market with 50% informed traders to 50% positive feedback traders with two-state Ornstein-Uhlenbeck dividend process. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Normalized profits are volume weighted profits per period. Each simulation was a run for 1000 time steps. Profits, dispersion and skewness are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.3452$, $\mu^{low} = 0.7$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

Table 2.17: Profits –Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Male:Female 50:50			
Positive profits	0.978	0.979	0.218
	(0.086)	(0.081)	
Dispersion	1.995	1.900	0.000
	(0.550)	(0.483)	
Skewness	6.918	6.780	0.000
	(2.777)	(2.544)	
Outperforming	41%	59%	0.000
	(0.043)	(0.043)	
Positive return periods	480	480	
	(14.199)	(14.199)	
Male:Female 95:5			
Positive profits	0.965	0.966	0.025
	(0.084)	(0.079)	
Dispersion	1.966	1.871	0.000
	(0.533)	(0.463)	
Skewness	6.857	6.686	0.000
	(2.758)	(2.500)	
Outperforming	41%	59%	0.000
	(0.043)	(0.043)	
Positive return periods	487	487	
	(14.243)	(14.243)	

Note: Results for market with 50% informed traders to 50% positive feedback traders with two-state Ornstein-Uhlenbeck dividend process. Profits analyzed here are positive normalized profits generated by male positive feedback traders and female positive feedback traders. Normalized profits are volume weighted profits per period. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Outperforming is the fraction of periods that the given gender outperforms the other gender. Each simulation was a run for 1000 time steps. Positive profit measures are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. p-values from pairwise Sign tests. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.3452$, $\mu^{low} = 0.7$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.001$, $\kappa^M = 0.003$, $T = 1000$, $N = 1000$.

positive feedback traders. The larger the gap between the mean dividends of those two states, the higher the volatility of returns (volatilities in Table 2.14 are significantly higher than the volatility in Table 2.10 at 99% confidence level). Compared to the results from the baseline model and the AR(1) scenario, results for the two-state OU process show significantly higher levels of return volatilities and higher profits for the informed traders. Consistent with previous discussions, normalized gains or losses obtained by female positive feedback traders are significantly higher than those of male traders. However, when the gap between the two state means is large, male traders' performance is inferior to females', even conditional on positive earnings being generated.

Our baseline economy and the extensions here all show that volatility of returns decreases in the male proportion of positive feedback traders and informed traders make positive net profits over the trading periods. When traders respond differently to positive and negative outcomes, prices are less volatile in markets with more male traders. Meanwhile, male positive feedback traders do worse than female traders in terms of both average profit and the dispersion of average per share returns.

2.4.7 Discussion

Scientists, policy makers and the popular press that have argued that having more female traders would make financial markets more stable. Using an asset pricing model that incorporates a link between risk preferences and trader performance we show that the effects of a more balanced gender composition are more nuanced. An increase in the proportion of female traders may actually increase the volatility of returns; however, the chances of extreme events, such as crashes, are reduced. Further, while female traders outperform their male counterparts in terms of average earnings, the best (and the worst) performing traders are likely to be male. In an environment of highly selective performance-based evaluation, such as that seen in financial firms, one would expect the population to be increasingly biased towards male traders even though they on average underperform. As such the overly male culture of financial firms may itself be driven by testosterone and reward systems. In order to increase the number of female traders it may be necessary to fundamentally change the bonus culture of investing.

2.5 Part II: Cortisol and Volatility

In this section, we look into the effects of cortisol on traders' risk preferences and present the results from the analysis of this model.

2.5.1 Heterogeneous Beliefs, Physiological Reactions and Risk Aversion

We consider heterogeneity in trader's investor sentiment in the group of positive feedback traders, being optimistic or pessimistic about future market returns. The type of investor sentiment is denoted by l. Let θ^l represent the sentiment indicator, which captures the degrees of optimism or pessimism about market condition for the coming period. In period t, traders with sentiment type l estimate price and dividend of risky asset as

$$E^l_{PF,t}[p_{t+1} + y_{t+1}] = \theta^l E_{PF,t}[p_{t+1} + y_{t+1}] \tag{2.17}$$

with $\theta^l > 1$ for optimistic traders and $0 < \theta^l < 1$ for pessimistic traders.

Positive feedback traders adopt the same methods in estimating asset returns as described in Equation (2.10) and (2.11), while individuals differ in investor sentiments due to differences in interpretations of market information. In each period, optimal demand of traders is determined by their risk aversion, conditional expectation and conditional variance of future excess returns per share, while decision making is also influenced by market uncertainty.

Let σ_t denote the implied volatility of the risky asset in period t. Consider a smoothing parameter λ in the volatility estimation, $0 < \lambda < 1$. In period t, the variance estimation for period $t+1$ is given by

$$\sigma^2_{t+1} = (1-\lambda)u^2_t + \lambda\sigma^2_t \tag{2.18}$$

where u_t is the log market return in period t and the variance estimation becomes an exponentially weighted moving average of past variances. This approach is frequently used in measuring variance both historically and implicitly.

In addition to the individual sentiments, positive feedback traders are separated by genders (j). Each trader type has a function $C^j_{h,t}$, which reflects the change in cortisol levels in response to market uncertainty. Although the exact associations between cortisol, market uncertainty and risk aversions are not know, experimental studies have demonstrated several key features. Increased (decreased) market uncertainty leads to rising (falling) levels of cortisol, which would increase (decrease) risk aversion (e.g., Van Honk et al., 2003; Coates and Herbert, 2008; Kandasamy et al., 2014). A number of functional forms would describe such relationship. We adopt one such function $C^j_{h,t}$ which models the change in cortisol levels in response to market uncertainty and has an increasing and asymptotically bounded form

$$C^j_{h,t} = \eta^j \arctan[\ln(\frac{\sigma_{t+1}}{\sigma_t})], \eta^j > 0 \tag{2.19}$$

where η^j measures the degree of cortisol fluctuation of sub-group j. With increased levels of market uncertainty ($\ln(\frac{\sigma_{t+1}}{\sigma_t}) > 0$), traders would have an increased level of cortisol ($C^j_{h,t} > 0$), while a decrease in market volatility leads to falling cortisol levels.

Given the changes in levels of cortisol, traders' levels of risk aversion vary according to the following function

$$a^j_{h,t} = a^j_{h,t-1}(1 + \zeta C^j_{h,t}), \zeta > 0 \tag{2.20}$$

where elevated (declined) levels of cortisol increase (decrease) traders' levels of risk aversion. Parameter ζ measures the magnitude of the effect of cortisol on traders' risk aversions.[19] Traders become less (more) risk-averse when market presents reduced (heightened) uncertainty. For simplicity, we consider informed traders with fixed risk aversions, while risk preferences of positive feedback traders vary over time.

In our model, female and male traders are homogeneous in understanding historical market information and estimating excess returns, while traders' investment decisions differ given their heterogeneity in hormonal responses under uncertainty. Given the increased (decreased) market uncertainty, male traders experience greater elevations (drops) in their levels of cortisol and thus risk aversions increase (decrease) more than that of female traders. Traders in the market make trading decisions according to their beliefs, investor sentiments and time-varying risk preferences. The price of the risky asset is determined by demand and supply in the market, while the implied market uncertainty is affected by price movements. Levels of cortisol change in response to changing market conditions, which affect agents' risk preferences and therefore their trading decisions.

In next section we present the parameterization and results for the model described above. Traders' behaviors and market stability are analyzed numerically as the consideration of endogenous risk aversion makes the model analytically intractable.

2.5.2 Parametrization

We consider four types of investor sentiments with degrees of optimism or pessimism $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$ and test for different densities at each θ^l.[20] In computing the implied volatility, the smoothing parameter is set as $\lambda = 0.98$. In

[19]Parameter values are calibrated on the basis of recent experimental studies, see Section 2.5.2 for details.

[20]We also considered the scenario that traders are neither optimistic nor pessimistic, while outcomes of traders could be represented by the average profits of optimistic and pessimistic traders.

the industry, estimations of the smoothing parameter are based on the maximum likelihood approach, resulting in values between 0.90 and 1.[21] Different degrees of optimism or pessimism and the smoothing parameter are also tested and the results are qualitatively similar.

The degrees of cortisol fluctuation as a response to changing market volatility are calibrated based on the results of Coates and Herbert (2008). In their study, levels of cortisol in male traders rose by 68% over the 8-day period when the market volatility rose by 18.7%. The degree of cortisol response for male traders, η^M, is computed as the daily cortisol fluctuation, which is approximately 3.2828. As for female traders, the degree of cortisol fluctuation is considered being half as responsive as male traders according to Kirschbaum et al. (1992). The degree of cortisol's impact on risk aversions, ζ, is computed based on Kandasamy et al. (2014). In their study, levels of risk aversion in traders rose by 44% when their levels of cortisol were raised pharmaceutically by 68% over the 8 days. We compute the value of ζ as the daily cortisol impact on risk aversion, which is 0.696 approximately. The combinations of η^F, η^M and ζ as well as the asset market settings mean that traders' level of risk aversions lies between 0 and 11.[22]

The total number of time steps in each simulated time series is $T = 1000$. The innovation of asset price is path dependent as the asset allocation of each trader in each time step influences market prices, implied volatility and trading decisions in future periods. For each parameter combination, we perform 1000 repetitions of the simulation (denoted by N), with different random draws from the dividend process. To maintain comparability between different parameter combinations, the same 1000 dividend paths are used in each case. Other parameters including $\bar{y}$, ε_t, R, p^*, Var, c and g are the same as Section 2.4.2. The parameters used in the simulations are shown in Table 2.18.

2.5.3 Market Stability

In this section we present results showing the effects of cortisol on traders' risk preferences and market behavior.

We focus on two types of gender compositions of traders with positive feedback trading strategies, namely, a realistic composition of 95% men to 5% women and a balanced composition of 50% men and 50% women. In addition to gender, traders are different in their interpretations of market information, being optimistic or pess-

[21] For instance, RiskMetrics (1995) proposes the value $\lambda = 0.94$, while higher λ is frequently used in recent years.

[22] Results are qualitatively similar for other relative scales between η^F and η^M as long as $\eta^F < \eta^M$.

Table 2.18: Baseline Parametrization

Parameter	Meaning	Value
$\bar{y}$	Mean dividend	1
ε_t	Noise component	$U(-1,1)$
R	Risk-free return	1.01
p^*	Initial fundamental value	100
Var	Conditional variance of excess return	1
c	Weight on most recent percentage price change	0.2
g	Weight on most recent dividend yield	0.5
λ	Smoothing parameter for implied volatility	0.98
η^F	Degree of cortisol fluctuation for female traders	1.6414
η^M	Degree of cortisol fluctuation for male traders	3.2828
ζ	Degree of cortisol's impact on risk aversions	0.696
T	Number of time steps	1000
N	Number of runs	1000

imistic about future market outlook. We present two types of aggregate market sentiment, i.e., a neutral market and an optimistic market. In neutral market, collective outlook for the market is neutral, while the aggregate opinion on asset returns in the optimistic market is higher than current level of returns.

Table 2.19 presents results for moments of asset returns. The volatility of returns with the realistic gender composition is significantly lower than that of balanced population in the neutral market (Sign test, Male: Female 95:5 vs. 50:50, $z = -31.4647$, $p = 0.000$), while male-dominated market is more volatile than the market with balanced composition for the optimistic market (Sign test, $z = -2.9409$, $p = 0.0033$). Moving to the equal representation of male and female traders does not reduce volatility in the neutral market due to the complexity of traders' behaviors and interactions of traders. In particular, traders' risk attitudes are influenced by the market movement with male traders being more sensitive to market uncertainty. It shows that increasing the proportion of female traders reduces the average volatility in the market with optimistic or pessimistic market sentiment but not for the neutral market. For both the neutral market and optimistic market, realistic composition results in higher kurtosis than the balanced composition, with greater likelihood of extreme returns.[23]

Table 2.19: Moments of Returns

Market Measure	Male:Female 50 : 50	Male:Female 95 : 5	Male:Female 50 : 50 vs. Male:Female 95 : 5 (p-value)
Neutral Market			
Volatility (%)	0.3231	0.3202	0.0000
	(0.00331)	(0.00329)	
Kurtosis	2.3562	2.3789	0.0000
	(0.1075)	(0.1132)	
Optimistic Market			
Volatility (%)	0.3383	0.3385	0.0033
	(0.0113)	(0.0137)	
Kurtosis	2.3680	2.3983	0.0000
	(0.1093)	(0.1162)	

Note: Results for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

The results for the neutral market are influenced by the market timing and various scenarios for a trader entering the market. Given wild movements in neutral market and increased volatility, trading willingness (i.e., risk-taking) is greatly reduced for both male traders and female traders. Concerns about market uncertainty would reduce the excessive trading of positive feedback traders. They will then have little effect on market prices, while the asset price stabilizes driven by informed traders. When the market calms down, traders would become less risk-averse and they will trade more. They will then have a greater effect on market prices and potentially drive trends. Concerns about uncertainty could moderate the trading behaviors and reduce fluctuations in market volatility. For a male trader under stressed market

[23]For the market with majority of pessimistic traders, impact of male/female composition on market volatility is similar to that of optimistic market.

conditions, they become more risk-averse than female traders in the same position and so have a diminished effect on price movement. While male traders trade more through declining volatility, the effect of their moderated trading behaviors in stressed market outweighs the intensified trading behaviors under normal market conditions. As a result a greater proportion of male traders in the neutral market reduces overall volatility.

In an optimistic or pessimistic market, positive feedback traders could drive trends and increase the overall market volatility.[24] Although these positive feedback traders become more risk-averse in stressed market, average volatility is driven up by their trading under normal market conditions. With greater sensitivity to market uncertainty, the group of male traders become more risk-averse than female traders in stressed market, while the effect of their moderated trading behaviors under such scenario is overturned by the intensified trading during low volatility periods. As a result, markets with realistic composition of traders is more volatile than the balanced composition when the market is optimistic or pessimistic in aggregate.

Compared to the neutral market, a market with more optimistic traders is more volatile on average, as such market has a higher trading volume with greater divergence of traders' opinions (e.g., Sign test for Male: Female 95:5, Optimistic vs. Neutral, $z = 28.6186$, $p = 0.000$). Trade often happens between those traders with different estimations of the future stock returns. In addition to the higher average volatility, optimistic market also exhibits larger dispersion of volatility and higher kurtosis of asset returns compared to the neutral market (e.g., Brown-Forsythe test for the variance of volatility with Male: Female 95:5, Optimistic vs. Neutral, F statistic$=$ 868.4109, $p = 0.000$; Sign test for Kurtosis with Male: Female 95:5, $z = 15.5268$, $p = 0.000$). Table 2.20 shows that average trading volume is higher in the optimistic market than the neutral market with more trades in the second half of entire trading horizon for both neutral and optimistic market.[25] On average, trading willingness is higher in the optimistic market compared to the neutral market. In particular, male trader' risk aversions are much lower when they trade in the optimistic market than in the neutral market.[26] For the optimistic market, it is the greater trading willingness of male traders that leads to the higher average volatility of market with realistic composition than the balanced composition.

For both neutral market and optimistic market, male traders have lower risk aversions in the second half of trading compared to the first half (e.g., Sign test

[24] The market with more pessimistic opinions would have similar properties as the optimistic market though the price trends are on the opposite directions.

[25] We separate the 1000 periods of trading into two parts, time 1 to 500 being 1st Half of trading and the remaining being the 2nd Half.

[26] Sign tests were conducted for pairwise comparisons and the differences are statistically significant at 99% (e.g., for the 1$^{\text{st}}$ Half Male RA with Male: Female 95:5, Optimistic vs. Neutral, $z = -6.9254$, $p = 0.000$).

Table 2.20: Trades and Risk Aversions (RA)

Market Measure	Male:Female 50 : 50	Male:Female 95 : 5	Male:Female 50 : 50 vs. Male:Female 95 : 5 (p-value)
Neutral Market			
1st Half Trades	0.6539	0.6398	0.0000
	(0.0090)	(0.0098)	
2nd Half Trades	0.6737	0.6680	0.0000
	(0.0100)	(0.0111)	
1st Half RA - Male	4.3450	4.1231	0.0000
	(0.0846)	(0.0643)	
- Female	3.7108	3.6147	0.0000
	(0.0335)	(0.0272)	
2nd Half RA - Male	4.0432	3.9366	0.0000
	(0.0856)	(0.0662)	
- Female	3.7423	3.6957	0.0000
	(0.0341)	(0.0281)	
Optimistic Market			
1st Half Trades	0.7403	0.7268	0.0000
	(0.0174)	(0.0207)	
2nd Half Trades	0.7717	0.7693	0.0000
	(0.0232)	(0.0279)	
1st Half RA - Male	4.2427	4.0869	0.0000
	(0.1622)	(0.1038)	
- Female	3.7520	3.6864	0.0000
	(0.0330)	(0.0381)	
2nd Half RA - Male	3.8884	3.8426	0.0000
	(0.1929)	(0.1409)	
- Female	3.7572	3.7435	0.0000
	(0.0395)	(0.0292)	

Note: Results for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps, with time 1 to 500 being 1st Half of trading and the remaining being the 2nd Half. Trade and risk aversion measures are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

for neutral market with Male: Female 95:5, 2nd Half vs. 1st Half, $z = -30.6425$, $p = 0.000$), while females are more risk-averse in the second half than they were in the first half (e.g., Sign test for neutral market with Male: Female 95:5, 2nd Half vs. 1st Half, $z = 30.5160$, $p = 0.000$). This is due to the heterogeneity in traders' reactions to market uncertainty. When there is an increase (decrease) in market volatility, concerns about (reassurance from) market uncertainty increase (decrease) traders' risk aversions with mediator cortisol. Risk aversions of male traders have greater variability as market moves. On average, market shows slightly lower levels of fluctuations in the second half of trading, which lead to the lower risk aversions of male traders in the second half than first half. However, female traders experience much smaller changes in risk aversions and small movements of market volatility make their risk aversions being slightly higher in the second half. Traders' concerns about heightened market uncertainty could mitigate excessive risk-taking behaviors and promote stable market liquidity during those highly volatile periods. This is closely related to the practices of riding the waves of volatility in the industry- trading less (more) when volatility spikes (plunges). Additionally, strategies of traders also affect market properties with greater stability of returns when there are more informed traders. Market stability are largely affected by composition of traders, traders' heterogeneous trading strategies and reactions to market uncertainty.

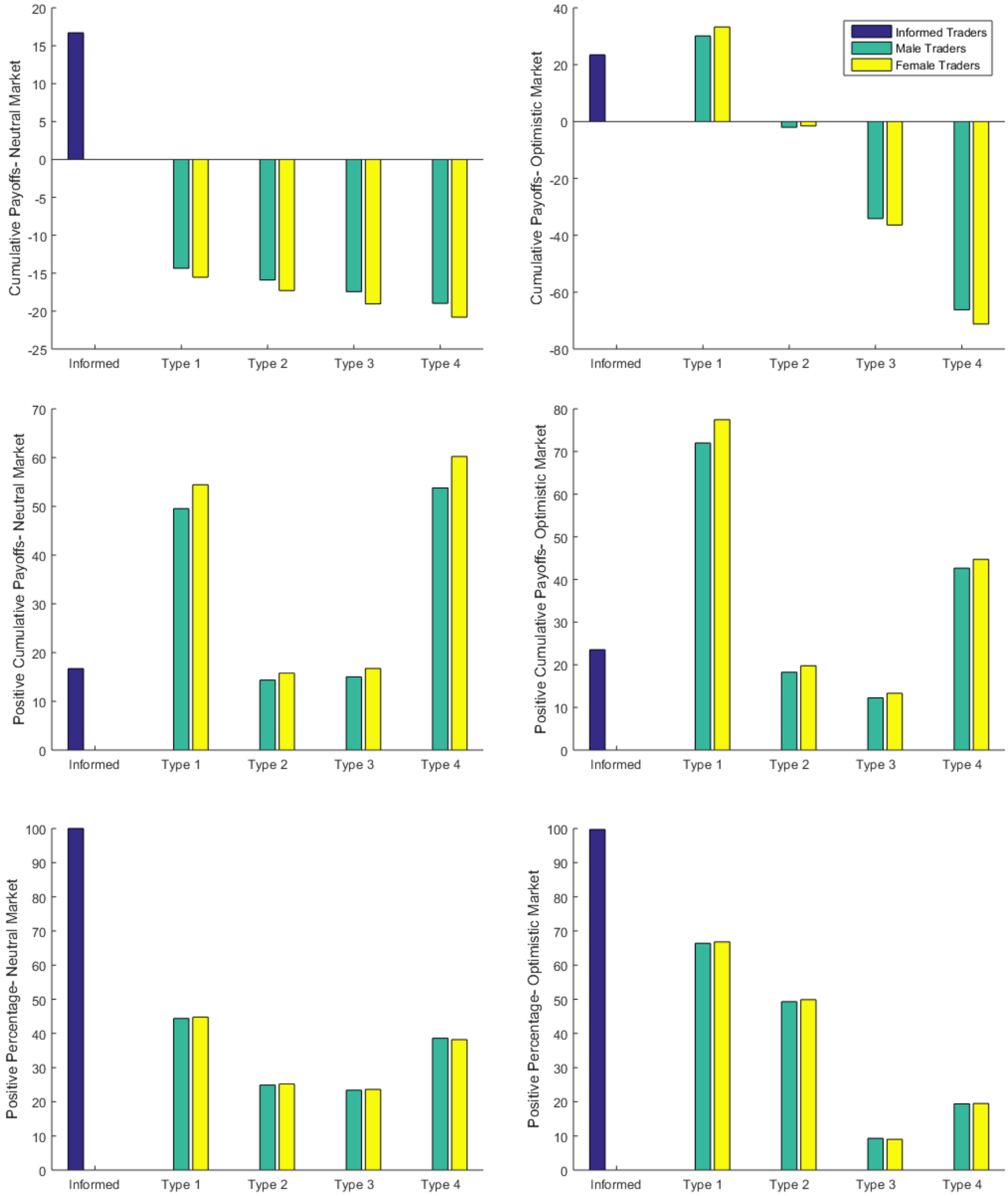
2.5.4 Trader Performance

In this section, we examine the relative performance of traders. Figure 2.2 shows the cumulative profits of traders in the market with half informed traders and half positive feedback traders. In our model, informed traders make positive cumulative payoffs over time under both neutral market and optimistic market, while their profits are higher with the realistic gender composition (see also Table A.1 for detail). On average, positive feedback traders lose money although there are certain fractions of positive feedback traders achieve long run profits in the optimistic market. Traders with over-pessimistic (type 1 in Figure 2.2) and over-optimistic (type 4) opinions have greater variations in their profits with higher chances of being successful than the cautiously optimistic (type 3) or cautiously pessimistic traders (type 2).[27]

Positive feedback traders as a group make lower losses when there are more male traders in the market. Within the group of positive feedback traders, traders with optimistic investor sentiments underperform those pessimistic traders in the neutral market. Particularly, female traders lose more than male traders on average under

[27]Type 1, Type 2, Type 3 and Type 4 represent traders with degrees of optimism or pessimism $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$ respectively.

Figure 2.2: Cumulative Payoffs- Neutral Market and Optimistic Market



Note: Figures for market with 50% informed traders to 50% positive feedback traders and 95% to 5% male female traders within positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, are called Type 1, Type 2, Type 3 and Type 4 respectively, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

both balanced composition and realistic composition. In optimistic market, prices are driven-up by traders, where minority group with pessimistic opinions outperforms the optimistic group on average.

While female traders lose more than male traders over the long-run, their profits are more dispersed than that of male traders due to their lower sensitivity to market uncertainty and the large losses generated under stressed market conditions. In order to assess the performance of best performing male and female traders, we separate traders' payoffs into profits and losses. Table 2.21 presents the positive trading outcomes of male and female traders with positive feedback trading strategy, where normalized profits are volume weighted profit per period. The results show that top male traders earn lower profits than top female traders under the neutral market setting, while top male traders outperform in optimistic and pessimistic market.

In neutral market, female traders earn more than male traders when profits are made due to the greater variability of female traders' profits. In addition, with the same trading strategies female traders' positive returns surpass that of male traders more frequently. For the optimistic market, top male traders earn higher profits than top female traders though male traders outperform female traders slightly less frequently. As real financial market could become optimistic or pessimistic over short trading horizons, male traders could become top performers over short term.[28] Given concerns about market uncertainty, female traders are likely to be best performers in markets with neutral investor sentiment, while male traders are more likely to success in optimistic or pessimistic market.

2.5.5 Discussion

Stock markets are characterized by the volatile returns. It is well known that traders in the finance industry often ride the waves of volatility, trading more when volatility plunges and less when volatility spikes. Such trading behaviors might be explained by the associations between cortisol, risk preferences and market uncertainty. Recent studies have shown that behaviors of traders are influenced by market uncertainty via the mediation of cortisol with increased levels of cortisol under heightened market uncertainty. Moreover, chronic elevations in levels of cortisol would affect risk preference of traders. Such hormonal responses are greater in males traders compared to female traders, while the effects of male traders in financial markets are more nuanced. We investigate market stability in a dynamic asset pricing model with traders having individual differences in beliefs, investor sentiments, and heterogeneous physiological responses to market uncertainty. Our results show that market with more male traders could become less volatile than that of balanced popula-

[28]Similar to optimistic market, male traders make higher profits than female traders in pessimistic market conditional on positive profits are made.

Table 2.21: Normalized Profits- Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Neutral Market			
Positive profits	0.6321	0.6323	0.0000
	(0.0219)	(0.0218)	
Dispersion	0.5810	0.5761	0.0000
	(0.0250)	(0.0239)	
Skewness	1.2112	1.1642	0.0000
	(0.1263)	(0.1126)	
Outperforming	46.88%	53.12%	0.0000
	(0.0284)	(0.0284)	
Positive return periods	451	451	
	(15.2112)	(15.2112)	
Optimistic Market			
Positive profits	0.7244	0.7233	0.0000
	(0.0172)	(0.0169)	
Dispersion	0.4537	0.4466	0.0000
	(0.0129)	(0.0116)	
Skewness	0.3409	0.2737	0.0000
	(0.0755)	(0.0672)	
Outperforming	49.68%	50.32%	0.0000
	(0.0316)	(0.0316)	
Positive return periods	496	496	
	(13.2636)	(13.2636)	

Note: Results for market with 50% informed traders to 50% positive feedback traders and 95% male to 5% female traders within the group of positive feedback traders. Profits analyzed here are positive normalized profits generated by male positive feedback traders and female positive feedback traders. Normalized profits are volume weighted profits per period. Outperforming is the fraction of periods that the given gender outperforms the other gender. Each simulation was a run for 1000 time steps. Positive profit measures are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

tion under neutral market sentiment, while male-dominated market is more volatile compared to the market with balanced composition under optimistic or pessimistic market sentiment. Concerns about heightened market uncertainty mitigate excessive risk-taking behaviors of male traders in the neutral market and reduce large swings in asset returns, while the returns exhibit greater fluctuations in optimistic and pessimistic market due to the established trends. Male traders are likely to be best performers in optimistic or pessimistic market, while female traders are more likely to success in markets with neutral investor sentiment.

2.6 Part III: Combined Impact of Testosterone and Cortisol in Financial Markets

In this section, we examine the combined the impact of testosterone and cortisol on traders' risk preferences and the financial market.

2.6.1 Physiological Reactions and Risk Aversion

In each period, trader's behaviors are affected by their risk aversions, investment sentiments, conditional expectation and conditional variance of future excess returns per share, while the trading outcomes as well as the market uncertainty would influence their risk aversions via the mediation of testosterone and cortisol.

As described in Section 2.4 and 2.5, we consider that the levels of testosterone response to traders' levels of fulfillment (Equation (2.13)) and levels of cortisol response to market uncertainty (Equation (2.19)). Based on the changes in levels of cortisol and testosterone, traders' level of risk aversion varies according to the following function

$$a^j_{h,t} = a^j_{h,t-1}(1 - \gamma F^j_{h,t})(1 + \zeta C^j_{h,t}), \gamma > 0, \zeta > 0 \tag{2.21}$$

where elevated testosterone levels ($F^j_{h,t} > 0$) decrease traders' levels of risk aversion ($a^j_{h,t} < a^j_{h,t-1}$) holding market volatility unchanged. Parameters γ and ζ measure the magnitudes of the effects of testosterone and cortisol on traders' risk aversions respectively.[29] On one hand, traders that achieved good (bad) trading outcomes become less (more) risk-averse in the subsequent trading period due to their elevated (depressed) testosterone levels holding the market volatility unchanged. On the other hand, traders become less (more) risk-averse when the market presents less (more) uncertainty given zero trading profits.

[29] Parameter values are calibrated on the basis of recent experimental studies, see Section 2.6.2 for details.

In the modeled economy, female and male traders have homogeneous understandings about the historical asset returns and estimations of excess returns though their investment decisions differ given heterogeneity in risk aversions. With comparable trading profits (losses) and stable volatility in market, male positive feedback traders experience greater elevations (drops) in levels of testosterone and thus their risk aversions decrease (increase) more than that of female positive feedback traders. Traders in the market make trading decisions according to their beliefs, investor sentiments and time-varying risk preferences. The price of the risky asset is determined by the collective demand and supply in the market. Realized returns from trading are affected by price movements and dividends. It is the actual individual trading outcomes together with overall market uncertainty that cause fluctuations of levels of testosterone and cortisol, affecting agents' risk preferences and therefore their trading decisions.

In next section we present the calibration of the model and results showing the effects of behavioral and physiological factors on market stability.

2.6.2 Parametrization

The degree of testosterone fluctuations for male traders, κ^M, is calibrated on the basis of experimental studies. According to the study of Coates and Herbert (2008), trader's level of testosterone rose by 74%, when the trader achieved 6-day winning streak with twice his average daily profits. We compute the value of κ^M as the daily testosterone fluctuation, which is 0.0874 approximately. According to Cueva et al. (2015), the levels of testosterone in female traders are less than half of that in males' saliva on average, with variability around half of males. Thus, the degree of testosterone fluctuation for female traders, κ^F, is considered to be half of κ^M. The degree of testosterone's impact on traders' risk aversions, γ, is calibrated based on the experimental study of Apicella et al. (2008). In their study, traders' risk aversions decreased by 16.6% when the levels of testosterone rose by 33.33%.

Other parameters including $\bar{y}$, ε_t, R, p^*, Var, c, g, η^F, η^M, ζ, T and N are the same as Section 2.5.2. These values of κ^F, κ^M, η^F, η^M, γ and ζ as well as the financial market settings mean that traders' levels of risk aversion range between 0 and 14. The parameters for the numerical analysis are presented in Table 2.22.

2.6.3 Market Stability

In this section we show how traders with hormone mediated risk preferences and heterogeneous market sentiment affect the financial stability.

We focus on two types of gender compositions, namely, a realistic composition with of 95% male to 5% female and a balanced composition with of 50% male to

Table 2.22: Baseline Parametrization

Parameter	Meaning	Value
$\bar{y}$	Mean dividend	1
ε_t	Noise component	$U(-1,1)$
R	Risk-free return	1.01
p^*	Initial fundamental value	100
Var	Conditional variance of excess return	1
c	Weight on most recent percentage price change	0.2
g	Weight on most recent dividend yield	0.5
λ	Smoothing parameter for implied volatility	0.98
κ^F	Degree of testosterone fluctuation for female traders	0.0437
κ^M	Degree of testosterone fluctuation for male traders	0.0874
η^F	Degree of cortisol fluctuation for female traders	1.6414
η^M	Degree of cortisol fluctuation for male traders	3.2828
γ	Degree of testosterone's impact on risk aversions	0.4974
ζ	Degree of cortisol's impact on risk aversions	0.696
T	Number of time steps	1000
N	Number of runs	1000

50% female. Moreover, the market is populated by individuals with optimistic and pessimistic investor sentiment. We present two types of aggregate market sentiment, namely, a neutral market and an optimistic market. In the neutral market, traders' collective outlook for the market is neutral, while the aggregate opinion on asset returns in the optimistic market is higher than current level of returns.[30]

Table 2.23 presents results for return volatility under neutral market and optimistic market given different gender representations. The volatility of returns with the realistic gender composition is significantly lower than that of balanced population for both neutral market and optimistic market. Increasing the female representation up to the balanced term does not reduce volatility. This is due to the interactions between heterogeneous trading strategies, investor sentiments and changing preferences of individual traders, as traders' risk attitudes are affected by market uncertainty and their own trading results. It shows that increasing the proportion of female traders reduces the extreme volatility events in markets with optimistic or pessimistic market sentiment but not for the neutral market (e.g., Brown-Forsythe test for variance of volatility in Optimistic market, Male: Female 50:50 vs. 95:5, F statistic= 27.2643, $p = 0.000$; for Neutral market, $p = 0.4507$).

We can view the distribution of results as a range of possible scenarios for a trader entering the market. During normal market conditions (i.e., non-volatile), if a trader successfully secured profitable trades, their risk aversions go down and they will take on larger positions. They will then have a larger effect on market prices and potentially drive trends. When traders lose money, they will become more risk-averse and take smaller positions under normal market conditions. Additionally, when the market becomes stressed (with increased volatility), trading willingness (i.e. risk-taking) is greatly reduced with the same trading outcomes. Particularly, successful traders in the market with heightened volatility would be more cautious and reduce their trading, while unsuccessful traders are encouraged to trade had the market volatility decreased. Therefore, orders are likely to be more balanced. Traders' decisions are thus affected by both their profits and the market volatility. Particularly, risk aversions are largely influenced by market conditions, compared to a trader's own trading outcome. According to our numerical results given calibrated hormonal factors, traders' risk aversions would change more given a percentage change in market volatility than with the same percentage change in trading outcomes. For traders achieved unconventional profits from turbulent market, the accelerated market volatility would largely moderate their excessive risk-taking behaviors.

Compared to the neutral market, a market with more optimistic traders would be more volatile on average (e.g., Sign test with Male: Female 95:5, Optimistic

[30]The market with majority of pessimistic traders would exhibit opposite price information to the optimistic market.

Table 2.23: Moments of Returns

Market Measure	Male:Female 50 : 50	Male:Female 95 : 5	Male:Female 50 : 50 vs. Male:Female 95 : 5 (p-value)
Neutral Market			
Volatility (%)	0.3243	0.3209	0.0000
	(0.0035)	(0.0034)	
Kurtosis	2.2982	2.3001	0.1547
	(0.1017)	(0.1052)	
Optimistic Market			
Volatility (%)	0.3393	0.3389	0.0000
	(0.0116)	(0.0140)	
Kurtosis	2.3071	2.3141	0.0000
	(0.1033)	(0.1080)	

Note: Results for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\kappa^F = 0.0437$, $\kappa^M = 0.0874$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\gamma = 0.4974$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

vs. Neutral, $z = 27.7964$, $p = 0.000$), as such market triggers more trades between traders with different estimations of the future stock returns. Accompanied with the higher level of volatility, it also exhibits larger dispersion and higher kurtosis in the asset returns for the optimistic market. A market with more pessimistic opinions would become symmetric to the optimistic market. On average, trading volume is higher in the optimistic market compared to the neutral market, while there are more trades in the second half of entire trading horizon for both realistic and balanced gender compositions in both neutral market and optimistic market. There is greater willingness to trade in the optimistic market compared to the neutral market (see Table 2.24). For both male and female traders, risk aversions are significantly lower when they trade in the optimistic market than in the neutral market (e.g., Sign test for 1st Half Male RA, Optimistic vs. Neutral, $z = -8.6963$, $p = 0.000$, see also Table 2.24).

Under the neutral market setting, average risk aversion of male traders is significantly lower in the second half of trading compared to the first half, while females are slightly more risk-averse in the second half than the first half. This is due to the heterogeneity in traders' reactions to both trading results and market uncertainty. As traders make profits, their risk aversions would decrease given the stable market uncertainty (i.e., impact of testosterone), or increase when traders face increased market volatility and concerns about heightened market uncertainty outweigh the effect of trading profits (i.e., effect of cortisol dominates). Such concerns about heightened market uncertainty could mitigate excessive risk-taking behaviors and promote stable market liquidity during those volatile periods. This is closely related to the practices of riding the waves of volatility in the industry- trading less (more) when volatility spikes (plunges).[31] Traders' trading strategies and heterogeneous responses to market condition would then determine their trading outcome, which is presented in the following section. In addition, strategies of traders also affect market properties with higher stability of returns when there are more informed traders. Therefore, market stability and trading behaviors are largely affected by the compositions of market participants and their heterogeneity in trading strategies, investor sentiments, and hormonal reactions to profits and market uncertainty.

2.6.4 Trader Performance

Informed traders make positive cumulative payoffs over time for both neutral market and optimistic market, while their profits are higher under the realistic gender composition (see Figure 2.3 and Table A.2 for detail). For the market with neutral investor sentiment, positive feedback traders lose money on average though there

[31] See for example Morningstar, 2015.

Table 2.24: Trades and Risk Aversions (RA)

Market Measure	Male:Female 50 : 50	Male:Female 95 : 5	Male:Female 50 : 50 vs. Male:Female 95 : 5 (p-value)
Neutral Market			
1st Half Trades	0.6691	0.6610	0.0000
	(0.0109)	(0.0132)	
2nd Half Trades	0.6947	0.6954	0.0000
	(0.0168)	(0.0212)	
1st Half RA - Male	4.2440	4.0278	0.0000
	(0.0796)	(0.0615)	
- Female	3.6642	3.5680	0.0000
	(0.0319)	(0.0262)	
2nd Half RA - Male	3.9352	3.8455	0.0000
	(0.0896)	(0.0772)	
- Female	3.6862	3.6430	0.0000
	(0.0357)	(0.0323)	
Optimistic Market			
1st Half Trades	0.7478	0.7368	0.0000
	(0.0264)	(0.0317)	
2nd Half Trades	0.7666	0.7625	0.0000
	(0.0406)	(0.0478)	
1st Half RA - Male	4.1400	3.9883	0.0000
	(0.1565)	(0.0996)	
- Female	3.7040	3.6378	0.0000
	(0.0309)	(0.0365)	
2nd Half RA - Male	3.7744	3.7410	0.0000
	(0.1891)	(0.1410)	
- Female	3.6962	3.6842	0.0000
	(0.0396)	(0.0311)	

Note: Results for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps, with time 1 to 500 being 1st Half of trading and the remaining being 2nd half. Trade and risk aversion measures are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\kappa^F = 0.0437$, $\kappa^M = 0.0874$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\gamma = 0.4974$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

are certain fractions of positive feedback traders achieve long run profits. Traders with over-pessimistic (type 1 in Figure 2.3) and over-optimistic (type 4) opinions have more dispersed performance with greater chances of being successful than the cautiously optimistic (type 3) and pessimistic groups (type 2).

In neutral market, traders with optimistic opinions are likely to lose more than pessimistic traders. In addition, trading outcomes of male and female traders are also affected by the gender composition of traders. With realistic gender composition, traders' payoffs exhibit lower dispersion. Particularly, female traders lose less than male traders on average, when they trade in male-dominated market. In optimistic market, prices are driven-up by traders, where minority group with pessimistic opinions outperforms the optimistic group on average. For the real financial markets, behaviors of traders might tilt towards optimistic or pessimistic market sentiment over short periods, which could create profits for some positive feedback traders.

While male traders on average lose more than female traders over the long-run, their profits are more dispersed than that of female traders. In order to assess the performance of top male traders and top female traders, we separate the trading outcomes of traders into profits and losses, while normalized profits are volume weighted profit per period. Table 2.25 presents the positive trading outcomes of male and female traders with positive feedback trading strategy. The results show that top male traders earn higher profits than top female traders under the neutral market setting, while top female traders outperform in optimistic or pessimistic market.

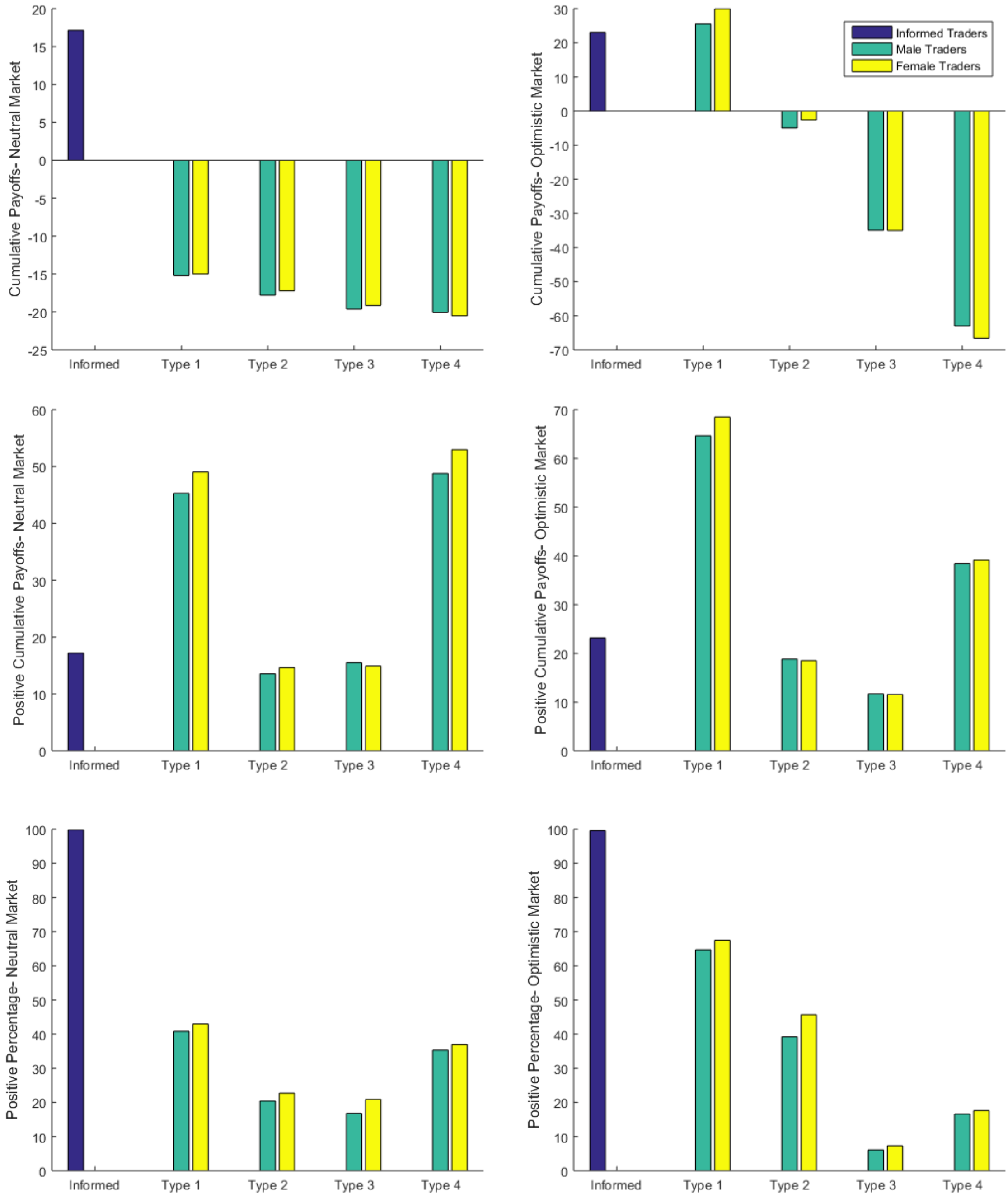
In neutral market, male traders earn more than female traders when profits are made, while their profits are more positively skewed compared to female traders. Top male traders in such market achieve much higher profits than top female traders though average performance of the male trader group is worse than female group. Moreover, real financial market could become optimistic or pessimistic over short trading horizons, where top female traders could make higher profits.[32] Male traders are likely to be best performers in markets with neutral investor sentiment, while female traders are more likely to success in optimistic or pessimistic market.

2.6.5 Discussion

Stock prices can change dramatically over short time period, while the economic fundamentals often show much lower fluctuations. It is well known that volatility often reverts back to normal levels driven by asset values and investors' trading

[32] Similar to optimistic market, female traders make higher profits than male traders in pessimistic market, given positive profits are made.

Figure 2.3: Cumulative Payoffs- Neutral Market and Optimistic Market



Note: Figures for market with 50% informed traders to 50% positive feedback traders and 95% to 5% male female traders within positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, are called Type 1, Type 2, Type 3 and Type 4 respectively, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. Pairwise Sign test were conducted and all values are significantly different at 99%. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\kappa^F = 0.0437$, $\kappa^M = 0.0874$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\gamma = 0.4974$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

Table 2.25: Normalized Profits- Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Neutral Market			
Positive profits	0.6747	0.6601	0.0000
	(0.0309)	(0.0266)	
Dispersion	0.6503	0.6279	0.0000
	(0.0449)	(0.0321)	
Skewness	1.3660	1.2946	0.0000
	(0.2357)	(0.1470)	
Positive return periods	471	464	0.0000
	(19.5473)	(16.4687)	
Optimistic Market			
Positive profits	0.7168	0.7247	0.0000
	(0.0256)	(0.0205)	
Dispersion	0.5358	0.4815	0.0000
	(0.0668)	(0.0318)	
Skewness	0.7514	0.4774	0.0000
	(0.3018)	(0.1764)	
Positive return periods	491	496	0.0000
	(17.6275)	(13.3410)	

Note: Results for market with 50% informed traders to 50% positive feedback traders and 95% male to 5% female traders within the group of positive feedback traders. Profits analyzed here are positive normalized profits generated by male positive feedback traders and female positive feedback traders. Normalized profits are volume weighted profits per period. Outperforming is the fraction of periods that the given gender outperforms the other gender. Each simulation was a run for 1000 time steps. Positive profit measures are captured over the 1000 periods of trading in each run and then averaged over 1000 runs. Standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\kappa^F = 0.0437$, $\kappa^M = 0.0874$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\gamma = 0.4974$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

activities. Our study points out the possible behavioral and physiological attributes of financial stability, where the mean-reverting property of market volatility is due to traders' changing behaviors mediated by steroid hormones. Research has shown that behaviors of traders are influenced by their profits and market uncertainty via the mediation of steroid hormones, in particular, cortisol and testosterone. Such hormonal responses are greater in male traders compared to female traders, while the effects of male traders on financial markets are more nuanced. We examine market stability in a dynamic asset pricing model with traders having individual differences in beliefs, investor sentiments, and heterogeneous physiological responses to market uncertainty and trading outcomes across genders. Our results show that male-dominated market could become less volatile due to male traders' greater sensitivity to market uncertainty compared to female traders. Although successful male traders are likely to show greater reductions in risk aversions than females with the same profit, concerns about heightened market uncertainty mitigate more of males' risk-taking behaviors. Male traders are likely to be best performers in market with neutral investor sentiment, while female traders are more likely to success in optimistic or pessimistic market. This study is, to the best of our knowledge, the first to demonstrate potential effects of traders' gender mix on financial markets through time-varying trader-specific risk preferences.

Chapter 3

Information in High Frequency Market Microstructure

Abstract

Financial markets have gone through significant changes over the last decade with the advent of high frequency trading technology. Computerized traders often have immediate access to market data, observing the order book instantaneously with co-location of their trading systems at the exchange sites, while human traders only know the market condition with a delay. Meanwhile, traders might have information about fundamental value and trade on that. In this chapter, we investigate the role of two different types of information in a high frequency market microstructure. Optimal strategies and market characteristics are determined through a unique numerical technique. We find that information on contemporaneous fundamental value is more valuable than the information on contemporaneous limit order book status.

3.1 Introduction

Financial markets have experienced a wide range of changes over the last few decades. With the development of electronic trading exchanges, a group of high speed traders equipped with sophisticated algorithms came into existence, taking advantage of the electronic trade-matching platforms. Currently, the majority of the leading stock exchanges are electronic limit order markets, while most stock contracts are no longer traded using open outcry (floor trading). Algorithmic trading (automated trading) is often defined as the process of using computer algorithm to follow pre-programmed instructions for trading (e.g., Hendershott et al., 2011). A subcategory of algorithmic trading is known as high frequency trading. High frequency trading corresponds to trading activities that employ algorithmic technologies to process signals and order flow information in the markets, and in response implements trading strategies within extremely small time intervals. It is characterized by high speeds, high turnover rates, short holding periods and low latency order transmission. Unlike other categories of algorithmic trading, the focus of high frequency trading is on making very short duration trades and earning a small profit per trade. High frequency traders have an informational advantage over 'human' traders as pre-programmed computers are faster in processing and reacting to market data. In the meantime, computerized trading has limitations in analyzing both qualitative and quantitative information, which is crucial in understanding the fundamental value of an asset. In this study, we aim to shed light on the value of these two different types of information, namely, information on order book status and on the fundamental value in high frequency market microstructure.

Following the May 2010 Flash Crash, firms undertaking high frequency techniques came under increased focus. High frequency trading volume varies across equity markets, while it is estimated to be 50% or higher of total volume (e.g., SEC, 2010). As noted in SEC (2014), high frequency traders hence become a dominant component of current market structure, which could affect all aspects of market performance. High frequency traders employ a diversity of strategies (e.g., Goldstein et al., 2014). Particularly, many high frequency traders follow dealing and arbitrage strategies, acting as market makers given their short holding periods and the proprietary trading strategies (e.g., Brogaard et al., 2014; Jovanovic and Menkveld, 2016). Hagstromer and Norden (2013) find that market making strategies constitute 63% to 72% of entire high frequency trading volume. In fact, high frequency traders replace traditional market makers with their market making behaviors detected in price paths (e.g., Menkveld, 2013). Unlike traditional market makers, high frequency traders provide liquidity for profits and there is no commitment to provide liquidity continuously (see Virtu Financial, 2014 for detail). High frequency traders' informational advantage in order flow and their fast order modification are useful in trading both across security markets and in correlated derivative markets.

Previous studies on the specialist markets often focus on the information asymmetry where market makers are uninformed and their orders might be adversely selected by informed traders (e.g., Glosten and Milgrom, 1985; Kyle, 1985). Informed traders in these studies are advantaged in observing the fundamental value of the asset and trade on such information, while uninformed traders learn from the market prices. In the electronic age, information flow and price adjustments are extremely fast-paced, while traders might trade on information that are multidimensional. Computerized trading strategies are often advantaged in processing market data and could receive direct feeds through co-location of their systems, and such market information might create profitable trading opportunities. Thus, information asymmetry could contain different dimensions in the high frequency market microstructure including the above mentioned two types of information. In a recent study, O'Hara (2015) describes the transformations of financial markets with the advent of high frequency traders and discusses the informational advantage of high frequency traders in processing trading information.

Our study contributes to the literature by focusing on the impact of two different types of information on the high frequency market microstructure. We present a continuous-time trading game in a limit order market with infinite horizon. In common with most studies of trading in dynamic limit order markets, we consider the trade on one risky asset. There are two types of risk-neutral traders in the mathematical model, computerized traders and human traders. Traders in the market might have observation lags in knowing the fundamental value of the risky asset and the order book status. We consider a market with symmetric information and then introduce information asymmetry to study the effect of information on the behavior of traders. We examine the trading strategies with the numerical approach of Pakes and McGuire (2001) and Goettler et al. (2005) in identifying the Markov perfect equilibrium. Goettler et al. (2009) construct a dynamic model to analyze traders' decision of information acquisition in a limit order market, in which optimal strategies are identified numerically through an approximation of the true Markov perfect equilibrium. Bernales (2015) and Chiarella and Ladley (2015) use the same technique to look at behavior of traders in dynamic limit order markets. In a departure from those studies, our focus is to explore the impact of two different types of information on the market with computerized traders and human traders. Particularly, we analyze the profitabilities of traders and market characteristics under different information settings of the dynamic trading game.

We find that information on contemporaneous fundamental value is more valuable than the information on contemporaneous limit order book status. Information on contemporaneous order book status is valuable for human traders in the market as it reduces their trading costs and risks. Computerized traders could increase their profits by acquiring information on the contemporaneous fundamental value. With complete information, spread between the best ask and best bid is narrower, while liquidity at the best quotes is lower than the market with asymmetric information. Our study also shows that both computerized traders and human traders earn higher profits than before due to improved market efficiency, when computerized traders trade much faster than human traders.

The rest of the chapter is organized as follows. Section 3.2 briefly reviews the relevant literature on high frequency trading and dynamic limit order markets. Section 3.3 sets out the model of asynchronous trading game with computerized traders and human traders. Section 3.4 presents details on the analysis and discusses the results. Section 3.5 concludes.

3.2 Literature

This chapter is related to the fast growing theoretical literature on high frequency trading. Several models introduce information asymmetry where algorithmic traders know the fundamental value due to their speed advantage (e.g., Bernales, 2015; Biais et al., 2015; Bongaerts and Van Achter, 2016; Jovanovic and Menkveld, 2016). However, previous studies do not consider two further dimensions of information, in terms of order flow information and information on the fundamental value.

Bernales (2015) investigates the effects of algorithmic traders' advantages in trading speed and information of the fundamental value on traders' behavior and market quality. In such a dynamic trading game, slow traders are exposed to increased risks of adverse selection given the existence of algorithmic traders and change their trading behaviors substantially. The study shows that algorithmic traders with only informational advantage could improve global welfare, while algorithmic traders with only speed advantage would reduce global welfare. Biais et al. (2015) develop a three-period model and find that fast traders exert negative externalities on slow traders due to the superior information of fast traders. In their model, investment in fast-trading technologies could enable traders faster access in exploiting trading opportunities and processing information on the fundamental, where the equilibrium level of investment in fast-trading technology decreases with technology costs. The authors propose that the introduction of a tax on investments in fast-trading technology might be helpful in creating a socially optimal level of such investment and avoiding the socially wasteful arms race in high frequency technology. Jovanovic and Menkveld (2016) present a model of high frequency market makers and find that fast and informed liquidity providers could raise welfare by reducing informational friction. However, slow traders in such market face increased adverse selection risk if high frequency market makers get information on the asset before other traders, reducing market welfare. Fricke and Gerig (2016) study the impact of market clearing frequency on market quality and find that market quality is maximized at intermediate batch auction intervals neither too fast nor too slow.

The theoretical literature models high frequency traders in different ways. Some studies view high frequency traders as market makers, who are fast in order modifications in response to changing market condition (e.g., Ait-Sahalia and Saglam, 2016; Jovanovic and Menkveld, 2016). In this view, high frequency traders narrow bid-offer spreads and mitigate adverse selection risk of slow traders. Other studies consider high frequency traders as aggressive traders, who are liquidity-demanding and trade before others in response to news, increasing adverse selection costs of slow traders (e.g., Biais et al., 2015; Foucault et al., 2016). Cartra and Penalva (2012) examine the impact of high frequency trading on market quality in a model with traditional market makers, high frequency traders and liquidity traders. Their results show that high frequency traders induce microstructure noise.

There are a number of studies providing empirical evidence that high frequency traders are primary providers of liquidity, mitigating intraday price volatility (e.g., BIS, 2011; Lepone, 2011; Hagstromer and Norden, 2013). With regard to market-making activities of high frequency traders, empirical studies reach a general agreement that high frequency traders narrow the bid-ask spread, reduce microstructure noise and thus enhance market quality (e.g., Carrion, 2013; Brogaard et al., 2014). On the other hand, aggressive high frequency traders that do not engage in the provision of liquidity could make huge profits at the expense of other traders in the market (e.g., Baron et al., 2016).

This study is also related to earlier work on assessing the impact of information on market microstructure in human-mediated markets (e.g., Glosten and Milgrom, 1985; Kyle, 1985). These studies assume an information asymmetry where market makers are uninformed. Informed traders buy from (sell to) market makers when there is good (bad) news, while market makers learn from these informed trades. Hollifield et al. (2006) and Goettler et al. (2009) look into behavior of traders in limit order markets without market makers. They analyze order choice of traders under the impact of adverse selection risk.

3.3 Model

In this study, we focus on the behavior of traders and examine the role of information in the high frequency market microstructure. Traders in the market trade in one risky asset through submissions of market orders or limit orders.

3.3.1 Traders and Market Characteristics

We consider a continuous time dynamic trading game (with infinite horizon) in a limit order market with two types of traders. One type is represented by computerized traders (C), who use computer algorithm to process market information. The second type of traders are human traders (H), who are traditional traders in financial markets. Traders care about the fundamental value of the asset and they may trade for private reasons such as long-term investment, liquidation and tax considerations.

Computerized traders randomly enter into the market following a Poisson process at rate λ^C. In addition, they can also re-enter the market and modify their unexecuted orders where re-entry follows a Poisson process at rate λ^C_{re}. Human traders enter into the market randomly, following a Poisson process at rate λ^H. For those human traders that have unexecuted limit orders, they might also re-enter the market to modify or cancel their orders. The re-entry process of human traders follows a Poisson process at rate λ^H_{re}. Each trader has one share to buy or sell and exits the market after the order submission.

The limit order market starts with an empty order book. At time t, the order book (denoted by L_t) is a collection of unexecuted limit orders that have not yet been canceled. The distance between any two adjacent prices is constant and is referred to as tick size d. Thus, the order book is described by a discrete set of prices $\{p^i\}$ and the associated quantities demanded (or supplied) for each tick i. At time t, the listed number of shares at price tick i is described by l^i_t, with buy side being $l^i_t > 0$ and sell side orders $l^i_t < 0$. The best bid on the limit order book is the highest quote submitted by the buy side traders, denoted by $B_t(l^i_t) = \max\{p^i | l^i_t > 0\}$, while the best offer price is the lowest limit sell price on the order book, $A_t(l^i_t) = \min\{p^i | l^i_t < 0\}$. When the order book is empty, the best bid price is represented by $B_t(l^i_t) = -\infty$, and the best offer price is $A_t(l^i_t) = +\infty$. Transactions follow price and time priority.

3.3.2 Information Sets and Valuations

In this section, we present information observed by computerized traders and human traders as well as their valuations of the risky asset.

In the limit order market, past execution price and volume of the asset are public information. In addition, each trader in the market has private information about their own trading and submission history. Regarding the random arrivals, we assume that all traders (C and H) have full knowledge about the stochastic processes of the arrival for both types of traders (i.e., λ^C, λ^H, λ^C_{re} and λ^H_{re}). This becomes part of the information set used by traders in submitting orders.

Let v_t represent the fundamental value of the asset at time t. Fundamental value of the asset updates through time according to a Poisson process at rate λ^v. Each time when an update occurs, the fundamental value increases or decreases by one tick. Traders may have imperfect information about the fundamental value of the risky asset. We assume that traders in the market observe the fundamental with a lag τ, where they observe fundamental value $v_{t-\tau}$ when they enter into the market at time t. In addition to the common value (fundamental value) of the risky asset, each trader j (computerized traders and human traders) has a private value towards the risky asset (denoted by ν^j). The private value of each trader represents the trader's private needs for trading and any additional value created after execution.[33] The private value for trader j is a random draw from a known distribution F. Each trader trades one unit of the risky asset. Prior to entering, trader j knows the private value (i.e., actual draw). Traders are informed of the distribution of the private valuations, while the valuation is private information of the trader.

Let h denote the type of traders, $h \in \{C, H\}$ and $I_{h,t}$ the information set for type h trader at time t. Traders with an order book lag ζ^h observe the limit order book $L_{t-\zeta^h}$ when they come to the market at time t.[34] Traders' information set includes their knowledge of past price information, observations of fundamental value and order book status, private past trading and private value of the trader.

When all traders have the same lags in observing the fundamental value and limit order book respectively, there is symmetric information in the market. In this study, we first consider a market with complete information, where all traders know the contemporaneous fundamental value and limit order book instantaneously, $\tau = 0$ and $\zeta = 0$. We then analyze the effect of information on the behavior of traders, with computerized traders and human traders having different information lags in observing the contemporaneous fundamental value and limit order book.

3.3.3 Actions and Strategies

In the limit order market, both limit order and market order are allowed. However, sets of feasible actions of computerized traders and human traders could be quite different depending on traders' valuation and order book status.

In the dynamic trading game, traders arrive at the market randomly and choose optimal trading decisions that maximize the present value of expected utility. Let a denote an action taken by a trader, $a = (p, q)$, where p is the price quote for quantity demanded q

[33]For instance, if the risky asset is a hedging asset for a trader's existing portfolio, benefits from holding the hedged position become part of private valuation of the trader.

[34]Observation lags in order book might arise from the differences in receiving market data and reaction time taken to process market information. For instance, computerized traders might receive direct data feeds through co-location of their systems, while human traders might have a processing lag.

$$q = \begin{cases} 1, & \text{a buy order} \\ -1, & \text{a sell order} \\ 0, & \text{no order} \end{cases} \tag{3.1}$$

Price quote p describes the choice of order. For instance, when a trader submits a buy order ($q = 1$) at a price $p \geq A_t$, it executes immediately at the best ask price (A_t), becoming a market buy order at time t. For a buy order at time t quoted at $p < A_t$, it is added to the limit buy orders on the order book with the designated quote p. In addition, the price quote of limit orders and time of submission then determine the priority of order execution.

Both computerized traders and human traders in the limit order market are considered to be risk-neutral, while the utility is expected payoff from trading discounted back to the time of entry. The discount rate (denoted by ρ) captures the delaying cost of transactions or potential lost opportunity for future trades when limit orders are submitted. Traders' observation of the fundamental value is denoted by $v_{h,t}$, where trader j's overall valuation for the risky asset is represented by $v^j_{h,t} = v_{h,t} + \nu^j$.

The actions depend on the traders' private information, while the private information includes trader's observation of order book and fundamental value, past trading information and valuations of the trader. For the rest of the paper, we call the private information the trader's own state s. The set of actions that a trader can take under the state s is $A(s)$, where an action is a price quantity pair. Let $\Phi(t_r|\tilde{a}, s, \nu)$ be the probability of order execution at time t_r given the action $\tilde{a}$ taken by a trader in state s at time $\hat{t}$. Each market order submitted has an execution probability of 1, while execution probabilities for limit orders quoted far from the fundamental value converge asymptotically to zero. Let $f(v|s, \hat{t})$ be the density function of the fundamental value of the risky asset at time $\hat{t}$ in state s. The density function depends on state s which takes into account traders' information about the fundamental value of the asset. We normalize, $\hat{t}$, the time of entry, to be 0 and the re-entry time to be t_r for simplicity of notation. Prior to re-entry, the expected payoff from an order submitted by a type h trader is

$$\pi_h(s, \tilde{a}, t_r) = \int_0^{t_r} \int_{-\infty}^{+\infty} e^{-\rho t}[(v_h + \nu - \tilde{p})\tilde{q}]\Phi(t_r|\tilde{a}, s, \nu) f(v|s, \hat{t}) dv_h dt \tag{3.2}$$

Consider the probability density function of the random re-entry time denoted by $R(\cdot)$, which is determined by the re-entry processes of the computerized traders (with λ^C_{re}) and human traders (with λ^H_{re}). Let s_r be the state when the trader re-enters at time t_r given the previous state s and action $\tilde{a}$. The probability that state

s_r takes place at time t_r is $\varpi(s_r|\tilde{a}, s, t_r)$. Therefore, the value to an agent of being in state s, $V(s)$, is given by the Bellman equation of the trader's optimization problem,

$$V(s) = \max_{\tilde{a} \in A(s)} \int_0^\infty [\pi_h(s, \tilde{a}, t_r) + e^{-\rho t_r} \int_{s_r \in S} V_h(s_r)\varpi(s_r|\tilde{a}, s, t_r) ds_r] dR(t_r|s) \tag{3.3}$$

Traders' quantity $\tilde{q}$ may contain two elements, namely, no submission or submission according to their own trading side. For instance, the quantity demanded from a buy-type trader's viewpoint is $\tilde{q} \in \{0, 1\}$. For those traders with a private valuation of 0, they may sell the asset at a price above the fundamental value, buy it at a price below or decide not to trade, with $\tilde{q} \in \{-1, 0, 1\}$. The optimal strategy chosen by each trader is determined by the state specific maximization problem.

3.3.4 Model Solution

The model is solved numerically as the dynamic trading game is analytically intractable. Particularly, with the high dimensional state space in our model, a solution of the trading game is hard to obtain with standard numerical approaches. Therefore, we use the numerical approach introduced by Pakes and McGuire (2001), and the extensions in Goettler et al. (2005, 2009) to identify a Markov perfect equilibrium. This approach identifies the equilibrium of the dynamic game with a large state space by considering only those recurring states. In this algorithm, each type of traders begins with initial beliefs about expected payoffs to different actions, and updates their beliefs when they observe the realized payoffs given their actions. After playing the game for a long period of time, traders' expected payoffs for each action converge to the realized payoffs and the optimal trading decision in a given state is exactly the same if a trader observes such a state in the future. This is when the equilibrium is reached.

In our model, traders randomly arrive and choose optimal actions that maximize their expected payoffs given the observed state. Their trading results also depend on actions taken by other traders in the states leading up to the current state. The order book is updated dynamically with the submission of orders, while each order submitted would change the order book and the state for later traders. After a large number of order submissions and belief updating, traders' optimal decisions and expected payoffs in a state s^* become the same optimal actions and expected payoffs when they recognize the state s^* in later periods. This is when the equilibrium is reached. In order to examine the effect of information on traders' behavior in the high frequency market, we run the trading game for a further billion events and fix the beliefs of traders (as in Bernales, 2015; Chiarella and Ladley, 2015). During the last billion events, statistics containing traders' behaviors, profitabilities and market properties are collected, allowing us to examine the high frequency market microstructure.

3.3.5 Belief Updating Process

Consider a trader entering into the market at time t in state s. Suppose that $U_t(\tilde{a}|s)$ is the expected payoff of action $\tilde{a}$ in state s at time t. Let $\tilde{a}^*$ be the optimal action in state s at time t. If this action is a limit order (or a modification of previously submitted limit order), and this limit order is not executed before the traders' re-entry time t', updating process of trader's expected payoff is as follows

$$U_{t'}(\tilde{a}^*|s) = \frac{n_{\tilde{a}^*,s}}{n_{\tilde{a}^*,s}+1} U_t(\tilde{a}^*|s) + \frac{1}{n_{\tilde{a}^*,s}+1} e^{-\rho(t'-t)} J(s', y_{t'}) \tag{3.4}$$

where $n_{\tilde{a}^*,s}$ is a counter that records the number of times that action $\tilde{a}^*$ has been chosen in state s. $J(s', y_{t'})$ denotes the continuation value of the order when the trader re-enters the market and observes the state s' at time t'.

If the optimal action $\tilde{a}^*$ is a limit order which is executed at a later time t' due to market order submitted by another trader, the expected payoff of optimal action $\tilde{a}^*$ for the limit order submitter is updated as follows

$$U_{t'}(\tilde{a}^*|s) = \frac{n_{\tilde{a}^*,s}}{n_{\tilde{a}^*,s}+1} U_t(\tilde{a}^*|s) + \frac{1}{n_{\tilde{a}^*,s}+1} e^{-\rho(t'-t)} (\nu + v_{t'} - \tilde{p})\tilde{q} \tag{3.5}$$

Alternatively, if the optimal action $\tilde{a}^*$ is a market order, the expected payoff of optimal action $\tilde{a}^*$ in state s is updated as:

$$U_t(\tilde{a}^*|s) = \frac{n_{\tilde{a}^*,s}}{n_{\tilde{a}^*,s}+1} U_t(\tilde{a}^*|s) + \frac{1}{n_{\tilde{a}^*,s}+1} (\nu + v_t - \tilde{p})\tilde{q} \tag{3.6}$$

Therefore, the submission and execution of a market order would trigger the belief updating process of two states.

We check for convergence of the model using the same approach as Bernales (2015) and Chiarella and Ladley (2015). We compare the realized payoffs and expected payoffs for all states visited during this period. Differences between realized payoffs and expected payoffs are measured by the mean absolute deviations between realized payoffs and expected payoffs and weighted by the number of times that the state is observed. The model is converged if the weighted average of mean absolute deviation is less than 0.02 and the correlation between the realized payoffs and expected payoffs is higher than 0.99. The trading game runs until the convergence criteria is reached. After the convergence is achieved, the model runs for a further billion events to collect statistics without capturing additional noise due to the updating process.

3.4 Numerical Analysis

In this section, we present the parameterization and results of the model described in Section 3.3. For each set of parameters, multiple runs of optimization are carried out to ensure that our model converges to the same equilibrium. The statistics summarized in this section are collected when the model has reached equilibrium.

3.4.1 Parameterization

The values of parameters controlling computerized traders and human traders' visits and re-entry frequency are based on empirical data. The average number of traders' visit per period is based on the analysis of Hagstromer and Norden (2013), who present the average number of trades per stock per day being 7522 across the 30 most traded Swedish stocks in August 2011. We calculate the entry speed by spreading the total number of shares traded over the 6.5 hours of actual trading time per day with two traders for each transaction. This is equivalent to 0.64 trader per second. Based on this data, we set $\lambda^C = \lambda^H = 0.64$. According to the study of Hagstromer and Norden (2013), the median lifetime of limit orders in the high frequency market is about 10 seconds.[35] Based on this data, we therefore set $\lambda^C_{re} = \lambda^H_{re} = 0.1$. In Section 3.4.4, we test the effect of computerized traders' trading speed on market quality by considering $\lambda^C > \lambda^H$ and $\lambda^C_{re} > \lambda^H_{re}$. We also tested other values and our results are consistently robust.

We assume that traders in the market observe the fundamental value of the risky asset with a lag τ^h, where the support of possible lags in seconds is $\{0, 4, 8\}$. For traders' lags in observing the order book status, we consider $\zeta^h \in \{0, 4, 8\}$.[36] We focus on two types of market. In the first type of market, all traders have complete information about contemporaneous fundamental value and limit order book status, where observation lags for all traders are $\tau = 0$ and $\zeta = 0$. In the second type of market, there is information asymmetry between computerized traders and human traders in observing the fundamental value and limit order book. We present results for three cases with asymmetric information. In the first case, human traders observe contemporaneous fundamental value and limit order book instantaneously ($\tau^H = 0$, $\zeta^H = 0$), while computerized traders know the order book instantaneously and observe the fundamental value with a lag ($\tau^C = 8$, $\zeta^C = 0$). For simplicity, we denote this case by $\tau^C = 8$ as all other lags are zero. In the second case, computerized traders observe contemporaneous fundamental value and limit order book

[35] In Hagstromer and Norden (2013), limit orders submitted by high frequency traders last between 2.77 to 7.63 seconds. In Section 3.4.4, we consider the computerized traders' re-entry on average every 5 seconds with $\lambda^C_{re} = 0.2$.

[36] The discrete lags are adopted here to limit the dimension of the state space as compared to the continuously distributed lags.

instantaneously, while human traders observe the contemporaneous fundamental value but observe the order book with a lag (denoted by $\zeta^H = 8$). In the third case, computerized traders observe contemporaneous fundamental value with a lag and observe order book instantaneously, while human traders know the order book with a lag and observe fundamental value without lags (denoted by $\tau^C = 8$, $\zeta^H = 8$). The last case is close to the realistic market setting, where human traders have informational advantage in observing the fundamental value and computerized traders are advantaged in observing the contemporaneous order book status. Human traders have informational advantage in learning the contemporaneous fundamental value of the particular asset since they study both quantitative and qualitative information of that firm, while analyzing both quantitative and qualitative information is hard for automated trading. Computerized traders often have immediate access to market data, observing the order book instantaneously with co-location of their trading systems at the exchange sites, while human traders only know the market condition with a short delay.

Similar to Goettler et al. (2009) and Bernales (2015), we assume that the private values of all traders follow discrete distribution with support $\{-8, -4, 0, 4, 8\}$ and cumulative distribution function of $\{0.15, 0.35, 0.65, 0.85, 1\}$. This private value distribution is based on the findings of Hollifield et al. (2006) with stocks on Vancouver Stock Exchange. For the group of traders with a private valuation of 0, they may buy the asset at a price below the fundamental value or sell it at a price above, making profits from mispricings. Our results are robust to alternative distributions.

Like Bernales (2015) and Chiarella and Ladley (2015) the volatility is calculated based on Zhang (2010), who presents the daily volatility of U.S. stock returns of 0.033. We consider the average stock price being \$67, and each tick being 0.01 with price movement being one tick.[37] Under these assumptions, the fundamental value is updated on average every 4.99 seconds, with the number of price movements per second $\lambda^v = 0.2$. We refer to this as the high volatility regime and contrast this with a low volatility regime where $\lambda^v_{low} = 0.15$. We put the discounting rate $\rho = 0.2$ and examine the robustness of the model with different values.

3.4.2 Profitability

Table 3.1 presents the results showing the effect of information on traders' profitabilities. Like Hollifield et al. (2006), profit is defined as the payoffs from trades discounted to the point when a trader entered the market. In the benchmark setting, both computerized traders and human traders know the contemporaneous

[37] According to Strategas Research Partners, the average stock price for an S&P 500 company is \$67 now compared with a \$30-\$50 average range that an average stock price has roughly traded in since 1980. Results are qualitatively similar for other values of stock prices and daily volatility.

fundamental value and limit order book instantaneously, while there is no difference between those two types of traders. We present three cases with asymmetric information, where computerized traders and human traders have different lags in observing contemporaneous fundamental value and limit order book status.

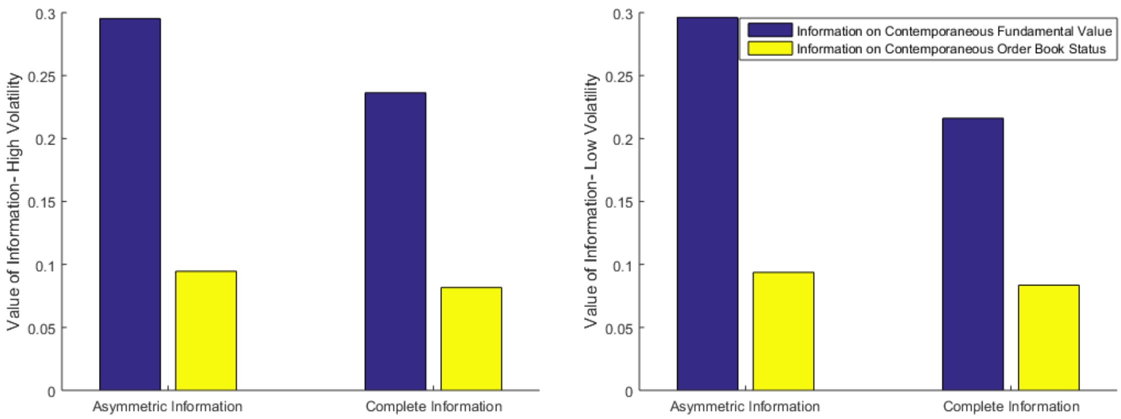
Table 3.1: Profitability

	Valuation	Benchmark Profit	With Asymmetric Information		
		$(\tau = 0, \zeta = 0)$	$(\tau^C = 8)$	$(\zeta^H = 8)$	$(\tau^C = 8, \zeta^H = 8)$
High Volatility					
H	0	0.8524	0.7931	0.6843	0.6245
H	4	3.1108	3.0928	3.0889	3.0662
H	8	6.6019	6.6636	6.5266	6.5523
H	(all groups)	3.4808	3.4748	3.3991	3.3802
C	0	0.8525	0.6011	0.9803	0.7387
C	4	3.1123	2.9165	3.1185	2.8789
C	8	6.6013	6.3240	6.5968	6.1721
C	(all groups)	3.4812	3.2448	3.5207	3.2254
Low Volatility					
H	0	0.8756	0.7473	0.6747	0.6103
H	4	3.1102	3.0898	3.0771	3.0521
H	8	6.5777	6.6825	6.5440	6.5575
H	(all groups)	3.4801	3.4654	3.3966	3.3717
C	0	0.8757	0.6064	0.9579	0.7521
C	4	3.1085	2.9349	3.1104	2.8732
C	8	6.5776	6.3564	6.6136	6.1466
C	(all groups)	3.4795	3.2634	3.5157	3.2195

Note: Results for market with Human Traders (H) and Computerized Traders (C). Benchmark setting is with symmetric information, where all traders in the market know the contemporaneous fundamental value and order book status instantaneously ($\tau = 0$, $\zeta = 0$). Profits with asymmetric information are computed when computerized traders know the fundamental value with a lag ($\tau^C = 8$), human traders know the order book status with a lag ($\zeta^H = 8$), or computerized traders know the fundamental value with a lag and human traders know the order book status with a lag ($\tau^C = 8$, $\zeta^H = 8$). The last case is close to the realistic market setting. All other lags are zero. Standard errors for all profitability measures are sufficiently small since we use a large number of simulated events. Parameters: $\lambda^H = 0.64$, $\lambda^H_{re} = 0.1$, $\lambda^C = 0.64$, $\lambda^C_{re} = 0.1$, $\lambda^v_{high} = 0.2$, $\lambda^v_{low} = 0.15$, $\rho = 0.2$.

Figure 3.1 shows the values of information on contemporaneous fundamental value and information on contemporaneous order book status. The value of information on contemporaneous fundamental value is first calculated as the profit improvement for computerized traders, moving from the third case with asymmetric information to the second case (Asymmetric Information in Figure 3.1). With different informational content, the value of information on contemporaneous fundamental value could also be calculated as the difference in the profits of computerized traders between the first case with asymmetric information and the benchmark market, i.e., moving into the market with complete information (Complete Information in Figure 3.1). As for the value of information on contemporaneous order book status, it is first calculated as the difference in the profits of human traders achieved in the third case and the first case with asymmetric information (Asymmetric Information in Figure 3.1). The other representation for the value of contemporaneous order book information is the difference in the profits of human traders between the second case with asymmetric information and the benchmark market. Our results show that the value of information on contemporaneous fundamental value is greater than the value of information on contemporaneous order book status.

Figure 3.1: Value of Information



Note: Figures for market with Human Traders (H) and Computerized Traders (C). Values of information are calculated based on the profits of traders in Table 3.1. The value of information on contemporaneous fundamental value is first computed as the difference in the profits of computerized traders, moving from the third case with asymmetric information to the second case (Asymmetric Information bars). With different informational content, the value of information on contemporaneous fundamental value for the Complete Information in the figure is computed as the difference in the profits of computerized traders between the first case with asymmetric information and the benchmark market, i.e., moving into the market with complete information. The value of information on contemporaneous order book status is first computed as the difference in the profits of human traders achieved in the third case and the first case with asymmetric information (Asymmetric Information bars). The value of information on contemporaneous order book status for the Complete Information is computed as the difference in the profits of human traders between the second case with asymmetric information and the benchmark market. Parameters: $\lambda^H = 0.64$, $\lambda^H_{re} = 0.1$, $\lambda^C = 0.64$, $\lambda^C_{re} = 0.1$, $\lambda^v_{high} = 0.2$, $\lambda^v_{low} = 0.15$, $\rho = 0.2$.

On average, human traders gain from trading activities considering their private values although the net monetary transfers excluding the private values often become negative. The results in Table 3.1 show that traders' profits decrease when the observation lag of those traders increases conditional on no changes for the other type of traders. When human traders observe the order book status with a lag, their profits are lower compared to the benchmark market setting with greatest percentage decrease for the subgroup of human traders with zero private valuation. Human traders as a group might make higher profits than computerized traders in markets with asymmetric information. More importantly, human traders' profit levels depend mainly on their own information and are rarely affected by the changes in computerized traders' observation lags.

For computerized traders, information about contemporaneous fundamental value is highly valuable. In the market with information asymmetry, learning the exact difference between fundamental value and price quotes on the limit order book improves computerized traders' profitability (comparing the second and the third case). In the second case of asymmetric information, human traders would earn less as computerized traders trade with fewer mistakes. It shows that the computerized traders' information on fundamental value would induce economic damage for human traders in the limit order market. Compared to the realistic market setting, profits are higher in the benchmark market with traders having complete information. Thus, both human traders and computerized traders in the realistic market would have temptations of acquiring information and eliminating their information disadvantages. Unlike human traders, profit levels of computerized traders are affected by the information of both computerized traders and human traders. In particular, when we compare the benchmark market with the asymmetric information scenario, computerized traders' profits are higher when human traders are disadvantaged in observing order book status. Table 3.1 also shows that information about order book status is valuable for human traders in the high frequency market.

In order to understand how those two different types of information affect the market and sources of traders' profits it is necessary to consider the costs and risks related to the trading activities. While market orders are executed immediately, the additional immediacy cost (i.e., difference between best quotes and fundamental) of trading could be high. Limit orders on the other hand, have price advantages while the time until execution could be quite long and may not be executed at all. In addition, limit buy (sell) orders could be picked-off by other traders when asset value at execution becomes lower (higher) than the fundamental value at the time of submission.

As presented in Table 3.2, limit orders submitted by the group of human traders with zero private value, have the highest probability of being picked-off in the realistic market. This is due to their frequent submissions of limit orders at the best quotes, which are more likely to be picked-off than less aggressive limit orders. Although human traders perfectly observe the contemporaneous fundamental value, their limit orders are exposed to picked-off risks due to human traders' observation lags in order book status as well as the limitation in order modification.

Table 3.2: Trading Costs

		Valuation	Benchmark	With Asymmetric Information		
			$(\tau = 0, \zeta = 0)$	$(\tau^C = 8)$	$(\zeta^H = 8)$	$(\tau^C = 8, \zeta^H = 8)$
High Volatility						
Picked off Fraction	- H	0	0.1096	0.1496	0.1563	0.1668
	- H	4	0.0774	0.0794	0.0759	0.0736
	- H	8	0.0392	0.0307	0.0437	0.0369
Picked off Fraction	- C	0	0.1096	0.1623	0.1106	0.1427
	- C	4	0.0769	0.0786	0.0854	0.0885
	- C	8	0.0392	0.0366	0.0410	0.0445
Effective Spread	- H		3.5669	2.4108	3.5662	2.5412
	- C		3.5644	2.3033	3.5670	2.2714
Low Volatility						
Picked off Fraction	- H	0	0.0848	0.1351	0.1351	0.1447
	- H	4	0.0603	0.0651	0.0631	0.0592
	- H	8	0.0323	0.0232	0.0339	0.0292
Picked off Fraction	- C	0	0.0847	0.1448	0.1018	0.1251
	- C	4	0.0646	0.0629	0.0706	0.0733
	- C	8	0.0325	0.0283	0.0315	0.0365
Effective Spread	- H		3.7101	2.3842	3.4665	2.5211
	- C		3.7689	2.2600	3.4661	2.1980

Note: Results for market with Human Traders (H) and Computerized Traders (C). Benchmark setting is with symmetric information, where all traders in the market know the contemporaneous fundamental value and order book status instantaneously ($\tau = 0$, $\zeta = 0$). Statistics with asymmetric information are computed when computerized traders know the fundamental value with a lag ($\tau^C = 8$), human traders know the order book status with a lag ($\zeta^H = 8$), or computerized traders know the fundamental value with a lag and human traders know the order book status with a lag ($\tau^C = 8$, $\zeta^H = 8$). The last case is close to the realistic market setting. All other lags are zero. Standard errors for all picked off fraction and spread measures are sufficiently small since we use a large number of simulated events. Parameters: $\lambda^H = 0.64$, $\lambda^H_{re} = 0.1$, $\lambda^C = 0.64$, $\lambda^C_{re} = 0.1$, $\lambda^v_{high} = 0.2$, $\lambda^v_{low} = 0.15$, $\rho = 0.2$.

For computerized traders, limit orders could also be picked-off by other traders.

As computerized traders observe the contemporaneous fundamental value in the benchmark market, limit orders submitted by them have lower chances of being picked-off compared to the realistic market. On average, limit orders submitted by human traders are exposed to highest picked-off risk when human traders observe the order book with a lag, and computerized traders know the contemporaneous fundamental value.

Meanwhile, transaction costs for traders are represented by the effective spread in Table 3.2. Effective spread is computed as twice of the difference between mid-price at time of submission and the execution price. On average, effective spread is greater than the actual spread and traders often trade at less favorable prices due to low liquidity at the best quotes (see also in Table 3.3). Human traders pay higher costs to transact in the realistic market, as they trade more through limit orders which are behind the best quotes and less through limit orders between the best quotes than the computerized traders. In such market, human traders frequently trade through limit orders at and behind the best quotes. If human traders observe the order book status instantaneously, their trading strategies shift towards limit order submissions both between and at the best quotes. The decreased submissions of behind quotes limit orders reduce the effective spread of human traders.

3.4.3 Market Quality and Order Types

Table 3.3 presents the market characteristics in the high frequency market. The market with complete information has the narrowest bid-offer spread, while an increase in observation lags would widen the bid-offer spread. However, those tighter spreads in benchmark market do not compensate for the lack of depth.[38] Compared to the realistic market setting, liquidity at the best quotes is lower when traders know better the order book status or the fundamental value of the asset. Tracking risk is the standard deviation of the differences between fundamental value and the mid-price of the asset, which represents the price efficiency in the market.

When human traders observe the order book status instantaneously and computerized traders observe fundamental value with a lag, tracking risk is lower compared to the realistic market, representing greater efficiency in market prices.[39] The ability of human traders to observe order book status instantaneously and incorporate such information into market prices is beneficial for the market as a whole. This is why computerized traders earn higher profits when human traders acquire information

[38] The book depth in limit order markets provides an indication of liquidity. The higher the number of buy and sell orders at each price, the higher the depth of the market.

[39] Additionally, speed of trading affects the price efficiency in the market. With faster computerized traders in the market, tracking risk becomes lower, improving price efficiency (see Section 3.4.4).

Table 3.3: Market Quality

	Benchmark	With Asymmetric Information		
	$(\tau = 0,\ \zeta = 0)$	$(\tau^C = 8)$	$(\zeta^H = 8)$	$(\tau^C = 8,\ \zeta^H = 8)$
High Volatility				
Spread	1.8468	2.2488	1.9259	2.2775
Quantity at Best Quote	0.8605	1.0351	0.8922	1.0571
Buy/Sell Quantity	1.2760	1.8568	1.5170	2.0184
Tracking Risk	1.1543	1.0722	1.1862	1.1294
C Participation	0.4993	0.5205	0.4866	0.5121
Low Volatility				
Spread	1.8598	2.1975	1.9012	2.2551
Quantity at Best Quote	0.8365	1.0770	0.9238	1.0835
Buy/Sell Quantity	1.2125	1.9029	1.5431	2.0333
Tracking Risk	1.1521	1.0289	1.1568	1.0852
C Participation	0.4992	0.5189	0.4872	0.5142

Note: Results for market with Human Traders (H) and Computerized Traders (C). Benchmark setting is with symmetric information, where all traders in the market know the contemporaneous fundamental value and order book status instantaneously ($\tau = 0$, $\zeta = 0$). Statistics with asymmetric information are computed when computerized traders know the fundamental value with a lag ($\tau^C = 8$), human traders know the order book status with a lag ($\zeta^H = 8$), or computerized traders know the fundamental value with a lag and human traders know the order book status with a lag ($\tau^C = 8$, $\zeta^H = 8$). The last case is close to the realistic market setting. All other lags are zero. Tracking risk is the standard deviation of the differences between fundamental value and the mid-price of the best bid and the best ask. C participation is the fraction of orders submitted by computerized traders in the market. Standard errors for all market quality measures are sufficiently small since we use a large number of simulated events. Parameters: $\lambda^H = 0.64$, $\lambda^H_{re} = 0.1$, $\lambda^C = 0.64$, $\lambda^C_{re} = 0.1$, $\lambda^v_{high} = 0.2$, $\lambda^v_{low} = 0.15$, $\rho = 0.2$.

on the order book status (see Table 3.1 for profits with asymmetric information). Markets with greater transparency of order book are attractive to traders and display lower levels of microstructure noise. When computerized traders know the contemporaneous fundamental value, tracking risk is higher than the realistic market. Computerized traders trade more through market orders and aggressive limit orders, and they are willing to trade when they see profitable trading opportunities.

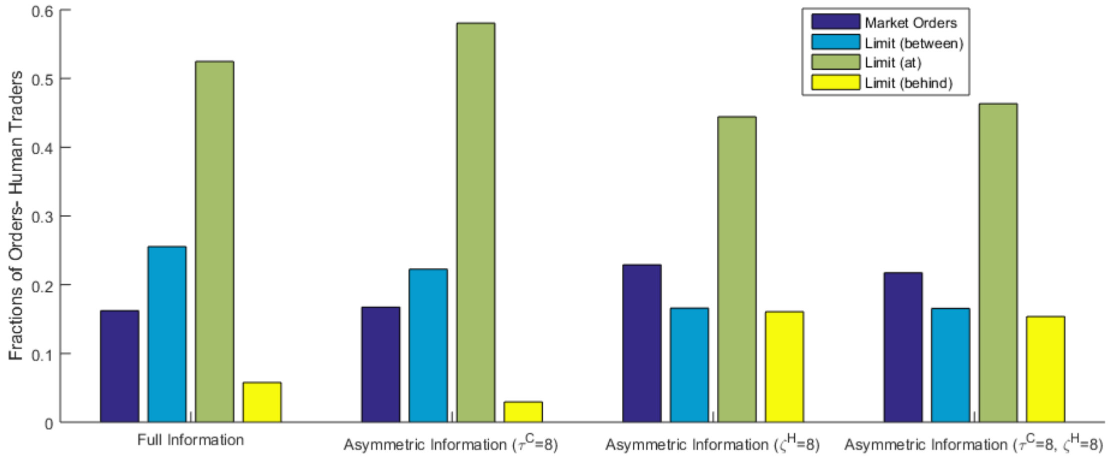
The order submissions of human traders and computerized traders are presented in Figure 3.2 (see also in Table B.1). Fractions of orders submitted by each group of traders are computed for market orders and limit orders. Limit orders are further categorized into three groups, i.e., between the best quotes, at the best quotes and behind the best quotes. On average, traders with high private values (i.e., $\nu = 4, 8$) execute more through market orders and limit orders at the best quotes under symmetric information scenario, aiming to realize their private values in a short time. For human traders with zero private valuation, most of their submissions under the realistic market setting are limit orders at and behind the best quotes, receiving the immediacy costs paid by others. With zero private valuation, those human traders rarely use market orders or limit orders between the best quotes due to the high trading costs of market orders and picked-off risk associated with aggressive limit orders. Computerized traders on the other hand, trade more through limit orders at the best quotes under the realistic market setting. In addition to limit orders at the best quotes, computerized traders often make markets by submitting limit orders between the best quotes, providing liquidity to the market and making profits from the spreads.

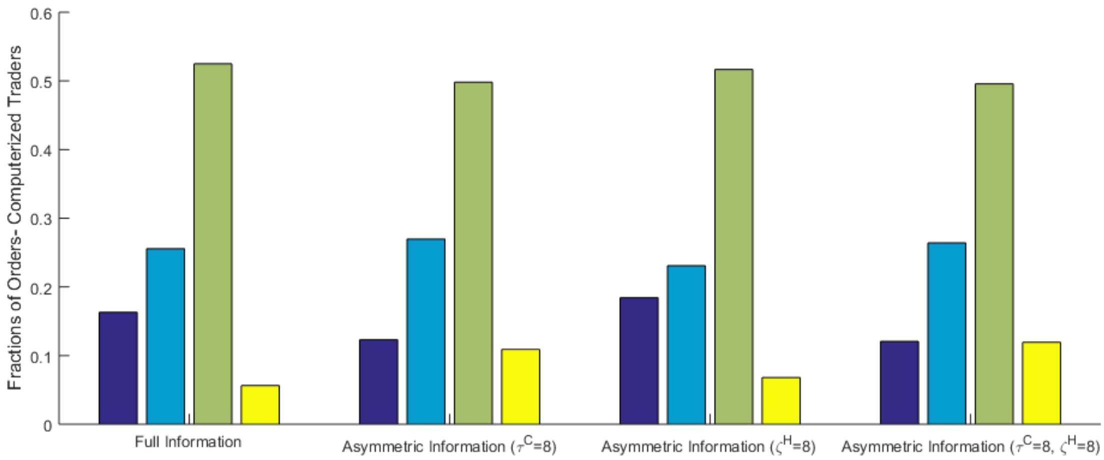
When human traders have no lags in observing the order book status (case one under asymmetric information), they submit more aggressive limit orders (limit orders between and at the best quotes) as they are less fear of being picked-off and willing to realize profits sooner. For human traders, knowledge of contemporaneous order book reduces their submissions of limit orders behind the best quotes, which lead to decreases in time to execution and picked-off risk. Meanwhile, computerized traders under such scenario would reduce aggressive submissions and increase their submissions of limit orders behind the best quotes, which are less likely to be picked-off. If computerized traders observe the contemporaneous fundamental value, their liquidity provision is reduced, while computerized traders consume liquidity at times through increased market order submissions.

3.4.4 Speed Advantage

The analysis presented above shows the effects of different types of information on traders' behavior and the high frequency market, where traders are homogeneous in

Figure 3.2: Orders- Human Traders and Computerized Traders





Note: Figures for market with Human Traders (H) and Computerized Traders (C). Fractions of market orders and limit orders are shown first for the benchmark setting, with limit orders categorized into orders at the best quotes, between the best quotes and behind the best quotes. Benchmark setting is with symmetric information, where all traders in the market know the contemporaneous fundamental value and order book status instantaneously ($\tau = 0$, $\zeta = 0$). Fractions of market orders and limit orders with asymmetric information are computed when computerized traders know the fundamental value with a lag ($\tau^C = 8$), human traders know the order book status with a lag ($\zeta^H = 8$), or computerized traders know the fundamental value with a lag and human traders know the order book status with a lag ($\tau^C = 8$, $\zeta^H = 8$). The last case is close to the realistic market setting. All other lags are zero. Parameters: $\lambda^H = 0.64$, $\lambda^H_{re} = 0.1$, $\lambda^C = 0.64$, $\lambda^C_{re} = 0.1$, $\lambda^v_{high} = 0.2$, $\rho = 0.2$.

trading speed. Most studies on high frequency trading, however, address the speed advantage of computerized traders (e.g., Bernales, 2015; Ait-Sahalia and Saglam, 2016). Following pre-programmed instructions, high frequency traders in financial markets are characterized by their high speeds, high turnover rates and low latency order transmission. In this section, we present results of the model with computerized traders having speed advantage in order submission and modification.

The profitability of human traders and computerized traders are presented in Table 3.4. Similar to the results in Section 3.4.2, human traders under the realistic market setting earn higher profits, while levels of profits are higher for the scenario with symmetric information compared to the realistic market. Both human traders and computerized traders earn higher profits on average in the market where computerized traders have speed advantage. This is due to the fact that when traders trade fast, their waiting costs decrease.

Contrary to the homogeneous speed environment, human traders' information on order book would reduce average profits of computerized traders when computerized traders trade more frequent than human traders. As human traders observe the order book instantaneously, they reduce mistakes in order submissions that are related to order book status. Table 3.4 also shows that participation of computerized traders in the market is above 60%, which is close to the empirical evidence in Hagstromer and Norden (2013).

Table 3.4: Profitability- Different Speed

	Valuation	Benchmark Profit	Profit- Asymmetric Information		
		$(\tau = 0, \zeta = 0)$	$(\tau^C = 8)$	$(\zeta^H = 8)$	$(\tau^C = 8, \zeta^H = 8)$
High Volatility					
H	0	0.7805	0.7869	0.6076	0.5994
H	4	3.1995	3.1905	3.1467	3.1307
H	8	6.7791	6.7797	6.6905	6.6689
H	(all groups)	3.5476	3.5467	3.4480	3.4332
C	0	0.7919	0.5595	0.8846	0.6702
C	4	3.2052	3.0346	3.1887	3.0381
C	8	6.7794	6.5406	6.7729	6.4931
C	(all groups)	3.5537	3.3448	3.5729	3.3651
C Participation		0.6382	0.6601	0.6310	0.6407
Low Volatility					
H	0	0.7571	0.7568	0.6166	0.5948
H	4	3.1985	3.1863	3.1552	3.1199
H	8	6.7924	6.7840	6.6712	6.6596
H	(all groups)	3.5442	3.5370	3.4484	3.4246
C	0	0.7744	0.5824	0.8763	0.6988
C	4	3.2034	3.0470	3.1991	3.0418
C	8	6.7898	6.5543	6.7573	6.4670
C	(all groups)	3.5507	3.3606	3.5698	3.3672
C Participation		0.6365	0.6566	0.6208	0.6444

Note: Results for market with Human Traders (H) and Computerized Traders (C). Benchmark setting is with symmetric information, where all traders in the market know the contemporaneous fundamental value and order book status instantaneously ($\tau = 0$, $\zeta = 0$). Profits with asymmetric information are computed when computerized traders know the fundamental value with a lag ($\tau^C = 8$), human traders know the order book status with a lag ($\zeta^H = 8$), or computerized traders know the fundamental value with a lag and human traders know the order book status with a lag ($\tau^C = 8$, $\zeta^H = 8$). The last case is close to the realistic market setting. All other lags are zero. C participation is the fraction of orders submitted by computerized traders in the market. Standard errors for all profitability measures are sufficiently small since we use a large number of simulated events. Parameters: $\lambda^H = 0.64$, $\lambda^H_{re} = 0.1$, $\lambda^C = 1$, $\lambda^C_{re} = 0.2$, $\lambda^v_{high} = 0.2$, $\lambda^v_{low} = 0.15$, $\rho = 0.2$.

3.5 Conclusion

High frequency traders play an important role in financial markets in terms of information transmission and liquidity provision. Trading behaviors of those computerized traders have significant impact on market quality and profitability of human traders. With super fast data transmission and co-location of their system, high frequency traders observe market data and order flow information ahead of 'human' traders. While high frequency traders better know the order book, computerized trading still has limitations in analyzing qualitative information alongside the quantitative information. Human traders on the other hand, are often professional traders who specialize in a particular asset and might have informational advantage in observing the contemporaneous fundamental value of the asset. Our study examined the effect of these two different types of information on traders in the high frequency market microstructure. We introduced a dynamic trading game between computerized traders and human traders in the limit order market, where traders are risk-neutral and trade in one risky asset. Optimal strategies and market characteristics were determined through a unique numerical technique. We found that information on contemporaneous fundamental value is more valuable than the information on contemporaneous limit order book status. Information on contemporaneous order book status is valuable for human traders in the market and reduces their trading costs and risks. When computerized traders trade much faster than human traders, both computerized traders and human traders earn higher profits than before due to improved market efficiency.

Chapter 4

Thesis Conclusion

This thesis studies behaviors of financial market where traders behave in distinct ways due to differences in beliefs, behavioral factors, physiological responses or technology used in trading. In previous studies, testosterone and cortisol have been shown to affect risk preferences in traders (e.g., Coates and Herbert, 2008; Kandasamy et al., 2014; Cueva et al., 2015). Particularly, levels of testosterone and cortisol have been shown to be influenced by trading outcomes and market uncertainty respectively, with such levels in men being more sensitive to both effects than women. As the trading floors are overwhelmingly dominated by men, these effects could have significant impact on markets. However, it is difficult to generalize the effects of hormonal influences on the market as a whole. As these hormonal influences are complex and tend to affect different types of behavior under different market conditions differently, in this thesis the influences of testosterone and cortisol are separately investigated first and then the overall impact is examined. Chapter 2 contributes to the literature by exploring how the hormonal influences and their interactions might affect traders and the overall financial market in a mathematical model. Chapter 3 contributes to the literature by examining the impact of two different types of information on traders in the high frequency market microstrucutre.

The first part of Chapter 2 looks into the effects of testosterone on trading behaviors and on financial markets. Incorporating a link between trader performance and financial risk preferences in a simple asset pricing framework, we show that the effects of male traders' behaviors could be more nuanced given the mediation of testosterone in our mathematical model. Increasing the proportion of female traders up to the balanced composition might not stabilize the market; however, the chances of crashes and frenzies are reduced. Male traders on average underperform female traders; however, the best performing traders are likely to be male. Secondly, we examine effects of cortisol on traders' behaviors and on the market stability with traders having individual differences in trading strategies, investor sentiments and responses of cortisol levels to market uncertainty in the mathematical model. Our results show that the practices of riding volatility waves could be explained by the associations between cortisol, market uncertainty and risk preferences. We find that in the market with neutral investor sentiment male traders could stabilize the market as their risk-taking behaviors are more moderated given concerns about heightened market uncertainty. In the third part of Chapter 2, we study the overall effect of the hormonal influences on financial markets. Results from our model show that the effect of market uncertainty outweighs the effect of trading outcomes on traders' risk preferences. Male-dominated market could be less volatile while volatility itself might revert back to the normal level after periods of fluctuations.

Chapter 3 explores the impact of two different types of information on the high frequency market. With the proliferation of high frequency trading technology, financial markets have gone through significant changes in terms of information transmission. We introduce a dynamic trading game between computerized traders and human traders in the limit order market, where traders' strategies are determined through a unique numerical technique. Our results show that information on contemporaneous fundamental value is more valuable than the information on contemporaneous limit order book status. Information on contemporaneous order book status is valuable for human traders in the market, reducing their trading costs and risks.

Appendix A

to Chapter 2

A.1 Cumulative Payoffs- with Cortisol

Table A.1: Cumulative Payoffs

	Male:Female 50 : 50			Male:Female 95 : 5		
	Mean	Positive(%)	Profits	Mean	Positive(%)	Profits
Neutral Market						
Informed Traders	17.2523	100	17.2523	16.7015	100	16.7015
Male - Type 1	-14.1057	43.9	47.9974	-14.3614	44.4	49.5527
- Type 2	-15.6228	24.5	13.7469	-15.9029	24.9	14.3524
- Type 3	-17.1399	23.3	14.1795	-17.4444	23.4	15.0366
- Type 4	-18.6569	38.2	51.9207	-18.9859	38.6	53.7878
Female - Type 1	-15.5271	44.3	53.6801	-15.5440	44.8	54.4347
- Type 2	-17.3097	24.5	15.5712	-17.2987	25.2	15.7784
- Type 3	-19.0923	23.1	16.3500	-19.0533	23.6	16.7423
- Type 4	-20.8750	38.2	58.5596	-20.8080	38.2	60.2267
Optimistic Market						
Informed Traders	23.8002	99.7	23.8808	23.4544	99.7	23.5347
Male - Type 1	30.2521	67.1	70.5120	30.0978	66.4	72.0178
- Type 2	-1.8451	49.1	18.0669	-2.0125	49.3	18.2547
- Type 3	-33.9423	8.9	11.9022	-34.1229	9.3	12.2518
- Type 4	-66.0395	18.8	41.7010	-66.2332	19.4	42.6629
Female - Type 1	33.5411	67.4	76.5840	33.2701	66.8	77.4767
- Type 2	-1.5094	49.9	19.6070	-1.5625	49.9	19.7675
- Type 3	-36.5600	8.6	13.1838	-36.3951	9.0	13.3318
- Type 4	-71.6106	19	44.1866	-71.2278	19.5	44.7326

Note: Results for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, are called Type 1, Type 2, Type 3 and Type 4 respectively, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. Pairwise Sign tests were conducted and all values are significantly different at 99%. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

A.2 Cumulative Payoffs- with Testosterone and Cortisol

Table A.2: Cumulative Payoffs

	Male:Female 50 : 50			Male:Female 95 : 5		
	Mean	Positive(%)	Profits	Mean	Positive(%)	Profits
Neutral Market						
Informed Traders	17.5371	99.9	17.5549	17.1515	99.8	17.1923
Male - Type 1	-15.3259	40.8	44.4430	-15.2139	40.8	45.2743
- Type 2	-17.9375	19.9	13.4119	-17.7807	20.4	13.5564
- Type 3	-19.7772	16.8	15.0722	-19.6194	16.8	15.5075
- Type 4	-20.1633	35.3	47.9481	-20.0836	35.3	48.7802
Female - Type 1	-15.4510	42.9	49.1539	-15.0028	43.0	49.0446
- Type 2	-17.7252	22.1	14.6970	-17.2100	22.7	14.6207
- Type 3	-19.7078	20.2	15.2152	-19.1515	20.9	14.9385
- Type 4	-21.0654	36.6	53.4272	-20.5134	36.9	52.9661
Optimistic Market						
Informed Traders	23.4240	99.6	23.5450	23.0673	99.6	23.1913
Male - Type 1	26.1966	64.9	65.3248	25.5237	64.7	64.6434
- Type 2	-4.8899	39.5	19.0083	-4.9566	39.2	18.8276
- Type 3	-35.5502	5.9	11.6888	-34.9289	6.1	11.6964
- Type 4	-64.0927	16.3	38.3258	-63.0005	16.6	38.4333
Female - Type 1	30.6598	67.4	69.9504	29.9454	67.5	68.4853
- Type 2	-2.7389	46.0	18.6888	-2.6186	45.7	18.5247
- Type 3	-35.9871	6.8	12.1659	-35.0056	7.3	11.5657
- Type 4	-68.3724	17.1	40.1967	-66.6266	17.6	39.1421

Note: Results for market with 50% informed traders to 50% positive feedback traders. Male:Female is the proportion of male traders to female traders within the group of positive feedback traders. Each simulation was a run for 1000 time steps. Market statistics are averaged over 1000 runs, standard deviations across runs in parenthesis. The degrees of optimism or pessimism, $\theta^l \in \{0.85, 0.95, 1.05, 1.15\}$, are called Type 1, Type 2, Type 3 and Type 4 respectively, with corresponding density $w^l \in \{0.25, 0.25, 0.25, 0.25\}$ for neutral market and $\{0.2, 0.25, 0.25, 0.3\}$ for optimistic market. Pairwise Sign tests were conducted and all values are significantly different at 99%. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\lambda = 0.98$, $\kappa^F = 0.0437$, $\kappa^M = 0.0874$, $\eta^F = 1.6414$, $\eta^M = 3.2828$, $\gamma = 0.4974$, $\zeta = 0.696$, $T = 1000$, $N = 1000$.

Appendix B

to Chapter 3

B.1 Orders Submitted by Human Traders and Computerized Traders

Table B.1: Orders

	Valuation	Market	With Asymmetric Infomration			Limit Order	With Asymmetric Infomration			Limit Order	With Asymmetric Infomration			Limit Order	With Asymmetric Infomration		
		Order	(τ^C=8)	(ζ^H=8)	(τ^C=8, ζ^H=8)	Between	(τ^C=8)	(ζ^H=8)	(τ^C=8, ζ^H=8)	At	(τ^C=8)	(ζ^H=8)	(τ^C=8, ζ^H=8)	Behind	(τ^C=8)	(ζ^H=8)	(τ^C=8, ζ^H=8)
High Volatility																	
H	0	0.1424	0.0701	0.1297	0.0916	0.1982	0.1680	0.1064	0.0995	0.6161	0.7619	0.4960	0.5332	0.0433	0.0000	0.2679	0.2758
H	4	0.1436	0.1807	0.2586	0.2454	0.2579	0.2005	0.1902	0.1859	0.4969	0.5460	0.4074	0.4533	0.1016	0.0729	0.1439	0.1154
H	8	0.2156	0.2845	0.3330	0.3692	0.3248	0.3325	0.2186	0.2376	0.4485	0.3759	0.4212	0.3712	0.0111	0.0072	0.0272	0.0220
H	(all groups)	0.1622	0.1673	0.2290	0.2173	0.2553	0.2227	0.1659	0.1656	0.5247	0.5805	0.4443	0.4634	0.0577	0.0295	0.1608	0.1537
C	0	0.1426	0.0404	0.1400	0.0528	0.1985	0.1920	0.2207	0.2100	0.6155	0.6419	0.6060	0.6538	0.0434	0.1257	0.0333	0.0834
C	4	0.1458	0.0971	0.1729	0.0846	0.2603	0.2976	0.1981	0.2689	0.4939	0.4838	0.4936	0.4870	0.1000	0.1216	0.1354	0.1594
C	8	0.2149	0.2770	0.2596	0.2586	0.3215	0.3378	0.2934	0.3258	0.4547	0.3179	0.4355	0.3090	0.0089	0.0673	0.0116	0.1066
C	(all groups)	0.1631	0.1232	0.1844	0.1208	0.2556	0.2696	0.2309	0.2642	0.5249	0.4982	0.5166	0.4956	0.0564	0.1090	0.0680	0.1193
Low Volatility																	
H	0	0.1512	0.0663	0.1250	0.0862	0.2054	0.1560	0.1044	0.0961	0.6064	0.7777	0.5090	0.5583	0.0370	0.0000	0.2616	0.2593
H	4	0.1508	0.1852	0.2632	0.2465	0.2697	0.1930	0.1880	0.1908	0.4757	0.5584	0.4122	0.4581	0.1038	0.0634	0.1366	0.1047
H	8	0.2033	0.3014	0.3434	0.3677	0.3272	0.3285	0.2238	0.2445	0.4617	0.3660	0.4087	0.3678	0.0078	0.0041	0.0241	0.0200
H	(all groups)	0.1648	0.1711	0.2313	0.2151	0.2635	0.2139	0.1655	0.1677	0.5161	0.5899	0.4479	0.4741	0.0557	0.0250	0.1552	0.1431
C	0	0.1511	0.0418	0.1241	0.0522	0.2053	0.1826	0.2108	0.2041	0.6067	0.6439	0.6338	0.6597	0.0369	0.1317	0.0312	0.0840
C	4	0.1363	0.1036	0.1786	0.0870	0.2623	0.2971	0.1934	0.2649	0.5016	0.4926	0.5003	0.4888	0.0998	0.1067	0.1277	0.1592
C	8	0.2032	0.2925	0.2704	0.2569	0.3252	0.3356	0.3025	0.3321	0.4628	0.3048	0.4184	0.2988	0.0088	0.0671	0.0087	0.1122
C	(all groups)	0.1592	0.1298	0.1839	0.1212	0.2601	0.2648	0.2281	0.2624	0.5265	0.4998	0.5248	0.4954	0.0542	0.1057	0.0632	0.1209

Note: Results for market with Human Traders (H) and Computerized Traders (C). Fractions of market orders and limit orders are shown first for the benchmark setting, with limit orders categorized into orders at the best quotes, between the best quotes and behind the best quotes. Benchmark setting is with symmetric information, where all traders in the market know the contemporaneous fundamental value and order book status instantaneously ($\tau = 0$, $\zeta = 0$). Fractions of market orders and limit orders with asymmetric information are computed when computerized traders know the fundamental value with a lag ($\tau^C = 8$), human traders know the order book status with a lag ($\zeta^H = 8$), or computerized traders know the fundamental value with a lag and human traders know the order book status with a lag ($\tau^C = 8$, $\zeta^H = 8$). The last case is close to the realistic market setting. All other lags are zero. Standard errors for all order fractions are sufficiently small since we use a large number of simulated events. Parameters: $\lambda^H = 0.64$, $\lambda^H_{re} = 0.1$, $\lambda^C = 0.64$, $\lambda^C_{re} = 0.1$, $\lambda^v_{high} = 0.2$, $\lambda^v_{low} = 0.15$, $\rho = 0.2$.

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