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Abstract

Steroid hormones, such as testosterone, have been shown to affect risk preferences in financial traders with high levels leading to excessive risk-taking. Hormone levels, in turn, are affected by trading outcomes as well as by gender - males are more sensitive to stimuli than females. We develop a model to investigate the effects of hormones on financial market stability and trader performance. An increase in the proportion of female traders does not necessarily make markets less volatile; however, it reduces the occurrence of market crashes. Male traders on average under-perform females, although the best performing individuals are more likely to be male.

Keywords: Gender; Hormones; Endogenous risk preference; Market stability; Trader performance
JEL Classification: G10, G02, D02.

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1 Introduction

In the past decade, there has been considerable discussion 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] It was also mentioned that traders 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., *The Guardian*, 2012; *Time*, 2012) and policy makers (e.g., Lagarde, 2013) that a more balanced gender ratio would reduce volatility and help stabilize markets. Our objective in this paper is to study this issue: we develop a theoretical model 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 in the blood stream; Garbarino et al., 2011, pre-natally via digit ratios) 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). 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 terms 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).

It is the greater sensitivity to gains and losses that has led to some policy makers,

[1] See for example *The Guardian*, 2011, *Time*, 2012, 2013.

academics and the popular press to call for a reduction in the proportion of male traders in financial markets in order to enhance stability. However, even when 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, price movements 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. An interesting result of our model is that an increase in the proportion of female traders makes 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) and Brock and Hommes (1998). In our model, informed and positive feedback traders 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 as well as the market uncertainty. Traders who make profits become less risk-averse, whereas those who make losses become more so. We incorporate these effects in our model by allowing a trader's risk preference to vary in response to the results of recent trades. 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. 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 in our model 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 the asset prices. 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 likely to be male. As we discuss more in the concluding section, our results indicates a possible difficulty of changing the gender balance of the trading population in a culture that only rewards star traders.

The rest of the paper is organized as follows. Section 2 briefly reviews the relevant literature on asset pricing methods and the role of hormones in mediating financial behaviors and risk preferences. Section 3 sets out our model incorporating heterogeneous beliefs and time-varying endogenous risk preferences. Section 4 presents details on the impact of testosterone on market and individual behaviors. Section 5 concludes.

2 Related Literature

Our paper is related to the literature concerning physiological effects on economic behavior. While research in this area is still ongoing and clearly more work needs to be done to establish the exact pathway through which the physiological factors like hormones affect specific aspects of behavior, there is by now enough evidence to make the case linking hormones, risk preferences and their effects on actions and performances of financial traders.[2]

Outcomes and hormonal fluctuations have been shown to be related by several studies. Apicella et al. (2014), for instance, show that trading results (monetary rewards) of males affect their circulatory hormone levels with high performance linked to higher levels of testosterone. Coates and Herbert (2008) examine the relation between levels of testosterone and trading performance using a sample of male traders and find testosterone level in the morning being positively correlated with profits during the day. While Kivlighan et al. (2005) study individual's endocrine responses to competitive settings (rowing) varied significantly by gender. This study finds that not only do men have higher baseline testosterone levels than women, the levels for men change significantly more than that of women in the post-event phase. The reason for this greater responsiveness 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).

There are also studies showing the relation between outcomes and risk aversion. Hoffmann and Post (2017) find investors' risk tolerance to be positively related to their return experience. They study how personal return and risk experience drive updates in individual investors' beliefs and preferences with brokerage records and monthly survey data. They find that investors' risk tolerance is positively related to

[2]There is also the literature studying the relation between hormones and social behavior more broadly. We omit discussing this literature here but it is somewhat related and we would be happy to provide references upon request.

their return experience. Filippin and Gioia (2018) study the effect of competition on subsequent risk-behavior and find heterogeneity between genders. They carry out a laboratory experiment in which competition occurs in the Coin Task (a real effort task that consists of recognizing the value and the country of a Euro's origin). They see significant relative difference between men and women in how outcomes affect their risk aversion - men become more risk averse after losing while risk-aversion among women is practically unaffected.

Finally there is also work showing the relation between hormones and risk aversion. Coates and Gurnell (2017) survey this work showing fluctuations in classical endocrine pathways to be a significant determinant of changing risk preferences. Apicella et al. (2008) and Apicella et al. (2014) both find circulatory testosterone to be positively correlated with risk taking in men. Coates and Page (2009) investigate associations between prenatal testosterone levels and financial risk preferences. They look at the digit ratio's of real traders and find that increases in testosterone lead to greater risk-taking. Cueva et al. (2015) studied the role of administered testosterone and find that it is associated with greater financial risk-taking.

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. These findings are in agreement with the meta-analysis of Eckel and Fullbrunn (2015) who show that the size and frequency of price bubbles are decreasing in the proportion of females in experimental markets. Holt et al. (2017) whilst demonstrating a similar result for markets with a changing fundamental value, in the case of a market with a flat fundamental value they find no effect of gender composition.

Our paper is also related to the literature on traders with wrong beliefs (sometimes called irrational traders in the literature) in that we particularly consider on the effect of hormones on speculative technical traders. 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 Chiarella et al. (2006) and Brock and Hommes (1998) where the interaction of trading strategies results in persistent and substantial deviations from the fundamental value.[3]

3 The Model

The model is constructed in the spirit of De Long et al. (1990b), based on the frameworks of Chiarella (1992), Brock and Hommes (1998) and in particular that of Chiarella, Dieci, and Gardini (2006). 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

[3]For more discussions on heterogeneous agent-based models in finance, see surveys by Hommes (2006) and LeBaron (2006).

asset purchased or shorted at price p_t at time t. Wealth of agents evolves according to

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

In period t, each type of trader has an expectation of the excess return per share of the risky asset for the coming period $t+1$ and therefore the price and dividend return in that 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. Expectations are formed based on information up to and including the current period t, we detail in the next section how these are calculated. Similarly the price p_t in the above is the price at which the market clears based on expectations, and information available, at time $t-1$.

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

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

subject to Equation (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

$$Var_{h,t}[w_{t+1}] = Q_{h,t}^2 Var_{h,t}[p_{t+1} + y_{t+1} - Rp_t] \tag{3}$$

where the conditional variance of excess returns is assumed to be fixed over time and normalized to $Var_{h,t} = Var$ for all traders.[4] The optimal quantity for trader-type h is

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

the following[5]

$$Q_{h,t} = \frac{E_{h,t}[p_{t+1} + y_{t+1} - Rp_t]}{a_{h,t}Var} \tag{4}$$

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

$$\sum n_h Q_{h,t} = Q_{st} \tag{5}$$

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

$$E_{h,t}[p_{t+1} + y_{t+1}] - Rp_t = a_{h,t}VarQ_{st} \tag{6}$$

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

$$E_t[p^*_{t+1} + y_{t+1}] = Rp^*_t \tag{7}$$

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.[6]

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

$$y_t = \bar{y} + \varepsilon_t \tag{8}$$

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

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

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

future dividend is the mean $\bar{y}$.[7]

3.1 Beliefs

Informed traders estimate the gross return per share according to

$$E_{I,t}[p_{t+1} + y_{t+1}] = E_t[p^*_{t+1} + y_{t+1}] \tag{9}$$

where $E_t[p^*_{t+1} + y_{t+1}]$ is the common, amongst informed traders, 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

$$E_{PF,t}[p_{t+1}] = p_t(1 + c(\frac{p_t - p_{t-1}}{p_{t-1}}) + (1-c)E_{PF,t-1}[\frac{p_t - p_{t-1}}{p_{t-1}}]) \tag{10}$$

where c is the weight on the most recent percentage observation, $0 < c < 1$. Note at time t the price p_t (and all previous prices) are known therefore giving a unique belief regarding the capital gain at $t+1$. The expected dividend is estimated in the same way,

$$E_{PF,t}[y_{t+1}] = p_t(g(\frac{y_t}{p_{t-1}}) + (1-g)E_{PF,t-1}[\frac{y_t}{p_{t-1}}]), 0 < g < 1 \tag{11}$$

where g is the weight on the most recent dividend yield. Positive feedback traders rely

[7] Our results are robust to alternative dividend processes, namely, the first order auto-regressive process (AR(1)) and the two-state Ornstein-Uhlenbeck (OU) process, see Appendix A. Under the two-state OU process the model generates serially uncorrelated returns.

on only past prices and dividends in making their trading decisions.

Trade therefore happens between these two types of traders when there are disagreements on the asset value and price movements. In every period, the demands of both types of trades are calculated from their expectations via Equation (4). The asset price, p_t, is then determined endogenously by demand and supply as specified by Equation (5). The substitution results in a quadratic equation in one unknown, p_t, with all other terms being known. The positive route is selected as the price.

3.2 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 above). 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

$$Z_{h,t} = sgn(\frac{\Delta r_t}{E_{h,t-1}[p_t + y_t - Rp_{t-1}]})|\Delta r_t| \tag{12}$$

Where *sgn* is the sign function returning 1 for values > 0, -1 for values < 0 and 0 otherwise. We define a positive (negative) outcome as the occasion when traders correctly (incorrectly) estimate the sign of the excess return, $Z_{h,t} > 0$ ($Z_{h,t} < 0$). i.e. all positive profits are deemed positive outcomes.[8] The absolute value of this term, controlled by Δr_h, defines the degree to which this is positive or negative.[9] We also considered other ways of defining the positive outcome from trading as the true functional

[8]This is calculated via the *sgn* function. If the expectation and realization are the same sign then the function will be positive. If they differ the output will be negative. In practice the denominator is almost never 0 due to continuously distributed dividends. In the exceptionally rare case (with 64 bit machine precision) that it is zero the sign is defined by the sign of the numerator.

[9]This includes both those occasions when profits are greater than, and those when they are less than, the traders expectation as positive outcomes as long as they are positive.

form of humans' responses to trading performance is only known approximately. One such alternative measure is $Z_{h,t} = sgn(\frac{\Delta r_t}{E_{h,t-1}[p_t+y_t-Rp_{t-1}]}-1)|\Delta r_t - E_{h,t-1}[p_t+y_t-Rp_{t-1}]|$, in which a positive outcome happens when the realized profit is greater than the expected excess return per share, $\frac{\Delta r_t}{E_{h,t-1}[p_t+y_t-Rp_{t-1}]} > 1$. With this alternative measure of positive outcomes, results are qualitatively similar to those with Equation (12).

Within each type of trading strategy (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) whilst testosterone levels are also 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

$$F^j_{h,t} = \kappa^j \frac{2}{\pi} \arctan(Z_{h,t}), \kappa^j > 0 \tag{13}$$

where κ^j measures the degree of testosterone fluctuations of sub-group j and the constant $\frac{2}{\pi}$ ensures that the function $F^j_{h,t}$ is centered around 0 with range $(-\kappa^j, \kappa^j)$.[10] 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, $\kappa^M > \kappa^F$

[10] Although note the range of this function does not qualitatively change the results.

(see for example Kivilighan et al., 2005). 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.[11] However, results are qualitatively similar when we allow for both informed traders and positive feedback traders having heterogeneous time-varying risk preferences (see Appendix B).

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

$$a_{h,t}^{j} = a_{h,t-1}^{j}(1 - \gamma F_{h,t}^{j}), \gamma > 0 \tag{14}$$

where elevated testosterone levels ($F_{h,t}^{j} > 0$) decrease traders' levels of risk aversion thereafter ($a_{h,t}^{j} < a_{h,t-1}^{j}$). Parameter γ measures the magnitude of the effects of testosterone on traders' risk aversions.[12] 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 feed-

[11]This separation also captures the intuition that positive feedback traders represent speculators, such as day traders, who often work in the highly male-dominated workplaces discussed above. 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.

[12]Parameter values are calibrated on the basis of recent experimental studies, see Section 4.1 for details.

back 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.

4 Results

In this section we present results from the analysis of the model by considering the impact of testosterone on trader behavior. 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.

4.1 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 $p^* = 100$.[13] The conditional variance of excess returns per share Var, is normalized to 1 and the level of risk aversion for informed traders, a_I, is fixed at 3. The initial level of risk aversion at the start of the simulation for both male and female positive traders is also set to 3 for both groups in order to more clearly highlight the effects of the hormonal mechanism. While in experimental studies (e.g., Hartog et al., 2002) risk aversion in men is estimated to be 30% lower than for women, including this within the model did not qualitatively change our results. We, therefore, have chosen to omit it in order to more clearly show the effect of the endogenous risk aversion process.

[13] These parameters satisfy the no-bubble condition. See Brock and Hommes (1998) for a detailed analysis of the no-bubble condition.

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 $g = 0.5$.[14]

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 around half as variable as those of male traders. 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 aversion, γ, is calibrated based on the experimental study of Apicella et al. (2014). In their study, individuals have to split an amount of money between a riskless and risky investment. They found that an individuals risk aversion is reduced by 1.413% when the levels of testosterone rose by 1%. From from this we compute the sensitivity of risk aversion to $\gamma = 0.2569$.

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 1.

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

Table 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
a_I	Level of risk aversion for informed traders	3
c	Weight on most recent percentage price change	0.2
g	Weight on most recent dividend yield	0.5
κ^F	Testosterone sensitivity for female traders	0.04865
κ^M	Testosterone sensitivity for male traders	0.0973
γ	Testosterone's impact on risk aversions	0.2569
T	Number of time steps	1000
N	Number of runs	1000

4.2 Market Stability

In this section we show how traders with testosterone mediated risk preferences affect overall market stability. To do this we consider three cases. The first two illustrate the hormonal effects for 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.[15] 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.[16] In the following discussion we refer to the first of these two as the real composition and the second as the balanced composition. [17]The final case is a benchmark in which hormones do not play a role and both informed traders and positive feedback traders have fixed levels of risk aversions, i.e. $\gamma = 0$.

Table 2 reports results examining market stability. 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, $z = -31.5912$, $p = 0.000$).[18] Contrary to popular opinion, 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

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

[16]See for instance "Too much testosterone, too much confidence" in *The Guardian*, 2012.

[17]Note in using these ratio's we implicitly specify that the choice of trading strategy is not determined by gender.

[18]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.

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. Even though the positive feedback traders can be lucky in some periods, on average they will have many more periods of being successful than otherwise. The greater testosterone fluctuations of male traders increase 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.[19] The same mechanism is even more evident in the benchmark market, in this case the losing traders do not reduces their positions at all resulting in substantially higher volatility.

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, $z = 31.2117$, $p = 0.000$). At the same time these markets also have a larger dispersion of volatility (Brown-Forsythe test, F statistic=10.1495, $p = 0.000$), 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 the extreme event or bubble. The larger proportion of male traders exacerbates this effect resulting in more extreme returns 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 positive feedback

[19]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.

Table 2: Moments of Returns

Market Measure	Male:Female 50 : 50 I	Male:Female 95 : 5 II	Benchmark (Non-Hormonal) III	p-value (I vs. II)
Volatility (%)	0.125	0.105	0.442	0.000
	(0.030)	(0.033)	(0.011)	
Skewness	0.004	0.004	0.009	1.000
	(0.084)	(0.094)	(0.068)	
Kurtosis	2.667	2.871	2.312	0.000
	(0.291)	(0.463)	(0.095)	

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 test. Results from Benchmark market (III) are significantly different from I and II, all p-values being 0. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

traders can not establish trends, when they do it results in higher volatility with more male traders. In the benchmark setting, without hormonal effects these trends do not establish and so a lower kurtosis is observed.

Taken together these results have substantial implications for the debate concerning financial market stability. Increasing the proportion of female traders in the market will 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.

4.3 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.

Table 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 in the proportion of male traders in the market (Sign test, Male: Female 50:50 vs. 95:5, $z = 28.9981$, $p = 0.000$). As explained in Section 4.2, price volatility decreases in the proportion of male positive feedback traders due to increased risk aversions. As the male positive feedback traders trade less the price of the risky asset becomes largely driven by informed traders and so becomes closer to the fundamental value. As a result there is little disagreement in the market and so little trade. With male positive feedback traders less active 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

Table 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	0.153	-0.163	-0.142	0.000	0.000	0.000
	(0.023)	(0.027)	(0.022)			
Dispersion	1.163	1.310	1.090	0.000	0.000	0.000
	(0.104)	(0.160)	(0.078)			
Skewness	1.624	-2.149	-1.320	0.000	0.000	0.000
	(0.613)	(0.903)	(0.455)			
Male:Female 95:5						
Normalized profits	0.144	-0.145	-0.126	0.000	0.000	0.000
	(0.024)	(0.025)	(0.021)			
Dispersion	1.212	1.237	1.050	0.000	0.000	0.000
	(0.143)	(0.152)	(0.079)			
Skewness	1.920	-2.029	-1.252	0.000	0.000	0.000
	(0.828)	(0.895)	(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. 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: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

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 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. The distribution exhibits 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 those of female traders. In order to analyze the profits and losses separately, the distributions of payoffs are partitioned by sign. Table 4 presents these statistics. The results for profitable periods reveal an important result. The best-performing male traders earn significantly more than the top-ranking female traders (Maximum Positive Profits - Sign test, male vs. female, $z = 31.5912$, $p = 0.000$). Whilst there is little difference between the average profits of male and female traders, conditional on profits being positive, male trader payoffs additionally display significantly larger dispersion and higher positive skewness than those of female traders.

Table 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, conditional on positive profits, is little different from that of female traders. Rather than skills it is the excessive risk-taking behavior that makes the best performing traders more likely to be male.

These findings have concerning implications for financial firms, regulators and those

Table 4: Profits – Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Male:Female 50:50			
Positive profits	0.5981	0.5965	0.0022
	(0.0344)	(0.0283)	
Dispersion	0.8029	0.6446	0.0000
	(0.1323)	(0.0640)	
Skewness	2.8864	2.0043	0.0000
	(0.7573)	(0.4297)	
Outperforming	30%	70%	0.0000
	(0.0754)	(0.0754)	
Positive return periods	465	465	
	(13.8335)	(13.8335)	
Maximum positive profits	6.0035	4.1556	0.0000
	(1.6331)	(0.8102)	
Male:Female 95:5			
Positive profits	0.5921	0.5905	0.0017
	(0.0334)	(0.0280)	
Dispersion	0.7589	0.6263	0.0000
	(0.1235)	(0.0611)	
Skewness	2.7563	1.9383	0.0000
	(0.7478)	(0.4215)	
Outperforming	31%	69%	0.0000
	(0.0774)	(0.0774)	
Positive return periods	467	467	
	(14.1855)	(14.1855)	
Maximum positive profits	5.6248	4.0077	0.0000
	(1.5367)	(0.7911)	

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: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

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.

4.4 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 paper 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 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.

Table 5: Moments of Returns

Measure	Informed:Positive Feedback		p-value
	50 : 50	70 : 30	50 : 50 vs. 70 : 30
Volatility (%)	0.105	0.080	0.000
	(0.033)	(0.028)	
Skewness	0.004	0.003	0.001
	(0.094)	(0.089)	
Kurtosis	2.871	2.758	0.000
	(0.463)	(0.387)	

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: $\bar{y} = 1$, $\varepsilon_t \sim U(-1,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

The results in Table 5 show that positive feedback traders are capable of destabilizing the market. The larger the proportion of these traders, the higher the volatility of returns.[20] Volatility of returns in a market with 70% informed traders to 30% positive feedback traders is significantly lower than the scenario with 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

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

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. Similar results have been shown by Brock and Hommes (1998) and Chiarella et al. (2006) amongst others. 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. Traders who lose money and become 'depressed' over time might consider switching strategies. Allowing traders to do this would not change the results qualitatively. We tested the model with both types of traders having hormonal effects and observed the same relationships. As the informed traders make profits, the increase in demand from male informed traders pushes the price back towards the fundamental, reducing volatility.

5 Conclusion

Scientists, policy makers and the popular press 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 trading results we show that the effects of a more balanced gender composition maybe more nuanced. An increase in the proportion of female traders may increase the volatility of returns under certain market conditions; 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 given the impact of testosterone.

We study the effect of change in gender balance on the overall market return; specifically, we examine a counterfactual scenario where the gender composition of traders is drastically different from what it is in the current reality and observe its effect on market outcomes. Nevertheless, one could wonder whether or not there might be forces that would provide resistance to attempts to bring a more balanced gender composition in the financial markets. This brings us to the important topic of how traders are evaluated in the financial firms where they work. Our formal model keeps fixed the set of traders to observe how trading performance affects their future behavior and the effect that has on the market. This is done specifically to highlight the effect of gender differences of traders, abstracting away from any other factor that might affect the market outcomes. In real life one of those factors would presumably be a change in the set of traders who trade - in particular, one would expect successful traders to be given prominence and the less successful ones perhaps even replaced. While we plan to examine these various other dynamic effects in our future research, it is clear that the ultimate effects of changes in gender balance will depend on how firms recruit new traders and also how they reward or let go their existing set of traders. 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: for example, to move away from a system that disproportionately rewards "best performers" to one that rewards more the consistent profit makers even though the amount of profits made (per period) may be more modest.

The work we have presented in this paper in an important step in modeling the relationship between hormones and market stability. The physiological pathways underlying the relationship between stimuli, hormonal responses and risk aversion are, however, still being explored. The model we present intuitively captures the key relationships observed experimentally in the literature. There are aspects of this relationship that are still not currently understood, for instance as we highlight above whether gains should be measured relative to zero (no profit/loss) or the traders expectation. In the same way where is little evidence about whether changes in hormone levels are symmetric in response to equal stimuli and whether that symmetry is the same between men and women. As this literature develops and our understanding of these relationships improves our theoretical framework may be refined to provide further predictions for investigation. The model could similarly be extended to look at other elements of preferences. In this paper we have focused on risk aversion - the willingness of individual to take risks of a given magnitude, however, other elements may also affect trading behavior such as enjoyment of trading itself. Systematic differences between genders along these lines could be added to the model to understand the interacting motivations effecting an individuals willingness to trade.

Appendices

A 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 auto-regressive process, AR(1),

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

where the White noise $\{\varepsilon_t\}$ 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 4.2, 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 A.1). Returns are more stable with an increased proportion of informed traders relative to positive feedback traders (see Table A.2). The relative performance of traders is in line with that of Section 4.3 (see Table A.3). 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. Consistent with our main results, the greater dispersion of volatility due to a larger male proportion of positive feedback traders persists with AR(1) type dividends (Brown-Forsythe test for variance of volatility, F statistic= 4.8237, $p = 0.028$). 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 A.1: Moments of Returns

Market Measure	Benchmark (Non-Hormonal) I	Male:Female 50 : 50 II	Male:Female 95 : 5 III	p-value (II vs. III)
Volatility (%)	0.8431	0.5358	0.5146	0.0000
	(0.0291)	(0.0522)	(0.0570)	
Skewness	0.0110	0.0031	0.0028	0.0177
	(0.1083)	(0.1117)	(0.1130)	
Kurtosis	3.0006	3.0646	3.0842	0.0000
	(0.2235)	(0.2485)	(0.2675)	

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. Results from Benchmark market (I) is significantly different from II and III, all p-values being 0. Parameters: $b = 0.639$, $\rho = 0.361$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

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

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

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

Table A.2: Moments of Returns

Measure	Informed:Positive Feedback		p-value
	50 : 50	70 : 30	50 : 50 vs. 70 : 30
Volatility (%)	0.515	0.479	0.000
	(0.057)	(0.049)	
Skewness	0.003	0.002	0.003
	(0.113)	(0.111)	
Kurtosis	3.084	3.052	0.000
	(0.267)	(0.253)	

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: $b = 0.639$, $\rho = 0.361$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

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.[21] 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 $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\varepsilon_t \sim N(0,1)$.[22] Tables A.5, A.6, A.7, and A.8 present results on market stability and traders' performance.

[21] The probability of staying in the same state for the next period is denoted by α.

[22] In order to compare with the other two dividend processes, the pair of state means ($\mu^{high} = 1.0576$, $\mu^{low} = 0.95$) 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 satisfying the conditions and results are qualitatively similar for other paired values.

Table A.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	0.164	-0.174	-0.153	0.000	0.000	0.000
	(0.035)	(0.039)	(0.034)			
Dispersion	1.631	1.790	1.553	0.000	0.000	0.000
	(0.178)	(0.254)	(0.142)			
Skewness	1.510	-1.927	-1.271	0.000	0.000	0.000
	(1.039)	(1.376)	(0.850)			
Male:Female 95:5						
Normalized profits	0.158	-0.159	-0.139	0.000	0.000	0.000
	(0.037)	(0.037)	(0.033)			
Dispersion	1.697	1.729	1.518	0.000	0.000	0.000
	(0.235)	(0.249)	(0.146)			
Skewness	1.760	-1.854	-1.230	0.000	0.000	0.000
	(1.288)	(1.372)	(0.868)			
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: $b = 0.639$, $\rho = 0.361$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

Table A.4: Profits –Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Male:Female 50:50			
Positive profits	0.7899	0.7898	0.0149
	(0.0576)	(0.0516)	
Dispersion	1.2460	1.0701	0.0000
	(0.2397)	(0.1387)	
Skewness	3.8636	3.1123	0.0000
	(1.3397)	(0.9255)	
Outperforming	32%	68%	0.0000
	(0.0787)	(0.0787)	
Positive return periods	470	470	
	(11.7737)	(11.7737)	
Male:Female 95:5			
Positive profits	0.7827	0.7820	0.0820
	(0.0580)	(0.0525)	
Dispersion	1.2058	1.0516	0.0000
	(0.2292)	(0.1372)	
Skewness	3.7750	3.0785	0.0000
	(1.3213)	(0.9216)	
Outperforming	33%	67%	0.0000
	(0.0771)	(0.0771)	
Positive return periods	473	473	
	(11.5674)	(11.5674)	

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: $b = 0.639$, $\rho = 0.361$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

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 positive feedback traders. 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. Male traders marginally outperform female traders conditional on profits are made under the realistic gender composition.

Our baseline economy and the extensions here all show that volatility of returns decreases in the male proportion of positive feedback traders given the impact of testosterone 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.

Table A.5: Moments of Returns

Market Measure	Benchmark (Non-Hormonal) I	Male:Female 50 : 50 II	Male:Female 95 : 5 III	p-value (II vs. III)
Volatility (%)	0.982	0.662	0.642	0.000
	(0.075)	(0.087)	(0.091)	
Skewness	0.031	0.017	0.015	0.009
	(0.288)	(0.481)	(0.507)	
Kurtosis	6.877	13.625	14.600	0.000
	(1.873)	(4.140)	(4.553)	

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. Results from Benchmark market (I) is significantly different from II and III, all p-values being 0. Parameters: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

Table A.6: Moments of Returns

Measure	Informed:Positive Feedback		p-value
	50 : 50	70 : 30	50 : 50 vs. 70 : 30
Volatility (%)	0.642	0.609	0.000
	(0.091)	(0.085)	
Skewness	0.015	0.012	0.548
	(0.507)	(0.543)	
Kurtosis	14.600	16.202	0.000
	(4.553)	(4.916)	

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: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

Table A.7: 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	0.181	-0.192	-0.169	0.000	0.000	0.000
	(0.040)	(0.044)	(0.038)			
Dispersion	1.891	2.072	1.803	0.000	0.000	0.000
	(0.242)	(0.336)	(0.196)			
Skewness	1.682	-2.099	-1.449	0.000	0.000	0.000
	(1.442)	(1.795)	(1.253)			
Male:Female 95:5						
Normalized profits	0.175	-0.176	-0.154	0.000	0.000	0.000
	(0.042)	(0.043)	(0.038)			
Dispersion	1.965	2.002	1.763	0.000	0.000	0.000
	(0.305)	(0.323)	(0.196)			
Skewness	1.917	-2.014	-1.402	0.000	0.000	0.000
	(1.680)	(1.774)	(1.256)			
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: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

Table A.8: Profits –Positive Outcomes

	Male	Female	Male vs. Female (p-value)
Male:Female 50:50			
Positive profits	0.8802	0.8800	0.0003
	(0.0710)	(0.0641)	
Dispersion	1.4610	1.2654	0.0000
	(0.3047)	(0.1851)	
Skewness	4.2266	3.5418	0.0000
	(1.5081)	(1.1668)	
Outperforming	32%	68%	0.0000
	(0.0798)	(0.0798)	
Positive return periods	471	471	
	(11.8543)	(11.8543)	
Male:Female 95:5			
Positive profits	0.8725	0.8718	0.0059
	(0.0710)	(0.0651)	
Dispersion	1.4153	1.2441	0.0000
	(0.2895)	(0.1813)	
Skewness	4.1416	3.5074	0.0000
	(1.4896)	(1.1577)	
Outperforming	33%	67%	0.0000
	(0.0790)	(0.0790)	
Positive return periods	473	473	
	(11.5073)	(11.5073)	

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: $\lambda^{high} = 1$, $\lambda^{low} = 1.3$, $\mu^{high} = 1.0576$, $\mu^{low} = 0.95$, $\alpha = 0.99$, $\sigma = 1$, $\Delta t = 1$, $\varepsilon_t \sim N(0,1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

B Extension with Informed Traders Having Time Varying Risk Preferences

In this section we consider the populations of both informed and positive feedback traders being composed of male and female individuals with time-varying risk preferences.

Table B.1 reports the risk aversion of male and female traders in the market with 50% informed traders and 50% positive feedback traders. Informed traders have lower risk aversion compared to the positive feedback traders. On average, male traders have higher risk aversion compared to female traders, which is driven by the high risk aversion among the male positive feedback trading group. For informed traders, willingness to trade is higher among men compared to women. As for traders with the positive feedback trading strategy, male traders have lower willingness to trade on average.[23]

[23]Results on market quality are consistent with the previous simulations in Section 4.2.

Table B.1: Risk Aversions (RA)

Measurement	Male Traders	Female Traders	Male vs. Female (p-value)
Male:Female 50 : 50			
Both Types of Strategies	4.222	3.297	0.000
Informed Traders	1.175	1.870	0.000
	(0.599)	(0.430)	
Positive Feedback Traders	7.269	4.724	0.000
	(2.554)	(0.898)	
Male:Female 95 : 5			
Both Types of Strategies	3.884	3.217	0.000
Informed Traders	1.272	1.956	0.000
	(0.574)	(0.399)	
Positive Feedback Traders	6.497	4.477	0.000
	(2.063)	(0.763)	

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. 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. p-values from pairwise Sign tests. Parameters: $\bar{y} = 1$, $\varepsilon_t \sim U(-1, 1)$, $R = 1.01$, $p^* = 100$, $Var = 1$, $c = 0.2$, $g = 0.5$, $\kappa^F = 0.04865$, $\kappa^M = 0.0973$, $\gamma = 0.2569$, $T = 1000$, $N = 1000$.

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