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ESSAYS ON INFORMATION AGGREGATION, HERDING, AND VOLATILITY IN FINANCIAL MARKETS

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Abstract

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Many violations of the efficient market hypothesis, such as bubbles. crashes. and "fat tails" in the distribution of returns. are difficult to address using a representative agent framework because in such a setting the departures from equilibrium occur only through some external perturbation. An alternative approach, sometimes referred to as the "complex systems" view. emphasizes the importance of interactions between agents. Even if each individual agent's optimization problem is known, outcomes of their interactions are probabilistic, implying that markets can evolve "spontaneously" towards an unstable state. Particularly. in a situation where traders may have private information related to the payoff of a financial assets their individual actions may trigger a cascade of similar actions by other traders. While the mechanism of a chain reaction through information revelation can potentially explain a number of stylized facts in finance, such behavior remains notoriously difficult to identify empirically. This is partly because many theoretical underpinnings of herding. such as informational asymmetry, are unobservable and partly because the complex agent-based models of herding do not yield closed-form solutions to be used for direct econometric tests. In addition, such models have been criticized for their lack of economic microfoundations. The following chapters represent a step towards

filling both of these gaps. First. I identify evidence of herding behavior by institutional investment managers during the collapse of the recent real estate bubble using an established empirical approach. Then. agent based "stochastic herding" model is introduced and tested with an alternative technique of "detection by distribution". Subsequently this framework is extended to better understand the mechanisms driving extreme volatility in the dollar-yen foreign exchange market to show that traders' tendency to herd around information about the possibility of high yield currency crashes can result in self-fulfilling prophecy without a major exogenous shock. The parameter measuring the "thickness" of the tail of the probability distribution of jumps in foreign exchange rates is proportional to the herding intensity by currency speculators. I employ Bayesian econometrics to test the theoretically predicted relationships between this "tail risk" parameter and a number of economic variables related to carry trade activity. The final chapter focuses explicitly on the types of macroeconomic information that traders use to price such extreme events in foreign exchange markets. Since "stochastic herding" provides a plausible data generating mechanism for "rare event," the empirical units of observation utilized in this work have been carefully selected to match this description. Thus. in looking at domestic stock market we focus on institutional investment managers that liquidate their entire positions, not the incremental adjustments, while the examination of foreign exchange markets abstracts from Gaussian volatility and focuses on rare realized volatility jumps and deep out-of-money options used to price such events.

To Gail Mitchell Hoyt

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Chapter 1

Introduction and Overview

The first section of this chapter outlines main findings and contribution of the dissertation. The second section overviews related empirical and theoretical literature on herding behavior, drawing a contrast between herding due to informational cascades and the stochastic herding mechanism employed in this paper.

1.1 Main Findings

In the first chapter, I use a unique dataset on long positions of institutional investors in New York Stock Exchange to test an implication of asset bubble theory that bubbles are associated with high degree of investor herding. I focus on herding behavior resulting from informational cascades, whereby investors trade based upon observing the decisions of others while ignoring their own private information. I track institutional positions in 121 real estate investment trusts. The PE ratios for these investment vehicles grossly exceeded the market average from 2003 until their prices collapsed in 2007. Consistent with several asset bubble theories, my results indicate that the collapse in the share prices of REITs was preceded by high degree of imitative behavior. I also find that herding was higher within these securities relative to S&P500 stocks and relative to the pre-bubble period of 1999-2002.

The second chapter, written jointly with Makoto Nirei, demonstrates that the behavior of institutional investors around the downturn of the U.S. equity markets in 2007 is consistent with stochastic herding in attempts to time the market. We consider a model of large number of institutional investment managers who simultaneously decide whether to remain invested in an assets or liquidate their positions. Each fund manager receives imperfect information about the market's ability to supply liquidity and chooses whether or not to sell the security based on her private information as well as the actions of others. Due to feedback effects the equilibrium is stochastic and the "aggregate action" is characterized by a power-law probability distribution with exponential truncation predicting occasional "explosive" sell-out events. We examine highly disaggregated institutional ownership data of publicly traded stocks to find that stochastic herding explains the underlying data generating mechanism. Furthermore, consistent with market-timing considerations, the distribution parameter measuring the degree of herding rises sharply immediately prior the sell-out phase. The sell-out phase is consistent with the transition from subcritical to supercritical phase, whereby the system swings sharply to a new equilibrium. Specifically, exponential truncation vanishes as the distribution of fund manager actions becomes centered around the same action – all sell.

The third chapter, written jointly with Makoto Nirei, applies the stochastic herding approach to explain extreme volatility in currency markets populated by large numbers of carry traders. When domestic monetary policy considerations introduce an interest rate wedge between two countries, a trader can make a profit by borrowing at low interest in one country to fund the purchase of a higher yielding asset in the other. That is. unless the high yield currency depreciates sharply. We model strategic traders trying to profit from such interest rate differential at the expense of exposing themselves to currency crash risk. Because all such "carry traders" are concerned with the same type of foreign exchange risk they seek the same information and extract signals from each others' actions. In this environment. a random termination of a carry position can trigger a herd effect causing others to do the same. As the traders simultaneously pile on the low interest currency to repay their liabilities the fears of high yield currency crash become self-fulfilling. Such dynamics imply that sudden appreciations (depreciations) of low (high) yield currencies, although rare, are not independent events. This hypothesis is corroborated by the distribution of realized volatility jumps in the Japanese yen. which has served as a funding currency in carry trade. Yen *appreciation* jumps exhibit dependence and extreme variability, whereas *depreciation* jumps appear to be white noise. Consistent with our model predictions. we find that higher volume of carry trade positions increases the "tail risk" of sharp yen *appreciation* directly, while lower margin requirements and higher option implied risk premia only raise the likelihood of sharp *appreciation* indirectly through their effect via the actions of carry traders.

The final chapter, written jointly with my adviser Michael Hutchison, investigates market perceptions of the risk of large exchange rate movements by using information gleaned from risk reversal contracts and macroeconomic news surprises. We focus on the height of the carry trade period in Japan (March 2004 through December 2006). Concerns about sharp yen appreciation were particularly evident during the period of heavy carry trade activity and are more likely to show up in the price of risk. We focus on "big" news surprises that are more likely to convey information about the risk of large changes in the exchange rate, consider a broad set of news, and investigate the direct impact of news on the value of dollar yen risk reversals. We also consider the effect of the value of risk reversals on the yen carry trade, using non-commercial open interest positions in futures markets as a proxy for carry trade activity. Overall, we find that macroeconomic news is an important determinant of risk reversals during periods of heavy carry trade volume. Moreover, there is a close link between risk reversals and non-commercial futures positions. We calculate a substantial effect of macroeconomic news on carry trade activity, with risk reversals (the cost of hedging) as the transmission mechanism.

1.2 Stochastic Herding and Related Literature

Related arbitrage literature includes Shleifer et al. (1990) who show that rational traders will tend to ride the bubble because of risk aversion. Abreu and Brunnermeier (2003) model a continuous time coordination game in which the market finally crashes when a critical mass of arbitrageurs synchronizes their trades. In such a setting, it is futile for well-informed rational arbitrageurs to act on some piece of information unless a mass of other arbitrageurs will do so also. The coordination element coupled with information asymmetries create an incentive for fully rational investors to base their actions on the actions of others, i.e. herd. Scharfstein and Stein (1990), Bikhchandani et al. (1992), Banerjee (1992), and Avery and Zemsky (1998) have formulated a theory of informational cascades, a type of herding that takes place when agents find it optimal to completely ignore their private information and follow the actions of others in a sequential move game.[1] Because players select their actions sequentially the system will eventually but unexpectedly swing from one stable state to another. In contrast, in our framework herding is stochastic following Nirei (2006*b*, 2008) with some foundation going back to probabilistic herding in the famous ant model of Kirman (1993).[2] Only a fraction of agents synchronize, the size of the fraction in turn depends on the realization of private signals. Stochastic herding emerges because strategic complementarity makes it optimal for some agents to place higher value on the informational content of the actions of others' relative to own private signals. This setup differs from pure informational cascades similarly to Gul and Lundholm (1995) in that in our case, as in theirs, none of the information goes unused. As a result of stochastic herding, transition

[1]See Chari and Kehoe (2004) for the application of information cascades to financial markets.

[2]Alfarano et al. (2005) and Alfarano and Lux (2007) extend the Kirman model in a different direction: they focus on the ability of the model with asymmetric transition probabilities of different types of traders to match higher moments in financial returns, whereas the stochastic herding approach focuses on the mapping of heterogeneous information onto the agents' action space.

between states only happens with certain probability.

The probability distribution of herding agents is derived from the threshold rule governing their actions. This is similar to the threshold-based switching strategy employed by Morris and Shin (1998) in the Global Games approach. However, unlike the Global Games, the threshold value of the signal determining whether or not an investment manager chooses to liquidate her position fluctuates endogenously with the actions of others. Endogenously fluctuating threshold can generate cascading behavior whereby agents continuously lower their threshold belief for liquidating an assets as they observe more and more liquidation around them. This leads to a non-trivial possibility of an "explosive" event in which the vast majority of investment managers liquidate simultaneously causing the liquidity to dry up. In this manner, we show that even if private signals about future market liquidity are normally distributed, the resulting aggregate action will follow a highly non-normal distribution implying stylized facts such as volatility clustering and fat tails in the distribution of financial returns.[3]

Empirical studies of herding have mostly focused on abnormal changes in institutional portfolio composition as evidence of herding(see Nofsinger and Sias (1999), Kim and Nofsinger (2005), and Jeon and Moffett (2010) for the ownership change portfolio approach).[4][5] Sias (2004) examines herding among institutional

[3]Our approach also bears some relationship to the studies of markets for information such as Veldkamp (2006*a*) who identifies herding as an element of intrinsic instability because it makes markets respond disproportionally to seemingly trivial news.

[4]In related empirical studies McNichols and Trueman (1994) finds herding on earnings forecasts, Welch (2000) finds that security analysts herd, and Li and Yung (2004) finds evidence of institutional herding in the ADR market.

[5]Laboratory studies of herding in speculative attacks include Brunnermeier and Morgan (2004)

investors in NYSE and NASDAQ by using a more direct measure that looks at the correlation in the changes of an institution's holdings of a security with last period changes in holdings of other institutions. Our empirical approach is more closely related to Alfarano et al. (2005) and Alfarano and Lux (2007), in that we examine the goodness of fit of the empirical distribution to the theoretical distribution implied by the model instead of performing quantile or regression analysis like the earlier works.

If agents are unsure about the accuracy of their private signal about future market liquidity and are prone to follow the actions of others within the same stock-investor-type group, then, because of the complementarity of their market-timing strategies, the probability of observing large outliers is much higher compared to the case when investors act independently. Specifically, if the behavior of traders can be described by stochastic herding then the distribution of their actions will exhibit exponential rather than Gaussian decay. Moreover, the exponential decay will vanish and the distribution will approach a pure power law in the state of self-organized criticality when all agents herd on the same action.

In a related work, Farhi and Gabaix (2008) describes a number of data generating processes with feedback effects that have been known to produce power law distributions. However, we depart from their approach in several ways. Gabaix et al. (2006) derive power-law scaling in trading activity from the power-law distribution in the size of the traders, while we obtain this result from the interactions

and Cheung and Friedman (2009).

of same-size traders. In other words, we obtain power-law scaling without imposing major parametric assumptions on exogenous variables. Instead, it suffices that the signals about the true state are informative in the sense of satisfying the Monotone Likelihood Ratio Property (MLRP). For instance, as in this paper, the information and the true state can follow a bivariate normal distribution. One advantage of developing this empirical approach is its potential, given the right data, to quantify the "hidden tail risk" and provide advance warning of an impeding instability by identifying a system with high degree of choice interdependence based on the distribution of aggregate action.

Chapter 2

Bubbles and Herding: Evidence from the NYSE Real Estate Stocks

2.1 Introduction

The collapse in the prices of real estate backed securities in August 2007 provides ample material for testing asset pricing theories. Modern literature on speculative bubbles and crushes dates back to Blanchard (1979) and Blanchard and Watson (1983). Cooperative behavior of investors is a common feature of models describing persistent overpricing of an asset relative to its fundamental value (a bubble) or a sudden collapse of such overpricing (a crash). For instance Abreu and Brunnermeier (2002) challenge the efficient market hypothesis on the basis that fully rational traders can trade based on investor sentiment alone while ignoring the underlying fundamentals of a financial asset. They call this *synchronization risk* and offer it as a possible explanation why mispricing can persist despite the presence of rational arbitrageurs in the market. Thus, instead of correcting the mispricing right away, rational traders will attempt to time the market by acting on the basis of the sentiment of other investors. This introduces an element of coordination among investors thus creating a third motive for entering a position in a financial asset: in addition to noise trading and fundamental trading, the incentive to time the market leads to *synchronized* trading, Abreu and Brunnermeier (2003).

For illustrative purposes consider the following price dynamics of a bubble asset from Zhou and Sornette (2008):

$$\frac{dB}{dt} = \mu dt + \sigma dW - \kappa dj \tag{2.1}$$

Equation (2.1) is the standard Brownian motion plus a discrete jump, κ, that corresponds to the bursting of a bubble. dj is an indicator function with a value of either 0 or 1. As a key element that determines the time (if at all) of the bursting of the bubble Abreu and Brunnermeier (2003) emphasize *coordination* while Zhou and Sornette (2008) calls it local self-reinforcing imitation between traders. According to Sornette self-reinforcing imitation first leads to the blossoming of a bubble, but then through progressive strengthening may cause a crash as it increases the crash hazard rate. Where in Zhou and Sornette (2008) the crash hazard rate is given by:

$$E_t[dj] = h(t)d_t \tag{2.2}$$

Thus crash hazard rate is the probability of a discrete jump (a crash) in the price process in equation (2.1) conditional on the fact the the crash has not yet occurred. In order to predict the timing of the crash based on crash hazard rate Zhou and Sornette (2008) infers a particular signature of investor herding from price movements, but does not measure herding, i.e. track imitation, directly.

I attempt to measure the degree of herding directly. Such work is scant because data on actual holdings of securities is rare and or proprietary. One reliable source of investor holdings data is Securities and Exchange Commission (SEC). Institutional investor are required by law to file quarterly reports of their long positions in publicly traded securities in the so-called 13F filings. Knowing how investors' positions change in time and relative to each other it is possible to construct a sensible measure of investor herding. I adopt Sias (2004) approach for measuring herding behavior among institutional investors to determine whether a bubble asset is characterized by excess institutional herding and whether the degree of herding increases in time as the crash approaches. I focus on a sample of 121 shares real estate investment trusts (REITs). These are closed end funds that specialize in real estate investments traded on New York Stock Exchange (NYSE). As a class, these shares experienced a dramatic rise in PE ratios relative to the market (proxied here by S&P500) beginning around 2003Q1 then crashed dramatically in August 2007.

2.2 Data

My main data sources are 13F Filings (SEC) that track institutional investors in US stock holdings. including 121 real-estate stocks. These were obtained from Thomson Financial Ownership Database. I obtained data on prices, price-earning ratios. earnings per share. dividend yields. and assets per share from Datastream (again Thomson Financial) for the period 1999Q1 through 2008Q1. Related work using 13F filing is scant, partly due to the limitations of the series. For example the 13F database tracks only long positions. (Brunnermeier and Nagel (2004).Sias (2004). Sias (2007). Hardouvelis & Stamatiou(2008)). I have information on the following investors with holdings of real estate stock: Hedge Funds. Bank Trusts, Corporations, Endowment Funds. Insurance Companies, Pension Funds. Investment Advisors. Individual Investors. Research Firms. and Venture Capitalists.

Figure 3.4 [about here]

Figure 3.4 shows PE ratios of the 121 Real Estate Stocks (REITS) and the S&P500 Index (TOTMK). It suggests that REITS stocks were overvalued for the period 2003 to 2007 as their PE ratio more than doubled during that period relative to the market.[1]

Table 2.1 [about here]

[1]Tables 2 10, 2 11 and 2 12 list the tickers and fund names corresponding to the 121 real estate stocks under scrutiny.

Table 2.1 lists descriptive statistics for institutional investor types and stocks in my sample. The tabulations are in 8 quarter intervals from March 2000 through March 2008. Panel A shows that investment advisors occupy the highest share of investors in my sample. On average 63 percent of all investors are investment advisors. Hedge funds constitute the second highest share of investors with 15 percent of all observations on average. The proportion of different investors by type stays relative constant over the same period. The market cap of each investor type in real estate stocks is roughly proportional the numbers of investors in each category. One exception are the insurance companies, whose holdings of real estate stock are lower than pension funds for the entire period, despite their higher number. Panel C reports the number of real estate securities with at least one, 20, 50, and 100 institutional investors. There is also a notable increase in the number of securities with more than 50 institutional investors. In March 2000 approximately 30 percent of real estate securities had more than 50 investors, this percentage increased to 78 percent by March 2008.

2.3 Herding

Past literature categorizes herding into several non-mutually exclusive categories: informational cascades, reputational herding, investigative herding, and empirical herding. Informational cascades occur when investors ignore their own private information and instead trade based upon observing decisions of previous actors, Bikhchandani et al. (1992). Reputational herding results from investors farcing reputational cost from acting different from the herd or market leader, Trueman (1994). Investigative herding occurs when investors' information is positively cross-sectionally correlated because they follow the same signals, Hirshleifer et al. (1994). Finally, empirical herding refers to herding without a specific model or explanation. Sias (2004) findings are most consistent with institutional investors herding as a result of inferring information from each other's trades, which falls under informational cascades.

2.3.1 Simple Model

Following Sornette (2003) denote $N(i)$ as the number of institutional investors within a network of trader i. The investors trade at price $p(t-1)$ at time $t-1$ based on all previous information. Let $s_i(t-1)$ be a strategy of investor i at time $t-1$, this strategy is either buy, sell, or hold. The investors realize capital gain or loss based on the realization of $p(t)$. where the asset price variation is simply proportional to the aggregate sum of all traders' actions, $\sum_{i=1}^{N} s_i(t-1)$. Since the price moves with the general opinion $\sum_{i=1}^{N} s_i(t-1)$, the best strategy is to buy if it is positive, i.e. more buy orders than sell orders, and sell if the sum is negative, i.e. more sell orders than buy orders. This simple framework yields a strategy that maximizes investor i's expected payoff. i's position choice should be of the sign of the actions of all other investors:

$$s_i(t) = sign\left(K \sum_{j \ni N_i} s_j(t-1) + \epsilon_i\right) \tag{2.3}$$

where K is the proportionality constant between market depth and the aggregate buy/sell orders and is inversely proportional to the market depth. The time lag in the RHS of (2.3) is there to reflect information cascades theory of herding, where information takes one time period to disseminate. Aggregating equation (2.3) over all institutions investing in security k should imply positive correlation between institutional demand for that security over consecutive quarter is in fact they follow imitative strategies.

2.3.2 Empirical Methodology

I estimate the degree of herding among institutional investors in real estate securities during the bubble period following Sias (2004). He defines herding among institutional investors as following each other in and out of the same securities over time.

Following the methodology of Sias (2004) I construct a measure of the fraction of institutional investors trading security k that are buyers at time t:

$$Buy\Delta_{k,t} = \frac{InsitutionsBuying_{k,t}}{InsitutionsBuying_{k,t} + InsitutionsSelling_{k,t}} \tag{2.4}$$

Standardizing variable $Buy\Delta_{k,t}$ so that it has zero mean and unit variance, the standardized raw fraction of buying institutions can be expressed as:

$$\Delta_{k,t} = \frac{Buy\Delta_{k,t} - Bu\bar{y}\Delta_t}{\sigma(Buy\Delta_{k,t})} \tag{2.5}$$

where $Bu\bar{y}\Delta_t$ is the cross-sectional average, across all real estate stocks, of the fraction of institutional investors that are buyers at time t and $\sigma(Buy\Delta_{k,t})$ is the cross-sectional standard deviation of raw fraction of buying institutions in quarter t. If institutional investors follow each other in and out of the same securities or if they follow their own last quarter trades, then the fraction of institutions buying in the current quarter will be positively correlated with the fraction of institutions buying in the previous quarter. This implies a positive coeffient on lagged standardized fraction of buyers in the following regression:

$$\Delta_{k,t} = \rho\Delta_{k,t-1} + \epsilon_{k,t} \tag{2.6}$$

Thus, a positive and statistically significant estimate of ρ will indicate the presence of institutional herding in the given class of securities. In addition Sias (2004) shows that the slope coefficient from equation (2.6) can be written as (proof in the appendix):

$$
\begin{aligned}
\rho_\imath &= \left[\frac{1}{(K-1)\sigma(Buy\Delta_{\imath,k,t})\sigma(Buy\Delta_{\imath,k,t-1})}\right] \\
&\times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{\imath,k,t}} \frac{\left(D_{\imath,k,t}-Bu\bar{y}\Delta_{\imath,t}\right)\left(D_{\imath,k,t-1}-Buy\bar{\Delta}_{\imath,t-1}\right)}{N_{\imath,k,t}N_{\imath,k,t--1}}\right] \\
&+ \left[\frac{1}{(K-1)\sigma(Buy\Delta_{\imath,k,t})\sigma(Buy\Delta_{\imath,k,t-1})}\right] \\
&\times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{\imath,k,t}} \sum_{n=1,n\neq m}^{N_{\imath,k,t-1}} \frac{\left(D_{\imath,k,t}-Bu\bar{y}\Delta_{\imath,t}\right)\left(D_{\imath,k,t-1}-Buy\bar{\Delta}_{\imath,t-1}\right)}{N_{\imath,k,t}N_{\imath,k,t-1}}\right]
\end{aligned}
\tag{2.7}
$$

where $N_{k,t}$ is the number of institutional investors trading stock k in quarter t and $D_{\imath,k,t}$ is a dummy variable that equals one (zero) if trader n is a buyer (seller) of security k in quarter t. Similarly. $N_{k,t-1}$ is the number of institutional investors trading stock k in quarter $t-1$, $D_{\imath,k,t-1}$ is a dummy variable that equals one(zero) if trader n is a buyer (seller) of security k in quarter t-1, and Dm,k,t-1 is a dummy variable that equals one (zero) if trader $m (m \neq n)$ is a buyer (seller) of security k in quarter $t-1$.

The first term on the right hand side in equation (2.7) is the portion of the correlation that results from institutional investors following their own last quarter trades. If institutional investors in REITs follow their own last quarter trades within this class of securities this term will be positive. whereas if they tend to reverse their last quarter transactions this term will be negative.

The second term on the right hand side of equation (2.7) is the main focus of this study. It is the proportion of the correlation that results from institutional investors following other institutional investors in and out of the same securities. This term will be positive (negative) if institutional investors in REITs tend to accumulate (abandon) securities that other institutional investors have purchased (sold) in the previous quarter. This term measures the degree imitative behavior and corresponds to the degree of institutional herding in REITs. The higher the second term on the right hand side of equation (2.7), the higher is the *synchronization risk* formulated by Abreu and Brunnermeier (2003)

2.4 Results

2.4.1 Abnormal Herding Preceded REITs Share Price Collapse

Figure 2.2 shows the plot of the second term on the right hand side of (2.7), which corresponds to the degree of institutional herding in REITs, against the end of quarter average share price of the 121 real estate investment trusts in my sample. Herding is measured along the lest axis, where a value of .2 would indicate that 20 percent of institutional demand for REITs shares was associated with demand for the same shares by other institutional investors in the previous quarter. The average share price of REITs is measured along the right axis. The standard deviation of the herding estimate is approximately .09 or 9 percent.

Figure 2.2 [about here]

Notice the sudden spike in herding behavior in 2006Q3, or 2 quarters before the rapid decline in the share prices of REITs. It is equal to .34, more than three times the standard deviation. This indicates that in 2006Q3 approximately 34 percent of institutional demand for securities issued by real estate trust funds was associated with the purchases of the same funds by other institutions in the previous quarter. Such dramatic increase in imitative behavior shortly before the collapse of the asset price bubble in REITs is supportive of the notion of *synchronization risk* , Abreu and Brunnermeier (2003), and of self reinforcing imitation that increases the crash hazard rate of a bubble assset Zhou and Sornette (2008). Of course, given the data limitations the evidence is not conclusive. The most important shortcoming being that I use quarterly data to make inferences regarding investor behavior. It is much more likely that portfolio reallocation decisions of this type by institutional investors are conducted at much higher frequencies. However, it is encouraging that results are supportive of the prominent theories in this field even using 13F filings, which only track long positions at meager quarterly frequency as mentioned before. Note that by construction the coefficient is negative if bullish period is followed by a massive sell off. This is exactly what happened at the end of 2007Q1.

2.4.2 Regression Approach

In addition to manually computing one of its components, I estimate the correlation coefficient ρ in equation (2.6). I sequentially include several controls to account for the two main motives for buying securities cited in the literature. I include lag returns on each stock to control for momentum (or feedback) trading by institutional investors. It may be the case that institutions appear to follow each other in and out of the same stocks because they are momentum traders, and lagged fraction of institutions buying may simply proxy for lagged returns. To account for trading based on fundamentals, I include growth in dividend yield, growth in earnings per share, and growth in assets per share. These control variables account for the the other two types of investors commonly cited in the literature: chartists and fundamentalists, Cheung and Friedman (2009). Because returns enter into the regression with a one period lag relative to the fundamentals, I avoid the multiculliniarity problems associated with correlation between stock price and the underlying firm fundamentals.

$$\Delta_{k,t} = \rho\Delta_{k,t-1} + \beta_1 R_{k,t-1} + \beta_2 dy_{k,t} + \beta_3 eps_{k,t} + \beta_4 apsh_{k.t} + \epsilon_{k,t} \qquad (2.8)$$

Here R represents log returns and dy, eps, $apsh$ stand for logarithm of the change in dividend yield, earnings per share, and assets per share respectively. Because of the uncertainty associated with the data generating process and several shortcomings of my panel data (discussed in detail below), I estimate the coefficients in equation (2.5) using Difference and System General Method of Moments (GMM) approaches developed by Arellano and Bond (1991) and Arellano and Bover (1995) and Bond et al. (2002) respectively.

Efficient GMM estimates are obtained by performing Generalized Least Squres on (2.8) scaled by the covariance matrix of the instruments for RHS variables, where, depending on the exact specification, GMM instruments for RHS variables using all available lags. My panel dataset exhibits several characteristics which necessitate the use of GMM to obtain unbiased coefficients. First, small number of time periods (41 quarters) relative to the size of the cross-section. Second, autocorrelation in the dependent variable, $\Delta_{k,t}$, implies dynamic panel bias, which is taken into account by either Difference or System GMM approach. Third, because the cross-section consists of different stocks it is plausible that the data exhibits autocorrelation within individuals. Finally, uncertainly regarding the data generating process means that independent variables may be correlated with fixed effects and the error term.

The System approach uses GMM on the system of two equations: the original equation and one with all regressors transformed by differencing. It then performs a forward orthogonal transform to produce the augmented dataset by left-multiplying the original by an augmented transformation matrix, Roodman (2006). This approach is appropriate for unbalanced panels, such as mine, because it preserves sample size in panels with gaps. The crucial assumption of System GMM is that first differences of instrumental variables are uncorrelated with fixed effects.

2.4.3 GMM Estimation Results

Table 2.2 reports regression results on a balanced panel of 75 real-estate stocks during what I characterize as the bubble period based on their average PE ratio relative to S&P500 (Figure 2.1). The panel is balanced because I only focus on the 75 stocks that have persisted in the 13F filing data each quarter for the period of 1999Q1 through 2008Q1. I do this in order to be able to compare the degree of herding in the control sample of real-estate stocks in the pre-bubble period of 1999 through 2002. Panel A reports results of Difference GMM. The coefficient, $\hat{\rho}$, on Lag Fraction Buy, $\Delta_{k,t-1}$, is statistically significant under 99 percent confidence and is fairly stable to the inclusion of control variables. $\hat{\rho}$ ranges from 0.176 to 0.182 indicating that in the real estate sector stocks between 2003Q1 and 2007Q4 the cross-sectional correlation between institutional demand this quarter and last quarter averaged approximately 18 percent, even after controlling for feedback and fundamental-based trading. The coefficient on lag returns is insignificant under all four specifications indicating that momentum trading was not a major factor in institutional investors' decision to take long positions in real estate stocks during the bubble period, at least at the quarterly level data. However, one of the fundamental factors, growth in earnings per share, is positive and significant under 95 percent level of confidence under specification (2.4). Overall, Difference GMM results indicate that during the bubble period herding played a much larger role in institutional investors' decision to take long positions in real-estate stocks than fundamentals or past returns.

Table 2.2 [about here]

2.4.4 Comparison to Pre-Bubble Period

At 18 percent, the coefficient on lag trades is almost two times larger than that found by Sias (12 percent) using institutional ownership data for 1983Q1 through

1997Q4 for all of NYSE, NASDAQ, and American Stock Exchange stocks. This may indicate a higher than normal degree of herding in my sample of real estate stocks during the bubble period of 2003Q1 through 2007Q4. To see whether the degree of herding was in fact higher for the same stocks during the period of abnormally high PE ratios I run the Difference GMM estimation on the same sample of real estate stocks for the period of 1999Q1 through 2002Q4, during which the average PE ratio for real estate stocks approximated that of the S&P500. I report the results in Table 2.2. Panel A reports Difference GMM results for the period of 2003Q1 through 2007Q4, while panel B reports Difference GMM coefficients for the pre-bubble period of 1999Q1 through 2002Q4. Again, the coefficient on Lag Fraction Buy which represents herding is stable to the inclusion of controls for feedback and fundamentalist trading. The first line of Panel B indicates that on average 13 percent of institutional demand for real estate securities correlated with last quarter demand during this period. This is approximately 5 percentage points lower than during the bubble period, but only 1 percentage point different from the market-wide average found by Sias. Overall, comparison to the pre-bubble control sample supports the finding that the degree of herding among institutional investors is higher for securities characterized by overpricing based on their PE ratios.

2.4.5 Comparison to S&P500 Stocks

The second control sample I use consists of stocks in the S&P500 Index. Table 2.3 reports the GMM coefficients on both samples controlling for feedback trading. Note that in contrast to the real estate stocks, the coefficient on lag returns for S&P500 stocks is positive and significant under 1 percent confidence level indicating that momentum trading played an important role in institutional demand for securities representing the entire NYSE but not for real estate stocks. Finally, the coefficient on last quarter institutional demand, Lad Fraction Buy, at 0.176 compared to 0.161, is higher for real estate securities than for S&P500 stocks during the period of 2003Q1 through 2007Q4. This means the correlation of current institutional demand with that of past quarter was 1.5 percent higher in real estate securities than in the S&P500 stocks. This provides weak support for the hypothesis that the degree of herding is higher within the class of securities presumed to be in a bubble.

Table 2.3 [about here]

2.4.6 Robustness Checks

2.4.6.1 Bounding GMM Estimate Using OLS and LSDV

Panel B of Table 2.4 shows the results for regular OLS, and Panel C shows regression results with Least Squares Dummy Variables (LSDV). Theoretically, the unbiased coeffient on Lag Fraction Buy, $\Delta_{k,t-1}$, obtained through GMM estimation should lie within the bounds set via OLS and LSDV regressions. If not, then GMM may not be the appropriate estimation method for this data.

Table 2.4 [about here]

Dynamic panel bias means that the lagged dependent variable, $\Delta_{k,t-1}$, is endogenous to the fixed effects in the error term. This implies that $\hat{\rho}$, the coefficient on $\Delta_{k,t-1}$, obtained via OLS is correlated positively with the error term and is biased upward since $\hat{\rho}$ obtained through OLS attributes some of the predictive power to $\Delta_{k,t-1}$, whereas in reality part of the predictive power belongs to the stock's fixed effects. One way to address fixed effects is by applying a mean-deviations transform to each variable, where the mean is computed at the level of the stock. Running OLS on the data transformed in this way yields Within Group estimator, which produces the same coefficients as LSDV estimator but with slightly lower standard errors. This procedure accounts for fixed effects, but does not eliminate dynamic panel bias, Roodman (2006). This implies that in contrast to the upward biased OLS coefficient on Lag Fraction Buy, the LSDV coefficient will be biased downward. The unbiased GMM estimate should thus lie within the bounds formed by OSL and LSDV estimates. As Panel B of Table 2.4 shows, the estimate of ρ obtained via OLS ranges from 0.297 to 0.300. Panel C shows the same estimate obtained via LSDV and it ranges from 0.101 to 0.103. Comparing these to $\hat{\rho}$ obtained via Difference GMM shown in Panel A it is evident that $\hat{\rho}_{gmm}$ is within bounds set by OLS and LSDV for all four specifications, suggesting that GMM is in fact the appropriate estimation procedure for this dataset.

2.4.6.2 Fixed Effects

Although the 121 real estate securities in the sample, 75 of which persist throughout the entire sample period of 1999Q1 through 2007Q4. generally fall into the same sector of the economy. they still represent investment vehicles that are quite diverse in their focus and strategies. For instance some specialize in commercial properties, while others focus on residential real estate. To confirm that the dataset in fact exhibits stock specific fixed effects, an assumption that justified the use of GMM. I also conduct Hausman specification test. The results for both sample periods are presented in Table 2.5 and are quite stark. The difference between consistent fixed effect coefficients and asymptotically efficient random effect coefficients is systematic for the time period of 1999Q1 through 2002Q4 as well as 2003Q1 through 2007Q4. with probability of committing type-1 error being zero. It also appears that the bias caused by ignoring fixed effects during the latter period is higher. with absolute difference in coefficients of 0.147 compared to 0.068 for 1999Q1 through 2002Q4.

Table 2.5 [about here]

2.4.6.3 Stationarity

To make sure that the data is stationary the RHS variables enter the regression in log-differences. Thus in equation (2.7). $R_{k,t}$ stands for $ln(P_{k,t}) - ln(P_{k,t-1})$. $dy_{k,t}$ stands for $ln(DY_{k,t}) - ln(DY_{k,t-1})$, $eps_{k,t}$ represents $ln(EPS_{k,t}) - ln(EPS_{k,t-1})$, and $apsh_{k,t}$ represents $ln(APSH_{k,t}) - ln(APSH_{k,t-1})$. I run two stationarity tests for panel data: Hadri (2000) stationarity test for heterogeneous panel data and Levin and Chu (2002) panel unit-root test.Hadri (2000) approach is a residual Lagrange Multiplier test for the null hypothesis that the time series of each cross section unit is stationary around a level or deterministic time trend against the alternative of at least a single unit root. The results for 2003Q1 though 2007Q4 and 1999Q1 through 2002Q4 are reported in Tables 2.6 and 2.7 respectively. Here, Z(mu) is the uncorrected standardized statistic and Z(tau) is the standardized statistic corrected for degrees of freedom. While log returns and dividend yield growth appear stationary under either homoskedasticity or heteroskedasticity assumptions, the null of unit-root cannot be rejected for my variable of interest, Fraction Buy. A critical assumption of Hadri (2000) is that of cross sectional independence among individual time series in the panel.

Tables 2.6 & 2.7 [about here]

I also perform a Levin and Chu (2002) panel unit-root test. The test assumes that each individual unit in the panel shares the same AR(1) coefficient, but allows for time effects, a time trend, and for individual effects. Like Hadri (2000), the null of Levin, Lin, and Chu (2002) test is that of nonstationarity. The results are reported in Tables 2.8 and 2.9.

Tables 2.8 & 2.9 [about here]

2.5 Conclusion

I applied the methodology for measuring institutional herding developed by Sias (2004) to the study of asset bubbles. Using a sample of 121 closed-end funds that specialize in real estate investments and whose shares experienced a dramatic increase in price followed by a collapse in the Summer of 2007, I attempt to identify whether investors in these securities followed each others' trades while ignoring other relevant information. Because of the difficulty in obtaining data on investor positions, most studies in this area make behavioral inferences by observing prices. In contrast, I attempt to measure herding directly using data on institutional holdings. Consistent with theories posed by

Table 2.1: Descriptive Statistics

	Mar-00	Mar-02	Mar-04	Mar-06	Mar-08
Panel A: Number of Institutional Investors					
Bank and Trusts	42	70	59	58	49
Hedge Funds	60	124	87	84	84
Insurance Companies	23	35	26	25	22
Investment Advisors	295	460	366	337	311
Pension Funds	20	29	25	24	20
All Others	13	22	20	14	12
Panel B: Capitalization in Millions ($)					
Bank and Trusts	1.010	2.060	3.950	8.370	7.710
Hedge Funds	3.180	6.490	7.920	14.400	15.300
Insurance Companies	737	1,920	2.780	3.310	4.150
Investment Advisors	15,700	34.600	65,800	112,000	120.000
Pension Funds	3.220	7,810	12,000	10.400	8.360
All Others	1.010	1.810	2.730	5.680	7.700
Panel C: Number of Real Estate Securities with:					
> 1 trader	95	96	102	121	121
> 20 traders	74	84	99	114	117
> 50 traders	39	62	77	88	94
> 100 traders	3	25	30	32	24
Total Real Estate Securities	95	96	102	121	121

Source: Spectrum data, available through Thompson Financial Ownership Database.

Table 2.2: Herding: During and Before "The Bubble"

	(1)	(2)	(3)	(4)
Panel A: 2003Q1 - 2007Q4				
Lag Fraction Buy	0.178	0.182	0.180	0.176
	(0.035)***	(0.035)***	(0.042)***	(0.042)***
Returns	0.003	−0.007	−0.026	−0.041
	(0.036)	(0.036)	(0.036)	(0.041)
Growth in Divident Yield		−0.070	−0.035	−0.033
		(0.113)	(0.109)	(0.097)
Growth in Earning/Share			0.459	0.660
			(0.282)	(0.262)**
Growth in Assets/Share				2.488
				(1.908)
Number of Stocks	75	74	72	71
Observations	1425	1406	1187	1169
Panel B: 1999Q1 - 2002Q4				
Lag Fraction Buy	0.133	0.135	0.123	0.126
	(0.040)***	(0.039)***	(0.046)***	(0.046)***
Lag Returns	0.203	0.325	0.053	−0.040
	(0.385)	(0.406)	(0.546)	(0.581)
Divident Yield Growth		0.047	0.116	0.117
		(0.044)	(0.101)	(0.109)
Earning/Share Growth			−0.160	−0.086
			(0.613)	(0.625)
Assets/Share Growth				0.978
				(3.016)
Number of Stocks	75	74	74	73
Observations	1050	1036	958	938

Note: Standard errors in parentheses; **significant at 5 percent; *** significant at 1 percent.

Table 2.3: Herding: Real Estate Sector vs. S&P 500, 2003Q1 - 2007Q4

	(1) Real Estate	(2) S&P500
Lag Fraction Buy	0.176	0.161
	(0.035)***	(0.027)***
Lag Returns	0.008	0.039
	(0.035)	(0.014)***
Number of Stocks	75	479
Observations	1500	9121

Note: Standard errors in parentheses; ** significant at 5 percent; *** significant at 1 percent.

Table 2.4: Herding: GMM. OLS. and LSDV

	(1)	(2)	(3)	(4)
Panel A: Difference GMM				
Lag Fraction Buy	0.178	0.182	0.180	0.176
	(0.035)***	(0.035)***	(0.042)***	(0.042)***
Lag Returns	0.003	−0.007	−0.026	−0.041
	(0.036)	(0.036)	(0.036)	(0.041)
Divident Yield Growth		−0.070	−0.035	−0.033
		(0.113)	(0.109)	(0.097)
Earning/Share Growth			0.459	0.660
			(0.282)	(0.262)**
Assets/Share Growth				2.488
				(1.908)
Number of Stocks	75	74	72	71
Observations	1425	1406	1187	1169
Panel B: OLS				
Lag Fraction Buy	0.298	0.300	0.297	0.284
	(0.031)***	(0.031)***	(0.033)***	(0.034)***
Lag Returns	0.027	0.015	−0 005	−0.007
	(0.042)	(0.044)	(0.044)	(0.043)
Divident Yield Growth		0.014	0.005	0.003
		(0.022)	(0.031)	(0.031)
Earning/Share Growth			0.084	0.104
			(0.060)	(0.063)*
Assets/Share Growth				0.067
				(0.261)
Number of Stocks	75	75	75	75
Observations	1500	1480	1269	1251
Panel C: LSDV				
Lag Fraction Buy	0.102	0.103	0.101	0.101
	(0.028)***	(0.028)***	(0.028)***	(0.028)***
Las Returns	−0.008	−0.008	−0.010	−0.010
	(0.041)	(0.041)	(0.041)	(0.041)
Divident Yield Growth		−0.011	−0.008	−0.008
		(0.024)	(0.024)	(0.024)
Earning/Share Growth			0.127	0.127
			(0.066)*	(0.066)*
Assets/Share Growth				0.016
				(0.025)
Number of Stocks	75	75	75	75
Observations	1251	1251	1251	1251

Note Standard errors in parentheses, **significant at 5 percent, *** significant at 1 percent.

Table 2.5: Hausman Test

	Fixed Effects	Random Effects	Difference	S.E.
	Panel A: 2003Q1 - 2007Q4			
Lag Fraction Buy	0.153	0.301	-0.147	0.0106
Lag Returns	0.001	0.001	−0.000	.
Dividend Yield Growth	−0.010	−0.008	−0.002	.
Earning/Share Growth	0.013	0.009	0.004	.
Assets/Share Growth	−0.006	−0.007	0.001	0.003
Prob>Chi^2	0.000			
	Panel B: 1999Q1 - 2002Q4			
Lag Fraction Buy	0.228	0.297	−0.068	0.010
Lag Returns	0.068	0.087	−0.019	0.009
Dividend Yield Growth	−0.004	−0.004	0.000	0.000
Earning/Share Growth	0.014	0.020	−0.006	0.003
Assets/Share Growth	0.073	0.083	−0.0010	0.014
Prob>Chi^2	0.000			

Note: Fixed effects yields consistent coefficients while random effects yield efficient coefficients. H0: difference in coefficients is not systematic.

Table 2.6: Hadri (2000) Panel Unit Root Test, 2003Q1 - 2007Q4

eps	Z(mu)	P-value	Z(tau)	P-value
		Fraction Buy		
Homo	9.144	0.0000	6.579	0.0000
Hetero	7.301	0.0000	6.250	0.0000
SerDep [a]	5.912	0.0000	8.600	0.0000
		Log Returns		
Homo	−6.422	1.0000	−6.465	1.0000
Hetero	2.294	0.0109	−4.835	1.0000
SerDep	−2.711	0.9966	3.899	0.0000
		Dividend Yield Growth		
Homo	3.342	0.0004	−3.270	0.9995
Hetero	9.643	0.0000	−3.019	0.9987
SerDep	8.596	0.0000	8.455	0.0000

Note: H0: all 74 time series in the panel are stationary processes. Homo: homoskedastic disturbances across units. Hetero: heteroskedastic disturbances across units. SerDep: controlling for serial dependence in errors (lag trunc = 3)

Table 2.7: Hadri (2000) Panel Unit Root Test, 1999Q1 - 2002Q4

eps	Z(mu)	P-value	Z(tau)	P-value
	Fraction Buy			
Homo	6.304	0.0000	6.095	0.0000
Hetero	6.160	0.0000	2.142	0.0161
SerDep [a]	4.388	0.0000	10.524	0.0000
	Log Returns			
Homo	−0.587	0.7215	0.118	0.4529
Hetero	-0.696	0.7568	−0.283	0.6113
SerDep	1.848	0.0323	10.018	0.0000
	Dividend Yield Growth			
Homo	−4.091	1.0000	−3.747	0.9999
SerDep	0.591	0.2774	9.277	0.0000

Note: H0: all 74 time series in the panel are stationary processes; Homo: homoskedastic disturbances across units; Hetero: heteroskedastic disturbances across units; SerDep: controlling for serial dependence in errors (lag trunc = 3)

Table 2.8: Levin-Lin (2002) Unit-Root Test, 2003Q1 - 2007Q4

	Fraction Buy	Log Returns	Dividend Yield Growth
	−0.838	−1.246	−1.089
	(0.034)**	(0.040)**	(0.041)**
Observations	1425	1425	1406
R-squared	0.30	0.40	0.33

Note: Standard errors in parentheses. ** significant at 5 percent; *** significant at 1 percent.

Table 2.9: Levin-Lin (2002) Unit-Root Test, 1999Q1 - 2002Q4

	Fraction Buy	Log Returns	Dividend Yield Growth
	−0.921	−1.203	−1.198
	(0.041)**	(0.041)**	(0.041)**
Observations	1050	1050	1036
R-squared	0.32	0.45	0.45

Note: Standard errors in parentheses; ** significant at 5 percent; *** significant at 1 percent

Table 2.10: List of Real Estate Stocks

Ticker	Name
ABR	Arbor Realty Trust Inc
ACC	American Campus Communities Inc
ADC	Agree Realty Corp
AEC	Associated Estates Realty Corp
AFR	Afren Plc
AFREX	AssetMark Real Estate Securities Fund
AHR	Anthracite Capital Inc
AHT	Ashford Hospitality Trust Inc
AIV	Apartment Investment and Management Co
AKR	Acadia Realty Trust
ALX	Alexander's Inc
AMB	AMB Property Corp
ANH	Anworth Mortgage Asset Corp
ANL	American Land Lease Inc
ARE	Alexandria Real Estate Equities Inc
AVB	AvalonBay Communities Inc
BDN	Brandywine Realty Trust
BEE	Strategic Hotels and Resorts Inc
BFS	Saul Centers Inc
BMR	BioMed Realty Trust Inc
BRE	BRE Properties Inc
BRT	BRT Realty Trust
BXP	Boston Properties Inc
CBL	CBL and Associates Properties Inc
CDR	Cedar Shopping Centers Inc
CLI	Mack-Cali Realty Corp
CLP	Colonial Properties Trust
CMO	Capstead Mortgage Corp
CPT	Camden Property Trust
CSA	Cogdell Spencer Inc
CSE	CapitalSource Inc
CT	Capital Trust Inc
CUZ	Cousins Properties Inc
DDR	Developers Diversified Realty Corp
DFR	Deerfield Capital Corp
DLR	Digital Realty Trust Inc
DRE	Duke Realty Corp
DRH	DiamondRock Hospitality Co
DX	Dynex Capital Inc
EDR	Education Realty Trust Inc
EGP	EastGroup Properties Inc
ELS	Equity Lifestyle Properties Inc

Source: Spectrum data, available through Thompson Financial Ownership Database.

Table 2.11: List of Real Estate Stocks (Cont'd)

Ticker	Name
EPR	Entertainment Properties Trust
EQR	Equity Residential
EQY	Equity One Inc
ESS	Essex Property Trust Inc
EXR	Extra Space Storage Inc
FBR	Friedman Billings Ramsey Group Inc
FCH	Felcor Lodging Trust Inc
FMP	Feldman Mall Properties Inc
FPO	First Potomac Realty Trust
FR	First Industrial Realty Trust Inc
FRT	Federal Realty Investment Trust
FUR	Winthrop Realty Trust
GCT	GVIC Communications Corp
GGP	General Growth Properties Inc
GRT	Glimcher Realty Trust
GTY	Getty Realty Corp
HCN	Health Care REIT Inc
HCP	HCP Inc
HIW	Highwoods Properties Inc
HME	Home Properties Inc
HPT	Hospitality Properties Trust
HR	Healthcare Realty Trust Inc
HRP	HRPT Properties Trust
HST	Host Hotels and Resorts Inc
IMH	Impac Mortgage Holdings Inc
IRC	Inland Real Estate Corp
JRT	JER Investors Trust Inc
KIM	Kimco Realty Corp
KRC	Kilroy Realty Corp
KRG	Kite Realty Group Trust
LHO	LaSalle Hotel Properties
LRY	Liberty Property Trust
LSE	CapLease Inc
LTC	LTC Properties Inc
LUM	Luminent Mortgage Capital Inc
LXP	Lexington Realty Trust
MAA	Mid-America Apartment Communities Inc
MAC	Macerich Co
MFA	MFA Mortgage Investments Inc
MPG	Maguire Properties Inc
MPW	Medical Properties Trust Inc
NCT	Newcastle Investment Corp

Source: Spectrum data, available through Thompson Financial Ownership Database.

Table 2.12: List of Real Estate Stocks (Cont'd)

Ticker	Name
NHI	National Health Investors Inc
NHP	Nationwide Health Properties Inc
NLY	Annaly Capital Management Inc
NNN	National Retail Properties Inc
NRF	NorthStar Realty Finance Corp
O	Realty Income Corp
OFC	Corporate Office Properties Trust
OHI	Omega Healthcare Investors Inc
OLP	One Liberty Properties Inc
PCH	Potlatch Corp
PCL	Plum Creek Timber Co Inc
PEI	Pennsylvania Real Estate Investment Trust
PGE	Progress Energy Ltd
PKY	Parkway Properties Inc
PLD	ProLogis
PPS	Post Properties Inc
PSA	Public Storage
RAS	RAIT Financial Trust
REG	Regency Centers Corp
RPT	Ramco-Gershenson Properties Trust
RWT	Redwood Trust Inc
RYN	Rayonier Inc
SFI	iStar Financial Inc
SHO	Sunstone Hotel Investors Inc
SKT	Tanger Factory Outlet Centers Inc
SLG	SL Green Realty Corp
SNH	Senior Housing Properties Trust
SPG	Simon Property Group Inc
SSS	Sovran Self Storage Inc
SUI	Sun Communities Inc
TCO	Taubman Centers Inc
TMA	Thornburg Mortgage Inc
UDR	UDR Inc
UHT	Universal Health Realty Income Trust
VNO	Vornado Realty Trust
VTR	Ventas Inc
WRE	Washington Real Estate Investment Trust
WRI	Weingarten Realty Investors
YSI	U-Store-It Trust

Source: Spectrum data, available through Thompson Financial Ownership Database.

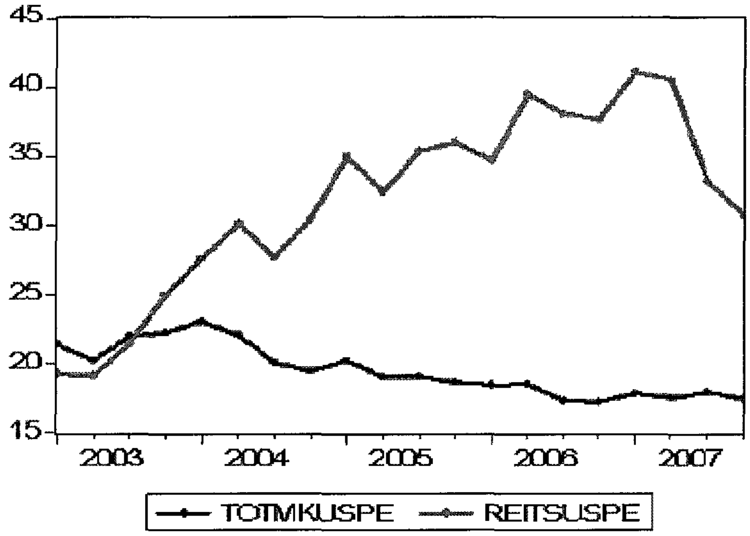


Figure 2.1: PE Ratios of Real Estate Stocks Ralative to S&P500

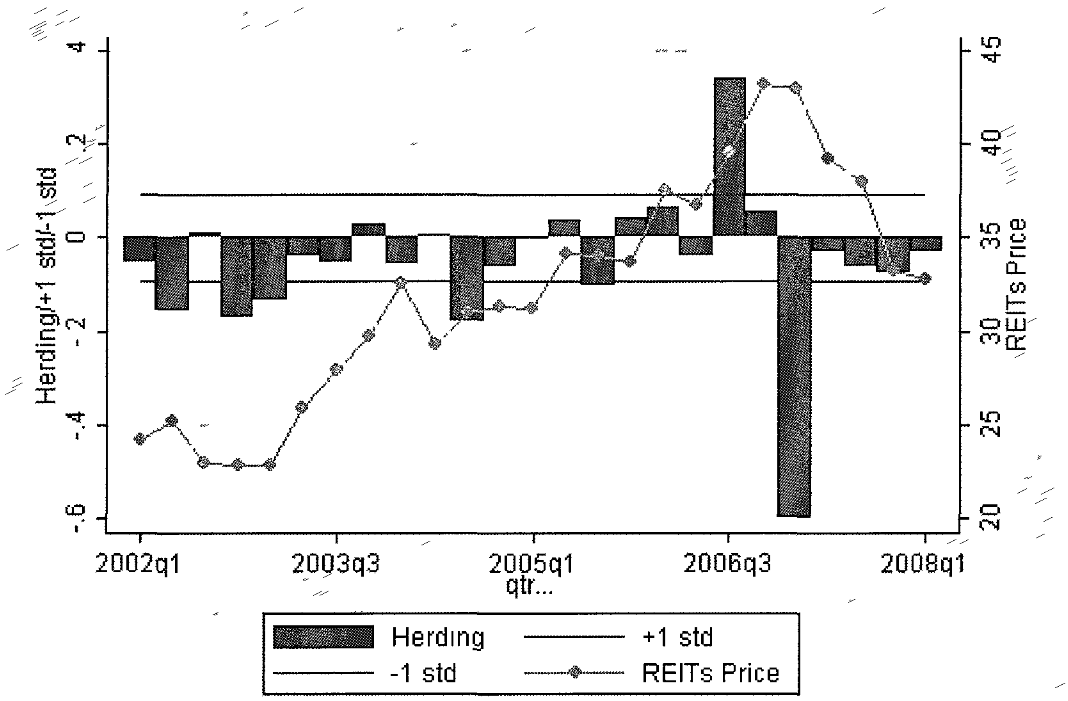


Figure 2.2: Herding and REITs Share Prices

Chapter 3

Stochastic Herding by Institutional Investment Managers

3.1 Introduction

The 2007 collapse of the U.S. asset bubble has provided researchers with the opportunity to look afresh into the causes of financial instability and crises, including the role played by herding behavior. One of the lesser known chapters in the unravellings of the 2007-2008 crisis has been a substantial sell-off of equities by institutional investors a few quarters before the general market downturn that began in earnest in the summer of 2007. Institutional investors manage between 60 and 70 percent of outstanding U.S. stocks and are regarded as sophisticated investors whose rising importance in capital markets has been extensively documented by Gompers and Metrick (2001) among others. As Figure 3.1 shows, managers of pension and endowments funds (who account for 48 percent of total market value of S&P 500 stocks or approximately 80 percent of total institutional holdings) began dumping S&P 500 stocks during 2006:Q2 and within four quarters virtually reverted their equity exposure to the pre-2003 level. Forced liquidation cannot explain such marked reduction in institutional stock ownership since at the time major risk indicators were still low and credit markets were not yet under stress[1]. Herding. on the other hand, can provide an alternative explanation. This is because in addition to funding risks institutional investment managers face what Abreu and Brunnermeier (2002. 2003) call "synchronization risk" – the risk of selling an overvalued stock too early. before a critical mass of other investors sells. or too late. after a critical mass of other investors sells. Missing the timing of the price correction in either case would lead to losses and underperformance relative to other managers in the short-run. Such incentive to synchronize with other investment managers due to short time horizons and relative performance considerations (Shleifer and Vishny (1997)) can lead to herd behavior.

We consider a model of large number of institutional investment managers who simultaneously decide whether to remain invested in an assets or liquidate their positions. The managers are rational but myopic. This feature is particularly suitable for modeling fund manager behavior whose performance is often evaluated on short-term basis and relative to other managers [2] The prospect of earning excess

[1] See Brunnermeier (2009) for the timing of the 2007-2008 liquidity and credit crunch

[2] Our model is intended to explain fund manager choice of action at quarterly frequency so implicitly we assume that each manager optimizes with one quarter ahead horizon Another class of investors whose behavior we do not model include individual investors and managers of funds with

returns by riding the trend for an additional time period is weighed against the possibility that a large enough number of fund managers will dump the stock today overwhelming the market liquidity and forcing the price to drop, resulting in losses for those who remain. Each fund manager receives imperfect information about the market's ability to supply liquidity. In Bayesian Nash equilibrium each manager chooses whether or not to continue holding the security based on her private information and the actions of other investment managers[3]. The equilibrium strategy of investment managers exhibits complementarity, since each fund manager is more likely to liquidate when a greater number of others are liquidating. Herding in this environment is stochastic because it turns out that in equilibrium each manager assigns greater weight to the actions of others than her own private information only with a certain probability. In the aggregate, the model predicts a non-trivial probability of "explosive" incidents of uniform coordination on the same action.

Whereas the central limit theorem characterizes an outcome of a simple information aggregation process, choice correlations (e.g. herding) leads to fat tail effects. In particular, the equilibrium fraction of investment managers that herd on the same action is described by a probability distribution that exhibits exponential

substantial restrictions on customer redemptions, access to a wider variety of investment instruments, and subject to less stringent regulations. These investors operate at a different performance horizon and have served as liquidity providers during such episodes as the 1987 stock market crash (Fung and Hsieh (2000)) to the more constrained institutional investors such as pension funds, endowment funds, and insurance companies that we focus on in this study.

[3]The reliance on the actions of others for information rather than making decision based on prices alone implies that not all interactions between agents are mediated through the market and that these interactions are not anonymous, Cowan and Jonard (2003). For instance, Shiller and Pound (1989) find that word-of-mouth communications are important for the trading decisions of both individuals and institutional investors.

decay. This probability distribution can be observed even before the "explosive" sell-out takes place potentially allowing us to quantify what Rajan (2006) has dubbed the "hidden tail risk."[4]

We examine quarterly data from 13F filings with the Securities and Exchange Commission (SEC) in which institutional investment managers report the number of shares under management for each individual security. We find that the distribution of the number of institutional investment managers selling off their shares several quarters before the peak of the S&P 500 index in 2007 is consistent with herding. The parameter capturing the degree of herding behavior rises over time until the first quarter of major institutional sell-off of S&P 500 stocks. The transition to the sell-off itself is consistent with self-organized criticality following Bak et al. (1997). As the exponential decay vanishes in the probability distribution of institutional trades we obtain a (pure) power law distribution. Once that happens, an explosive synchronization occurs sooner or later. Then, through the information revealed by the actions of others, it becomes common knowledge among traders that the bubble has burst. Accordingly, all traders choose sell. However, liquidation needs and other considerations at the fund level imply that traders' behavior may vary due to idiosyncratic reasons. Thus, we only observe an aggregate of idiosyncratic variations in behavior, which leads to a normal distribution due to the Central Limit Theorem. The symmetric behavior is not found on the buy side

[4]Morris and Shin (1999) also argue that choice interdependence among traders must be explicitly incorporated into estimates of "value at risk" and call for greater attention to game-theoretic issues since market outcomes depend on the actions of market participants.

in line with investors reacting differently to potential losses than to potential gains.

The paper is organized as follows. Section 3.2 presents the model of stochastic herding, derives the equilibrium distribution of herding agents, and conducts numerical simulations of the model. Section 3.3 examines the distribution of the actions by institutional investment managers from 2003:Q1 through 2008:Q1 covering both the run-up to and the collapse of the most recent U.S. equity bubble. In this section we compare the empirical distribution to the numerical simulations, evaluate the fit of the distribution implied by the model of stochastic herding against several alternatives, and overview the evolution of this behavior over time. Section 3.4 concludes.

3.2 Model

3.2.1 Threshold Switching Strategy

In this section, we present a model of stochastic herding of informed traders. Our model setup is motivated by Abreu and Brunnermeier (2003) in which traders try to time their exit from a bubble maket. In this setup, we apply an analytical tool shown by Nirei (2006*b*) in order to obtain the distributional pattern of traders' herding. This distributional form then motivates our empirical investigation in the next section on the distributions of the herd size of institutional traders before and during the sell-out period.

There are N informed institutional investment managers indexed by $i =$

$1, 2, \ldots, N$, for conciseness we will refer to them simply as traders. Each trader is endowed with one unit of risky asset. The trader gains $(g-r)p$ by riding on bubbles and loses βp if the bubble bursts. Trader i can either sell ($a_i = 1$) or remain in the same position ($a_i = 0$). Each trader observes the aggregate number of selling traders $a \equiv \sum_{i=1}^{N} a_i$ and a private signal x_i. Let α denote the fraction of selling traders $\alpha = a/N$.

Market liquidity is denoted by θ. [5] The informed traders cannot observe θ, but only observe a noise-ridden proxy $x_i = \theta + \epsilon_i$. x_i is a private information and ϵ_i is independent across traders.

The bubble bursts if the selling pressure by the informed traders overwhelms the liquidity provided by the noise traders. The burst occurs if $\alpha > \theta$. Informed traders' expected utility of holding the asset is:

$$(g-r)p \Pr(\theta \geq \alpha \mid x_i, a, a_i = 0) - \beta p \Pr(\theta < \alpha \mid x_i, a, a_i = 0), \tag{3.1}$$

and the expected utility of selling is 0. Then the optimal strategy is to sell if:

$$\frac{g-r}{\beta} < \frac{\Pr(\theta < \alpha \mid x_i, a, a_i = 0)}{\Pr(\theta \geq \alpha \mid x_i, a, a_i = 0)}, \tag{3.2}$$

[5] θ represent the liquidity provided by market participants other than institutional investors, such as individual investors or alternative investors (e.g. hedge funds) with lock up periods and greater choices of investment instruments thus not subject to short-term performance considerations. We do not model their behavior, hence refer to this group simply as noise traders.

or, equivalently,

$$\frac{g-r}{\beta} < \frac{\Pr(x_i, a, a_i = 0, \theta < \alpha)}{\Pr(x_i, a, a_i = 0, \theta \geq \alpha)}, \tag{3.3}$$

and hold otherwise.

3.2.2 Equilibrium

We make a guess that all traders follow a threshold rule that trader i sells if $x_i \leq \bar{x}(\alpha)$ and holds otherwise. We will verify this guess later. We consider a Nash equilibrium in which each trader does not have an incentive to deviate from the threshold rule at any observation (x_i, α), given that all the other traders obey the rule. When there are multiple equilibria for a realization of the private information (x_i). the outcome with the smallest a is selected. We denote the selected equilibrium by a^*. This equilibrium can be implemented by submission of supply schedule to a market maker. In this scheme, each trader submits their action of selling or holding conditional on α, and the market maker selects the smallest α such that it is equal to the aggregate supply conditional on α. The equilibrium can be interpreted as the outcome of a sequential trading where informed traders can sell immediately after observing the selling of other traders.

Define:

$$G(\bar{x}, a) = \Pr(x_j > \bar{x}(a) \mid \theta < a/N) \tag{3.4}$$

$$F(\bar{x}, a) = \Pr(x_j > \bar{x}(a) \mid \theta \geq a/N) \tag{3.5}$$

$$A(\bar{x}, a) = G(\bar{x}, a)/F(\bar{x}, a) \tag{3.6}$$

$$\delta(x_i, a) = \Pr(x_i, \theta < \alpha)/\Pr(x_i, \theta \geq \alpha) \tag{3.7}$$

$A(\bar{x}, a)$ represents the information revealed by a holding trader at the observed supply a. The information is expressed in the form of an odds ratio. $\delta(x_i, a)$ is the odds ratio obtained by the private information x_i.

Under the guessed threshold policy. the joint probability in (3.2) can be decomposed by the information revealed by the actions of traders. For example. when $a = 0$, the joint probability is written as:

$$\Pr(x_i, a = 0, a_i = 0, \theta < 0) = \Pr(x_i \mid \theta < 0) \Pr(x_j > \bar{x}(0) \mid \theta < 0)^{N-1} \Pr(\theta < 0) \tag{3.8}$$

Then, (3.3) is rewritten for $a = 0$ as:

$$\frac{g - r}{\beta} < A(\bar{x}(0), 0)^{N-1} \delta(x_i, 0) \tag{3.9}$$

Thus. $\bar{x}(0)$ is implicitly determined by:

$$\frac{g - r}{\beta} = A(\bar{x}(0), 0)^{N-1}\delta(\bar{x}(0), 0) \tag{3.10}$$

Now consider the case $a > 0$. If $a > 0$ were chosen to be an equilibrium. it reveals that no smaller supply $a' = 0, 1, \ldots, a-1$ is consistent with the supply schedule. since the market maker chooses the smallest a that is consistent with the supply schedule. Thus, the equilibrium reveals not only that there are a traders who sell conditional on a, but also that there are at least $a' + 1$ traders who sell at a' for each $a' < a$.

Therefore, there are a traders with private information $x_i < \bar{x}(a)$. there are at least a traders with private information $x_i < \bar{x}(a-1)$. there are at least $a - 1$ traders with $x_i < \bar{x}(a-2)$. and so forth up to that there is at least 1 trader with $x_i < \bar{x}(0)$. This set of conditions is equivalent to that there is one trader in each region $x_i < \bar{x}(a')$ for all $a' = 0, 1, \ldots, a-1$.

Consider the trader who would hold at $a' - 1$ but sell at a'. Define the information revealed by such a trader at equilibrium a as follows:

$$B(\bar{x}(a'), a) = \frac{\Pr(x_j \leq \bar{x}(a') \mid \theta < a/N)}{\Pr(x_j \leq \bar{x}(a') \mid \theta \geq a/N)} \tag{3.11}$$

Then. the selling condition (3.3) is rewritten for $a = 1$ as:

$$\frac{g-r}{\beta} < \delta(x_i, 1) A(\bar{x}(1), 1)^{N-2} B(\bar{x}(0), 1). \tag{3.12}$$

Then. $\bar{x}(1)$ is determined by $x_i = \bar{x}(1)$ that equates the both sides above. Generally. the threshold $\bar{x}$ is determined recursively by the equation:

$$\frac{g-r}{\beta} = \delta(\bar{x}(a), a) A(\bar{x}(a), a)^{N-1-a} \prod_{k=0}^{a-1} B(\bar{x}(k), a) \tag{3.13}$$

for $a = 0, 1, 2, \ldots, N-1$. We note that the posterior likelihood in (3.3) has three components: the private information x_i. the information revealed by holding actions of $N - 1 - a$ traders, and the information revealed by selling actions of a traders.

We assume that the prior belief on θ and the noise ϵ_i jointly follow a bivariate normal distribution with mean $(\theta_0, 0)$ and variance (σ_0^2, σ_e^2). Then (θ, x_i) also follows a bivariate normal distribution, since $x_i = \theta + \epsilon_i$. The normal distribution implies that:

$$\Pr(x_j > \bar{x} \mid \theta) < \Pr(x_j > \bar{x} \mid \theta'), \quad \text{for any } \theta < \theta' \tag{3.14}$$

Thus,

$$A(\bar{x}, a) = \frac{\Pr(x_j > \bar{x} \mid \theta < a/N)}{\Pr(x_j > \bar{x} \mid \theta \geq a/N)} < 1 \tag{3.15}$$

for any a and $\bar{x}$. Likewise.

$$B(\bar{x}, a) = \frac{\Pr(x_j \leq \bar{x} \mid \theta < a/N)}{\Pr(x_j \leq \bar{x} \mid \theta \geq a/N)} > 1. \tag{3.16}$$

The threshold policy has the following property.

Proposition 1. *The threshold function $\bar{x}(a)$ is increasing in a.*

Proof: See Appendix B.1.

Using the increasing threshold strategy, we obtain the existence of an equilibrium. To see that, define an aggregate response function as $\Gamma : \{0, 1, \ldots, N\} \mapsto \{0, 1, \ldots, N\}$ for a fixed realization of (x_i). Γ maps the observed a to the number of traders who decide to sell upon the observation a', given (x_i). Then, a' is the number of traders with $x_i < \bar{x}(a)$. Since $\bar{x}$ is increasing in a. Γ is a non-decreasing step function. Hence Γ has a fixed point in $\{0, 1, \ldots, N\}$ by Tarski's fixed point theorem.

Proposition 2. *An equilibrium a^* exists for each realization of a vector (x_i).*

Proof: See Appendix B.2.

Next. we construct a fictitios tatonnement process that converges to the equilibrium a^* as a means to characterize the equilibrium. First, we define $-H'/H$ as the hazard rate for the traders who have remained holding the asset to sell upon observing a. Let θ_1 denote the true parameter for the liquidity θ. Then $H(\bar{x}) = \int_{\bar{x}} e^{-\frac{(x_j - \theta_1)^2}{2\sigma_e^2}} dx_j / \sqrt{2\pi}\sigma_e$. We define $\mu(a)$ as the mean number of traders who do not sell upon observing $a-1$ but decide to sell upon observing a. Then:

$$\mu(a) = (H(\bar{x}(a-1)) - H(\bar{x}(a)))(N-a). \tag{3.17}$$

$\mu(a)$ is also expressed by the product of the increment in the threshold $\bar{x}(a+1)-\bar{x}(a)$, the hazard rate. and the number of traders who continue to hold the asset:

$$\mu(a) \sim \frac{H'}{H}(\bar{x}(a+1) - \bar{x}(a))(N-a) \to \frac{H'/H}{F_1/F} \frac{\log(B/A) + (\partial A/\partial \alpha)/A}{(G_1/F_1)/A - 1} \tag{3.18}$$

Now. as a fictitious tatonnement process, we consider a best response dynamics $a_{u+1} = \Gamma(a_u)$ that starts from $a_0 = 0$, where a_{u+1} denotes the number of traders with private information $x_i < \bar{x}(a_u)$. We can show that the best response dynamics can be regarded as a tatonnement which converges to the selected equilibrium a^*.

Proposition 3. *For any realization of θ and (x_i), the best response dynamics a_u converges to the equilibrium selected by the market maker, a^*.*

Proof. Suppose that the best response dynamics did not stop at a^*. Then there exists a step s so that $a_s < a^* < a_{s+1}$. But, the definition of a^* prohibits that there is any $a' < a^*$ such that the number of traders with $x_i < \bar{x}(a')$ exceeds a^*. Hence. there is no such s. ■

Unconditional on the realization of the private information, (a_u) can be regarded as a stochastic process. In the first step. a_1 follows a binomial distribution with population N and probability $\bar{x}(0)$. In the subsequent steps. the increment $a_{u+1} - a_u$ conditional on a_u follows a binomial distribution with population $N - a_u$ and probability $H(\bar{x}(a_{u-1})) - H(\bar{x}(a_u))$.

As $N \to \infty$. the binomial distribution asymptotically follows a Poisson distribution with mean $(N - a_u)(H(\bar{x}(a_{u-1})) - H(\bar{x}(a_u)))$. Now consider a special case where $\mu(a)$ defined in (3.17) is constant across a asymptotically as $N \to \infty$. Then. the asymptotic mean of the Poisson distribution above becomes $(a_u - a_{u-1})\mu$. A Poisson distribution with this mean is equivalent to $(a_u - a_{u-1})$-times convolution of a Poisson distribution with mean μ. Thus. in this particular case. the best response dynamics asymptotically follows a branching process with a Poisson distribution with mean μ. which is a population process that starts with the "founder" population with a_1 and each "parent" bears "children" whose number follow the Poisson with mean μ. The selected equilibrium a^* is the cumulated sum of the branching process. The following is known for the distribution function of the cumulated sum of a branching process.

Theorem 1. *Consider a branching process b_u, $u = 1, 2, \ldots$, in which the number of children born by a parent is a random variable with mean μ.*

1. *When $b_1 = 1$, the cumulated sum $Z = \sum_{u=1}^{\infty} b_u$ follows:*

$$\Pr(Z = z \mid b_1 = 1) \sim c^{-z} z^{-1.5} \tag{3.19}$$

for a constant $c \geq 1$ with the equality holding if and only if $\mu = 1$. The symbol "$\sim$"

means that the ratio of the both sides converges to a constant as $z \to \infty$.

2. *The branching process converges to zero with probability one if and only if* $\mu \leq 1$.

3. *If the number of children born by a parent follows a Poisson distribution with mean* μ, *then:*

$$\Pr(Z = z \mid b_1) = (b_1/z)e^{-\mu z}(\mu z)^{z-b_1}/(z-b_1)! \tag{3.20}$$

for $z = b_1, b_1 + 1, \ldots$.

4. *In addition to the previous assumption, if* b_1 *follows a Poisson distribution with mean* μ_1, *then:*

$$\Pr(Z = z) = \mu_1 e^{-(\mu z + \mu_1)}(\mu z + \mu_1)^{z-1}/z! \tag{3.21}$$

$$\sim (\mu e^{1-\mu})^z z^{-1.5} \tag{3.22}$$

The first item in this theorem implies that the number of traders in a herd follows a non-normal distribution function which exhibits a power-law decay with exponential truncation. The second item means that the best response dynamics converges with probability one, and thus it verifies that the best response dynamics serves as a valid fictitious tatonnement. The third and fourth terms further characterize the herd size distribution. This particular distribution forms our preferred hypothesis in the empirical investigation of the herd size distribution in the next section.

3.2.3 Numerical Simulations

Before we move on to our empirical investigation, we numerically compute the model threshold $\bar{x}(a)$ and the equilibrium α^*. The purpose of this simulatation is to show that the herd size distribution of the exact equilibrium α^* follows the same distribution as that we obtained above analytically under approximation. We set the parameter values as follows. The number of institutional investors is $N = 160$. The return from riding the bubble is $g = 0.1$, the interest rate is $r = 0.04$, and the discount by the burst of the bubble is $\beta = 0.82$. The liquidity θ follows a normal distribution with mean 0.5 and standard deviation 0.3. The noise ϵ_i follows a normal distribution with zero mean and standard deviation 1.

Figure 3.2 [about here]

Figure 3.2 plots the threshold function $\bar{x}(a)$ and the conditional mean function $\mu(a)$. The plot is truncated at the point $a = 140$, since for higher a we could not compute $\bar{x}$ because it is too large.

Figure 3.3 [about here]

We then simulate the distribution of equilibrium a. We compute a for each draw of a random vector (ϵ_i), and iterate this for 100000 times. We observe $a = 0$ for 72908 times, and observe $a = 140$ (the upper bound) for 1215 times. Figure 3.3 plots the histogram of the all 100000 observations. In Figure 3.3, it is clear that a is distributed similarly to an exponential distribution for $0 < a < 50$. There is no incident of $a > 50$ except for the 691 "explosive" incidents in which case basically all the traders decide to sell.

Figure 3.4 [about here]

Figure 3.4 plots the blowups of the histogram for $0 < a < 160$. The left panel plots the histogram in linear scale and the right panel plots it in semi-log scale. The distribution exhibits exponential tail and forms a straight line on semi-log scale characteristic of non-Gaussian decay and a heavy tail. This is due to the persistent outliers due to the non-randomness in the underlying data generating process. The shape of the probability density function of the equilibrium distribution of a d is illustrated in Figure 3.9 in the Appendix. It is closely related to a Gamma distribution, but with the shape parameter restricted to actual the value of the variable, thus effectively attenuating the tail beyond a "typical" Gamma.

3.3 Evidence from Institutional Equity Holdings

3.3.1 Data Description and the Unit of Observation

We study the behavior of institutional investment managers around the latest run-up and the subsequent collapse of the U.S.stock market associated with the asset bubble of the 2000s. Specifically, we examine institutional investor holdings of stocks included in the S&P 500 index during the period from 2003:Q1 through 2008:Q1. As has been discussed in the introduction, institutional investors increased their equity holdings markedly between 2003:Q1 and 2006:Q1 after which point the majority of them, especially pension and endowment funds, began reducing their stock portfolios to the pre 2003 levels. This episode provides a unique opportunity to examine the role played by herding in the propagation of such massive adjustment. Herding behavior is especially suspect because this marked adjustment in institutional portfolios preceded the onset of the credit crisis and cannot be attributed to forced liquidations.

We use data on institutional equity holdings from Spectrum database available through Thompson Financial[6]. Thus, we utilize two sources of variation in stock holdings not commonly found in data: the variation across individual investors and the variation across a group of closely related securities. This means that instead of observing one realization of the aggregate action during each period one can observe a sample of data points large enough to get an insight into the underlying data generating mechanism by looking at its distribution. Each observation in the sample is a group of institutional investors that fall within same class (e.g. banks, pension funds, etc.) holding the same stock. The data is complied from quarterly 13F filings with SEC in which institutional investment managers with over $100 million under discretionary management are required to report their long positions in exchange traded stocks, closed-end investment companies, equity options and warrants.

Table 3.1 [about here]

[6]Studies that utilize 13F data include Gompers and Metrick (2001), Brunnermeier and Nagel (2004), Sias (2004), and Hardouvelis and Stamatiou (2009)

Table 3.1 shows the breakdown of institutional investment managers in our sample by type for each quarter from 2003:Q1 through 2008:Q1. Pension and endowment funds comprise the largest reporting category ranging between 71% and 80% of all instutional investment managers. Investment advisers comprise the second largest categoy followed by investment companies, insurance companies, and banks. For instance, in 2008:Q1 the dataset includes 2,119 pension and endowmnets funds, 521 investment advisers, 96 investment companies, 19 insurance companies, and 9 banks.

Table 3.2 [about here]

As Table 3.2 illustrates, institutional investors hold the majority of outstanding U.S. equities, as proxied by the S&P 500 stocks. The share of institutional holdings rose from 53% in 2003:Q1 to 67% in 2006:Q1 then declined steadily through 2008:Q1. Pension and endowment funds are the most dominant category accountring for more than four fifth of total institutional holdings of S&P 500 stocks.

Table 3.3 [about here]

The high degree of disaggregation in the Spectrum data allows us to group institutional investment managers into stock-investor-type groups, $N(j,k)$, where j indicates an S&P500 stock and k indicates institutional investor type. For example, N(APPL, Banks and Trusts) is the number of banks and trusts that own Apple stock. Only groups with 10 traders or more are included in the sample. Table

3.3 shows the summary statistics. The number of quarterly observations for $N(j,k)$ ranges from 1,535 to 1,882. The size of the groups varies considerably, with quarterly mean ranging from 114 to 146, and quarterly maximum ranging from 1,046 and 1,222. Each quarter $a(j,k)$ out of $N(j,k)$ institutions in each group liquidate their holdings. Institutional managers dumping more than 80% of their holdings are counted into $a(j,k)$[7] but the results are generally robust to different cutoff levels.

3.3.2 Summary Statistics

Table 3.4 shows quarterly summary statistics for $a(j,k)$. Note the stark difference between 2006:Q2 through 2007:Q1 and the surrounding quarters. During 2006:Q2 through 2007:Q1 the mean $a(j,k)$ is between 104 and 117 compared to 2 and 4 in other quarters and the maximum during this four quarter period ranges from 1057 to 1114 compared to 23 and 347 during other quarters. The corresponding *fraction* of institutions liquidating a stock, $a(j,k)/N(j,k)$, controls for any group size effect in the values of $a(j,k)$. Table 3.5 shows the summary statistics for $a(j,k)/N(j,k)$ confirming that during the period of 2006:Q2 through 2007:Q1 is associated with large a large liquidation of stocks by institutional investment managers. The mean fraction of institutional managers liquidating a stock jumped to the 79% and 89% range from the earlier range of 3% to 4%. Moreoever, during this four quarter

[7]The model of stochastic herding yields prediction regarding an "extreme" event, namely a complete liquidation of a position in a security. Realistically, large block holders, such as institutional investors, are restricted in their ability to unload a substantial number of shares at once, therefore we interpret the sale of 80% or greater share as an extreme event. The results are robust to different levels of cutoff, however, choosing the cutoff at 100% as stipulated by the model greatly reduces the number of observations while missing valuable information contained in extremely large sales approaching 100%.

period some stock-investor type groups experienced complete liquidation as seen from the maximum $\alpha(j, k)$'s of 100%. In sum, the summary statistics of $a(j, k)$ and $a(j, k)/N(j, k)$ in Tables 3.4 and 3.5 illustrate a regime change in institutional equity holdings during 2006:Q2 through 2007:Q1 when the vast majority were dumping their S&P 500 stocks. We refer to this period as the sell-out phase.

Table 3.4 & Table 3.5 [about here]

Focusing on the two quarters immediately preceding the sell-out phase. the summary statistics of $a(j, k)$ and $a(j, k)/N(j, k)$ show a rise in both mean and maximum values compared to previous quarters indicating a possible shift in institutional investment managers' behavior beginning to take place. The mean of $a(j, k)$ increased to 4 during 2005:4 and 2006:Q1 compared to 2 to 3 during all preceding quarters (Table 3.4) and the maximum $a(j, k)$ is 105. more than double the value during the four preceding quarters. The corresponding fraction. $\alpha(j, k)$, also rose during 2005:Q4 and 2006:Q1 compared to the preceding quarters (Table 3.5). This increase in the average and in the tail of the distribution of aggregate selling behavior may indicate greater degree of synchronization immediately before the regime change in 2006:Q2. In the remainder of the section we conduct distributional analysis motivated by the model of stochastic herding to examine whether the attenuation in the distribution of $a(j, k)$ during the run-up to the sell-out phase is a result of greater choice correlations and herding by institutional investment managers as opposed to being driven by random events.

3.3.3 Analysis of distribution

The left panel of Figure 3.5 shows the histogram empirical $a(j,k)$ for the entire sample period (2003:Q1 through 2008:Q1). The histogram bears close similarity to the numerical simulations of the model in Figure 3.3. Like the simulated a. the distribution of empirical $a(j,k)$ exhibits exponential decay in the high probability mass region of low number of sellers along with a long tail indicating high probability of large outliers. The mean number of institutional fund managers dumping a particular stock is 23. while standard deviation is 79 and the maximum is 1114.

Figure 3.5 [about here]

To control for rare events on the "buy side" we also examine a symmetric indicator to $a(j,k)$ for fund managers who increase their holdings of an S&P 500 stock by more than 5 times (inverse of 0.80) during a given quarter. $b(j,k)$. For each stock-investor-type group we then construct the net measure as $a(j,k)-b(j,k)$ and normalize it by group size $N(j,k)$. The right panel of Figure 3.5 shows the histogram of the corresponding fraction. The bimodality of the distribution indicates the presence of "explosive" sellout events, with virtually no observations in the intermediate range. Moreover, such extreme switching from low activity to high activity level is only present on the sell side, indicating that coordination on the same action characterizes sellouts but not purchases by institutional fund managers.

Independent rare events, such as portfolio liquidations due to idiosyncratic shocks, should be well approximated by a Poisson distribution. On the other hand.

chain reaction through information revelation will cause $a(j,k)$ to be distributed according to Equation 3.22 (*Theorem 1*). Recall that in Equation 3.22, μ_1 represents the Poisson mean of the number of agents taking extreme action at the beginning of the tatonnement process independently (responding only to their private signal), while μ represents the total number of agents induced to follow the actions of the first-mover until the system settles at a new Bayesian Nash equilibrium. In other words, μ quantifies the degree of herding. If $\mu = 0$ then Equation 3.22 reduces to a probability density function of a Poisson distribution with arrival rate μ_1 indicating the absence of herding (portfolio liquidations are independent of each other). On the other hand, as $\mu \to 1$ the system tends to self organized criticality with "explosive" convergence on the same action. In the intermediate range, the probability distribution of $a(j,k)$ will exhibit exponential decay, with the speed of the decay dictated by μ. We can also think of μ as a measure of length of the tail of the distribution – larger μ implies that an initial outliers (itself governed by Poisson arrival rate μ_1) attracts greater probability mass to itself, effectively attenuating the tail.

Table 3.6 through Table 3.8 [about here]

The common benchmark distribution for rare independent events is Poisson. Table 3.6 shows the results of Kolmogorov-Smirnov goodness of fit test for Poisson distribution to $a(j,k)$. Poisson distribution is rejected at the 5% significance level with p-value=0 and the test statistic of 0.769 (three orders of magnitude larger than the critical value of 0.008). Apart from non-randomness, Poisson may also be rejected because the distribution of a discrete random variable with Poisson arrival rate asymptotes to normal in the limit. However, as Table 3.7 shows, the moments of $a(j,k)$ point at a highly non-normal distribution (consistent with the histograms in Figure 3.5). If non-randomness results from stochastic herding then Equation 3.22 should adequately characterize the probability distribution of emprical $a(j,k)$. Table 3.8 shows the associated maximum likelihood estimates (MLE) of the distribution parameters. The estimates for μ_1 and μ are 2.058 and 0.938 and are statistically significant at 1% level, indicating that stochastic herding is a plausible candidate for the underlying data generating metchanism of empirical $a(j,k)$.

Figure 3.6 [about here]

Figure 3.6 focuses on the four quarter period before the sell-out phase (2005:Q2 through 2006:Q1). The left panel of Figure 3.6 shows the histogram of empirical $a(j,k)$ with distribution exhibiting exponential tail similar to the simulation in Figure 3.4. The largest value in the histogram corresponds to 95. The right panel of Figure 3.6 shows the corresponding semi-log probability plot. The straight line formed by the observations of $a(j,k)$ on the semi-log scale indicates a non-Gaussian heavy tailed distribution with persistent outliers, indicative of non-randomness in the underlying data generating process. The solid line shows the fit corresponding to the stochastic herding outcome (of Equation 3.22) to the empirical distribution of $a(j,k)$. The line was formed by sampling the data from the proportional theoretical probability density (Equation 3.22) with parameters first estimating using empirical $a(j,k)$ via MLE and the proportionality constant set equal to the theoretical prediction for the power exponent of 1.5.

3.3.4 The Sell-Out Phase in 2006:Q2-2007:Q1

Figure 3.7 plots $a(j,k)/N(j,k)$ against the cumulative distribution (log rank over number of observations). The left panel corresponds to the 2005:Q2 through 2006:Q1 period, the four quarters preceding major institutional sales. The inverse of the slope of the semi-log plot provides an estimate of the mean parameter of an exponential distribution. A least squares regression for $a(j,k)/N(j,k)$ yields an estimate of the slope of -31.443 (standard error 0.055) with an R-squared 0.988. This examination of the semi-log plots favors a model that generates exponential rather than normal decay in $a(j,k)/N(j,k)$ during the final phase in the run-up to the shift in institutional behavior in 2006:Q2.

Figure 3.7 [about here]

The probability plot in the left panel also shows a convex deviation from the exponential tail as the size of observations approaches zero. This is consistent with a Gamma-type distribution, such as the distribution in Borel-Tanner family, which exhibits an exponential tail with a power decline near zero. Moreover, notice a small number of observations that lie very far from the probability mass. A Gamma-type distribution would produce such outliers because for small values of the shape parameter all observations drawn from a Gamma distribution will have the same expectation of the order $1/N$, but there is high probability that at least one observation will be much greater than the average (Kingman (1993)).

The intuition behind semi-log plots is as follows. Suppose the average perception of the value of fundamentals is strong and the mean fraction of institutional investment managers liquidating a particular stock is small. In the absence of selling cascades within some stock-investor-type groups the probability of observing a given value of $a(j,k)/N(j,k)$ would be declining at an increasing rate as we move further away from the mean. This Gaussian decay would produce a concave line in the semi-log plot. On the other hand, suppose investors are attempting to time the market by basing their actions on the actions of others. For example, within stock investor-type group a fund manager having observed a small fraction of other fund managers liquidating their holdings in a particular stock interprets this as the beginning of a "correction" and is induced to sell herself. If the conditions are so fragile that even in the absence of major changes in the fundamentals a number of investors are inclined to act as this hypothetical fund manager, then we would observe selling cascades within some stock-investor-type groups, creating outliers. Hence, if investment managers are locked in a herding regime then, even though the mean of the aggregate liquidation may still be low, the probability of observing large deviations from the mean will be higher than predicted by Gaussian decay that characterizes random deviations.

The right panel shows the semi-log probability plots of $a(j,k)/N(j,k))$ for 2006:Q2 through 2007:Q1. Consistent with transition from subcritical ($\mu < 1$) to supercritical phase ($\mu > 1$), this four quarter period is characterized by a state of "explosive" sell-outs. When the system is supercritical, there is a positive probability in which all the traders sell (explosion). Thus our model predicts a probability mass for fraction $a(j,k)/N(j,k) = 1$. If we allow for other randomness not considered in our model, then it is natural to think that the actual fraction is normally distributed around the mean close to 1.

The probability mass of $a(j,k)/N(j,k)$ is concentrated in the region between 0.8 and 1.0, indicating that the vast majority of institutional investors where dumping most of their S&P 500 stock. The relatively close fit of the normal distribution indicates that aggregate high mean value of $a(j,k)/N(j,k))$ is an informative summary statistic for the sell-out regime in the sense that the deviations from this high mean are random and the vast majority of institutions were liquidating their S&P 500 stocks during this period.

In sum, Figure 3.7 conveys two things. First, the sell-out ensued as early as 2006:Q2 and continued for approximately 4 quarters. Second, institutional investors in the stock market operated according to two different regimes during the duration of the bubble. During the run-up phase, the distribution of the aggregate action exhibits exponential decay, consistent with stochastic herding when the uncertainty over market timing actions of other institutional investment managers dominates. The exponential decay then vanishes during the sell-out phase. Such regime switching is consistent with transition from subcritical ($\mu < 1$) to supercritical phase ($\mu > 1$) with positive probability that all institutions act in unison (see

Theorem 1).

Our hypothesis is that the process that generated empirical $a(j,k)$ shown in Figure 3.6 is best described probability density in Equation 3.22. We fit the model implied distribution against three alternatives: a truncated normal. Gamma. and Exponential. Table 3.9 shows the results.

Figure 3.6 & Table 3.9 [about here]

The log likelihood values are higher for the model than any of the alternative distributions while truncated normal. which tests the possibility of Gaussian decay, has the smallest log likelihood value. In addition we conduct a non-nested goodness of fit test using Vuong's statistic. It is based on Kullback-Leibler information criterion which tests if the hypothesized models are equally close to the true model against the alternative that one is closer. Defining $l_i = logL(i; H_1) - logL(i; H_0)$ as the log likelihood ratio for each observation i, Vuong's statistic, $V \equiv (L_1 - L_0)/(\sqrt{N}Std(l_i))$, follows a standard normal distribution if the hypothesis H_0 and H_1 are equivalent. If $V > 1.96$ then H_0 of normal distribution is rejected in favor of H_1 of the model under 5% significance level. The Vuong statistics for the model (H_1) against H_0 that data follows either Gaussian, Gamma. or Exponential distributions are 30.393. 21.785. and 28.140 respectively rejecting H_0 in favor of the model.

Recall that μ_1 corresponds to the Poisson mean of the number of investors deciding to dump the stock when no one else is selling and μ quantifies that degree of herding which leads to attenuation of the tail of the distribution of $a(j,k)$. $\mu_1 = 2.068$ indicates approximately 2 managers within each group would have sold the stock even if no one else was selling. $\mu = 0.570$ indicates that on average during the 2005:Q2 through 2006:Q1 time period another fund manager would have chosen to follow the actions of these initial "random" sellers with a probability of 0.57.

3.3.5 Exponential Decay and the Rise of μ Over Time

Figure 3.10 through Figure 3.15 show quarterly semi-log probability plots of empirical $a(j,k)$ against the data simulated from the model and the two benchmark alternatives, Poisson and normal distributions. The data was simulated with distribution parameters first obtained via MLE using empirical $a(j,k)$.[8] A concave line corresponds to an accelerating probability decay in the tail characteristic of a Gaussian distribution while a straight line indicates decelerating exponential decay. The model of stochastic herding predicts that due to choice correlations the distribution of the number of institutional investment managers liquidating a particular stock will exhibit exponential decay because of the persistence of outliers due to choice correlation.

Figure 3.10 through Figure 3.15 [about here]

During the early quarters (Figure 3.10), Poisson captures the probability decay close to the mean however misses the exponential decay in the tail. A normal

[8] Note that for 2003:Q4, 2004:Q1, 2004:Q4 we show a second plot with estimation dropping one outlier.

distribution approximates the probability decline fairly well in 2003:Q2 when the probability mass in the empirical data follows a concave curve characteristic of the Gaussian decay. The fit of the model improves in 2003:Q4 and 2004:Q1, these are two quarters when mean and maximum of $a(j,k)$ temporarily increased (see Table 3.4). However, in both cases the empirical distribution exhibits bimodality and in both cases higher mean appears to have been driven by one outlier. It is nonetheless noteworthy that the tail of the distribution exhibits a rightward shift, as if pulled by the outliers but never lining up perfectly behind them.

The fit of the model improves substantially during 2006:Q1 (Figure 3.13), one quarter before the onset of the sell-off phase. The distribution of empirical $a(j,k)$ exhibits exponential decay, moreover the data points tend to from a more continuous line indicating higher instances of sell outs at intermediate values.

The following four quarters (2006:Q2 through 2007:Q1) the probability mass of $a(j,k)$ is concentrated around values an order of magnitude higher then in the previous period, indicating massive institutional dumping of stocks. Moreover, a more dense empirical plot indicates much greater incidence of $a(j,k)$ across all stock-investor type groups. However, during this period the distribution of $a(j,k)$ also exhibits bimodality, likely driven by heterogeneity in group sizes. This is because, as indicated in the discussion of Figure 3.7 in previous section, when controlling for group size via $a(j,k)/N(j,k)$, the bimodality disappears in favor of Gaussian decay around the mean close to 1.

After the sellout period the herding signature virtually vanishes – the empirical distribution of $a(j,k)$ is similar to the earlier periods of 2003 and 2004, with bimodal features (in 2007:Q2 and 2007:Q4 in particular) and the decay in the probability mass region approximated fairly well by a normal distribution.

Table 3.10 [about here]

Table 3.10 supplements graphical simulation analysis with quarterly MLE parameter estimates for the model. The last column shows the results of a non-nested goodness of fit test based on Vuong's statistic. If $V > 1.96$ then H_0 of normal distribution is rejected in favor of H_1 of the model under 5% significance level. The goodness of fit test confirms the inference made based on semilog probability plots and shows that the empirical distribution reject normal decay in favor of the model during all quarters except for 2006:Q2 through 2007:Q1. During the quarters when the model captures the empirical distribution the Poisson mean μ_1 is approximately 2 indicating that on average two investors in each stock-investor-type group, $N(j,k)$, chose to liquidated at random in the beginning of the tatonnement process. On the other hand, the estimates for μ, the degree of endogenous feedback, are rising from 0.347 in 2003:Q1 to 0.638 in 2006:Q1 indicating intensifying degree of herding up until sell-out phase.

The trend increase in μ, which accelerated during the last year before the sell-out phase, is shown in Figure 3.8. The estimate of μ in 2006:Q1 indicates that a random decision to dump the stock by an investment manager would have induced another investor to follow her action with a 64% probability. The rise of μ over time as the run-up on S&P 500 stocks continued is consistent with weakening fundamental anchors and a rising importance of market-timing considerations that make the system succeptible to herding. During the sell-out period the empirical data favors an alternate distribution, as seen by large negative Vuong's statistics. Note however that during the 2006:Q2 through 2007:Q1 period the estimates for μ range between 0.931 and 0.941 indicating that, although misspecified, the likelihood of a power-law with exponential truncation is maximized for μ close to 1, where $\mu = 1$ corresponds to the criticality at which exponential truncation vanished in favor of pure power law (consistent with semilog plots for this four quarter period shown in Figure 3.14). Finally, after the sellouts have subsided, exponential decay emerges once again but the estimates of μ remain below the 2006:Q1 level.

Overall, the rise of μ over time indicates that institutional investment manager actions increasingly exhibited contagious behavior intensifying the branching process until the sell-out phase. During the four quarters in 2003 the estimates of μ rise moderately after which point μ is approximately stationary until 2005:Q3, when μ begins to rise again until a sudden jump to the neighborhood of 1. This suggests that the population dynamics of fund manager behavior that we view as a the branching process with intensity μ transitioned from subcritical phase of $\mu < 1$ to a critical phase of $\mu = 1$ between 2006:Q1 and 2006:Q2. If in fact institutional fund managers learn about market liquidity, θ, by accumulating private information and observing aggregate action, then over time Bayesian learning ensures that beliefs about θ converge and the triggering action eventually occurs with probability 1[9]. This is because as private information, which is jointly normally distributed with the true θ hence informative, accumulates over time the average belief decreases causing some managers to liquidate even if no one else is liquidating. Their actions affect the threshold of others triggering a chain of liquidations. If sufficient amount of private information has been accumulated over time such that the average belief is low enough, then the chain reaction becomes "explosive" in the hence of self-organized criticality put forth by Bak et al. (1988). In Bak's sandpile model the distribution of the avalanche size depends on the slope of the sandpile. Our analog of the slope of the sandpile is the inverse of the average belief. At the criticality of $\mu = 1$ the distribution in Equation 3.22 becomes a pure power law and the branching process becomes a martingale, that is the conditional expectation then is that all managers liquidate next period if all are liquidating in the current period. Hence, then mean of $a(j,k)/N(j,k)$ approaching 1 in Table 3.5 sustained for four quarters and the symmetric distribution in the positive extreme of the histogram in the right panel Figure 3.5.

3.4 Conclusion

This paper has demonstrated that the behavior of institutional investors around the downturn of the U.S. equity markets in 2007 is consistent with stochastic herding in

[9] See Nirei (2006*a*) for a more general dynamic extension to information aggregation problem in financial markets

attempts to time the market. We considered a model of large number of institutional investment managers who simultaneously decide whether to remain invested in an assets or liquidate their positions. Each fund manager receives imperfect information about the market's ability to supply liquidity and chooses whether or not to sell the security based on her private information as well as the actions of others. Because of feedback effects the equilibrium is stochastic and the "aggregate action" is characterized by a distribution exhibiting exponential decay embedding occasional "explosive" sell-outs. We can obtained such "fat tail" distributions without imposing major parametric assumptions on exogenous variables. It suffices that the signals about the true state are informative in the sense of satisfying the MLRP. For instance, as in this paper, the information and the true state can follow a bivariate normal distribution.

We examined highly disaggregated institutional ownership data of publicly traded stocks from 13F filings with SEC to find that stochastic herding explains the underlying data generating mechanism. Moreover, consistent with market-timing considerations, the distribution parameter measuring the degree of herding rose sharply immediately prior the sell-out phase that began in earnest in 2006:Q2. The transition to the sell-out itself is consistent with transition from subcritical to supercritical phase as the system swung sharply to a new equilibrium with all agents coordinating on the same action. One advantage of developing this empirical approach is its potential, given the right data, to quantify "hidden tail risk" and provide advance warning of an impeding instability by identifying a system with high degree of choice interdependence based on the distribution of aggregate action. These considerations should be important for both regulatory policy and risk management.

Table 3.1: Number of managers in S&P 500 stocks, by institution type

Quarter	Banks		Insurance Companies		Investment Companies		Investment Advisors		Pension & Endowment Funds		Total
	Number	% tot	Number	% tot	Number	% tot	Number	% tot	Number	% tot	Number
2003q1	11	0 92	18	1 8	128	6 39	135	14 16	1579	76 74	1871
2003q2	11	0 87	19	1 98	130	6 42	137	14 16	1593	76 57	1890
2003q3	11	0 88	18	1 88	132	6 63	137	14 3	1590	76 31	1888
2003q4	10	1 01	21	1 71	121	5 95	131	13 74	1699	77 59	1982
2004q1	10	1 16	20	1 82	129	6 49	133	13 44	1742	77 09	2034
2004q2	10	0 99	20	1 81	133	13 29	136	6 4	1742	77 51	2041
2004q3	9	1 11	20	1 8	125	12 59	136	6 09	1735	78 41	2025
2004q4	10	1 2	20	1 68	117	11 44	166	6 97	1869	78 71	2182
2005q1	9	1 16	20	1 65	121	11 76	169	6 87	1877	78 56	2196
2005q2	8	1 08	20	1 64	119	11 22	170	6 73	1901	79 32	2218
2005q3	7	1 11	19	1 83	114	11 35	167	6 67	1855	79 04	2162
2005q4	8	0 96	19	1 62	114	10 96	187	7 18	1973	79 28	2301
2006q1	9	1 06	19	1 61	111	10 27	189	6 65	2024	80 41	2352
2006q2	10	1 16	18	1 59	106	9 9	204	7 3	2046	80 05	2384
2006q3	9	0 94	18	1 52	103	9 66	240	8 57	2014	79 3	2384
2006q4	9	1 12	17	1 4	102	9 43	333	11 98	2087	76 08	2548
2007q1	8	0 99	17	1 39	102	9 31	337	11 53	2124	76 78	2588
2007q2	10	0 97	18	1 38	101	8 84	384	13 47	2096	75 34	2609
2007q3	9	0 88	18	1 41	97	8 72	405	14 97	2058	74 01	2587
2007q4	9	0 96	18	1 34	97	8 34	516	17 54	2124	71 82	2764
2008q1	9	1 07	19	1 33	96	8 54	521	17 6	2119	71 41	2764

Notes The data is compiled from quarterly 13F filings with SEC in which institutional investment managers with over $100 million under discretionary management are required to report their long positions in exchange traded stocks, closed-end investment companies, equity options and warrants Source Spectrum database available through Thompson Financial

Table 3.2: Value of S&P 500 stocks; by institution type

Quarter	Banks			Insur Comp			Invest Comp			Invest Advisors			Pension & Endowment Funds			Total	
	$ Mil	% Tot	% Mkt	$ Mil	% Tot	% Mkt	$ Mil	% Tot	% Mkt	$ Mil	% Tot	% Mkt	$ Mil	% Tot	% Mkt	$ Mil	% Mkt
2003q1	95,900	0 92	1 20	209,000	1 8	2 61	466,000	6 39	5 81	95,900	14 16	1 20	3,350,000	76 74	41 77	8,020,000	52 58
2003q2	108,000	0 87	1 19	235,000	1 98	2 58	541,000	6 42	5 94	1,080,000	14 16	11 86	3,860,000	76 57	42 37	9,110,000	63 93
2003q3	111,000	0 88	1 21	258,000	1 88	2 82	588,000	6 63	6 43	1,090,000	14 3	11 93	3,970,000	76 31	43 44	9,140,000	65 83
2003q4	76,000	1 71	0 75	128,000	1 01	1 27	207,000	5 95	2 05	1,280,000	13 74	12 67	4,370,000	77 59	43 27	10,100,000	60 01
2004q1	130,000	1 16	1 25	231,000	1 82	2 22	648,000	6 49	6 23	1,270,000	13 44	12 21	4,700,000	77 09	45 19	10,400,000	67 11
2004q2	129,000	0 99	1 19	220,000	1 81	2 04	648,000	6 4	6 00	1,260,000	13 29	11 67	4,700,000	77 51	43 52	10,800,000	64 42
2004q3	126,000	1 11	1 17	222,000	1 8	2 06	642,000	6 09	5 94	1,200,000	12 59	11 11	4,740,000	78 41	43 89	10,800,000	64 17
2004q4	137,000	1 2	1 17	235,000	1 68	2 01	737,000	6 97	0 00	1,270,000	11 44	10 85	5,220,000	78 71	44 62	11,700,000	58 65
2005q1	131,000	1 16	1 21	231,000	1 65	2 14	716,000	6 87	6 63	1,200,000	11 76	11 11	4,780,000	78 56	44 26	10,800,000	65 35
2005q2	130,000	1 08	1 19	231,000	1 64	2 12	718,000	6 73	6 59	1,160,000	11 22	10 64	4,920,000	79 32	45 14	10,900,000	65 68
2005q3	124,000	1 11	1 11	242,000	1 83	2 16	694,000	6 67	6 20	1,200,000	11 35	10 71	5,090,000	79 04	45 45	11,200,000	65 63
2005q4	130,000	0 96	1 14	246,000	1 62	2 16	724,000	7 18	6 35	1,220,000	10 96	10 70	5,360,000	79 28	47 02	11,400,000	67 37
2006q1	137,000	1 06	1 15	262,000	1 61	2 20	752,000	6 71	6 32	1,150,000	10 27	9 66	5,680,000	80 36	47 73	11,900,000	67 07
2006q2	144,000	1 16	1 17	264,000	1 59	2 15	778,000	7 28	6 33	1,170,000	9 9	9 51	5,860,000	80 07	47 64	12,300,000	66 80
2006q3	117,000	0 94	0 91	283,000	1 52	2 19	962,000	8 56	7 46	1,210,000	9 66	9 38	6,020,000	79 32	46 67	12,900,000	66 60
2006q4	159,000	1 12	1 18	297,000	1 4	2 20	1,430,000	11 96	10 59	1,490,000	9 43	11 04	5,820,000	76 09	43 11	13,500,000	68 12
2007q1	155,000	0 99	1 14	303,000	1 39	2 23	1,260,000	9 31	9 26	1,440,000	11 55	10 59	6,030,000	76 76	44 34	13,600,000	67 56
2007q2	160,000	0 97	1 13	369,000	1 38	2 60	1,300,000	8 84	9 15	1,860,000	13 47	13 10	6,120,000	75 34	43 10	14,200,000	69 08
2007q3	158,000	0 88	1 11	371,000	1 41	2 61	1,700,000	8 72	11 97	2,080,000	14 9	14 65	5,750,000	74 01	40 49	14,200,000	70 84
2007q4	165,000	0 96	1 22	351,000	1 34	2 60	1,350,000	8 34	10 00	2,130,000	17 54	15 78	5,330,000	71 82	39 48	13,500,000	69 08
2008q1	141,000	1 07	1 18	302,000	1 33	2 52	1,200,000	8 54	10 00	1,870,000	17 64	15 58	4,710,000	71 41	39 25	12,000,000	68 53

Notes The data is compiled from quarterly 13F filings with SEC in which institutional investment managers with over $100 million under discretionary management are required to report their long positions in exchange traded stocks, closed-end investment companies, equity options and warrants Source Spectrum database available through Thompson Financial

Table 3.3: Descriptive Statistics: $N(j,k)$

Quarter	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Min.	Max.
2003q1	1842	114.292	149.127	2.559	11.377	10	1046
2003q2	1882	114.127	150.874	2.614	11.820	10	1105
2003q3	1856	115.715	150.238	2.561	11.425	10	1069
2003q4	1846	118.792	157.012	2.542	11.266	10	1130
2004q1	1878	121.276	159.835	2.527	11.153	10	1157
2004q2	1878	122.108	161.616	2.501	10.956	10	1150
2004q3	1859	119.288	160.445	2.510	11.013	10	1123
2004q4	1833	125.724	168.197	2.471	10.654	10	1145
2005q1	1546	136.618	179.986	2.329	9.530	10	1161
2005q2	1537	138.249	184.302	2.321	9.460	10	1187
2005q3	1562	133.021	179.158	2.333	9.483	10	1141
2005q4	1535	140.610	186.096	2.316	9.375	10	1170
2006q1	1543	142.454	191.480	2.259	8.979	10	1195
2006q2	1792	133.449	182.378	2.403	10.022	10	1205
2006q3	1788	133.964	180.705	2.454	10.339	10	1199
2006q4	1749	140.074	177.505	2.465	10.487	10	1197
2007q1	1720	143.072	181.797	2.401	10.020	10	1220
2007q2	1741	146.221	181.594	2.361	9.723	10	1222
2007q3	1738	141.282	174.153	2.425	10.185	10	1179
2007q4	1689	148.259	175.767	2.369	9.921	10	1179
2008q1	1697	144.060	171.584	2.405	10.210	10	1197

Notes: The Table shows the summary statistics for stock-investor-type groups, $N(j,k)$, where j indicates an S&P500 stock and k indicates institutional investor type. Only groups with 10 traders or more are included in the sample.

Table 3.4: Descriptive Statistics: $a(j,k)$

Quarter	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Min.	Max.
2003q1	1842	2.025	2.913	3.562	31 303	0	44
2003q2	1882	2.001	2.900	2.022	7.915	0	24
2003q3	1856	2.199	3.315	1.871	6.451	0	23
2003q4	1846	2.299	6.833	26 994	969.256	0	252
2004q1	1878	2.790	8.818	32.145	1240.280	0	347
2004q2	1878	2.458	3.835	3 523	22.887	0	40
2004q3	1859	2.257	3.583	3 511	22.647	0	37
2004q4	1833	2.241	5.006	10.326	202 711	0	123
2005q1	1546	2.983	3.905	4 128	37.587	0	57
2005q2	1537	2.688	4.341	3.362	20.006	0	43
2005q3	1562	2.745	4.307	3.374	20.452	0	42
2005q4	1535	3.731	5.143	2.503	12.181	0	47
2006q1	1543	4.047	6.773	4.320	42.251	0	105
2006q2	1792	103.974	160.417	2.647	11.524	0	1100
2006q3	1788	115.114	159.140	2.650	11.769	0	1114
2006q4	1749	112.678	150.512	2.686	12.063	0	1057
2007q1	1720	116.804	152.820	2.664	11.870	0	1080
2007q2	1741	3.036	5.233	7.707	123.917	0	112
2007q3	1738	3.659	4.685	3.010	24.035	0	63
2007q4	1689	3.117	4.645	3.761	30.523	0	57
2008q1	1697	3.727	4.535	2.734	18.262	0	55

Notes: The table shows summary statistics of $a(j,k)$. Each quarter $a(j,k)$ out of $N(j,k)$ institutions in each group liquidate their holdings. Institutional managers dumping more than 80% of their holdings are counted into $a(j,k)$.

Table 3.5: Descriptive Statistics: $a(\jmath,k)/N(\jmath,k)$

Quarter	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Min.	Max.
2003q1	1203	0.034	0.031	2.800	15.119	0.003	0.294
2003q2	1090	0.034	0.027	2.059	8.368	0.003	0.190
2003q3	985	0.032	0.030	9.969	182.945	0 004	0.636
2003q4	1088	0.038	0.050	8.490	113.689	0.001	0.811
2004q1	1425	0.040	0.046	8.971	134.281	0.003	0.820
2004q2	1222	0.039	0.035	2.469	13.055	0.002	0.364
2004q3	1133	0.038	0.033	2.518	14.814	0.003	0.357
2004q4	961	0.033	0.044	8.801	119.914	0 002	0.774
2005q1	1308	0.040	0.032	2.004	8.524	0.002	0.267
2005q2	947	0.034	0.026	2.175	10.577	0.003	0.222
2005q3	1088	0.035	0.030	2.711	14.756	0.002	0.304
2005q4	1218	0.041	0.028	2.353	13.414	0.003	0.300
2006q1	1012	0.042	0.028	1.999	8.378	0.004	0.200
2006q2	1540	0.846	0.094	-1.106	7.453	0.138	1.000
2006q3	1761	0.879	0.070	-1.133	9.861	0.154	1.000
2006q4	1731	0.786	0.089	-2.068	13.761	0.019	0.947
2007q1	1711	0.831	0.081	-3.081	28.491	0.005	1.000
2007q2	1180	0.032	0.027	2.807	13.823	0.003	0.229
2007q3	1253	0.040	0.029	1.766	6.964	0.002	0.208
2007q4	1110	0.030	0.022	1.835	7.409	0.004	0.143
2008q1	1280	0.038	0.026	1.952	8.835	0.004	0.231

Notes: The table shows quarterly summary statistics for the fraction of insitutional investment managers dumping their stock within in stock-investory type group ($\alpha(\jmath,k) \equiv a(\jmath,k)/N(\jmath,k)$).

Table 3.6: Kolmogorov-Smirnov test. Poisson distribution of $a(\jmath,k)$ over the entire sample, 2003:Q1 - 2008:Q1

Variable	Obs.	Test Result	p-value	Test Stat.	Critical Value
$a(\jmath,k)$	38.353	Reject	0.000	0.769	0.008

Notes: The table shows the results of Kolmogorov-Smirnov goodness of fit test for Poisson distribution to $a(\jmath,k)$.

Table 3.7: Test for normality of $a(j,k)$ over the entire sample, 2003:Q1 - 2008:Q1

Variable	Obs.	Mean	Std. Dev.	Skewness	Kurtosis
$a(j,k)$	38,353	22.745	79.264	6.368	54.868

Notes: The table shows the estimates of the moments of $a(j,k)$, pointing at a highly non-normal distribution.

Table 3.8: Distribution parameter estimates for $a(j,k)$ for the entire sample, 2003:Q1 - 2008:Q1.

Variable	Obs.	μ_1	μ	Log Likelihood
$a(j,k)$	38,353	2.058	0.938	99728.410
		(0.006)	(0.001)	

Notes: The probability density for the hypothesized distribution is $\Pr(X = x) = \mu_1 e^{-(\mu x+\mu_1)}(\mu x + \mu_1)^{x-1}/x!$

Table 3.9: Distribution parameter estimates for $a(j,k)$ for the 2005:Q2 - 2006:Q1 subsample.

	Distribution of $a(j,k)$							
	Model		Benchmark Distributions					
	Borel-Poisson		Trunc. Normal		Gamma		Exponential	
ML estimates	μ_1	2.058	mean	-97.461	α	1.103	β	4.781
		(0.029)		(7.152)		(0.021)		(0.072)
	μ	0.570	σ	20.000	β	4.335		
		(0.007)		(0.665)		(0.103)		
Log Likelihood	11148.789		10040.186		10925.596		10938.238	
Vuong's statistic	H_1		30.393		21.785		28.140	
Obs.	4,265							

Notes: The probability density for the hypothesized distribution is $\Pr(X = x) = \mu_1 e^{-(\mu x+\mu_1)}(\mu x + \mu_1)^{x-1}/x!$

Table 3.10: Quarterly distribution parameter estimates for $a(\jmath, k)$.

Quarter	Obs.	μ_1	s.e.	μ	s.e.	Log Likelihood	Vuong's Statistic
2003q1	1203	2.023	(0.053)	0.347	(0.015)	2610.493	31.048
2003q2	1090	2.164	(0.060)	0.374	(0.016)	2479.326	28.628
2003q3	985	2.368	(0.069)	0.429	(0.016)	2412.327	25.413
2003q4	1088	1.963	(0.054)	0.497	(0.014)	2614.313	3.588
2004q1	1425	1.880	(0.045)	0.489	(0.012)	3343.738	–
2004q2	1222	2.046	(0.053)	0.458	(0.014)	2905.715	28.048
2004q3	1133	2.103	(0.057)	0.432	(0.014)	2661.898	28.686
2004q4	1833	2.087	(0.061)	0.512	(0.014)	2392.407	10.572
2005q1	1308	1.984	(0.050)	0.437	(0.013)	3024.613	23.576
2005q2	947	2.155	(0.064)	0.506	(0.015)	2384.011	22.919
2005q3	1088	1.938	(0.054)	0.508	(0.014)	2644.548	24.945
2005q4	1218	2.022	(0.054)	0.570	(0.012)	3170.367	25.764
2006q1	1012	2.234	(0.064)	0.638	(0.012)	2891.608	13.442
2006q2	1540	7.103	(0.138)	0.941	(0.002)	8660.686	-26.826
2006q3	1761	7.527	(0.136)	0.936	(0.002)	9866.110	-27.776
2006q4	1731	7.765	(0.142)	0.932	(0.002)	9696.680	-26.172
2007q1	1711	8.124	(0.149)	0.931	(0.002)	9645.581	-25.912
2007q2	1180	2.181	(0.057)	0.513	(0.013)	2991.997	15.100
2007q3	1253	2.606	(0.065)	0.486	(0.013)	3291.732	25.806
2007q4	1110	2.360	(0.064)	0.503	(0.013)	2867.704	24.548
2008q1	1280	2.619	(0.065)	0.470	(0.013)	3323.552	25.452

Notes: The table reports quarterly MLE parameter estimates for the probability density of the hypothesized distribution. $\Pr(X = x) = \mu_1 e^{-(\mu x + \mu_1)}(\mu x + \mu_1)^{x-1}/x!$.

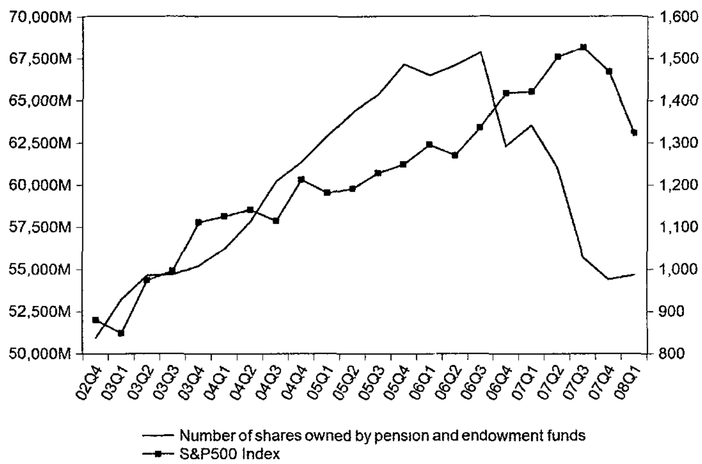


Figure 3.1: Number of shares (in millions) of S&P 500 stocks held by pension and endowment funds and the S&P 500 index.

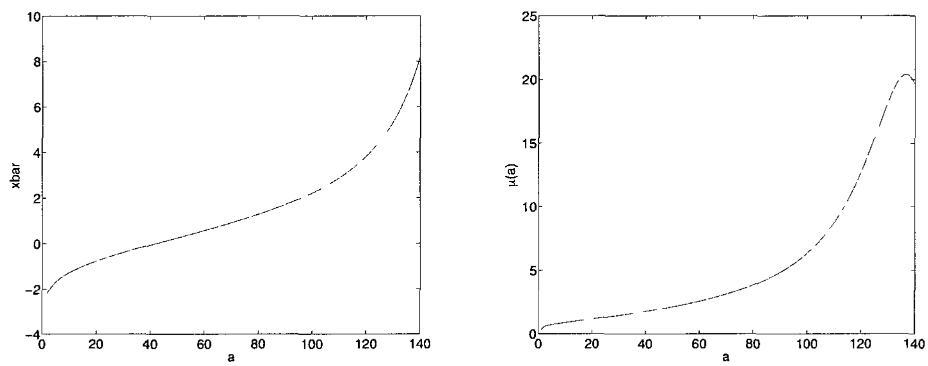


Figure 3.2: Left: threshold function $\bar{x}(a)$; Right: conditional mean $\mu(a)$

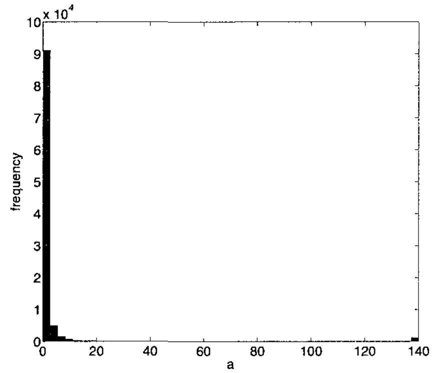


Figure 3.3: Histogram of a for $0 \leq a \leq 140$

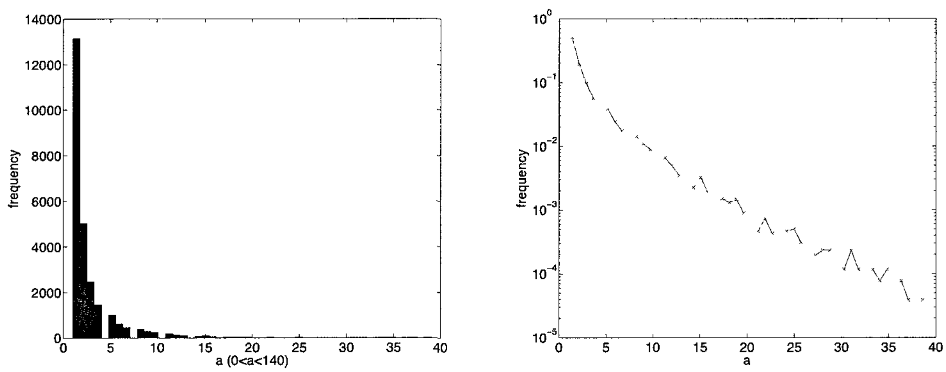


Figure 3.4: Histogram of a for $0 < a < 140$

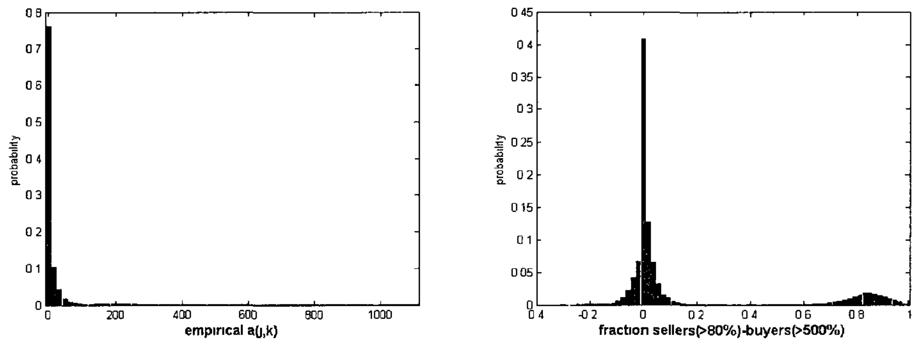


Figure 3.5: 2003:Q1 - 2008:Q1 (38,353 observations); *Left* histogram of empirical $a(j,k)$. *Right* histogram of $(a(j,k) - b(j,k))/N(j,k)$.

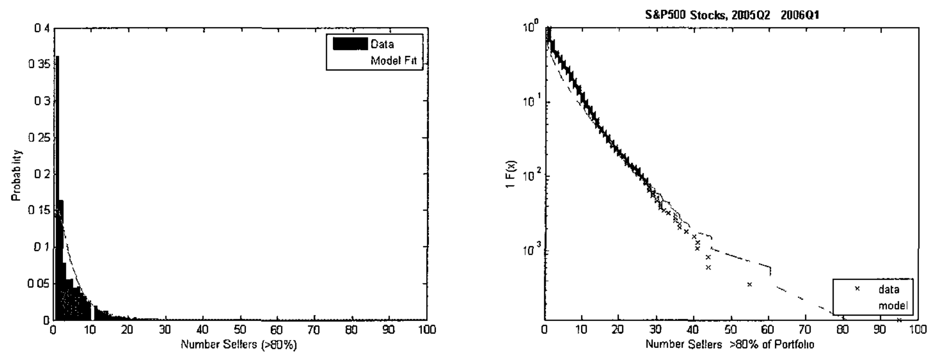


Figure 3.6: 2005:Q2 - 2006:Q1: *Left* histogram of empirical $a(j,k)$. *Right* semi-log probability plot of empirical $a(j,k)$ and the fitted model (red).

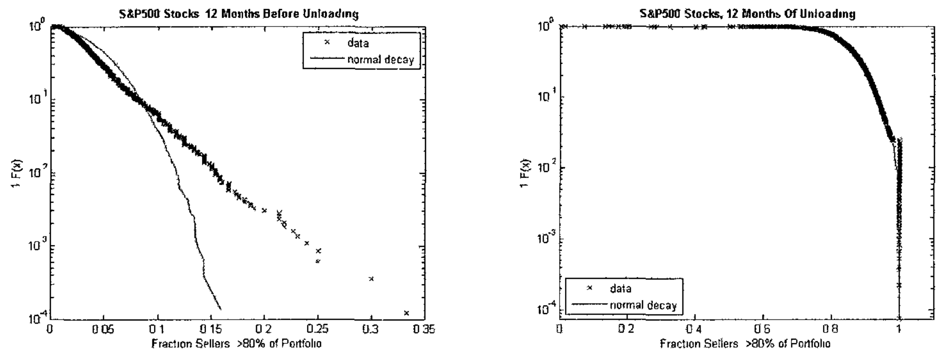


Figure 3.7: Semi-Log Probability Plots of $a(j,k)/N(j,k)$

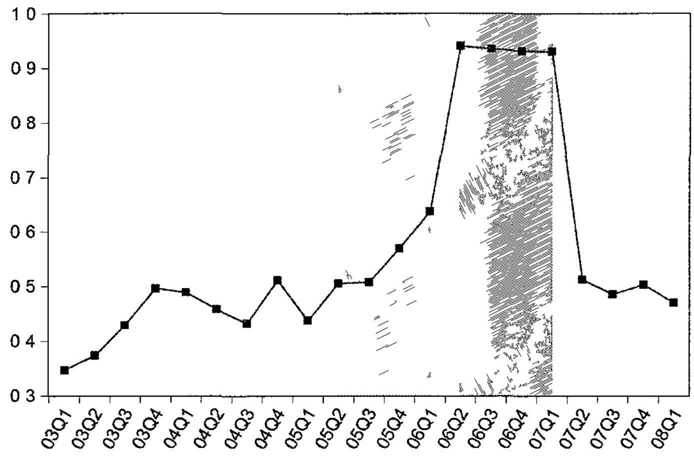


Figure 3.8: Herding – quarterly estimates of distribution parameter μ, which measures the probability of a "chain reaction" in response to a random liquidation by an investment manager.

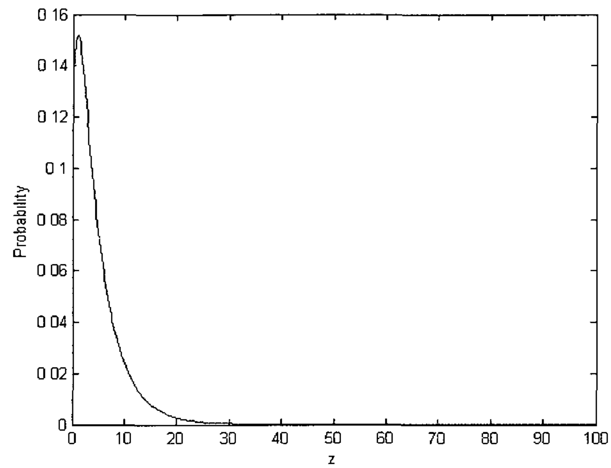


Figure 3.9: Plot of $\Pr(X = x) = \mu_1 e^{-(\mu x + \mu_1)}(\mu x + \mu_1)^{x-1}/x!$. Parameters estimated using 2005:Q2-2006:Q1 data on institutional investor holdings of S&P 500 stocks: $\mu_1 = 2.060$, $\mu = 0.547$.

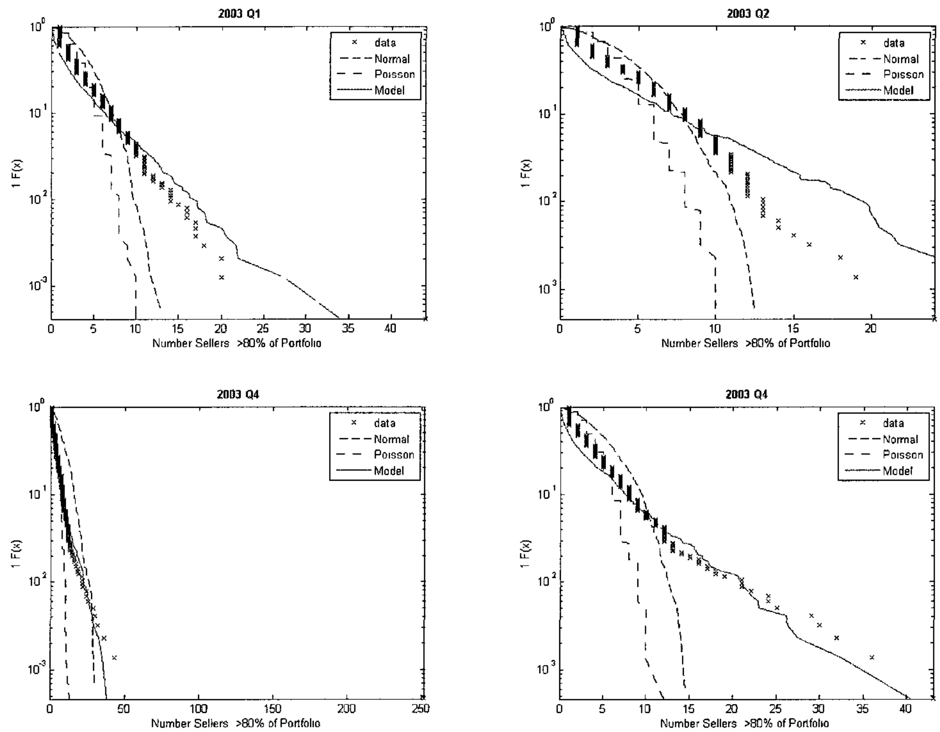


Figure 3.10: Semilog probability plot of $a(j,k)$ and comparison to data simulated using the model and the two alternatives, Normal and Poisson.

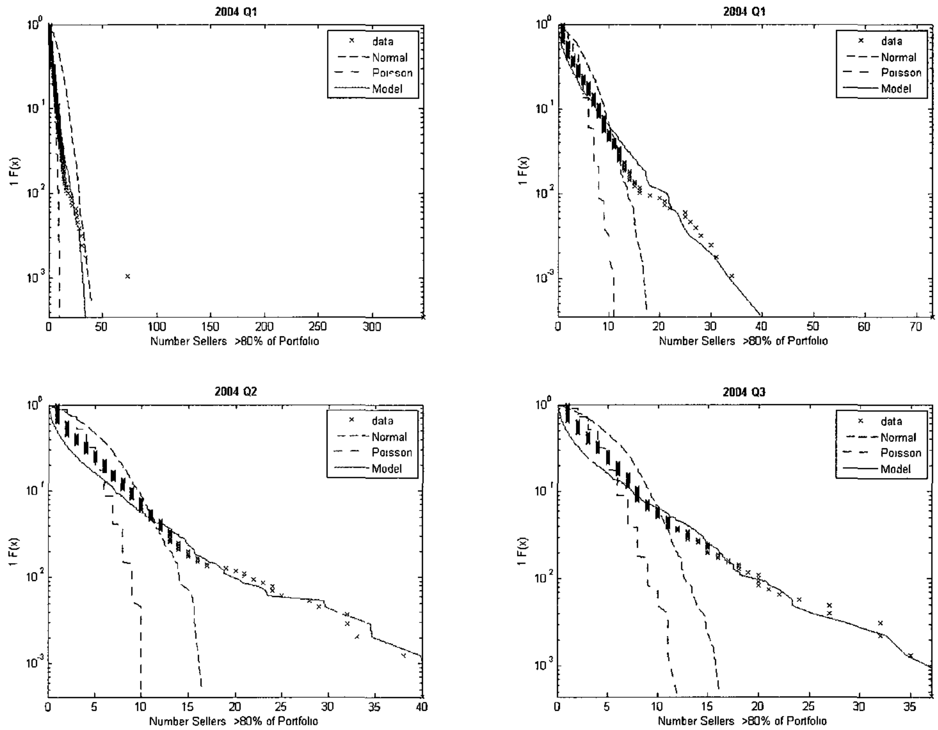


Figure 3.11: Semilog probability plot of $a(j, k)$ and comparison to data simulated using the model and the two alternatives, Normal and Poisson.

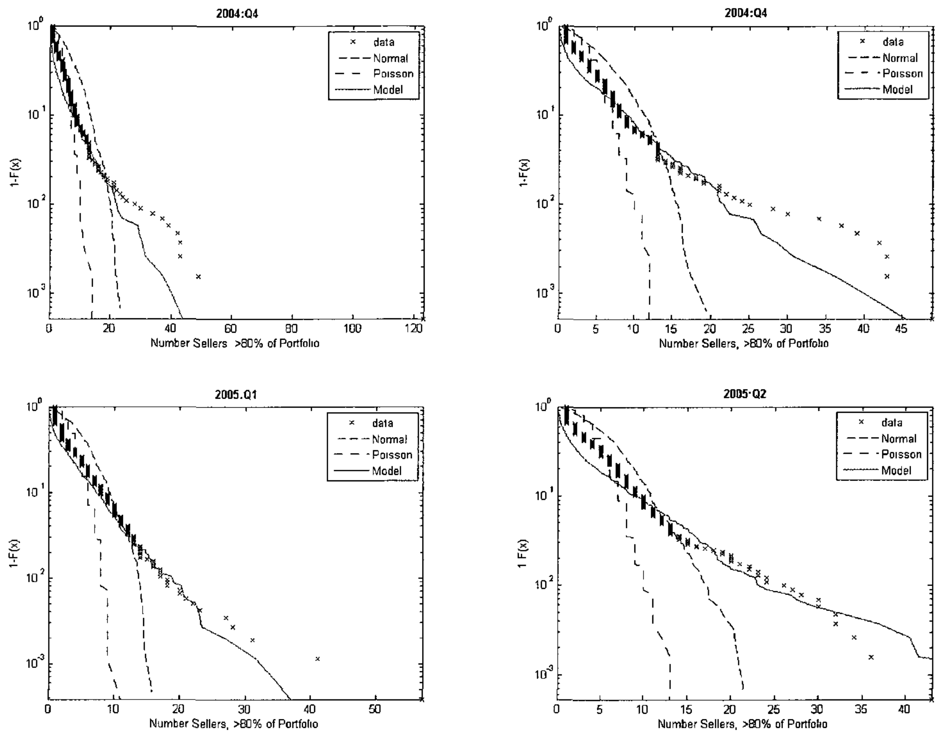


Figure 3.12: Semilog probability plot of $a(j,k)$ and comparison to data simulated using the model and the two alternatives, Normal and Poisson.

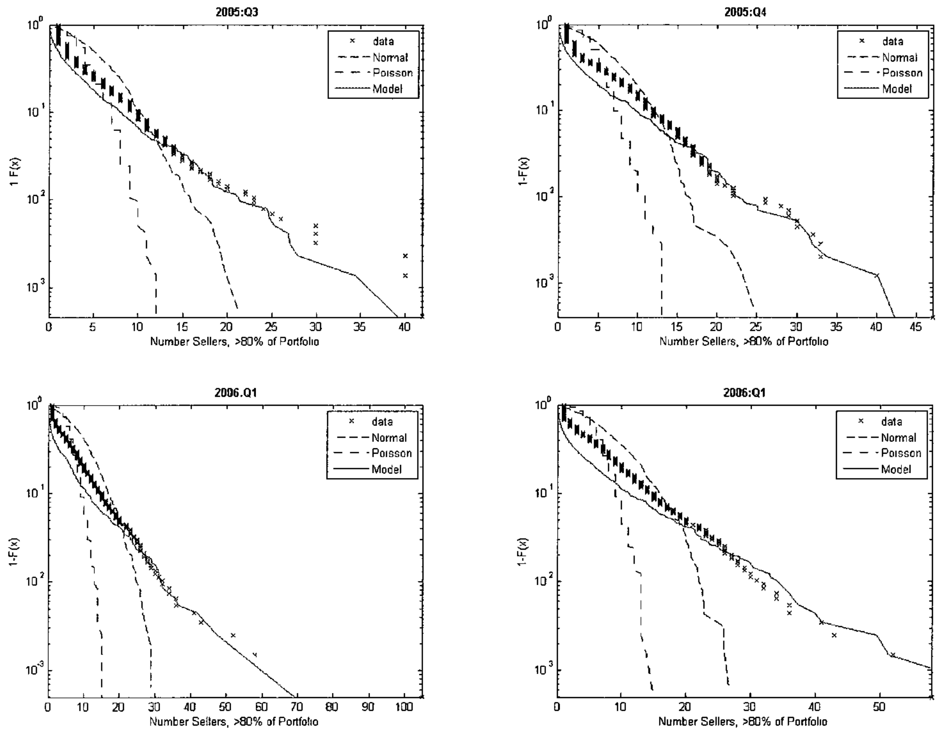


Figure 3.13: Semilog probability plot of $a(j,k)$ and comparison to data simulated using the model and the two alternatives, Normal and Poisson.

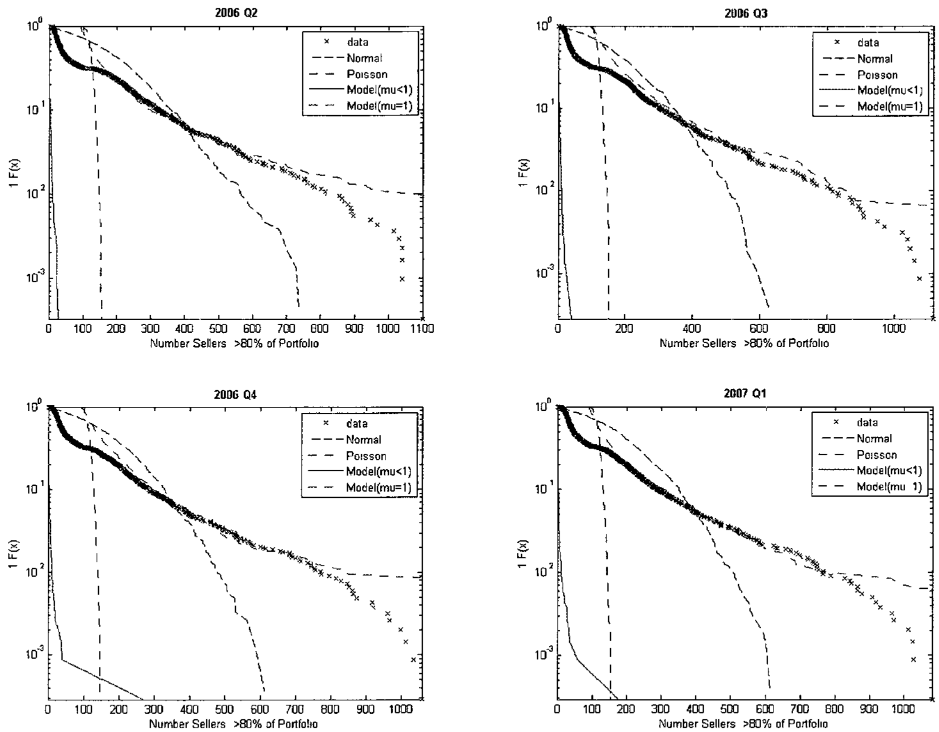


Figure 3.14: Semilog probability plot of $a(j,k)$ and comparison to data simulated using the model and the two alternatives, Normal and Poisson.

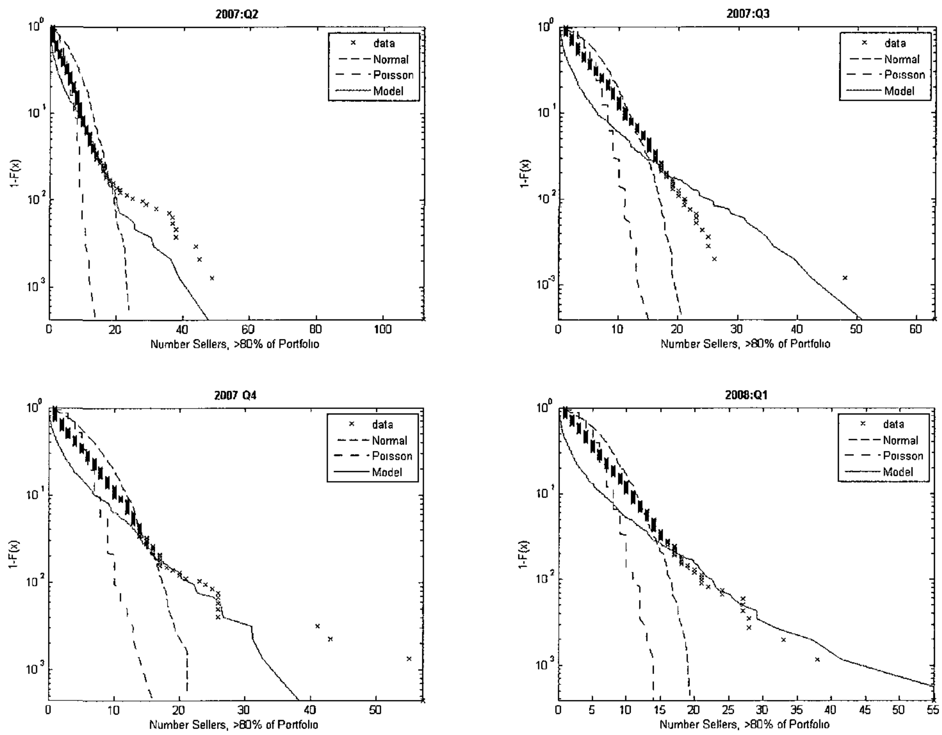


Figure 3.15: Semilog probability plot of $a(j, k)$ and comparison to data simulated using the model and the two alternatives, Normal and Poisson.

Chapter 4

Speculative Dynamics and Currency Crash Risk

4.1 Introduction

Foreign exchange returns of high (low) yield currencies tend to exhibit negative (positive) skewness – long duration of runs interrupted by abrupt crashes. Such apparent violation of the efficient market hypothesis combined with the loose fundamental anchoring of foreign exchange rates, also known as the *exchange rate disconnect puzzle* first documented by Mussa (1986) and Flood and Rose (1993), suggests that strategic behavior by traders can play an important role in exchange rate dynamics. Particularly, in a situation where traders may have private information related to future payoffs of a foreign investment, their individual actions may trigger a cascade of similar actions by other traders. Several features of carry trade make it especially susceptible to such a mechanism of chain reaction through information revelation.

Carry trade is a strategy in which an investor finances a long position in a high yield currency by borrowing in a low yield currency betting that the exchange rate will not change so as to offset the profits made on the interest rate differential.[1] Since central banks set short-term interest rates with domestic inflation considerations in mind, it allows carry traders to lock-in a profit from the interest rate differential, but the key uncertainty of an adverse exchange rate swing remains. In other words, carry traders knowingly expose themselves to foreign exchange rate risk. The profitability of their investment strategy is contingent on the violation of the uncovered interest parity (UIP) which is an ex-ante no-arbitrage condition predicting that excess returns from holding high interest rate currency must be eliminated through an expected depreciation of that currency. Plantin and Shin (2010) refer to the instant when exchange rate of high yield currency depreciatiates back to a commonly known fundamental level as "the day of reckoning".

We study the implications of this key "day of reckoning" uncertainty for strategic behavior of carry traders, and the consequences of their actions for foreign exchange volatility. Since all carry traders face a common risk, they learn about the likelihood of an adverse foreign exchange rate swing, not only from their private information, but also from the actions of others. This leads to strategic complementarity in their actions to engage in carry trade. Strategic complementarity is an important result since, as shown in a dynamic coordination game by Plantin and

[1] Burnside et al. (2007) and Hochradl and Wagner (2010) document persistent excess returns to carry trade strategies.

Shin (2010), it makes foreign exchange speculation destabilizing when coupled with the notion of "the day of reckoning." Plantin and Shin introduce strategic complementarity by the means of positive funding externality – the additional assumption that carry traders reduce funding costs for each other by exacerbating UIP violation when piling into a high yield currency. In contrast, we demonstrate that the aggregate uncertainty about the probability of the crash is by itself sufficient to make carry traders' actions strategic complements, leading to runs on the high yield currency punctuated by endogenous episodes of "explosive" carry unwinding. Furthermore. the collective unwinding in this environment is stochastic since it turns out that in equilibrium each carry trader assigns greater weight to the actions of others rather than her own private information only with a certain probability. The stochastic equilibrium outcome of our model takes from the stochastic herding approach of Nirei (2006*b*. 2008). This gives a result similar to the *stochastic bifurcation* equilibrium dynamics of Plantin and Shin (2010), whereby a small smooth change to a parameter value can lead the system to instantly swing to a new equilibrium.[2] However, we obtain this results in a simpler setting with the underlying mechanism being a chain reaction through information revelation about currency crash risk. Leverage in our model plays a secondary role. only exacerbating the pre-existing dynamics. The impact of leverage is highly non-linear. and suggests that there may exist an optimal percentage margin requirement on speculative positions which is a function of the interest rate differential between high and low yielding currencies.

[2]See Bass and Burdzy (1999) for a comprehensive treatment of stochastic bifurcation processes

The main empirical implication of stochastic herding in carry trade relates to the distribution of rare events in foreign exchange. Whereas the central limit theorem characterizes an outcome of a simple information aggregation process, choice correlations lead to fat tail effects. In particular, the equilibrium fraction of carry traders that herd on the same action is described by a probability distribution that exhibits a power decay with exponential truncation. Thus, the mechanism of stochastic herding may explain recent findings in option pricing literature that an exponentially dampened power-law provides a better approximation to rare events in foreign exchange returns than the traditional Merton's compound Poisson normal jump process (see Wu (2006) and Bakshi et al. (2008)). Furthermore, since an exponentially dampened power-law in the distribution of rare events in foreign exchange can be observed even before the "explosive" unwinding takes place it potentially allows us to quantify what Rajan (2006) has dubbed the "hidden tail risk."[3]

We test the goodness of fit of the distribution derived from the model to the realized volatility jumps in JPY/USD foreign exchange rate. The Japanese yen in particular has served as a funding currency in carry trade because of a prolonged "zero interest rate" policy of the Bank of Japan. Brunnermeier et al. (2009) find that yen has exhibited the highest degree of skewness among developed countries' currencies, and attribute this to large periodic yen appreciations caused by the unwinding of carry trade. Leptokurtic features arise if standard Brownian motion in the evolu-

[3]See for instance Jansen and de Vries (1991) and Longin (1996) who suggest that price fluctuations in normal times and rare market crashes are caused by the same mechanisms. Also, Morris and Shin (1999) argue that choice interdependence among traders must be explicitly incorporated into the estimates of "value at risk" and call for greater attention to the actions of market participants.

tion of financial returns is punctuated by periodic jumps. We examine daily jumps in the JPY/USD exchange rate extracted using a non-parametric method of bi-power variation following Barndorff-Nielsen (2004) and Barndorff-Nielsen and Shephard (2006). This method makes use of high-frequency data (five minute intervals) to take out intraday noise and isolate daily returns that evolved discontinuously (are inconsistent with Gaussian volatility component). We focus on time period from January 1. 1999 through February 1, 2007, thus the 1998 and 2008 crashes are just outside of our sample.

We find that positive and negative jumps in the JPY/USD exchange rate exhibit asymmetries consistent with carry trade: higher likelihood of large discrete yen appreciations coupled with serial correlation and non-linear dependence in yen *appreciation* jumps indicate that large yen appreciations tend to occur over consecutive days and may be non-random. In contrast, yen *depreciation* jumps are best described as white noise. The asymmetries are more pronounced when there is greater incentive to engage in carry trade, a higher interest rate differential between U.S. and Japan, and when the general level of uncertainty is higher, that is higher level of option implied volatility index (VIX).

Since jumps are extracted using a non-parametric method it allows for hypothesis testing regarding the underlying distribution. We find that for yen *appreciation* jumps a compound Poisson normal jump process, which serves as a good approximation if jumps are independent of each other. is strongly rejected in favor an exponentially dampened power-law. which is an outcome of stochastic herding by carry traders chasing information about the "crash risk." Simulation results with parameters estimated from the data confirm that the underlying data generating process is different for negative and positive jumps, with negative jumps subject to more extreme fluctuations. The contrast between simulation results of yen appreciation (negative) and yen depreciation (positive) jumps clearly captures the origins of the negative skewness of JPY/USD returns.

Finally, parametric restrictions from the model allow us to identify economic factors that lead to extreme volatility by intensifying the herd effect. In the analysis of subsamples we find that the key distribution parameter that captures the intensity of herding is higher during times of greater interest rate differential and higher values of VIX. Fitting the model in reduced form to the data, we find that higher level of speculative futures positions increases the "tail risk" directly, while lower margin requirements and higher option implied risk premia raise the likelihood of sharp yen appreciation only jointly with an accumulated carry position in the market. The impact of the volume of speculative futures on the "tail risk" is particularly robust, corroborating the key hypothesis that carry trade considerations play a destabilizing role in foreign exchange markets, even in periods not punctuated by "extreme crashes," such as the LTCM or the subprime episodes.

The study is organized as follows. Section 4.2 empirically motivates the key assumption of the model that "the day of reckoning" risk plays a central role in carry trade. Section 4.3 presents the model. Section 4.4 tests the model and examines the link between JPY/USD exchange rate volatility and carry trade. Section 4.5

concludes.

4.2 Evidence of the "Day of Reckoning" Fears in Yen Carry Trade

The top two panel of Figure 4.1 show the JPY/USD exchange rate and the U.S.-Japan interest rate differential from January 1. 1999 through February 1 2007. In strong violation of the UIP an increase in the interest rate spread corresponded with dollar appreciation against the yen in late 1999 through 2000 and again from 2004 through 2007.[4] For instance. Ichiue and Koyama (2008) estimate the UIP regression coefficient as low as -2.79 for the yen.[5] In line with a "peso" type problem. Farhi et al. (2009) interpret UIP violations as a compensation to carry traders for bearding the risk of periodic currency crashes, such as sharp yen appreciation in 2008 following the sub-prime crisis. The third panel of Figure 4.1 shows that this rise in ex-ante carry trade returns was accompanied by a decrease VIX, perhaps associated with a global search for yields during the 2000s. Finally. the bottom panel of Figure 4.1 shows that the dramatic rise in returns to JPY/USD carry trade in the 2004 through 2006 period was accompanied by an increase in non-commercial yen short futures positions on The Chicago Mercantile Exchange (CME). which are a common proxy for carry trade activity (see Klitgaard and Weir (2004). Galati, Heath and

[4] An appreciation of the high yield currency is an example of the forward premium puzzle and the violation of the uncovered interest parity (UIP) well documented by Hansen and Hodrick (1980) and Engel (1996)

[5] Under rational expectations a regression of exchange rate returns on in interest rate differential should yield a coefficient of 1

McGuire (2007), Brunnermeier et al. (2009) and Cecchetti et al. (2010)). Combined, these trends suggest that carry trade may have been a major factor in JPY/USD exchange rate dynamics during our sample period.

Figure 4.1 [about here]

Figure 4.2 shows the relationship between the market price of risk of large yen appreciation (as proxied by risk reversals[6]) and CME net non-commercial short yen futures positions (percent of total open interest). Risk reversals are options contracts used to hedge against the risk of substantial unidirectional price movement, and as such their values are often treated as a proxy for market expectations about sharp yen appreciation.[7]

Figure 4.2 [about here]

The negative values of risk reversals depicted in Figure 4.2 indicate higher implied volatility on extreme yen *appreciation* side during the entire 2004-2006 period. In other words, the overall market was hedging against sharp yen appreciation during the height of the yen carry trade. Moreover, note the close association between risk reversals and net speculative short positions in yen: when risk reversals become more negative (higher market expectation of sharp yen *appreciation*) net

[6] A risk reversal is a hedge against a large price movement in one direction constructed by a simultaneous purchase of deep out-of-money call and sale of deep out-of-money put option (usually 25 or 10 delta) of the same maturity (or vise-versa). The value itself is the implied volatility for the call minus the implied volatility of the put. For detailed guide to risk reversals see Galati, Higgins, Humpage and Melick (2007).

[7] Gagnon and Chaboud (2007) find that prices of deep out-of-money foreign exchange options indicate an overall market hedge against large yen appreciation and Farhi and Gabaix (2008) show that under certain conditions risk reversals contain information on currency"disaster risk premia"

speculative futures positions decline. In fact, in Chapter 4 it is shown that risk reversals Granger-cause non-commercial short positions under both 1 and 2 lag specifications and this effect is significant at 1 percent level. Furthermore, the effect is robust to controlling for the exchange rate, indicating that risk reversals contain important information to carry traders on the currency risk of their positions, supporting the notion that "day of reckoning" considerations are central to carry trade.

4.3 Model

4.3.1 Threshold Strategy for Carry Trade Unwinding

There are N informed risk neutral traders indexed by $i = 1, 2, \ldots, N$. Each trader can engage in a carry trade where she goes short in yen and long in dollars. Let $\Delta s > 0$ denote dollar appreciation and $\delta \equiv i - i^* > 0$ denote the interest rate differential between U.S. and Japan. Carry traders profit from UIP violation $(\Delta s + \delta) > 0$.

The return to carry trade is stochastic because exchange rate returns, Δs, are subject to crash risk. There are two state of the world. "High" and "Low," and Δs takes from two values, Δs_H and Δs_L, depending on the realization of the state, where $(\Delta s_H + \delta) > 0 > (\Delta s_L + \delta)$. We can think of the realization of "Low" state as the "day of reckoning" following Duffie et al. (2002), when the dollar return to holding an asset snaps back to a commonly known fundamental value.

Suppose that each trader has an existing carry position, $k > 1$, and one new addition of funds in yen. Traders maximize $E(\Delta s + \delta)k'$ by choosing k'. Since traders are risk neutral the optimal position is either $k' = k + 1$ or $k' = 0$. We call the trader's choice $k + 1$ as "stay," and 0 as "exit" of the carry trade.

Let m denote the number of exiting traders. We assume that exchange rate returns depend on the extent of the net outflow of funds from the carry currency. Thus Δs is a decreasing function of $mk - N + m$, where mk is the unwound amount of carry trades by exiting traders and, $N - m$ is the increase in the carry position by continuing traders. Each trader submits to a market maker her supply schedule, namely "stay" or "exit," conditional on m. The market maker then chooses m so that the number of the exiting traders coincides to the chosen m.

Each trader draws a private signal x_i, which is correlated with the state. The distribution of x_i is a common knowledge, where x_i is drawn from F if the true state is High and from G if the true state is Low. Let f and g denote the density functions of F and G, respectively. We assume that the odds ratio $f(x)/g(x)$ is increasing in x. Namely, F and G satisfy the monotone likelihood ratio property (MLRP). This assumption implies that a larger value of x conveys the information that it is more likely that the state is High rather than Low.

We conjecture that each trader employs a threshold strategy in which trader i stays in carry ($k' = k + 1$) if $x_i > \bar{x}$, and exits ($k' = 0$) otherwise. For a fixed m, a staying trader must be indifferent between stay or exit if she draws a private information at the threshold level $\bar{x}(m)$.

Thus $\bar{x}(m)$ must satisfy the indifference condition:

$$E(\Delta s + \delta \mid m, x_i = \bar{x}(m)) = 0. \tag{4.1}$$

Then.

$$(\Delta s_H + \delta)\Pr(\text{High} \mid x_i = \bar{x}(m), m) + (\Delta s_L + \delta)\Pr(\text{Low} \mid x_i = \bar{x}(m), m) = 0, \tag{4.2}$$

where “Pr” denotes a likelihood function. Equivalently. the threshold $\bar{x}$ is determined by the following equation:

$$\log \frac{\Pr(\text{High} \mid x_i = \bar{x}(m), m)}{\Pr(\text{Low} \mid x_i = \bar{x}(m), m)} = \log \frac{-\Delta s_L - \delta}{\Delta s_H + \delta}. \tag{4.3}$$

First, we note that:

$$\begin{aligned}
\frac{\Pr(\text{High} \mid x_i = \bar{x}(m), m)}{\Pr(\text{Low} \mid x_i = \bar{x}(m), m)} &= \frac{\Pr(\text{High}, x_i = \bar{x}(m), m)}{\Pr(\text{Low}, x_i = \bar{x}(m), m)}, && (4.4)\\
&= \frac{\Pr(x_i = \bar{x}(m) \mid \text{High}, m)}{\Pr(x_i = \bar{x}(m) \mid \text{Low}, m)} \frac{\Pr(m \mid \text{High})}{\Pr(m \mid \text{Low})} \frac{\Pr(\text{High})}{\Pr(\text{Low})}, && (4.5)\\
&= \frac{f(\bar{x}(m))}{g(\bar{x}(m))} \left(\frac{F(\bar{x}(m))}{G(\bar{x}(m))}\right)^m \left(\frac{1 - F(\bar{x}(m))}{1 - G(\bar{x}(m))}\right)^{N-1-m} \theta_0, && (4.6)
\end{aligned}$$

where θ_0 denotes the prior likelihood ratio, which is the prior belief on High divided by the prior belief on Low state. The term F/G expresses the likelihood ratio inferred by m exiting traders. and the term $(1-F)/(1-G)$ is the likelihood ratio inferred by staying traders. because the equation is based on the indifference condition for a staying trader and her own information is already included by the term f/g, we only count $N-1-m$ staying traders in this term. From equation (4.6), it is straightforward to show the optimality of the threshold rule: only if a trader draws an information greater than the threshold, i.e. $x_i > \bar{x}$, the left hand side of (4.3) exceeds the right hand side due to the MLRP, would the trader chooses to stay in carry.

The threshold rule has the following property.

Proposition 4. *The threshold function $\bar{x}(m)$ is increasing in m.*

Proof: See Appendix C.1.

Then we obtain:

$$\begin{aligned}\frac{d\bar{x}}{dm} &= \frac{-\log\frac{F(\bar{x})}{G(\bar{x})}+\log\frac{1-F(\bar{x})}{1-G(\bar{x})}+\frac{(\Delta s_L-\Delta s_H)(k-1)\Delta s'}{-(\Delta s_H+\delta)(\Delta s_L+\delta)}}{\frac{f'(\bar{x})-g'(\bar{x})}{f(\bar{x})/g(\bar{x})}+m\left(\frac{f(\bar{x})}{F(\bar{x}))}-\frac{g(\bar{x})}{G(\bar{x})}\right)+(N-1-m)\left(\frac{g(\bar{x})}{1-G(\bar{x})}-\frac{f(\bar{x})}{1-F(\bar{x})}\right)}\\ &> 0 \end{aligned} \tag{4.7}$$

This implies that traders' decisions exhibit strategic complementarity: when a trader decides to exit, it increases m and then $\bar{x}$, making other traders more likely to exit.

4.3.2 Equilibrium

We define an equilibrium as a mapping from a profile of realized private information (x_i) to an action profile with m "exits" and $N-m$ "stays", such that the number of traders with $x_i < \bar{x}(m)$ coincides with m for each realization (x_i). The equilibrium notion here is a standard rational expectations equilibrium in a market microstructure with a market maker and traders submitting supply schedules (Vives (2008)).

Next, following Nirei (2006*b*, 2008), we characterize the equilibrium by constructing a fictitious tatonnement process. We imagine that the market maker finds an equilibrium m as follows. At the initial step $s = 0$, the market maker starts with $m_{s=0} = 0$ and counts the number of traders who would exit according to their supply schedules given the information $m = 0$. If no trader exits, then the process stops here and $m = 0$ is chosen as an equilibrium. If $n_{s=0} > 0$ traders choose to exit, the step is increased to $s = 1$, and $m_{s=1}$ is set by $m_s = m_{s-1} + n_{s-1}$. If no traders other than the traders who chose to exit previously decide to exit, then the process stops and $m = m_s$ is chosen as an equilibrium. Otherwise, the step is increased and the process iterates until it stops. Nirei (2006*b*) has shown that this procedure always converges to an equilibrium, m, and the selected equilibrium is the smallest among potential equilibria.

The fictitious tatonnement process, m_s, $s = 0, 1, \ldots$, can be embedded to a stochastic process defined in the probability space of the private information profile (x_i). Namely, we can derive the probability distribution of m_{s+1} conditional on m_s before the realization of x_i. It is shown (Nirei (2006*b*)) that n_s follows a branching process in which the number of "children" born by a "parent" in step s follows a binomial distribution with a probability parameter p_s and population $N - m_s$, and if we increase N to infinity, the binomial asymptotically converges to a Poisson distribution with mean $\mu_s = \lim_{N\to\infty} p_s(N - m_s)$.

This property of the fictitious tatonnement process is utilized to characterize the equilibrium. The equilibrium m is the sum of n_s over s, the total number of "children" born in the branching process until it stops. Then, we can apply a powerful theorem by Otter (see Harris (1989)). Consider a branching process n_s, in which the mean number of children per parent is constant at μ, and the initial condition is $n_0 = 1$. Then the total population, $m = \sum_s n_s$, follows a dampened power-law distribution in the tail:

$$\begin{aligned} \Pr(m \mid m_0 = 1) &\sim m^{-1.5}(\mu e^{1-\mu})^m \\ &= C_0 m^{-1.5} e^{-\phi m} \end{aligned} \tag{4.8}$$

for a large m, where ϕ is a constant determined by the distribution of the number of children per parent. In our case, where the number of children follows a Poisson distribution, we further have $\phi = \mu - 1 - \log\mu$ for the case of $\mu < 1$ (Nirei (2006*b*)). The key parameter for the fluctuation of m is μ. When $\mu \leq 1$, the fictitious tatonnement n_s is a supermartingale, which stops in a finite step, and whose total population m is finite with probability one. Equation (4.8) and the relation between ϕ and μ implies that the mean and variance of m is determined by μ. A greater μ decreases ϕ and thus makes the exponential truncation point further in the tail of (4.8). $\mu = 1$ is the critical point at which (4.8) reduces to a pure power law distribution with indefinite mean. Thus, we observe that the model is capable of generating a substantial size of fluctuations in m when μ is close to 1. When μ is greater than 1. the fictitious tatonnement is "explosive" and there is a positive probability in which the process does not stop in a finite step. In our finite model. this event corresponds to the case, $m = N$.

In our model. μ_s is not constant over the tatonnement step s. However. we can infer the range of μ_s as follows. Suppose that the true state is "Low." For a large N. the mean number of traders who are induced to unwind the carry by observing an additional trader unwinding to the existing unwinding traders m is approximated by:

$$\mu_s \sim (N - m_s)g(\bar{x}(m_s))/(1 - G(\bar{x}(m_s)))(d\bar{x}(m_s)/dm), \tag{4.9}$$

where $d\bar{x}/dm$ is the increase in the threshold, $g/(1 - G)$ is the conditional density at the threshold level (i.e. the hazard rate), and $N - m_s$ is the number of staying traders at step s. Then.

$$\begin{aligned} \mu_s \quad = \quad & \lim_{N\to\infty} \frac{-\log\frac{F(\bar{x}_s)}{G(\bar{x}_s)} + \log\frac{1-F(\bar{x}_s)}{1-G(\bar{x}_s)} + \frac{(\Delta s_L-\Delta s_H)(k-1)\Delta s'}{-(\Delta s_H+\delta)(\Delta s_L+\delta)}}{\frac{1}{N-m}\frac{f'(\bar{x}_s)-g'(x_s)}{f(\bar{x}_s)/(1-G(\bar{x}_s))}} \\ + \quad & \frac{-\log\frac{F(x_s)}{G(\bar{x}_s)} + \log\frac{1-F(x_s)}{1-G(\bar{x}_s)} + \frac{(\Delta s_L-\Delta s_H)(k-1)\Delta s'}{-(\Delta s_H+\delta)(\Delta s_L+\delta)}}{\frac{m}{N-m}\left(\frac{f(\bar{x}_s)/g(\bar{x}_s)}{F(\bar{x}_s)/(1-G(x_s))} - \frac{1-G(\bar{x}_s)}{G(x_s)}\right)} \\ + \quad & \frac{-\log\frac{F(\bar{x}_s)}{G(\bar{x}_s)} + \log\frac{1-F(\bar{x}_s)}{1-G(x_s)} + \frac{(\Delta s_L-\Delta s_H)(k-1)\Delta s'}{-(\Delta s_H+\delta)(\Delta s_L+\delta)}}{\frac{N-1-m}{N-m}\left(1 - \frac{f(\bar{x}_s)/g(\bar{x}_s)}{(1-F(x_s))/(1-G(x_s))}\right)}, \end{aligned} \tag{4.10}$$

where $\bar{x}_s$ is a short-hand for $\bar{x}(m_s)$. For a fixed, finite m_s, we have:

$$\mu_s = \frac{-\log\frac{F(\bar{x}_s)}{G(\bar{x}_s)} + \log\frac{1-F(\bar{x}_s)}{1-G(\bar{x}_s)} + \frac{(\Delta s_H - \Delta s_L)(k-1)\Delta s'}{(\Delta s_H+\delta)(\Delta s_L+\delta)}}{1 - \frac{f(\bar{x}_s)/g(\bar{x}_s)}{(1-F(\bar{x}_s))/(1-G(\bar{x}_s))}}. \tag{4.11}$$

Note that:

$$\frac{-\log\frac{F(\bar{x})}{G(\bar{x})} + \log\frac{1-F(\bar{x})}{1-G(\bar{x})}}{1 - \frac{f(\bar{x})/g(\bar{x})}{(1-F(\bar{x}))/(1-G(\bar{x}))}} = \frac{\log\frac{f(\bar{x})/g(\bar{x})}{F(\bar{x})/G(\bar{x})} - \log\frac{f(\bar{x})/g(\bar{x})}{(1-F(\bar{x}))/(1-G(\bar{x}))}}{1 - \frac{f(\bar{x})/g(\bar{x})}{(1-F(\bar{x}))/(1-G(\bar{x}))}} > 1. \tag{4.12}$$

Thus, the fictitious tatonnement starts out as an explosive process near $m_s/N = 0$.

For a range of larger values of m_s, we can characterize μ as follows. Consider an alternative continuum version of our model in which there are a continuum of traders rather than finite N traders. Then, by the law of large numbers, we expect that the equilibrium fraction of exiting traders to be $G(\bar{x})$. Thus, we impose $m/N = G(\bar{x}(m))$ in the expression (4.11). Then:

$$\mu_s \approx \Lambda_1(\bar{x}) + \Lambda_2(\bar{x}) \times \frac{(\Delta s_H - \Delta s_L)(k-1)\Delta s'}{(\Delta s_H + \delta)(\Delta s_L + \delta)}, \tag{4.13}$$

where:

$$\Lambda_1 \equiv \frac{-\log\frac{F(\bar{x})}{G(\bar{x})} + \log\frac{1-F(\bar{x})}{1-G(\bar{x})}}{\frac{f(\bar{x})/g(\bar{x})}{F(\bar{x})/G(\bar{x})} - \frac{f(\bar{x})/g(\bar{x})}{(1-F(\bar{x}))/(1-G(\bar{x}))}}, \tag{4.14}$$

and

$$\Lambda_2 \equiv \frac{1}{\frac{f(\bar{x})/g(\bar{x})}{F(\bar{x})/G(\bar{x})} - \frac{f(\bar{x})/g(\bar{x})}{(1-F(\bar{x}))/(1-G(\bar{x}))}}. \tag{4.15}$$

Thus Λ_1 takes a value greater than 1 when $\bar{x}$ is small (and thus m is small) by the argument in Equation (4.12), whereas it takes a value less than 1 when $\bar{x} \to \infty$ (and thus $m \to N$). Thus, we can infer that μ_s travels from an explosive region to a dampening region (if k is small enough) as the fictitious tatonnement develops into a larger m. This suggests that the tatonnement generates m smaller than N when N is large enough. and the fluctuation of m follows the dampened power-law distribution.

To summarize. in the absence of strategic complementarity, a random realization of signals x_i about "High" or "Low" state would have induced some traders to unwind independently of one another. Then. at the completion of the tatonnement process the total population of unwinding traders m would have been drawn from a Poisson distribution with mean μ_1. For $N \to \infty$ the sum of Poisson events converges to a Normal distribution. On the other hand, chasing the common information about "the day of reckoning" introduces strategic complementarity. Then. an initial "independent" unwinding action drawn from a Poisson distribution with mean μ_1 triggers a chain reaction (a branching process) with intensity μ that stops in finite time for $\mu < 1$. As a result, m will be drawn from a population distribution that exhibits a power-law with exponential truncation in the tail. with the speed of exponential truncation, ϕ, inversely related to μ.

4.3.3 Leverage

In addition to issuing liabilities in low-interest currencies. carry trade can be conducted using currency forwards and futures on the margin (Gagnon and Chaboud

(2007)), since as long as covered interest parity (CIP) holds a long dollar short yen currency futures position profits from the UIP violation much like a long dollar bond short yen bond position.[8]

Let $0 < M \leq 1$ denote the margin requirement, such that $M = 1$ means that 100 percent of the dollar asset purchase must be financed by the trader's funds. Trading on the margin allows for leveraged positions. To simplify notation, assume that the interest rate in low yielding currency is approximately zero: $i^* \approx 0$. Then a carry trader who maximizes the expected value of next period's wealth faces the following budget constraint:

$$w' = (w - k') + \frac{1}{M} E(\Delta s + \delta) k', \tag{4.16}$$

where w denotes current wealth of which k' is invested in carry trade on the margin. The threshold condition (4.1) becomes:

$$E(\Delta s + \delta \mid m, x_i = \bar{x}(m)) = M. \tag{4.17}$$

Equation (4.17) illustrates the mitigating effect of a higher margin requirement. Since the return to carry trade must now cover the opportunity cost of foregone alternative uses of a trader's initial wealth, which she has instead pledged as collateral for carry trade, a higher margin requirement raises the required expected rate of return to satisfy the threshold rule. In equilibrium the intensity of

[8] For evidence that the deviations from CIP are rare and insignificant see for example Burnside et al. (2008).

the branching process, μ_s, depends on M in a complex non-linear fashion:

$$\mu_s \approx \Lambda_1(\bar{x}) + \Lambda_2(\bar{x}) \times \frac{(\Delta s_H - \Delta s_L)(k-1)\Delta s'}{(1+\delta-M)(\Delta s_H + \Delta s_L) + (\delta - M)^2}. \tag{4.18}$$

Equation (4.18) shows that the effect of M on μ_s is determined by the relative value of the percentage margin requirement to the percentage interest rate differential, δ. When M is close to 1, the denominator on the RHS of (4.18) is large, mitigating the effect of expected crash risk, $(\Delta s_H - \Delta s_L)$, and accumulated carry positions, k, on μ. On the other hand, when M approaches zero from above, especially when it falls below the value of δ, the denominator becomes small, magnifying the impact of crash risk and carry trade volume on μ_s.

Figure 4.3 [about here]

Figure 4.3 shows the relationship between the margin requirement and μ, holding other parameters constant. We set the interest rate differential equal to 4 percent and yen depreciation equal to 5 percent in "High" state and -4 percent in "Low" state. Total carry position is set at $k = 100,000$ units. The figure shows that when the margin requirement is high a reduction in margin requirement has virtually no effect on the intensity of the branching process measured by μ (herding). However, when the margin requirement is lowered below a certain threshold (in this case approximately 20 percent), then the branching process begins to intensify exponentially. Since μ is inversely related to the degree of exponential truncation in the tail of the distribution of m, a higher μ necessarily implies a thicker tail in the probability distribution of aggregate action, and hence more extreme volatility. Moreover, when the margin requirement reaches the second threshold (in this case approximately 10 percent) then μ is suddenly taken from subcritical ($\mu < 1$) to supercritical state ($\mu > 1$), implying an "explosive" episode of coordination on the same action (all carry trader unwind).

4.3.4 Exchange Rate

The function $\Delta s(mk - N + m)$ is constructed such that the dynamic pattern of exchange rates matches with the model when the static equilibrium of the model is repeated with evolving currency position k. Consider the case $k_0 = 0$. Then the effect of Δs on μ in (4.11) is negative, and thus we expect a high probability for staying behavior: $k' = 1$. In the next period, we set $k_1 = k' = 1$. We have a greater value of μ_s, and expect some probability of collective unwinding. When k becomes quite large, we expect an even higher probability of sudden unwinding because of a greater μ_s. Thus, we expect a small value of m and a gradual increase of k over periods, whereas the development of the carry accumulation is punctuated by a "sudden fall" when m takes some large positive value. In terms of the exchange rate, the currency appreciation Δs is a negative function of $mk - N + m$, and thus the dynamics of m corresponds to the long periods of gradual appreciation of the dollar punctuated by sudden crashes.

4.4 Evidence from Stochastic Volatility in the JPY/USD Exchange Rate

4.4.1 Data

We use intraday JPY/USD exchange rate data from Olsen and Associates. The data was collected from commercial banks by Tenfore and Oanda, and covers the January 1, 1999 to February 1, 2007 time-period. The data consists of the bid and the offer spot exchange rate at the end of every 5-minute interval over every 24-hour period. The quotes are indicative quotes, i.e. not necessarily traded quotes. In addition we construct a daily series of the interest rate spread between U.S. and Japan as the difference between the effective federal funds rate and Japan's uncollateralized overnight call rate, which are publicly available from the Federal Reserve Bank of New York and Bank of Japan respectively. Finally, we obtain daily data on the S&P 500 options implied volatility index (VIX) from Wharton Research Data Services (WRDS).

Figure 4.4 [about here]

The left panel of Figure 4.4 shows the normal kernel density plot of the JPY/USD exchange rate log-return series for our sample period. The leptokurtic features are apparent, with a fatter negative tail (yen appreciations). The right panel shows the associated quantile-quantile plot against a normal distribution (red line). Again, the negative tail exhibits a larger deviation from the normal hypothesis and has a higher number of data points in the extreme range. In the remainder of the section we provide statistical and economic analysis to better understand the underlying data generating process of these extreme realizations in the tails of the distribution of JPY/USD returns.

4.4.2 Extracting Jumps Using Bi-Power Variation

Consider a jump diffusion process for the evolution of foreign exchange rate returns:

$$ds(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dJ(t), \tag{4.19}$$

where $s(t)$ is log exchange rate, $\mu(t)$ is drift, $\sigma(t)$ represents Gaussian volatility component, and $W(t)$ is standard Brownian motion such that $dW(t) = \sqrt{dt}dz$ with $dz \sim N(0,1)$. The last term on the RHS represents the stochastic jump process, $\kappa(t)$ is the size of jump at time t and $dJ(t)$ is an indicator of jumps; $dJ(t) = 1$ with probability $\lambda(t)dt$ and 0 otherwise. A standard practice is to assume that jumps are independent of one another, and therefore to model their arrival rates with a Poisson process where $\lambda(t)$ would correspond to a Poisson arrival rate. In contrast, we do not make any parametric assumptions about $\kappa(t)$. Instead we use a non-parametric method of bi-power variation of Barndorff-Nielsen (2004) to estimate daily jumps as the difference between the total intra-day realized volatility, $RV_t(\Delta)$, and its continuous component, $BV_t(\Delta)$. $RV_t(\Delta)$ is the sum of square intraday discretely sampled Δ -period returns between time 0 and time t. If the intraday data is obtained at five minute intervals then $1/\Delta = 288$ is the number of daily data points. Barndorff-Nielsen (2004) show that in the limit (as $\Delta \to 0$) realized daily volatility approaches the continuously aggregated sum of square returns. Since returns from two adjacent intraday sample points share the persistent volatility but not the sporadic jumps. it follows that bi-power variation provides a reasonable proxy for the persistent component of the volatility:

$$BV_{t+1}(\Delta) \to \int_{t}^{t+1} \sigma^2(s)ds, \tag{4.20}$$

as $\Delta \to 0$.

Since realized volatility. $RV_{t+1}(\Delta)$, and bi-power volatility. $BV_{t+1}(\Delta)$, can be directly calculated from the observed returns, it follows that the jump component can be approximated as the difference of the two:

$$RV_{t+1}(\Delta) - BV_{t+1}(\Delta) \to \sum_{t<s\leq t+1} \kappa^2(s), \tag{4.21}$$

where positive and negative jumps are indexed according to the direction of the corresponding daily return: $\kappa_+(t+1) = I_{\Delta s(t+1)>0} \sum_{t<s\leq t+1} \kappa^2(s)$ and $\kappa_-(t+1) = I_{\Delta s(t+1)<0} \sum_{t<s\leq t+1} \kappa^2(s)$. with $I_{()}$ representing an indicator function for positive and negative daily returns respectively. We take additional steps to account for the finite sample bias. and in addition to reporting all jumps. we report jumps estimated with $\alpha = 0.05$ and 0.01 significance levels correcting for intraday noise. Choosing to estimate fewer but more probable jumps as opposed to a contin-

uous adjustment amounts to choosing a lower significance level α associated with critical value Φ_α. The details of this procedures are outlined in Appendix C.2.1.

4.4.3 Descriptive Statistics and Serial Correlation in Yen appreciation Jumps

Table 4.1 shows jump summary statistics. Mean absolute values of jumps in yen appreciations are higher for all α ranging between 0.019 and 0.044, compared to 0.16 and 0.36 for jumps in yen depreciations. Negative jumps (appreciations) also exhibit higher kurtosis. The maximum jump in appreciation is 2.959 compared to the maximum jump of 1.482 in yen depreciation. The last row of Table 4.1 reports Ljung-Box test statistic for white noise. Negative jumps exhibit a high degree of serial correlation with the Q-stat in the 133.5 to 161.9 range. Using a more restrictive $\alpha = 0.01$ criteria serial correlation is rejected for positive jumps selected. Overall, Table 4.1 indicates that jumps in yen appreciation are more rare than jumps in yen depreciation, but tend to be larger in magnitude and occur over several consecutive days, implying an element of predictability.

Table 4.1 [about here]

4.4.4 Sample Split by U.S.-Japan Interest Rate Differential and the VIX

Next we split the sample by the interest rate differential between U.S. and Japan, and by the level of VIX, focusing on $\alpha = 0.01$ jumps. If carry trade plays a significant role in the stochastic volatility of the JPY/USD exchange rate then the contrast between yen appreciation and yen depreciation jumps should be magnified when the incentive to engage in carry trade is high (high interest rate differential) and when overall market uncertainty is high (high level of VIX). Based on the historical time-series in Figure 4.1 we observe roughly two regimes in the interest rate differential and VIX. Throughout our sample period Japan maintained a zero-interest rate policy. while the dot-com collapse in the U.S. resulted in monetary easing beginning in late 2000. and the interest rate differential between the two countries fell to the level between 1 and 2 percent where it remained until the Fed began raising rates in 2004. Also. beginning in early 2003, the VIX settled at levels below 20 and exhibited a lower volatility. Therefore. we select 2 percent as the cutoff for the interest rate differential and 20 points as the cutoff for VIX (dashed lines).

Table 4.2 [about here]

Table 4.2 shows the associated statistics. Mean and maximum values for κ_- (yen *appreciation* jumps) are higher when the interest rate differential is high, 0.124 compared to 0.093 and 1.386 compared to 1.124 respectively. The difference is more pronounced when compared across subsamples split by VIX. When VIX is high κ_- mean and maximum are 0.140 and 1.386 compared to 0.078 and 0.510 when VIX is low respectively. In contrast. κ_+ (yen *depreciation* jumps) do not exhibit a higher mean or maximum when the differential is high. and only slightly higher mean when VIX is high. 0.099 compared to 0.082. Also, unlike yen appreciation jumps.

the jumps in yen depreciation exhibit no serial correlation. Overall, the comparison of summary statistics for jumps in realized volatility across different levels of the interest rate differential and VIX are consistent with the hypothesis that carry trade plays a role in the stochastic volatility in JPY/USD.

4.4.5 Non-Linear Dependence in Yen appreciation Jumps

Next we test for non-linear dependence in the jump series using the BDS test named after Brock, Dechert, and Scheinkman (1987). The BDS test can be thought of as non-linear counterpart of the Q-test.[9] The test was applied to find evidence of conditional heteroskedasticity in foreign exchange rate returns by Hsieh (1989), who found that nonlinearity in the return series entered through changing volatility. We are able to examine whether discrete changes in realized volatility exhibit non-linearity. The test embeds the time series of $\kappa(t)$ into m-dimensional vectors with overlapping entries, and computes the spatial correlation among the points in the m-dimensional space which are within tolerance radius ϵ of each other. Properly adjusted for the sample size and specially defined mean and variance, the correlation statistic asymptotically follows a standard normal distribution. We select m in the same way as the number of lags for the Q-test. In addition, we parametrize the test to maintain robustness to unusual or unknown distributions of the series: we choose the tolerance radius such that 0.7 of the total number of pairs of points in the sample lie within ϵ, and the $p-values$ are computed by bootstrapping based

[9]For detail see Brock et al. (1996).

on 1,000 repetitions. Table 4.3 shows the results.[10] After a minimal correction for itraday noise is employed (such as $\alpha = 0.05$) non-linear dependence is present only in yen appreciation jumps. and significant at 1 percent level for all m.

Table 4.3 [about here]

The BDS and the Q-test results indicate that yen *appreciation* jumps exhibit both serial correlation and non-linear dependence while the null of white noise cannot be rejected for yen *depreciation* . It follows that yen appreciation jumps exhibit an element of predictability and clustering while yen depreciation jumps are random noise. What this suggests is that continuous trends of yen depreciations (with purely random occasional jumps) were on occasion interrupted by sharp yen appreciation jumps whose persistence is clearly outside the domain of Guaissian noise.

4.4.6 Exponentially Dampened Power-law in the Distribution of Jumps

Quintos et al. (2001) and Candelon and Straetmans (2006) inspect the tail behavior of foreign exchange returns non-parametrically with the inference based on distribution quantiles. In contrast. the equilibrium of stochastic herding yields parametric restrictions on the tail distribution. Interestingly. it matches the empirical findings

[10]We also run the BDS test for jump series before separating into positive and negative samples to find strong evidence of non-linear dependence The results reported in the paper show that the time-series non-linearity comes from yen appreciation jumps

in options literature (Wu (2006)) that describes the Levy density of jump components, κ, as an exponentially damped power-law:

$$Pr(\kappa) \propto \begin{cases} \kappa^{-\zeta_+} e^{-\phi_+ \kappa} & , \kappa > 0 \\ |\kappa|^{-\zeta_-} e^{-\phi_- |\kappa|} & , \kappa < 0 \end{cases}$$

This specification is parsimonious enough to nest several families of jump processes. For instance the values of the power exponent $1 \leq \zeta < 3$ favor a Levy regime implying fat tails and undefined second moment while $\zeta > 3$ favors a Gaussian regime with finite variance.[11] Nirei (2006*b*, 2008) shows that an exponentially dampened power-law in the distribution of rare events arises in the environment characterized by periodic episodes of coordination in traders' actions. Hence, putting the above structure on the tail ultimately allows us to make inferences about the underlying data generating process.

In order to examine whether the tail distribution of κ follows a power-law we follow the methodology of Clauset et al. (2009). For each possible choice of cutoff values for the power-law tail in the distribution of κ, we estimate the power exponent via the maximum likelihood and calculate the Kolmogorov-Smirnov (KS) goodness-of-fit statistic. We then select the minimum cutoff, κ_{min}, that gives the minimum KS-statistic. Figure 4.5 shows the probability plots for positive and negative jumps

[11] In a panel study of different currencies Bakshi et al. (2008) estimates parameters of a jump diffusion processes with exponentially dampened power-law. They do not have observations on jumps separately, so they estimates ζ and ϕ for positive and negative jumps as a part of a richer parametrization scheme for the entire return process. Our study is the first to examine the goodness-of-fit of exponentially damped power-law model to empirical observations of jumps.

for each level of significance on a log-log scale. The fitted straight line on the log-log probability plot indicates that distributions of jumps exhibit strong power-law tails.

Figure 4.5 [about here]

Next we examine whether the power-law tails in yen *appreciation* jumps are subject to exponential truncation as stipulated by the model. Table 4.4 shows exponentially dampened power-law parameter estimates for negative jumps selected at three different significance levels against the two alternatives: Pareto (pure power-law) and lognormal (an alternative of random noise) distributions. Given that the distribution parameters are estimated from a relatively small number of observations in the tail we use The Bayesian Markov Chain Monte-Carlo (MCMC) method to estimate the fitted parameter uncertainty for the exponentially dampened power-law. Details of this procedure are provided in Appendix C.2.2.

Table 4.4 [about here]

The log likelihood values indicate that the exponentially dampened power-law is the preferred model for all three negative jump series. This is confirmed by the Akaike information criteria (AIC) and AIC corrected for small sample size (AICc). The estimates of ζ tend to decline as only significant jumps are selected, tending towards the borderline case of $\zeta = 2$. The estimates of the power-law exponent ζ in the neighborhood of 2 indicate that the data on yen *appreciations* was drawn from a process with infinite second moment, rather than Merton's compound Poisson normal process.

Table 4.5 [about here]

Table 4.5 shows exponentially dampened power-law parameter estimates for positive (yen *depreciation*) jumps. Once again a compound Poisson jump process is rejected in favor of a model that yields a power-law tail. However. in contrast to negative jumps. the positive jump data for $\alpha = 0.01$ favors a pure power-law (Pareto) distribution in the tail rather than exponentially dampened power-law as indicated by log likelihood and AIC values. Moreover. the power exponent $\zeta = 3.2$ indicates a regime closer to Gaussian. with a finite second moment rather than a Levy process. as was found for yen *appreciation* jumps. The difference in parameter estimates and in their behavior across jumps of different significance levels indicate that while both negative and positive jumps follow distributions with power-law tails, the underlying data generating processes are not the same. This is confirmed by the simulations of $\alpha = 0.05$ jumps shown in Figure 4.6. with the exponentially dampened power-law parameters from Tables 4.4 and 4.5.

Figure 4.6 [about here]

The top panel in Figure 4.6 corresponds to the simulated series, while the bottom panel displays the empirical observations of jumps. The amplitude in fluctuations is higher for both empirical and simulated series for the negative jumps. The simulation of the negative jump series matches the pattern of the data in generating small jump periods punctuated by extreme deviations. This is not the case for the positive jumps. The simulation based on distribution parameter estimates of positive jumps produces a series more even in magnitude, consistent with the lower variability of the observed positive jumps. Based on simulation results, we suspect that the underlying data generating process differs for negative and positive jumps, with negative jumps subject to more extreme fluctuations. The contrast between the simulation results of yen appreciation (negative) and yen depreciation (positive) jumps clearly captures the origins of the negative skewness of JPY/USD returns.

Finally, the model predicts the power exponent of 1.5 in the exponentially dampened power-law. Our empirical estimates for the exponent, conditional on the cut-off value for the tail selected based on the best fit for the Pareto distribution have yielded estimates of the exponent in the neighborhood of 2. This gap may be rectified by modifications on estimation and modeling. Table 4.6 illustrates that under an alternative selection criteria for the cut-off, κ_{min}, estimates of 1.5 for ζ are also within the feasible range. The lower cut-off on the tail observations has been selected as one standard deviation in the empirical jump data. Under this more inclusive specification the power-law exponent is 1.527 for negative jumps and 1.495 for positive jumps.

Table 4.6 [about here]

Alternatively, it is known that the power exponent ζ derived in the model is increased above 1.5 if the parameter μ is taken gradually from below the criticality $\mu < 1$ toward the criticality during the time span of observations. This mechanism is called a "sweeping" of control parameter towards a critical point (Sornette (2006)).

Recall the case in which we repeat the static equilibrium over periods where the currency position k is updated over the periods. When k is small, the tatonnement is likely to be subcritical, with $\mu < 1$, while μ is increased toward 1 as k increases. Thus, the effect of possible sudden yen *appreciation* due to the collective unwinding becomes more significant on the overall return when the volume of existing carry trade position is large. If our data is generated by such a process, the situation exactly falls in the scenario of the sweeping of a parameter where the key parameter μ gradually sweeps toward the criticality at 1. In this case, the observed jumps exhibit dampened power-law with exponent greater than 1.5. The exact value of the exponent depends on how the parameter μ is increased over periods.

4.4.7 Economic Determinants of the "Tail Risk"

The model imposes a number of restrictions on the relationship between $\phi = \mu - 1 - log(\mu)$ and the economic variables related to carry trade activity. We begin with a subsample analysis. Since the stochastic dynamics in carry trade are conditional on non-negligible positive carry, δ, we expect the distribution parameters to take on model-implied values when the interest rate differential between U.S. and Japan was relatively sizable. Table 4.7 shows distribution parameter estimates for subsamples of high and low interest rate differentials considered in the previous sub-section. The power exponent, ζ, for yen appreciation jumps is 2.007 when the differential is high (closer to 1.5 implied by the model) compared to 2.394 when the differential is low. The exponential truncation parameter ϕ is 1.250 when the interest differential is high compared to 1.410 when the differential is low. For both parameters the difference is approximately 2 standard deviations. significant at the 5 percent level. The lower ϕ during higher interest rate differential period indicates the exponential truncation point further in the tail of the distribution – a higher "tail risk." Intuitively, this means that when the interest differential is high a larger adjustment is induced by the same size perturbation. that is a larger number of traders. m, would have unwound their carry positions having observed an "independent" unwinding action of an initial trader $m_0 = 1$.

In addition to the interest rate differential we also split the sample by VIX. Although a risk-neutral setup is sufficient to generate the necessary dynamics, we expect higher risk aversion (also to the extent that it is associated with tighter funding constraints) to be associated with higher "tail risk" (lower ϕ). Table 4.8 shows distribution parameter estimates for subsamples split by the level of VIX. Consistent with the above hypothesis, when VIX is high then the exponentially dampened power-law has a higher log likelihood than a simple Pareto. We also get a considerably lower estimate of ϕ compared to when VIX is low, 0.620 versus 3.327. with the difference significant at 1 percent level.

Tables 4.7 & 4.8 [about here]

Figure 4.7 shows the kernel density plots of yen *appreciation* jumps for high and low VIX subsamples analyzed in Table 4.8. The figure confirms that lower ϕ during high VIX periods is associated with a more stretched tail of the distribution.

Thus, risk in the JPY/USD currency market appears to be directly linked to risk aversion and uncertainty in broader financial markets.

Figure 4.7 [about here]

The extreme case of $\phi = 0$ corresponds to the criticality of $\mu = 1$. Then, the model generates a pure power-law distribution for m and the branching process becomes a martingale, that is the conditional expectation then is that all managers liquidate next period if all are liquidating in the current period. At this stage, the feedback between traders is at a maximum and will eventually lead all traders to coordinate on the same action. The top panel of Figure 4.8 shows data simulated using a power-law fit to the negative jump series. The simulation approximates the general amplitude in the fluctuations of the empirical data shown in the bottom panel except for the one "catastrophic" event when the simulated jump exceeds 11 in absolute value. The simulation illustrates the ability of the model to incorporate "rare" disasters and day-to-day volatility in the same data generating process. This is because the estimates of the power exponent (tail index) for yen *appreciation* jumps favor a Levy regime with undefined second moment entailing the probability of an "extreme" event much higher than can be drawn from a Gaussian regime.

Figure 4.8 [about here]

The preceding analysis has shown that the crash risk of the carry currency rises exponentially as $\phi \to 0$. In order to better understand the economic determinants of such "tail risk", we conduct a structural examination of the dependence of

ϕ on the variables related to carry trade based on Equation (4.18). Equation (4.18) allows us to sign the impact of accumulated carry positions, k, expected "crash," $(\Delta s_H - \Delta s_L)$, and margin requirements, M, on ϕ. The second column of Table 4.9 lists the expected signs of the impact on ϕ, based on partial differentiation of μ with respect to each variable; recall that a higher intensity in the branching process μ implies exponential truncation further in the tail of the distribution hence lower ϕ. The fourth column of Table 4.9 lists the empirical proxies for k, $(\Delta s_H - \Delta s_L)$, and M respectively. We proxy for k with CME non-commercial short futures positions in the yen (which CFTC classifies as speculative), for $(\Delta s_H - \Delta s_L)$ we proxy with the values of risk reversals, and for M we use historical margin requirement data for yen futures trading obtained from the CME group[12] We use initial margin requirement data on speculative positions. In addition, we also control for risk aversion, denoted as ρ, using historical VIX. We do this for two reasons: first, to the extent that VIX proxies not only for risk aversion but also for funding conditions, it is an important variable for gaging speculative forces in foreign exchange, and second, since the value of risk reversals conveys option implied skewness *and* skewness risk premium, or equivalently $(\Delta s_H - \Delta s_L)\rho$, it is necessary to control for risk aversion separately with a proxy such as the VIX. While we were able to obtain data on non-

[12]CME Group sets four margin requirements for currency futures, namely initial and maintenance margins on speculators and hedgers/members. A sample margin requirement report is shown in Figure 4.13. A trader is classified as a "speculator" if the trader is not identified as hedging a foreign exchange exposure according to the entity's Statement of Reporting Trader (CFTC Form 40). The CFTC staff may re-classify the trader if they possess additional information about the trader's use of the futures market. The "speculator" or "non-commercial" category mostly includes professional money managers such as hedge funds and commodity trading advisers. A sample report if shown in Figure 4.14. For further details see http://www.cftc.gov/MarketReports/CommitmentsofTraders/.

commercial shorts and the VIX and CME initial speculative margin requirement in yen futures for the entire January 1, 1999 through February 1, 2007 period. the risk reversal data was only available as of September 2003.

Table 4.9 [about here]

Again, we use Bayesian econometrics, which provide convenient tools for treating distribution parameters themselves as stochastic. We use Bayesian MCMC implemented via Metropolis-Hastings (MH) method.[13][14] It is more parsimonious than Gibbs sampling in that it does not require a conjugate prior for each distribution parameter, but samples from a proportional probability distribution to the density to be calculated. We use an MH algorithm to sample from the following hierarchical model:

$$Pr(\kappa_j) \propto \kappa_j^{-1.5} e^{-\phi_j \kappa_j}, \text{ and} \tag{4.22}$$

$$\phi_j = \gamma_0 + \sum_{l=1}^{4} \gamma_{l,j} X_{l,j} + \epsilon_j;\ j = 1, 2 \ldots, J, \tag{4.23}$$

with priors,

$$\gamma_0 \sim N(\mu_0, \sigma_0), \tag{4.24}$$

$$\gamma_l \sim N(\mu_l, \sigma_l), \text{ and} \tag{4.25}$$

[13]The estimation was conducted with WinBUGS software following the Bayesian modeling framework outlined in Lunn et al (2000)

[14]See Chib and Greenberg (1995) for a comprehensive reference on Metropolis-Hastings algorithm

$$\tau_\epsilon \sim \Gamma(\alpha_\epsilon, \beta_\epsilon) \tag{4.26}$$

where $N(\cdot)$ and $\Gamma(\cdot)$ denote Normal and Gamma distributions. The hyper-parameters for γ_0 and γ_l's were selected such that prior means match the MLE estimates. We account for additional variability in ϕ via a random effects term, ϵ_j, whose precision is measured by τ_ϵ. We are most interested in obtaining the coefficient vector of γ_l's on the vector of four controls, $\mathbf{X} = [k,\ \rho,\ M,\ (\Delta s_H - \Delta s_L)]$: the volume of non-commercial yen short futures, VIX, the CME margin requirement, and risk reversals. The first three values are nominal, and therefore enter in logs. The risk reversals enter with a 1 day lag in order to avoid endogeneity issues due to the possible reverse causality from a yen appreciation jump to higher absolute value of risk reversals.

Table 4.10 [about here]

Table 4.10 shows the estimation results. The signs of the coefficients are consistent with model hypothesis: higher k and $(\Delta s_H - \Delta s_L)$ are associated with an increased "tail risk" of sharp yen appreciation (lower ϕ), while higher M is associated with lower risk (higher ϕ). The coefficients on non-commercial speculative short yen positions, k, are statistically significant under all specifications confirming our main hypothesis that carry trade plays a major role in stochastic volatility of the JPY/USD exchange rate. The coefficient on VIX is also negative indicating that higher VIX is associated with a more elongated tail on the yen appreciation side (or equivalently more negative skewness in JPY/USD as found in Brunnermeier et al.

(2009)), but becomes insignificant when controlling for speculative short positions. This indicates that risk aversion and funding considerations implicit in the value of VIX affect the skewness of the JPY/USD exchange rate primarily through changes in carry trader positions, k.

The coefficients on margin requirement and risk reversals, although of the hypothesized sign, are insignificant when added sequentially. For instance, the coefficient on M in specification (5) is 1.024 (standard error 0.719) indicating that M has statistically significant positive impact on ϕ at the 68% but not at the 95% confidence level. This may be due to much lower variability in the margin requirement which changed anywhere between 3 to 10 times per year during our sample period. Shorter sample in the case of risk reversals is another impediment. When we restrict the vector of controls of ϕ to a constant, lagged risk reversals, and random effect, then the coefficient on risk reversals more than doubles, and is statistically significant at 5 percent level.[15]

Figure 4.9 [about here]

Figure 4.9 shows the pairwise scatter plot of the sampled coefficients, where

[15]The inference of coefficient significance and correlations rest on the assumption of unbiasedness of the estimates. Figure 4.11 shows Bayesian MCMC diagnostic plots for γ_1 through γ_4. The first column plots the density of the samples. Symmetric bell curves indicate a good mixture and that a normal approximation to the standard errors is reasonable. The second column plots the rapidly declining autocorrelation function of the samples indicating a rapid mixing with estimates theselves approaching white noise. The third column shows a visual test for endogeneity via a scatter plot between sampled slope coefficients and the random effects component, τ_ϵ, which is bounded at zero from below. The scatter plots show a random spread consistent with exogeneity of the controls. Finally, Figure 4.12 shows Metropolis acceptance rates with acceptance rates reaching the stationary level around the commonly accepted level of 0.234 random walk MH algorythm within 1,000 to 2,000 samples; we discard the first 4,000 using the subsequent 10,000 for inference.

γ_1. γ_2. γ_3, and γ_4 are coefficients on CME speculative positions. VIX. CME margin requirement. and risk reversals respectively. While most scatter plots show a random spread (no multicollinearity) the scatter plot between γ_1 and γ_3 (γ_1 and γ_4) exhibit a negative (positive) correlation. Figure 4.10 shows the blowup plots for these coefficient pairs with best linear fit. The correlation between coefficients on speculative positions and margin requirement (γ_1 and γ_3) is -0.3528, and the correlation between coefficients on speculative positions and risk reversals (γ_1 and γ_4) is 0.1650, with $p-value$=0.0000 for both. Such complementarity between the effect of k. M, and $(\Delta s_H - \Delta s_L)$ has a ready economic interpretation based on Equation (4.18). Recall that both M^{-1} and $(\Delta s_H - \Delta s_L)$ affect the intensity of the chain reaction in carry unwinding multiplicatively with k. This indicates that tougher margin requirements have an effect of reducing the probability of extreme yen appreciation by mitigating the impact of carry trade activity. Similarly. expectations of sharp yen appreciation tend to be self-fulfilling and further increase the probability of extreme yen appreciation through the actions of carry traders.

To summarize. this subsection served the dual purpose of testing the implications of the model and identifying the sources of "tail risk" for rare but significant events of a sharp yen appreciation. The findings point at carry trade as the major factor. First. stochastic volatility on the yen appreciation side is more extreme when the incentive for currency speculation is higher (higher δ); second, stochastic volatility on the yen appreciation side is positively associated with a greater volume of speculative positions (proxied by CME non-commercial short yen futures contracts); and third, the effects of other financial variables, such as the VIX, margin requirement, and option implied expectations of yen appreciation risk appear to affect the probability of extreme yen appreciation through the carry trade channel.

4.5 Conclusion

This paper indetifies and empirically tests several features of speculative dynamics that contribute to such stylized facts as skewness and excess volatility in foreign exchange returns, otherwise known as the *exchange rate disconnect puzzle* . We model strategic traders trying to profit from the interest rate differential between two countries at the expense of exposing themselves to currency crash risk. The common uncertainty about the "day of reckoning" makes it rational for carry traders to infer information from each others' trades. This introduces an element of dependency in traders' actions leading to endogenous episodes of "explosive" carry unwinding via a chain reaction through information revelation. While the underlying dynamics are generated by the propensity of carry traders to herd, leverage can exacerbate the chain reaction in carry unwinding. The impact of leverage is highly non-linear, and suggests that there may exist an optimal percentage margin requirement on speculative positions which is a function of the interest rate differential between high and low yielding currencies.

In equilibrium, the distribution of the number of traders unwinding their positions fluctuates according to a power-law with exponential truncation, and with a linear price impact function, so too do the jumps in foreign exchange returns. The model yields a power-law exponent of -1.5 in the density function of jumps, which is found to be in the feasible range of our empirical estimates from the JPY/USD exchange rate.

Because of prolonged "zero interest rate" policy of the Bank of Japan, the Japanese yen in particular has served as a funding currency in carry trade. Consistent with day to day volatility dynamics being influenced by carry trade, only yen appreciation jumps exhibit dependence and follow a Levy regime with unbounded variation, while yen depreciation jumps are best described as white noise. In particular, we find that sharp yen appreciations over the period from January 1, 1999 through February 1, 2007 are more likely to follow an exponentially dampened power-law than Merton's compound Poisson normal process. The asymmetries and higher negative skew of JPY/USD returns are confirmed by simulations based on estimated distribution parameters. Since only yen appreciations would have been costly to carry traders producing different dynamics on the way up than on the way down, such asymmetries are consistent with the role of the yen as a funding currency in carry trade during our sample period.

Based on parametric restrictions from the model we identify economic factors that lead to extreme volatility by intensifying the herd effect. In the analysis of subsamples we find that the key distribution parameter that captures the intensity of herding is higher during times of greater interest rate differential and higher values of VIX. Fitting the model in reduced form to the data, we find that tougher margin requirements have an effect of reducing the probability of extreme yen appreciation by mitigating the impact of carry trade activity. Similarly, expectations of sharp yen appreciation tend to be self-fulfilling and further increase the probability of extreme yen appreciation through the actions of carry traders. The impact of the volume of speculative futures on the "tail risk" is particularly robust, corroborating the key hypothesis that speculative dynamics play a destabilizing role in foreign exchange markets.

Our data do not include "extreme" episodes in JPY/USD return volatility corresponding to the 1998 LTCM collapse and the 2008 sub-prime crisis. Yet, exponentially dampened power-law parameter estimates indicate that the data comes from a distribution that generates yen *appreciation* jumps with unbounded variation, essentially attributing rare market crashes and normal return volatility to the same underlying mechanism.

Table 4.1: Serial dependence and greater extremes in yen *appreciation* jumps.

	Yen Appreciation Jumps			Yen Depreciation Jumps		
	κ_-	$\kappa_-(\alpha = 0.05)$	$\kappa_-(\alpha = 0.01)$	κ_+	$\kappa_+(\alpha = 0.05)$	$\kappa_+(\alpha = 0.01)$
Prop.	0.474	0.246	0.172	0.485	0.239	0.167
Obs.	1255	650	455	1276	628	438
Mean	0.044	0.026	0.019	0.036	0.022	0.016
St. Dev.	0.113	0.097	0.073	0.079	0.068	0.055
Skew.	10.543	14.290	8.575	6.521	8.803	7.876
Kurt.	202.355	351.193	110.709	77.961	133.712	105.325
Min.	0.000	0.000	0.002	0.000	0.000	0.001
Max.	2.959	2.959	1.386	1.482	1.482	1.125
Q-stat	161.899***	79.366***	133.528***	38.296***	33.733***	3.828

Notes: The table shows summary statistics for realized volatility jumps in JPY/USD exchange rate. All jumps and jumps with $\alpha = 0.05$ and $\alpha = 0.01$. The Ljung-Box Q-test statistic (Q-stat) #lags=log(sample size); *,**, and *** indicate rejection of H_0 of white noise at 5%, 1% and 0.1% level of significance respectively. 01/01/1999 through 02/01/2007 sample period.

Table 4.2: Subsample summary statistics for realized volatility jumps in JPY/USD exchange rate.

	High Differential		Low Differential		High VIX		Low VIX	
	κ_-	κ_+	κ_-	κ_+	κ_-	κ_+	κ_-	κ_+
Prop.	10.51%	10.90%	6.69%	8.12%	9.34%	5.80%	7.83%	8.58%
Obs.	278	286	177	213	247	152	207	225
Mean	0.124	0.093	0.093	0.109	0.140	0.099	0.078	0.082
St. Dev.	0.160	0.089	0.113	0.098	0.177	0.126	0.080	0.107
Skew.	3.941	2.976	5.172	2.906	3.769	5.074	2.672	5.765
Kurt.	23.883	17.218	42.683	15.898	20.888	35.761	11.442	48.260
Min.	0.002	0.001	0.002	0.001	0.002	0.003	0.002	0.007
Max.	1.386	0.780	1.124	0.780	1.386	1.125	0.510	1.125
Q-stat	88.506***	1.399	46.481***	1.253	63.216***	4.708	25.4126***	3.616

Notes: Samples split at $(\imath^{US} - \imath^{JP}) = 2\%$ and VIX = 20 pts. Under a more conservative criteria only jumps significant at $\alpha = 0.01$ included. The Ljung-Box Q-test statistic (Q-stat) #lags=log(sample size); *,**, and *** indicate rejection of of white noise at 5%, 1% and 0.1% level of significance respectively. 01/01/1999 through 02/01/2007 sample period.

Table 4.3. Non-lnear dependence ın realized volatility jumps

	Yen Appreciation Jumps						Yen Depreciation Jumps					
	κ_-		$\kappa_-(\alpha = 0\ 05)$		$\kappa_-(\alpha = 0\ 01)$		κ_+		$\kappa_+(\alpha = 0\ 05)$		$\kappa_+(\alpha = 0\ 01)$	
dım	BDS-stat	prob	BDS-stat	prob	BDS-stat	prob	BDS-stat	prob	BDS-stat	prob	BDS-stat	prob
2	0 024***	0 000	0 015***	0 000	0 008**	0 016	0 009***	0 000	0 002	0 554	0 005	0 144
	(0 003)		(0 003)		(0 003)		(0 003)		(0 003)		(0 004)	
3	0 043***	0 000	0 025***	0 000	0 016***	0 008	0 017***	0 000	0 002	0 698	0 007	0 222
	(0 004)		(0 005)		(0 006)		(0 004)		(0 005)		(0 006)	
4	0 055***	0 000	0 028***	0 000	0 022***	0 002	0 019***	0 000	0 001	0 850	0 007	0 278
	(0 005)		(0 006)		(0 007)		(0 005)		(0 006)		(0 007)	
5	0 063***	0 000	0 029***	0 000	0 022***	0 006	0 020***	0 000	0 002	0 730	0 007	0 300
	(0 005)		(0 006)		(0 007)		(0 005)		(0 006)		(0 007)	
6	0 065***	0 000	0 027***	0 000	0 020***	0 010	0 021***	0 000	0 002	0 622	0 004	0 490
	(0 005)		(0 006)		(0 007)		(0 005)		(0 006)		(0 007)	

Notes The table show BDS test results, only yen *appreciatıon* jumps exhıbıt non-lınear dependence Standard errors ın parenthesıs, *,**, and *** ındıcate rejectıon of the null of I I D at 5%, 1% and 0 1% level of sıgnıficance respectıvely Test parametrızed to be most parsımonıous to unknown dıstrıbutıon ın the data so acceptance parameter selected such that 0 7 of the total number of paırs of poınts ın the sample lıe wıthın the acceptance radıus and p-values calculated by bootstrappıng based on 1,000 repetıtıons Embedıng dımentıon (m) chosed as log(sample sıze) of the data

Table 4.4: Distribution parameter estimates for yen *appreciatıon* jumps.

	κ_-			$\kappa_-(\alpha = 0\ 05)$			$\kappa_-(\alpha = 0\ 01)$		
Dıst	PL-Exp	PL	LogN	PL-Exp	PL	LogN	PL-Exp	PL	LogN
Param 1	ζ	ζ	μ	ζ	ζ	μ	ζ	ζ	μ
	3 110	3 183	-0 776	2 377	2 615	-1 618	2 246	2 704	-1 501
	(0 193)	(0 258)	(0 056)	(0 199)	(0 207)	(0 041)	(0 204)	(0 223)	(0 048)
Param 2	ϕ		σ	ϕ		σ	ϕ		σ
	0 080		0 463	0 528		0 564	1 040		0 528
	(0 021)		(0 040)	(0 018)		(0 029)	(0 023)		(0 034)
Log-Lıke	39 012	38 993	9 387	209 283	208 458	146 591	128 253	127 160	89 240
AIC	-74 024	-75 986	-14 774	-414 566	414 916	-289 182	-252 506	-252 320	-174 480
AICc	-73 845	-75 898	-14 595	-414 502	-414 884	-289 118	-252 406	-252 270	-174 380
Cutoff	0 291			0 107			0 124		
	(0 051)			(0 033)			(0 027)		
Taıl Obs	70			190			123		
	(141 455)			(57 801)			(40 092)		
Total Obs	1,255			650			455		

Notes Test the goodness of fit of exponentıally dampened power-law $Pr(\kappa) \propto \kappa^{-\zeta} e^{-\phi\kappa}$ (an outcome of dependent events) versus Pareto (pure power law) and log-normal (an outcome of ındependent events) The power exponent estımated vıa the maxımum lıkelıhood then select the mınımum cutoff κ that gıves the mınımum KS-statıstıc Standard errors ın parentheses Standard errors for ζ and ϕ calculated usıng Bayesıan MCMC method based on 10,000 sımulatıons

Table 4.5: Distribution parameter estimates for yen *depreciation* jumps.

	κ_+			$\kappa_+(\alpha = 0.05)$			$\kappa_+(\alpha = 0.01)$		
Dist.	PL-Exp	PL	LogN	PL-Exp	PL	LogN	PL-Exp	PL	LogN
Param 1	ζ	ζ	μ	ζ	ζ	μ	ζ	ζ	μ
	2.510	2.967	-1.502	2.928	3.065	-1.538	2.983	3.229	-1.547
	(0.202)	(0.224)	(0.036)	(0.203)	(0.286)	(0.045)	(0.203)	(0.395)	(0.047)
Param. 2	ϕ		σ	ϕ		σ	ϕ		σ
	1.125		0.466	0.321		0.475	0.642		0.435
	(0.018)		(0.026)	(0.026)		(0.032)	(0.032)		(0.034)
Log-Like.	198.864	197.884	142.702	145.335	145.234	99.382	117.424	117.284	84.037
AIC	-393.728	-393.768	-281.404	-286.670	-288.468	-194.764	-230.848	-232.568	-164.074
AICc	-393.549	-393.680	-281.225	-286.606	-288.436	-194.700	-230.748	-232.518	-163.974
Cutoff	0.134			0.132			0.136		
	(0.030)			(0.034)			(0.035)		
Tail Obs.	168			115			87		
	(111.917)			(74.413)			(64.540)		
Total Obs.	1,276			628			438		

Notes: Test the goodness of fit of exponentially dampened power-law $Pr(\kappa) \propto \kappa^{-\zeta} e^{-\phi\kappa}$ (an outcome of dependent events) versus Pareto (pure power-law) and log-normal (an outcome of independent events). The power exponent estimated via the maximum likelihood then select the minimum cutoff κ that gives the minimum KS-statistic. Standard errors in parentheses. Standard errors for ζ and ϕ calculated using Bayesian MCMC method based on 10,000 simulations.

Table 4.6: Model distribution parameter estimates with alternative cut-off for the tail.

	κ_-	$\kappa_-(\alpha = 0.05)$	$\kappa_-(\alpha = 0.01)$	κ_+	$\kappa_+(\alpha = 0.05)$	$\kappa_+(\alpha = 0.01)$
ζ	2.288	2.230	1.527	2.146	2.049	1.495
	(0.197)	(0.196)	(0.201)	(0.200)	(0.200)	(0.201)
ϕ	0.713	0.744	2.480	1.858	1.992	4.324
	(0.026)	(0.035)	(0.041)	(0.028)	(0.039)	(0.046)
Cutoff	0.113	0.097	0.073	0.079	0.068	0.055
Log Likelihood	286.250	237.038	244.226	538.233	428.577	421.284
Tail Observations	274	211	210	368	283	268
Total Observations	1255	650	455	1276	628	438

Notes: Exponentially dampened power-law $Pr(\kappa) \propto \kappa^{-\zeta} e^{-\phi\kappa}$ parameters estimated in the tail with cutoff at 1 standard deviation. Exponentially dampened power-law parameters re-estimated expanding cutoff for the tails of the distribution to 1 standard deviation bounds. Under this more inclusive specification a power law exponent of 1.5 is observed in the data. Standard errors in parentheses.

Table 4.7: Distribution parameter estimates. sample split by interest rate differential.

	High Interest Rate Differential						Low Interest Rate Differential					
	$\kappa_{-}(\alpha = 0\ 01)$			$\kappa_{+}(\alpha = 0\ 01)$			$\kappa_{-}(\alpha = 0\ 01)$			$\kappa_{+}(\alpha = 0\ 01)$		
Dist	PL-Exp	PL	LogN	PL-Exp	PL	LogN	PL-Exp	PL	LogN	PL-Exp	PL	LogN
Param 1	ζ	ζ	μ	ζ	ζ	μ	ζ	ζ	μ	ζ	ζ	μ
	2 007	2 569	-1 530	2 769	3 610	-1 461	2 394	2 874	-1 785	2 894	2 932	-1 745
	(0 194)	(0 406)	(0 057)	(0 200)	(0 690)	(0 052)	(0 204)	(0 511)	(0 065)	(0 198)	(0 439)	(0 081)
Param 2	ϕ		σ	ϕ		σ	ϕ		σ			σ
	1 250		0 561	2 408		0 355	1 410		0 487	0 094		0 531
	(0 060)		(0 041)	(0 100)		(0 038)	(0 106)		(0 047)	(0 114)		(0 059)
Log-Like	92 538	93 749	65 281	68 830	68 576	51 153	78 550	81 079	61 272	63 659	63 671	42 640
AIC	-173 555	-174 645	-107 208	-150 100	-151 519	-110 284	-281 040	-286 469	-230 115	-87 736	-95 227	-57 988
AICc	-173 417	-174 577	-107 070	-149 860	-151 401	-110 044	-280 896	-286 398	-229 970	-87 372	-95 051	-57 624
Cutoff	0 1138			0 1568			0 0975			0 1029		
	(0 063)			(0 049)			(0 031)			(0 024)		
Tail Obs	94			48			56			44		
	(46 707)			(55 433)			(32 467)			(21 661)		
Total Obs	278			286			177			152		

Notes Exponentially dampened power-law $Pr(\kappa) \propto \kappa^{-\zeta}e^{-\phi\kappa}$ parameters estimated for samples split at $(\imath^{US} - \imath^{JP}) = 2\%$ The power exponent estimated via the maximum likelihood then select the minimum cutoff κ that gives the minimum KS-statistic Standard errors in parentheses Standard errors for ζ and ϕ calculated using Bayesian MCMC method based on 10,000 simulations

Table 4.8: Distribution parameter estimates. subsample split by VIX.

	High VIX						Low VIX					
	$\kappa_-(\alpha = 0\ 01)$			$\kappa_+(\alpha = 0\ 01)$			$\kappa_-(\alpha = 0\ 01)$			$\kappa_+(\alpha = 0\ 01)$		
Dist	PL-Exp	PL	LogN	PL-Exp	PL	LogN	PL-Exp	PL	LogN	PL-Exp	PL	LogN
Param 1	ζ	ζ	μ	ζ	ζ	μ	ζ	ζ	μ	ζ	ζ	μ
	2 358	2 664	-1 466	2 719	3 398	-1 539	1 933	2 682	-2 131	2 885	3 035	-1 590
	(0 190)	(0 212)	(0 059)	(0 198)	(0 558)	(0 053)	(0 198)	(0 324)	(0 056)	(0 196)	(0 333)	(0 086)
Param 2	ϕ		σ	ϕ		σ	ϕ		σ	ϕ		σ
	0 620		0 564	1 999		0 387	3 327		0 526	0 223		0 509
	(0 060)		(0 043)	(0 098)		(0 039)	(0 099)		(0 040)	(0 120)		(0 063)
Log-Like	88 777	88 323	55 604	77 050	76 759	57 142	142 520	144 235	117 057	45 868	48 614	30 994
AIC	-173 555	-174 645	-107 208	-150 100	-151 519	-110 284	-281 040	-286 469	-230 115	-87 736	-95 227	-57 988
AICc	-173 417	-174 577	-107 070	-149 860	-151 401	-110 044	-280 896	-286 398	-229 970	-87 372	-95 051	-57 624
Cutoff	0 1257			0 1403			0 0651			0 1231		
	(0 019)			(0 037)			(0 019)			(0 025)		
Tail Obs	90			53			86			36		
	(17 934)			(36 537)			(23 712)			(34 358)		
Total Obs	248			213			207			225		

Notes Exponentially dampened power-law $Pr(\kappa) \propto \kappa^{-\zeta}e^{-\phi\kappa}$ parameters estimated for samples split at VIX = 20 pts The power exponent estimated via the maximum likelihood then select the minimum cutoff κ that gives the minimum KS-statistic Standard errors in parentheses Standard errors for ζ and ϕ calculated using Bayesian MCMC method based on 10,000 simulations

Table 4.9: Economic determinants of "tail risk" of yen appreciation.

Variable	Impact on ϕ	Description	Proxy
k	-	Cumulative carry position	CME non-commercial yen short futures positions Sample: 01/01/1999-02/01/2007 Source: CFTC
$(\Delta s_H - \Delta s_L)$	-	Expected dollar devaluation	Value of 10 delta 1-year yen-dollar risk reversal Sample: 09/28/2003-02/01/2007 Source: Bloomberg
M	+	Margin requirement	Initial speculator margin for yen futures on CME Sample: 01/01/1999-02/01/2007 Source: CME Group
ρ	-	Risk aversion	CBOE S&P 500 options implied volatility index (VIX) Sample: 01/01/1999-02/01/2007 Source: WRDS

Notes: Higher ϕ corresponds to faster exponential truncation in the tail of the probability distribution; ϕ is inversely related to the "tail risk". Although risk aversion (ρ) is not modeled explicitly, we control for it with VIX. We do this for two reasons: first, to the extent that VIX proxies not only for risk aversion but also for funding conditions it is an important variable for gaging speculative forces in foreign exchange and second, since the value of risk reversals conveys option implied skewness *and* skewness risk premium, or equivalently $(\Delta s_H - \Delta s_L)\rho$, it is necessary to control for risk aversion with a proxy such as the VIX.

Table 4.10: Impact of carry trade factors on the "tail risk".

	Dependent parameter: ϕ					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Commercial Shorts (k)	-1.201**		-1.220**	-1.912**	-1.945***	
	(0.542)		(0.592)	(0.739)	(0.734)	
Monte Carlo S.E.	0.016		0.020	0.028	0.025	
VIX (ρ)		-1.838***	-0.326	-1.292	-1.228	
		(0.581)	(0.985)	(1.004)	(0.966)	
Monte Carlo S.E.		0.026	0.031	0.028	0.024	
CME Margin Requirement (M)				1.019	1.024	
				(0.729)	(0.719)	
Monte Carlo S.E.				0.026	0.023	
Risk Reversals ($\Delta s_H - \Delta s_L$)					-0.685	-1.451**
					(0.944)	(0.711)
Monte Carlo S.E.					0.026	0.024
τ_ϵ	0.727	0.743	0.542	0.604	0.592	0.800
	(0.559)	(0.601)	(0.436)	(0.540)	(0.529)	(0.575)
Monte Carlo S.E.	0.050	0.053	0.037	0.048	0.036	0.030
Observations	123	123	123	123	24	24

Notes: Higher ϕ corresponds to faster exponential truncation in the tail of the probability distribution; ϕ is inversely related to the "tail risk". Results based on 10,000 samples after discarding the first 4.000 iterations as "burn-in". Standard errors in parenthesis. *, **. and *** indicate coefficients significant at 10%, 5%. and 1% level respectively under the normality assumption for the simulated parameter values.

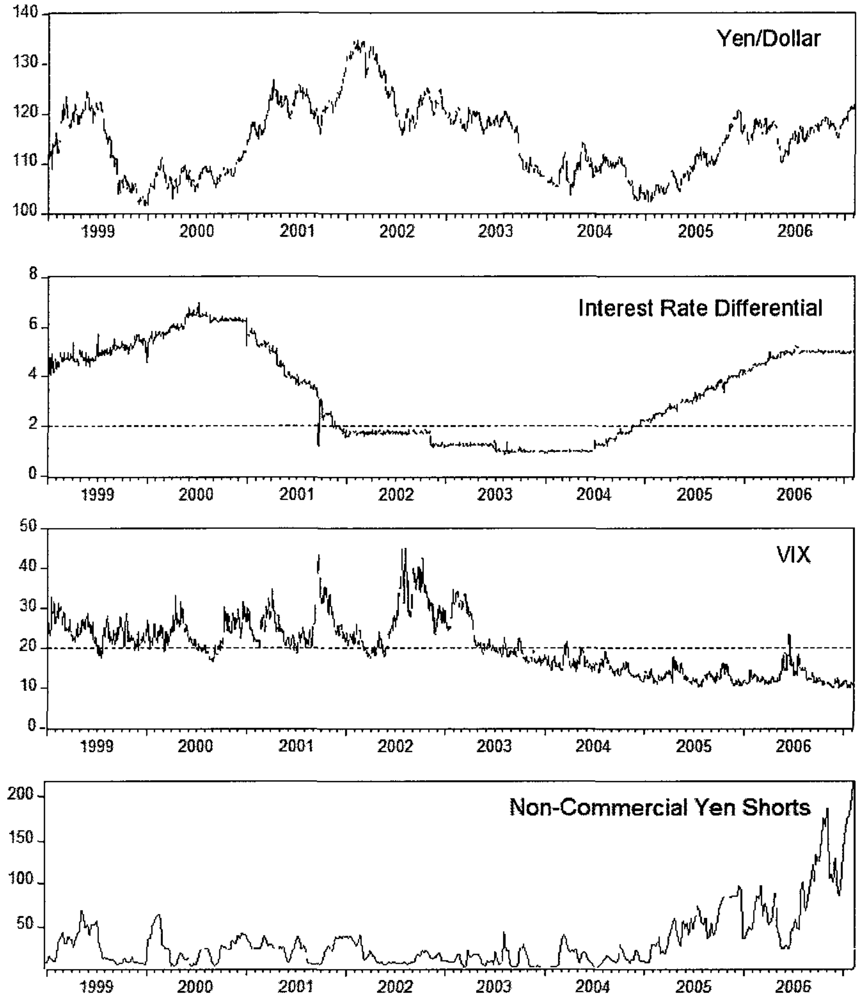


Figure 4.1: Daily time series of JPY/USD exchange rate, U.S.-Japan interest rate differential, CBOE VIX, and Non-commercial short futures positions in Yen.

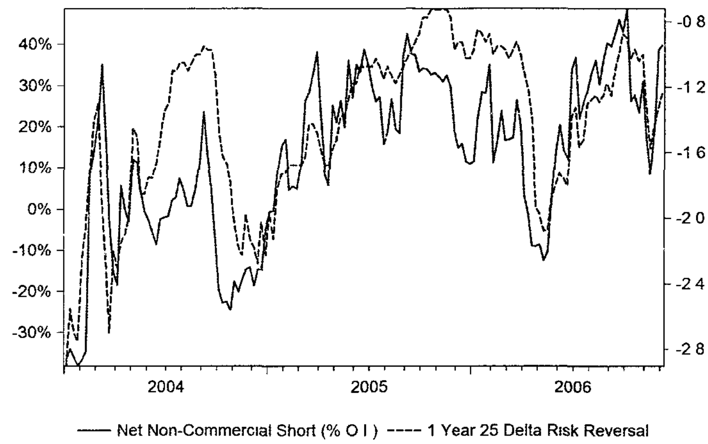


Figure 4.2: Speculative futures positions in yen and the cost of hedging against large yen appreciation.

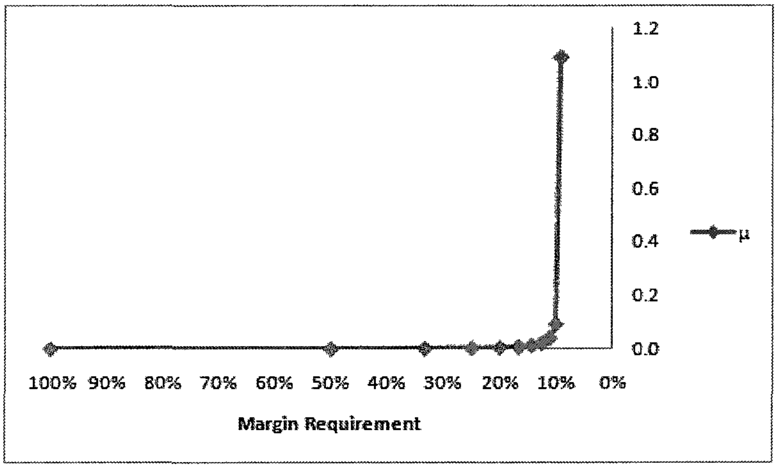


Figure 4.3: Margin requirement and the intensity of the branching process measured by μ (herding). Set $\Delta s_H = 0.05$, $\Delta s_L = -0.07$, $\delta = 0.04$, and $k = 100,000$.

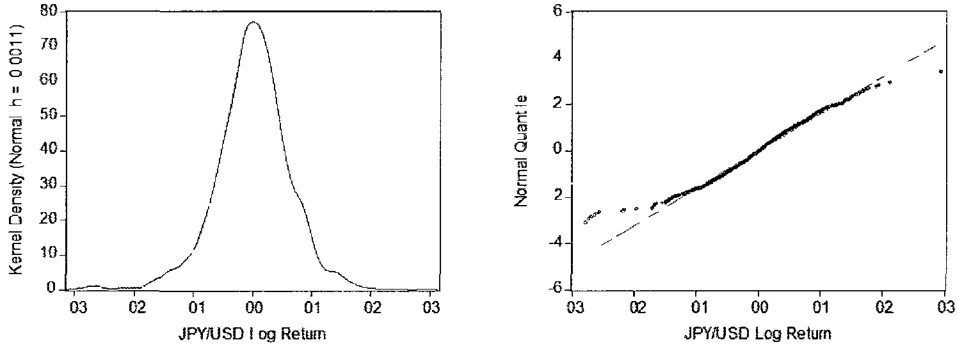


Figure 4.4: Distribution of JPY/USD Log Returns. *Left:* Kernel density; *Right:* Q-Q plot versus normal distribution.

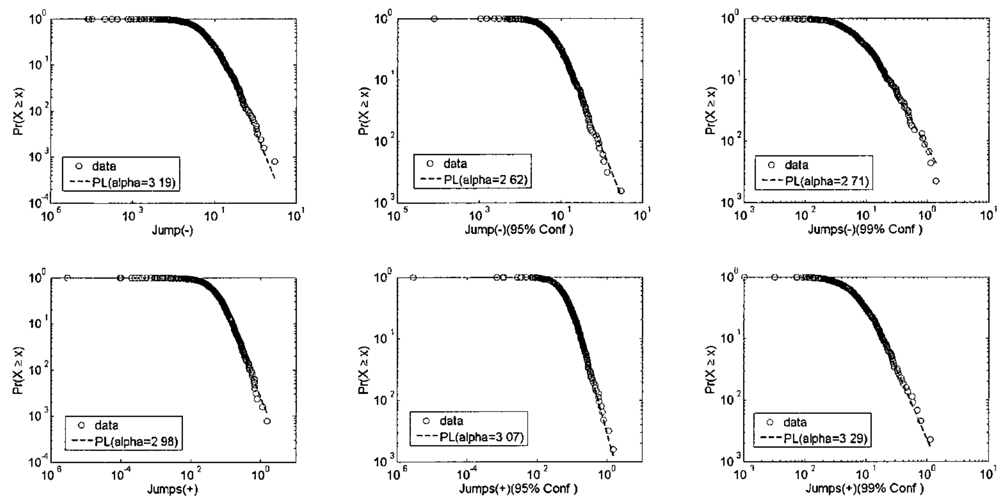
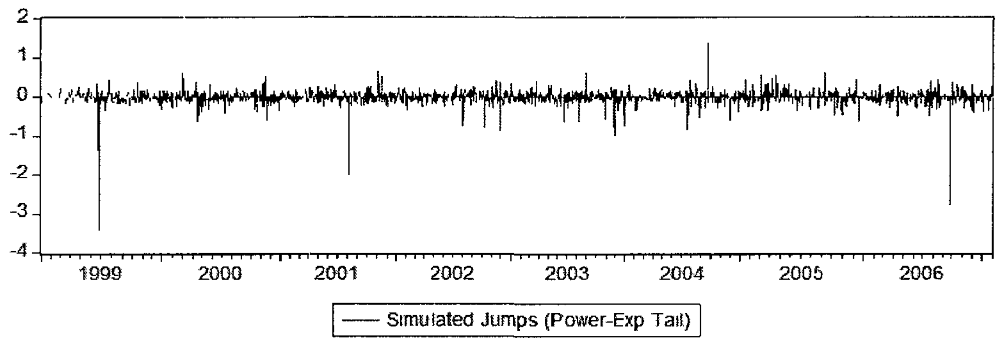


Figure 4.5: Power-law in the tail distribution of JPY/USD returns. *Top:* Yen appreciation jumps; *Bottom:* Yen depreciation jumps.



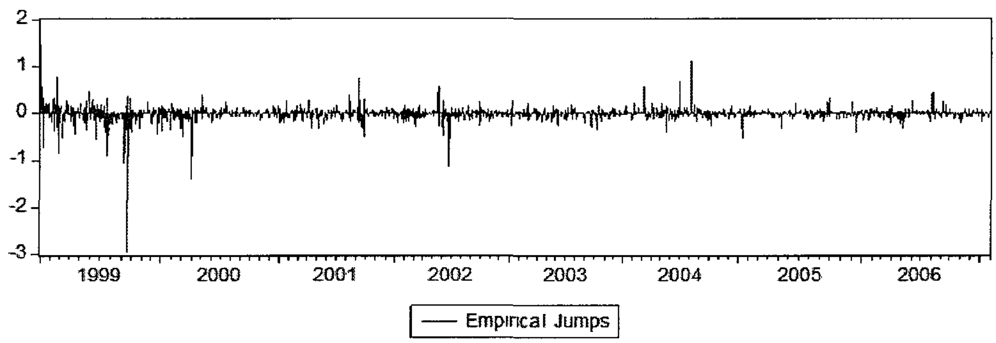


Figure 4.6: *Top:* Jumps in JPY/USD simulated using exponentially dampened power-law with parameters cutoff=0.124, ζ=2.246, ϕ=1.040 for κ_- and cutoff=0.136, ζ=2.983, ϕ=0.642 for κ_+; *Bottom:* Empirical realized volatility jumps series.

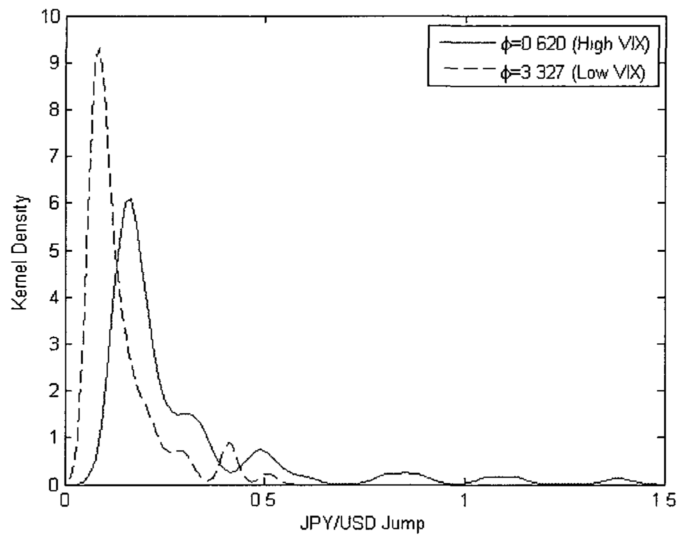
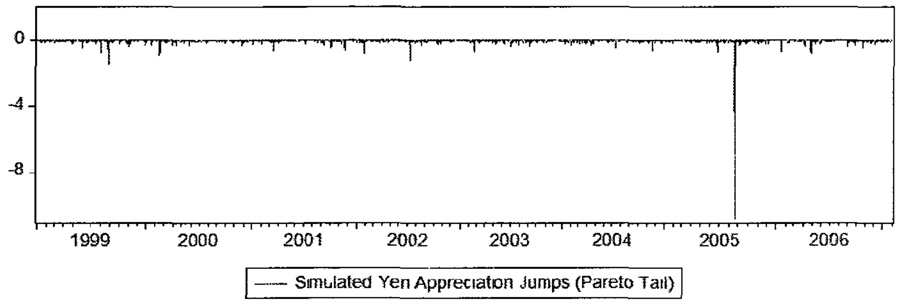


Figure 4.7: VIX and the “tail risk” of sharp yen appreciation.



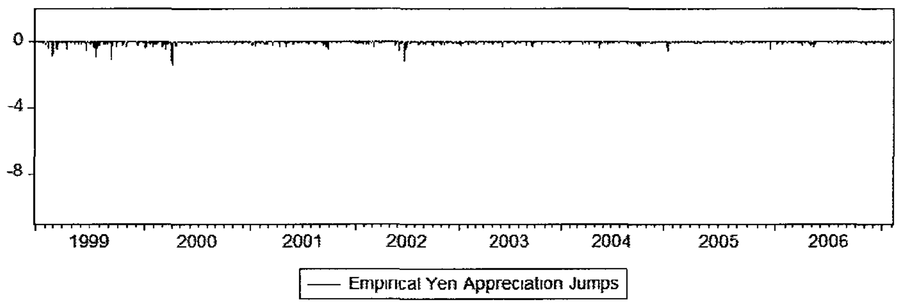


Figure 4.8: *Top:* Jumps in JPY/USD simulated using pure power-law with parameters cutoff=0.124, ζ=2.704; *Bottom:* empirical realized volatility jump series.

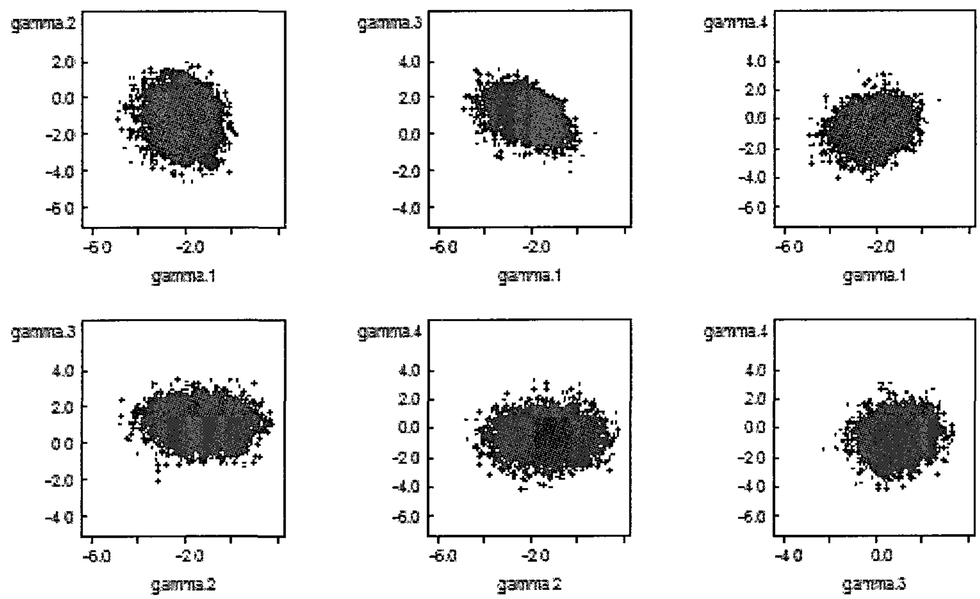


Figure 4.9: Scatter plot of sampled coefficients on CME speculative positions, VIX, CME margin requirement, and risk reversals.

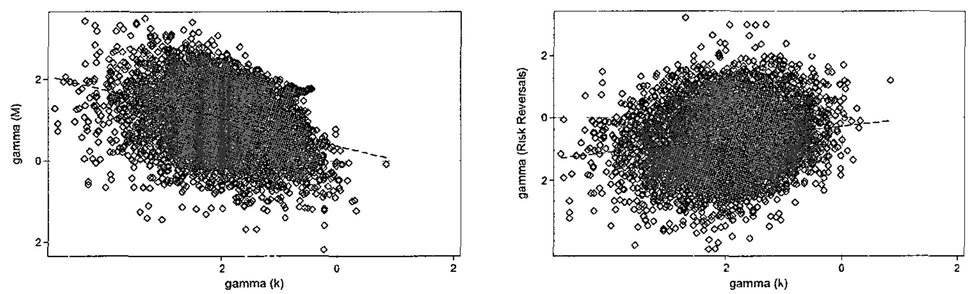


Figure 4.10: The blowup of selected scatter plots. *Left:* coefficients on speculative positions and margin requirement *Right:* coefficients on speculative positions and risk reversals.

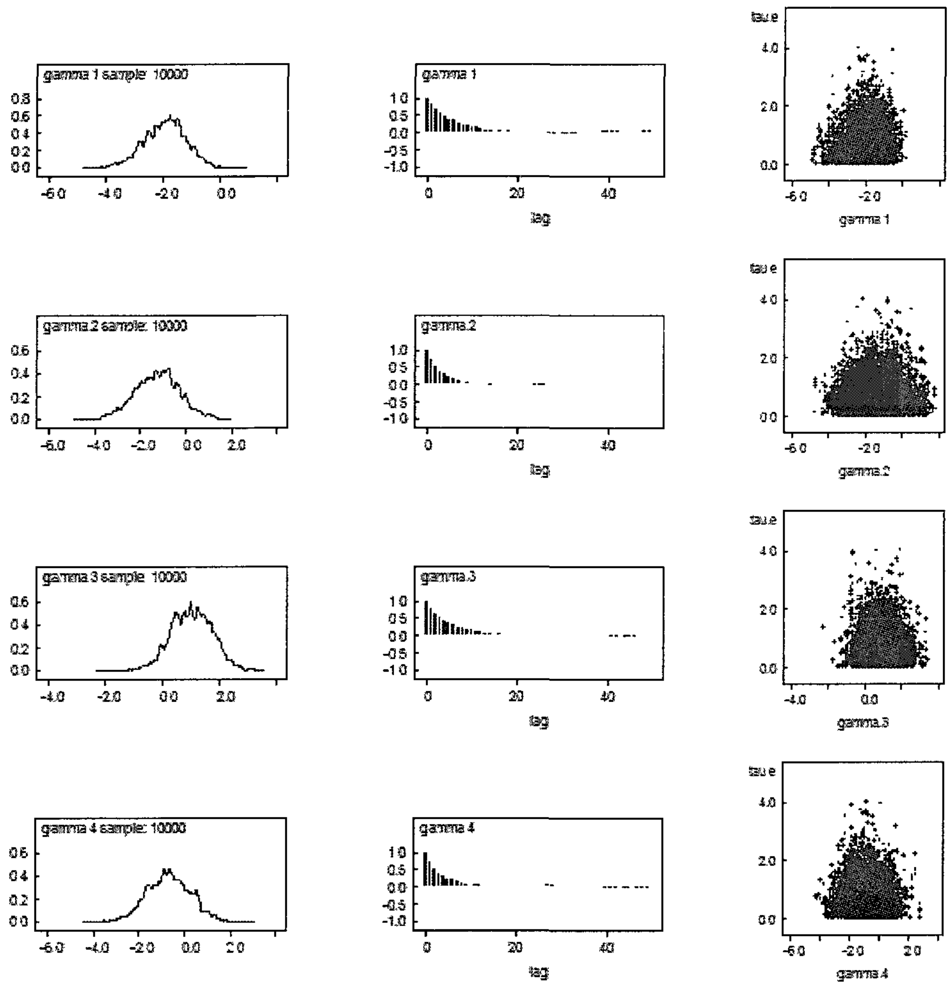


Figure 4.11: Bayesian MCMC diagnostic plots for specification (5).

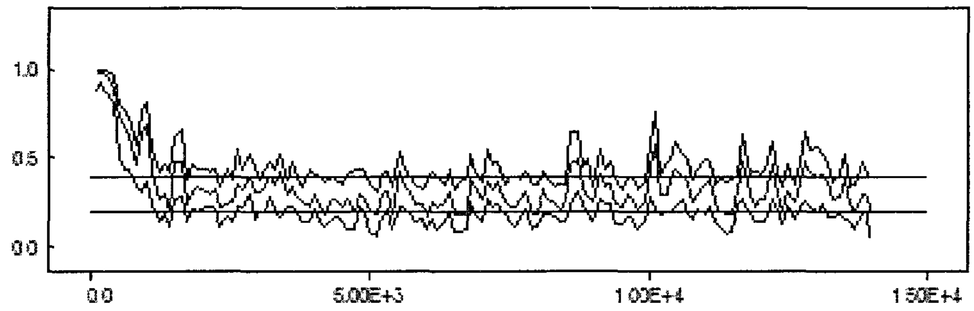


Figure 4.12: Metropolis acceptance rates for specification (5).

Japanese Yen (JY) Performance Bond History

Minimum Performance Bond Requirements

Futures Opening Day 5/16/1972

Options Opening Day 3/5/1986

	Initial	Maint		Initial	Maint		Initial	Maint
8/17/2007			**7/28/2005**			**7/7/2003**		
Spec	$2 700	$2 000	Spec	$2 700	$2 000	Spec	$1 890	$1 400
Hedge/Member	$2 000	$2 000	Hedge/Member	$2 000	$2,000	Hedge/Member	$1 400	$1 400
7/31/2007			**4/28/2005**			**3/6/2003**		
Spec	$2 025	$1 500	Spec	$2 160	$1 600	Spec	$2,160	$1 600
Hedge/Member	$1 500	$1 500	Hedge/Member	$1 600	$1 600	Hedge/Member	$1 600	$1 600
6/11/2007			**4/1/2005**			**12/5/2002**		
Spec	$2 430	$1 800	Spec	$2 363	$1 750	Spec	$2,295	$1 700
Hedge/Member	$1 800	$1 800	Hedge/Member	$1 750	$1 750	Hedge/Member	$1 700	$1 700
3/1/2007			**1/14/2005**			**5/30/2002**		
Spec	$2 700	$2 000	Spec	$2 565	$1 900	Spec	$2 430	$1 800
Hedge/Member	$2 000	$2 000	Hedge/Member	$1 900	$1 900	Hedge/Member	$1 800	$1 800
1/25/2007			**12/27/2004**			**4/9/2002**		
Spec	$2 160	$1 600	Spec	$2 228	$1 650	Spec	$2 700	$2 000
Hedge/Member	$1 600	$1 600	Hedge/Member	$1 650	$1 650	Hedge/Member	$2 000	$2 000
10/17/2006			**8/28/2004**			**3/12/2002**		
Spec	$2 430	$1 800	Spec	$2 430	$1 800	Spec	$1 890	$1 400
Hedge/Member	$1 800	$1 800	Hedge/Member	$1 800	$1 800	Hedge/Member	$1 400	$1 400
3/15/2006			**9/1/2004**			**8/1/2001**		
Spec	$2 700	$2 000	Spec	$2 700	$2 000	Spec	$2 025	$1 500
Hedge/Member	$2 000	$2 000	Hedge/Member	$2 000	$2 000	Hedge/Member	$1 500	$1 500
2/6/2006			**7/30/2004**			**5/3/2001**		
Spec	$3 105	$2 300	Spec	$2 835	$2 100	Spec	$2 835	$2 100
Hedge/Member	$2,300	$2 300	Hedge/Member	$2 100	$7 100	Hedge/Member	$2 100	$2 100
12/15/2005			**5/27/2004**			**3/1/2001**		
Spec	$3 510	$2,600	Spec	$3 105	$2 300	Spec	$2 025	$1 500
Hedge/Member	$2 600	$2 600	Hedge/Member	$2 300	$2 300	Hedge/Member	$1 500	$1 500
12/8/2005			**3/25/2004**			**2/1/2001**		
Spec	$2 025	$1 500	Spec	$2 228	$1 650	Spec	$7 835	$2 100
Hedge/Member	$1 500	$1 500	Hedge/Member	$1,650	$1 650	Hedge/Member	$2 100	$2 100
11/2/2005			**10/2/2003**			**1/4/2001**		
Spec	$2,295	$1 700	Spec	$1 755	$1 300	Spec	$2 025	$1 500
Hedge/Member	$1 700	$1 700	Hedge/Member	$1 300	$1 300	Hedge/Member	$1 500	$1 500

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Figure 4.13: Sample CME Margin Requirement Report (Source: CME Group.)

```
JAPANESE YEN - CHICAGO MERCANTILE EXCHANGE                                                     Code-097741
Commitments of Traders - Futures Only, November 2, 2010
----------------------------------------------------------------------------------------------------------
      :  Total  :                      Reportable Positions                          :  Nonreportable
      :-----------------------------------------------------------------------------    Positions
      :  Open   :        Non-Commercial        :     Commercial      :      Total      :
      : Interest :  Long   :  Short   : Spreading:  Long   :  Short   :  Long   :  Short   :  Long   :  Short
----------------------------------------------------------------------------------------------------------
      :         : (CONTRACTS OF JPY 12,500,000)                                      :
      :         :                                                                    :
All   :  140,062:   63,061    16,606       796    45,614    95,686   109,471   113,088:   30,591    26,974
Old   :  140,062:   63,061    16,606       796    45,614    95,686   109,471   113,088:   30,591    26,974
Other:        0:        0         0         0         0         0         0         0:        0         0
      :         :                                                                    :
      :         :        Changes in Commitments from: October 26, 2010               :
      :      212:    1,756    -1,570       252    -2,842     4,551      -834     3,233:    1,046    -3,021
      :         :                                                                    :
      :         :   Percent of Open Interest Represented by Each Category of Trader  :
All   :    100.0:     45.0      11.9       0.6      32.6      68.3      78.2      90.7:     21.8      19.3
Old   :    100.0:     45.0      11.9       0.6      32.6      68.3      78.2      90.7:     21.8      19.3
Other:    100.0:      0.0       0.0       0.0       0.0       0.0       0.0       0.0:      0.0       0.0
      :         :                                                                    :
      :# Traders :              Number of Traders in Each Category                   :
All   :      113:       42        26         8        20        31        65        64:
Old   :      113:       42        28         8        20        31        65        64:
Other:        0:        0         0         0         0         0         0         0:
      :----------------------------------------------------------------------------------------
      :                Percent of Open Interest Held by the Indicated Number of the Largest Traders
      :                          By Gross Position                          By Net Position
      :                  4 or Less Traders     8 or Less Traders     4 or Less Traders     8 or Less Traders
      :                     Long:     Short       Long      Short:      Long      Short       Long      Short
      :----------------------------------------------------------------------------------------
All   :                     29.5      52.4       40.2      60.4        29.4      51.0       40.9      58.9
Old   :                     29.5      52.4       40.2      60.4        29.4      51.0       40.9      58.9
Other:                      0.0       0.0        0.0       0.0         0.0       0.0        0.0       0.0
```

Figure 4.14: Sample CFTC Commitments of Traders Report (Source: CFTC)

Chapter 5

Impact of Macroeconomic Surprises on Carry Trade Activity

5.1 Introduction

One of the consequences of the zero-interest rate policy in Japan was the emergence of massive yen currency carry trade activity where investors borrowed in yen (funding currency) and bought higher-yield assets in other currencies (target or investment currency). Specifically, carry trade is a foreign exchange arbitrage strategy in which an investor borrows in a low interest rate currency and takes a long position in a higher interest rate currency betting that the exchange rate will not change so as to offset the profits made on the yield differential. For example, an investor can fund higher yielding deposits in the U.S. by borrowing from commercial banks in Japan at low interest. This strategy will necessitate a foreign exchange transaction to sell yen for U.S. dollars in order to convert yen liabilities into dollar assets. In addition to issuing liabilities in low-interest currencies. carry trade can be conducted using currency forwards and futures on the margin (Gagnon and Chaboud (2007)). For example. a hedge fund could enter a forward contract to sell yen for dollar at some future date. Such carry trade strategies generated persistent excess returns (e.g. Burnside et al. (2007); Darvas (2009); Hochradl and Wagner (2010)), but also exposed carry traders to substantial currency risk and large losses if the yen were to appreciate substantially (Gyntelberg and Remolona (2007)).

Figure 5.1 [about here]

Figure 5.1 shows the U.S.-Japan interest differential and the JPY/USD exchange rate during 2004-06 when the yen carry trade was at its height. The prolonged low interest policy and weak economy in Japan, during which short-term money market rates were continuously near zero. combined with a strong economy and rising interest rates in the U.S., led to a rising. large and persistent interest differential. The figure also shows that the JPY/USD depreciated on average over this period. but that trend depreciation was interrupted by several episodes of sharp appreciation and considerable volatility. The violation of uncovered interest parity (UIP)[1] [2] allowed profit opportunities (ex post) for carry traders, but the riskiness of this strategy was also exposed during the bouts of large yen appreciation.

[1] An appreciation of the high yield currency is an example of the forward premium puzzle and the violation of the uncovered interest parity (UIP) well documented by Hansen and Hansen and Hodrick (1980) and Engel (1996)

[2] Ichiue and Koyama (2008) estimate the UIP regression coefficient as low as -2 79 for the yen

One way to hedge against the risk of substantial yen appreciation is to enter into a risk reversal contract. A risk reversal contract is the simultaneous purchase of a deep out-of-money (OTM) call option and the sale of a deep OTM put option[3]. The holder of the risk reversal is hedging against sharp yen appreciation and accepting (unlikely) downside risk of sharp yen depreciation, taking on a one-sided bet. The payoff diagram for holding a risk reversal contract is shown in Figure 5.2. If yen (funding currency) appreciates sharply, the payoff is positive for the risk reversal. The opposite is true for sharp yen depreciation. Carry traders would lose on this risk reversal contract if the yen depreciates sharply, but this loss is more than offset by gains from holding an open yen carry-trade position. As such, the value of risk reversals are frequently treated as a proxy of expectations about the risk of very large changes in exchange rates[4]. During the "carry trade" period in Japan, when financial institutions were borrowing heavily in yen and investing in assets denominated in U.S. dollar and other currencies, the value of the risk reversal was always negative. This indicates a market hedge against sharp appreciation of the JPY/USD exchange rate.

Figure 5.2 [about here]

[3]A risk reversal is a directional bet on (or hedge against) a large price movement constructed by a simultaneous purchase of out-of-money call and sale of out-of-money put option (usually 25 or 10 delta) of the same maturity. The value itself is the implied volatility for the call minus the implied volatility of the put.

[4]Brunnermeier (2009) interpret such persistent UIP violations as a compensation to carry traders for the downside risk of sharp funding currency appreciation.

Two studies of which we are aware have investigated the empirical links between risk reversals[5] and official foreign exchange market intervention, using macroeconomic news in one case as control variables. Galati et al. (2005) estimate the effect of Japanese foreign exchange market intervention on the value of JPY/USD risk reversals along with other measures of dispersion in exchange rate expectations[6]. They consider daily data over January 1996 - November 2005 and find weak evidence that intervention operations impacts risk reversals. Disyatat and Galati (2007) study the impact of official intervention on the value of risk reversals in the Czech Koruna - Euro, using daily data over September 2001 to September 2002. They also find that intervention has a limited impact on risk reversals, but that macroeconomic news is not significant. (They consider several measures of price, output and unemployment surprises for the Czech Republic and Germany).

This paper similarly investigates market perceptions of the risk of large exchange rate movements by using information gleaned from risk reversal contracts and macroeconomic news surprises[7] but departs from previous work in several important ways. Firstly, we focus on the height of the carry trade period in Japan (March 2004 through December 2006), where the sample is delimited at the begin-

[5]Several related studies including Beber and Brandt (2006), Aijo (2008), and Chen and Gau (2010) investigate the impact of macroeconomic surprises on options implied higher moments, including option implied skewness, while Lahaye et al. (2010) study the effects macro announcements on jump components in realized volatility.

[6]Galati et al. (2005) consider the effect of intervention and macroeconomic news on several measures of expectations regarding exchange rate movements, one of which (skewness) is derived from the value of risk reversals.

[7]Evans and Lyons (2008) investigate the impact of macro news on order flow, while Hashimoto and Ito (2009) and Fatum et al. (2010) investigate high frequency responses to macro surprises in JPY/USD exchange rate.

ning by the cessation of the Bank of Japan large-scale intervention operations and ends before the financial crisis emerged. Our view is that concerns about sharp yen appreciation were particularly evident during the period of heavy carry trade activity and are more likely to show up in the price of risk. Secondly, we focus on "big" news surprises (greater than one standard deviation movements) that are more likely to convey information about the risk of large changes in the exchange rate. Thirdly, we consider a broader set of news than previous work – thirty three sources (18 U.S. series and 15 Japan series) – and the only study that investigates the direct impact of news other than intervention for the value of JPY/USD risk reversals. Fourthly, we consider the indirect effect of news through the value of risk reversals on the yen carry trade, using non-commercial open interest positions in future markets as a proxy for carry trade activity.

Overall, we find that macroeconomic news are an important determinant of risk reversals during periods of heavy carry trade volume. Estimates using predicted values based regression coefficients show that the cumulative impact of macroeconomic surprises can account for more than a third of the total change in risk reversals during particularly dramatic episodes of changing risk perceptions in the JPY/USD market. Moreover, there is a close link between risk reversals and NCMS positions (a proxy for carry trade activity), and this link is borne out in Granger causality tests. Using this metric, we are able to calculate the effect of macroeconomic news on carry trade activity, with risk reversals (the cost of hedging) as the transmission mechanism. Depending on the subsample and calculation method macroeconomic news surprises can translate into more than one third of the total adjustment in yen speculative positions.

The paper is organized as follows. Section 5.2 describes the data and institutional features of the carry trade and market for risk reversals. Section 5.3 presents the main empirical analysis and results. This section establishes a link between macroeconomic surprises and the value of risk reversals which is robust to a number of empirical model specifications. Unlike several previous studies that do not find a significant impact of macro surprises on risk reversals, we consider a larger sample of news types and, given that risk reversals price the probability of extreme exchange rate fluctuations, we identify large surprises. Section 5.4 investigates the link between risk reversals and carry-trade activity where, as a proxy for the latter, we use *open interest non-commercial short futures positions* (NCMS) *in yen on the* Chicago Mercantile Exchange (NCMS increased from 40,000 to over 160,000 during our sample period). By examining the correlations and through Granger-causality tests we establish a robust link between risk reversals and net NCMS showing that the short positions in yen decline (rise) following an increase (decrease) in the cost of insurance against a substantial yen appreciation. Section 5.5 concludes.

5.2 Data and Risk Reversals

5.2.1 Institutional Features

A risk reversal is a directional bet (or hedge) against large price swings. It is a contract long one unit out-of-the-money (OTM) (typically 25-delta[8]) FX call option and short one unit OTM FX put option. In other words it is the cost of buying insurance against large foreign currency appreciation. financed by providing insurance against large foreign currency depreciation. Figure 5.2, noted in the introduction, shows the payoff diagram for a risk reversal. The vertical distance between the zero-line and the parallel payoff segment represents the net option premium of the risk reversal (insurance premium). i.e. its market price.

More formally. the value of a risk reversal is equal to the implied volatility of an out-of-money call minus the implied volatility of an out-of-money put of the same moneyness and maturity. Garman and Kohlhagen (1983) applied the original Black and Scholes (1973) framework to foreign exchange options. We following Galati, Higgins. Humpage and Melick (2007) with the following representation of a price of a European foreign exchange call option:

$$C(X,\sigma) = \frac{1}{(1+\imath)T}\left(F \cdot \Phi(d_1(X,\sigma)) - X \cdot \Phi(d_2(X,\sigma))\right) \tag{5.1}$$

[8]The delta of an FX option measures its sensitivity to the spot exchange rate The strike price of a 25-delta option is far enough from the spot price such that the option premium exhibits only a 0 25 correlation with changes in the strike price

where,

$$d_1(X,\sigma) = \frac{ln(F/X) + (\sigma^2/2)T}{\sigma\sqrt{T}},\ d_2 = d_1 - \sigma\sqrt{T} \tag{5.2}$$

$$F = e^{(i-i^*)T}S \tag{5.3}$$

S represent the spot exchange rate, i and i^* are domestic and foreign interest rates, X is the strike price at maturity T, and Φ is the cumulative distribution of a standard normal. An option's delta represent its sensitivity to the changes in the exercise price. Risk reversals are constructed from out-of-money options with only 25% sensitivity to changes in the strike price. Then the call price has the following property:

$$\frac{\partial C(X,\sigma)}{\partial X} = 0.25 \tag{5.4}$$

Finally, a 25-delta risk reversal is the difference in the implied volatility of a 25-delta call and put option:

$$RR^{25\delta} = \sigma_c^{25\delta} - \sigma_p^{25\delta} \tag{5.5}$$

Under a symmetric risk-neutral distribution the value of risk reversal should be zero since both OTM call and put will have the same probability of landing at-the-money by the expiration date. Therefore, risk reversals only take on non-zero values if the risk-neutral distribution of foreign exchange returns is skewed, their value conveying the combined effect of expected skewness and skewness risk premium. This case is depicted by the asymmetric volatility smirk in Figure 5.3. A thick left tail (negative skewness) of return distribution is equivalent to a correlation between spot levels and implied volatilities (volatility smile). Negative values of risk reversals imply that out-of-money dollar puts have a higher probability of being exercised than out-of-money dollar calls indicating a market hedge against large yen appreciation (U.S. dollar depreciation).

Jain and Stafford (2006) find that yen rallies, carry trade unwinding, and bouts of risk aversion are correlated. Hence, risk reversals likely capture risk appetites of carry traders during the times of high cost of insurance against yen appreciation. Whether risk reversals are forward looking is still uncertain. Jain and Stafford (2006) find that sharp movements in spot are usually followed by risk reversal overvaluation as risk premium increases and implied skew in the following period is higher than the realized skewness of the return distribution. Examining data at daily frequency, Gagnon and Chaboud (2007) argue that during periods of high volatility movements in risk reversals postdate movements in exchange rates. At weekly frequency Carr and Wu (2007) find that JPY/USD and GBP/USD returns show positive correlations with changes in risk reversals. Farhi et al. (2009) find that monthly changes in nominal interest rates and risk reversals exhibit strong contemporaneous link. The same authors also find some evidence of exchange rate excess returns (relative to UIP) predictability with risk reversals - very high levels of risk reversals may predict currency appreciation.

Unlike the implied skewness of at-the-money options, risk reversals provide potentially useful information on market pricing of extremely large events[9]. Farhi and Gabaix (2008) formulate a general equilibrium model in which they show that under certain conditions risk reversals depict the difference in the resilience of the two country's export sector productivities to aggregate shocks.

5.2.2 Data

We obtain daily data on 1-month and 1-year 25-delta risk reversals from Bloomberg. We confine our sample to the tranquil period of active carry trade after the last episode Japanese official interventions that ended in March 2004 and before the beginnings of the emerging financial crisis in the middle of 2007. In all we end up with 715 daily observations excluding weekends from 03/18/2004 through 12/31/2006.

Our news data consists of a large number of time-stamped Japanese and U.S. macroeconomic announcements and preceding survey expectations of Fatum, Hutchison and Wu (2010) obtained from Bloomberg News Service[10]. Japanese news variables are chosen which are largely comparable to the U.S. news variables which in turn are significant in either the time-series analysis or the event study analysis of Andersen et al. (2003) in their investigation of the JPY/USD exchange rate.

[9]Risk reversals are also used indirectly along with other option derivatives to derive higher moments of risk neutral distributions. Galati et al. (2005) and Morel and Teletche (2008) study the relationship between official interventions in foreign exchange and market uncertainty. They use FX strangle and risk reversal prices to recover option implied higher moments of the risk-neutral FX return distribution.

[10]Japanese macro announcements are available from Bloomberg News Service as well as from the data banks of the Bank of Japan and the Japanese Cabinet Office.

Japanese news of particular interest. e.g. surprises regarding the Bank of Japan's TANKAN survey variables. are also considered[11]. In addition to the U.S. news variables suggested by Andersen et al. (2003), and we also consider news surprises regarding U.S. consumer and producer price indices. In total, the data includes announcements and survey expectations regarding 15 types of Japanese macro news and 18 types of U.S. macro news. The Japanese news variables are GDP (quarterly), Industrial Production, Capacity Utilization. Construction Orders. Overall Spending. Large Retail Sales, Trade Balance, Current Account. Retail Trade, Consumer Price Index. Consumer Confidence Index, TANKAN Large Manufacturing Index, TANKAN Non-Manufacturing Index. Leading Economic Index. and Monetary Base. The U.S. news variables are GDP. Non-Farm Payroll Employment. Industrial Production. Capacity Utilization, Personal Income, Consumer Credit, Consumer Spending, New Home Sales. Durable Goods Orders. Factory Orders, Business Inventories, Trade Balance, Producer Price Index. Consumer Price Index. Consumer Confidence Index, NAPM Index, Housing Starts, and Index of Leading Indicators.

Consistent with the recent literature on exchange rates and news, for each of the macroeconomic announcements in our data we follow Fatum, Hutchison and Wu (2010) and the broader literature in defining news surprises as the difference between the macroeconomic announcement and the preceding survey expectation of that announcement. Subsequently, we standardize each news surprise series in order

[11]The Bank of Japan website at www boj or jp/en/theme/research/stat/tk/index htm provides details (in English) regarding the TANKAN survey variables

to allow for a comparison of the relative influences of different types of news[12].

In addition we construct a daily series of interest rate spread between U.S. and Japan as the difference between the effective federal funds rate and Japan's uncollateralized overnight call rate. Both are publicly available from the Federal Reserve Bank of New York and Bank of Japan respectively.

We obtain the weekly futures positions data from the Commodity Futures Trading Commission (CFTC)'s Commitment of Traders (COT) report which is released at weekly frequency and reflects positions at the close of every business Tuesday. Among other variables, the OTC reports include weekly times-series of non-commercial trader long and short positions in yen as a percentage of total open interest. The CFTC defines open interest as the sum total of all futures contracts not yet offset by transaction, delivery or exercise. We construct the measure of CME net non-commercial short positions (NCMS) as a percentage of open interest (% O.I.) by subtracting non-commercial long from non-commercial short positions divided by total open interest in yen futures.

[12] A standardized news surprise is given by the unexpected component of the macroeconomic announcement divided by the associated sample standard deviation. Let $A_{q,t}$ denote the value of a given macroeconomic fundamental q, announced at time t. Let $E_{q.t}$ refer to the median value of the preceding market expectations for the given fundamental at announcement time t, and let $\hat{\sigma}_q$ denote the sample standard deviation of all the surprise components associated with fundamental q. The standardized surprise of macroeconomic fundamental q announced at time t is then defined as $S_{q,t} = (A_{q,t} - E_{q,t})/\hat{\sigma}_q$.

5.3 Empirical Results: Macro News and Risk Reversals

5.3.1 Preliminaries

The upper panel of table 1 reports summary statistics for the 1-month and 1-year risk reversal series in levels and in first differences. The maximum and minimum are (-0.05, -2.45) and (-0.725, -2.75) for 1-month and 1-year risk reversals respectively indicating that both series have remained negative throughout the sample period consistent with market hedge against sharp yen appreciation.

Table 5.1 [about here]

Augmented Dickey Fuller (ADF) and Phillips-Peron unit root tests are shown in the lower panel of Table 5.1. These tests indicate that the log levels were not stationary. The null hypothesis is that there exists a unit root. The third column shows the unit root test on the value of a one-year 25 delta risk reversal. The fourth column is the corresponding tests on first differences of the values. Both tests fail to reject the null hypothesis of a unit root in levels, but reject the null in first differences by a large margin (greater than 99% level of confidence). We therefore proceed to estimate our empirical model with the dependent variable in first difference form.

5.3.2 Estimation Results

Tables 5.2 and 5.3 report the results. We focus in our formal empirical analysis on one-year risk reversals, the longer maturity options, in order to capture the hedging horizons of carry traders[13]. Table 5.2 shows the baseline results where the regressions are estimated using OLS and all the macroeconomic surprises are included in the data set, i.e. we do not drop "small" surprises from the sample. Table 5.3 focuses on whether "large" changes affect the value of risk reversals, as would be expected since risk reversals reflect the risk of very large exchange rate changes. We use two criteria to select "large" surprises. The first approach is to consider only surprises outside "narrow bounds," i.e. exclude all surprises less than one standard deviation from the series specific mean value. The standard deviation is calculated based on all observations of the surprise variables, including days with no surprises. The second approach, which denote as "wide bounds," is a stricter criteria whereby the standard deviation is calculated on non-zero observations only, thus effectively making the exclusion bounds wider. The results reported in the two tables are similar and most of the discussion will focus on our preferred equation reported in Table 5.3.

Tables 5.2 & 5.3 [about here]

The two panels of Table 5.2 include the same news surprises, while the right-hand-side panel also controls for the exchange rate and the interest rate dif-

[13]The 1-month results are available upon request. These are generally weaker than the one-year results, consistent with the view that the carry trader horizon is for hedges of longer maturity.

ferential. The point estimates for those coefficient values which are significant are virtually identical in the two regressions. but controlling for exchange rates and the interest rate differential (right panel) give substantially higher explanatory power (higher R^2) and a better fit of the equation based on a large (absolute value) AIC statistic. Two U.S. news surprises (GDP and Consumer Credit) and three Japanese news surprises are significant (Trade Balance. Consumer Confidence and Overall Household Spending), in addition to the exchange rate and interest rate differential.

The value of including the exchange rate and interest rate differential is evident from the estimates in Table 5.2. so we include these variables in Table 5.3 where we focus on "large" news surprises. The left-hand-side panel is estimated using OLS and the right-hand-side is estimated using an ARMA(4,4) process, for both "large" surprise selection criteria. In particular. closer analysis of the errors of the initial estimation suggested both AR(4) and MA(4) terms were appropriate-based on a significant lag in the autocorrelation function and partial autocorrelation function, respectively-in the estimation. This model was chosen, relative to a simple OLS estimation, given the Akaike information criteria[14].

The right-hand-side panel of Table 5.3 shows that the same explanatory variables remain significant (U.S. GDP and Consumer Credit and Japan's Trade Balance, Consumer Confidence and Overall Household Spending) when only "large" surprises are considered. In addition. U.S. Personal Income and Japan's TANKAN

[14]These results are omitted for brevity but are available from the authors upon request Monday and Friday dummies were also included in the initial estimation but were not statistically significant Various values of p,q in the ARMA (p,q) process were considered and the $p = 4$ and $q = 4$ were selected based on the AIC criteria

Non-Manufacturing Index are highly significant under the "wide bounds" selection criteria. In all, three U.S. macro news surprises and four Japanese macro news surprises have a statistically significant impact on the value of risk reversals during our sample period.

How may the significant estimates be interpreted economically? Recall that the value of risk reversals remained negative throughout the carry trade sample we are investigating, indicating a market hedge against sharp yen appreciation. A negative (positive) coefficient value indicates higher (lower) risk of large yen appreciation. (A more negative value of risk reversals indicates greater combined effect of expected probability of sudden yen appreciation and of the associated risk premium.) It is perhaps easiest to interpret coefficients in terms of an exchange rate/balance-of-payments nexus. Higher U.S. GDP and U.S. Consumer Credit growth reduce the value of risk reversals, perhaps by increasing the expected size of the U.S. trade deficit and increasing the perceived risk of sharp yen appreciation against the dollar. A rise in Japan's Trade Balance also reduces the value of risk reversals and may be interpreted similarly in that it is an indication of a worsening U.S. external balance. On the other hand, the positive coefficients on the Japanese Consumer Confidence Index and Overall Household Spending, indicating less risk of major yen appreciation (a lower risk reversal in absolute terms), may be associated with expectations of a stronger Japanese economy and reduced trade surplus. U.S. Personal Income (positive coefficient) and TANKAN Non-Manufacturing Index (negative coefficient) indicate expectations of smaller U.S. and Japanese trade imbalances, respectively.

The standardization of the macro news surprises allows a comparison of the relative sizes of the coefficients. Since the expected value of each standardized news surprise series is zero, the coffecient obtained in the regressions with first differences of risk reversals as a dependent variable is an unbiased estimate of the impact of news surprises on the level of risk reversals as well. Consumer Credit has the highest coefficient in absolute value among U.S. surprises at -7.0 compared to -3.9 for U.S. GDP and 1.2 for Personal Income. Among the Japanese macro surprises Trade Balance has the highest coefficient in absolute value of -6.4 followed by Overall Household Spending with 4.8.

Figure 5.4 [about here]

We conduct a rough assessment of the cumulative impact of macroeconomic surprises on the value of risk reversals. In this section and the next, we focus on two subsamples of particularly dramatic changes in the value of risk reversals shaded in grey in Figure 5.4. The first period shaded in the figure, 01/07/2005 through 03/13/2006, corresponds to a substantive reduction in the absolute value of risk reversals from about -2.4 to -1.0. The second period shaded in the figure, 04/12/2006 through 05/172006, corresponds to a substantial increase in the absolute value of risk reversals from -1.0 to -2.0. The colored bars correspond to the impact of each news surprise type calculated by multiplying the regression coefficient by the value of the standardized surprise. The red bars, for instance, show the predicted effect on risk reversals of surprise U.S. GDP.

Table 5.4 [about here]

Table 5.4 shows the results for the two subsamples. The first two columns show the cumulative impact from surprise macro announcements for the first subsample, using both the "narrow band" for upper bound and the "wide band" for the lower bound regressions from table 3. The cumulative impact of macroeconomic surprises ranges from 0.32 to 0.37, accounting for 25-30% of the total change in the value of risk reversals over this episode. As shown in Figure 5.4, the net negative GDP and consumer credit news in the U.S., combined with negative trade balance news in Japan, led to a sharp reduction in the perceived risk of large yen appreciation. Recall that the R^2 in the baseline regression not controlling for exchange rate or interest rate was approximately 0.03 indicating that over the entire sample period surprise macro announcements explain approximately 3% of the variation in the value of risk reversals. However, focusing on a subsample of dramatic decline in the market value of risk we see that macro surprise announcements can account for over 30% of the cumulative change in the value of risk reversals.

Figure 5.4 [about here]

The third and fourth columns of Table 5.4 report the cumulative impact for the second subsample when the perceived risk of major yen appreciation jumped markedly. Figure 5.4 shows that the rise in absolute value of risk reversals (rise in perceived risk of large yen appreciation) during this episode is associated with several surprise announcements, namely a sharp unanticipated rise in the Japanese

Trade Balance and fall in Japanese Household Spending. These announcements accounted for approximately 10% of the total rise in absolute value of risk reversals during this episode.

5.4 Link to Carry Trade Activity

Despite the well-documented profitability of carry trade activity, aggregate flow volumes are difficult to measure because of diverse carry trade strategies[15] and data limitations. Following Klitgaard and Weir (2004), Galati, Heath and McGuire (2007), and Brunnermeier (2009) we proxy for carry trade activity with futures positions of non-commercial traders on the Chicago Mercantile Exchange (CME), which is the largest exchange for foreign exchange futures by volume[16].

Figure 5.5 [about here]

CFTC published Commitment of Traders (COT) report in which it classifies traders as non-commercial if they have no foreign exchange exposure to hedge and therefore presumably trade to make profit[17]. These traders on average hold

[15]For instance Hattori and Shin (2009) argue that carry trade can be accomplished through inter-office loans of multinational investment banks.

[16]Galati, Heath and McGuire (2007) also examine the currency denominations of international assets and liabilities of commercial banks available to the Bank of International Settlements (BIS). Focusing on Japan, Gagnon and Chaboud (2007) trace the balance sheets of not only the banking sector, but also Japan's official sector and private non-banking sector.

[17]A trader is classified as "commercial" or "non-commercial" by filing the Statement of Reporting Trader (CFTC Form 40). The CFTC staff may re-classify the trader if they possess additional information about the trader's use of the futures market. Furthermore, each trader receives a separate classification for each commodity depending on the traders' use of each market. In 2009 the CFTC began published the Disaggregated COT with more detailed trader classifications. Its own historical comparison between the two reports finds that historically the "non-commercial" category included professional money managers (such as hedge funds and commodity trading advisers) and

approximately 20 percent of total open interest positions in major currencies (Sun (2009)). Figure 5.5 shows the time series of non-commercial short positions and a simple rate of return to carry trade (following Hochradl and Wagner (2010)):

$$CR_{t+k} = (1 + i_{k,t}^{US}) S_{t+k}/S_t - (1 + i_{k,t}^{JP}) \tag{5.6}$$

where $i_{k,t}$'s denote the effective k-period deposit rates available in Japan and U.S. at time t. We use 1-month deposit rates. This trend is consistent with the expected behavior of carry traders increasingly going short Yen and long USD during the period of rising ex-ante returns to carry trade. Figures 5.6 plots the effective carry trade return against the number of traders taking on non-commercial short positions. Again, consistent with non-commercial short positions serving as the proxy for carry trade the association between the two series is positive.

Figures 5.7 & 5.8 [about here]

Figure 5.7 shows the time-series of net non-commercial short positions (NCMS) as percentage of total open interest (% O.I) (left) against 1-month and 1-year risk reversals (right). The series exhibit co-movement indicating that an increase in risk reversals towards smaller negative value (lower cost of insurance against Yen appreciation) is associated with an increase in speculative Yen short positions as proxied by CME non-commercial futures. Figure 5.8 shows the same

other "speculative" traders while the "commercial" category has included producers, merchants, processors, and swap dealers who use futures markets to offset risks incurred in over-the-counter markets. For further details see http://www.cftc.gov/MarketReports/CommitmentsofTraders/.

time-series plotted against each other in first differences. once again changes in net speculative Yen short positions appear to evolve with changes in risk reversals. The pair wise correlations between the non-commercial futures and 1-month and 1-year risk reversals are 0.58 and 0.73. respectively. We conduct Granger-causality tests at weekly frequency to examine whether risk reversals lead (predict) speculative futures positions or vice-versa:

$$\Delta NCMS_t = \sum_{j=1}^{2} \alpha_j \Delta NCMS_{t-j} + \sum_{j=1}^{2} \beta_j \Delta RR_{t-j}^{25\delta} + \sum_{j=1}^{2} \delta_j \Delta s_{t-j} + \epsilon_t \qquad (5.7)$$

$$\Delta RR_t^{25\delta} = \sum_{j=1}^{2} \alpha_j \Delta NCMS_{t-j} + \sum_{j=1}^{2} \beta_j \Delta RR_{t-j}^{25\delta} + \sum_{j=1}^{2} \delta_j \Delta s_{t-j} + \epsilon_t \qquad (5.8)$$

where $\Delta NCMS_t$ indicate change in net non-commercial short futures positions in yen as percentage of total open interest. $\Delta RR_t^{25\delta}$ indicate change in the value of 25-delta risk reversals. and Δs_t stands for change in the log of spot exchange rate. The Granger causality results, reported in Table 5.5, indicate that risk reversals lead (Granger-cause) net non-commercial yen short positions but that positions do not lead risk reversals. The results are robust to the inclusion of the lagged (log changes) exchange rate as a control. While all statistics are significant at the 1% level, the test-statistics are higher for 1-year risk reversals. For example, the cumulative effect (sum of the coefficients) of the 2-lag specification for 1-year risk reversals controlling for the exchange rate, is 30.38. A 100 basis point decrease in the absolute value of risk reversals over a two-week period is followed by a 30.4% increase in the net NCMS as a fraction of total open interest potions, i.e. a sharp reduction in the perceived risk of large yen appreciation leads to substantially more carry trade activity. Overall, Granger-causality results indicate that risk reversals convey important information on currency risk in excess of the exchange rate itself that is taken into account by non-commercial traders when deciding to take on an open interest futures position. Our findings are consistent with Brunnermeier (2009) who find that the value of risk reversals tends to decline together with carry trade activity when financial markets in the U.S. become unstable suggesting that it is mainly carry traders who rely on risk reversals to ensure their portfolios.

A simple "back of the envelope" calculation measuring the impact of macroeconomic surprises emanating from U.S. and Japan on carry trade activity transmitted during the two episodes of wide swings in risk reversals (a reduction in perceived risk and a rise in perceived risk) discussed in the previous section is informative. Figure 5.7 shows that the first episode (1/07/2005 through 03/13/2006), when perceived risk declined (-2.5 to -1.0), was accompanied by a switch from a 20% net long position to a 40% net short open position of non-commercial traders, indicating a sharp rise in carry trade activity. The second episode (04/12/2006 through 05/17/2006), when perceived risk increased sharply (-1.0 to -2.0), was accompanied by a large unwinding of short yen open positions-a switch form a 30% net short position to a 10% net long position for non-commercial traders.

Table 5.6 [about here]

The cumulative impact of news surprises on risk reversals is multiplied by the sum of the coefficients on $\Delta RR_{t-j}^{25\delta}$ in the Granger-causality equation (5.7) in Table 5.5. Table 5.6 shows the results. The first column of each panel corresponds to the conservative estimate obtained by multiplying the cumulative impact of macro surprises in excess of "wide bands" by the coefficient on $\Delta RR_{t-j}^{25\delta}$ in the specification of (5.7) with 1-lag. The second column yields a higher estimate by multiplying the cumulative impact of macro surprises in excess of "narrow bands" by the sum of the coefficients in the 2-lag Granger causality specification in equation (5.7).

Based on these calculations, during the first episode U.S. GDP and Consumer Credit surprises had the effect of increasing net NCMS share of total open interest by 2.9 and 6.0 percentage points, respectively, while Japan's Trade Balance surprises accounted for another 2.8 percentage point rise. In total, our estimates suggest that macroeconomic surprises account for 38% (11.2 percentage points) of the rise in NCMS positions as a share of total open interest in the first episode. During the second episode, the fall in NCMS positions is mainly attributable to Japanese news. Japan's trade balance contributing about -1.7 percentage points to the reduction in speculative positions on CME, while Japan's Overall Household Spending and Japan's Consumer Confidence surprises contributed around -0.9 and -0.3 percentage points, respectively. Overall, macroeconomic surprises emanating from U.S. and Japan accounted about 10% (-2.67 percentage points) of the fall in NCMS positions during this episode.

5.5 Conclusion

This paper investigates market perceptions of the risk of large exchange rate movements by using information gleaned from risk reversal contracts and macroeconomic news. We focus on the height of the carry trade period in Japan (March 2004 through December 2006), where the sample is delimited at the beginning by the cessation of the Bank of Japan large-scale intervention operations and ends before the financial crisis emerged. Concerns about sharp yen appreciation were particularly evident during the period of heavy carry trade activity and are more likely to show up in the price of risk.

We focus on "big" news surprises (greater than one standard deviation movements) that are more likely to convey information about the risk of large changes in the exchange rate, and consider a broad set of news – thirty three sources (18 U.S. series and 15 Japan series) – to investigate the direct impact of news other than intervention for the value of JPY/USD yen risk reversals. We also consider the effect of the value of risk reversals on the yen carry trade, using non-commercial open interest positions in futures markets as a proxy for carry trade activity.

Overall, we find that macroeconomic news is an important determinant of risk reversals during periods of heavy carry trade volume. U.S. GDP, Personal Income, and Consumer Credit and Japanese Trade Balance, TANKAN non-manufacturing index, Consumer Confidence, and Overall Household Spending have a statistically significant impact on risk reversals. Estimates using predicted values based on regression coefficients show that the cumulative impact of macroeconomic surprises can account for a significant portion of the total change in risk reversals during episodes of changing risk perceptions in the JPY/USD market. Moreover, there is a close link between risk reversals and net non-commercial futures positions, and this link is borne out in Granger causality tests. Using this metric, we are able to calculate the effect of macroeconomic news on carry trade activity, with risk reversals (the cost of hedging) as the transmission mechanism. Depending on the subsample and calculation method, macroeconomic news surprises can translate into more than one third of the total adjustment in yen speculative positions.

Table 5.1: Summary statistics and unit root test for risk reversal series

	1-month		1-year	
	(Levels)	(1st Differences)	(Levels)	(1st Differences)
	Summary Statistics			
Mean	-0.717	0.000	-1.375	0.000
Median	-0.650	0.000	-1.250	0.000
Maximum	-0.050	0.525	-0.725	0.250
Minimum	-2.450	-1.450	-2.750	-0.900
Std. Dev.	0.357	0.144	0.440	0.071
Skewness	-1.137	-1.693	-0.595	-3.169
Kurtosis	4.826	19.921	2.439	41.925
	Unit Root Tests			
Aug. Dickey-Fuller	-4.763***	-30.984***	-2.159	-26.808***
Phillips-Perron	-5.436***	-31.203***	-2.216	-26.815***
Observations	715	715	715	715

Notes: 3/18/2004 to 12/29/2006 sample period. Unit root test 10%, 5%, and 1% critical values for 1-month are -2.568888, -2.865412. and -3.439371 respectively. Unit root test 10%. 5%. and 1% critical values for 1-year are -2.568864. -2.865366, and -3.439268. *. **, and *** indicate coefficients significant at 10%, 5%. and 1% level respectively.

Table 5.2: Regression results of risk reversals on ALL macroeconomic announcement surprises

ALL Macro Surprises	Baseline(1)		Baseline(2)	
U.S. Announcements	Coef.	S.E.	Coef.	S.E.
GDP	-5.517**	(2.653)	-4.259**	(1.768)
Nonfarm payroll empoloyment	4.679*	(2.468)	0.616	(2.314)
Industrial production	-2.341	(3.396)	-2.679	(3.154)
Capacity utilization	-0.970	(3.025)	-1.853	(3.034)
Personal income	0.766	(1.507)	1.661	(1.295)
Consumer credit	-4.293*	(2.550)	-4.858*	(2.619)
Consumer spending	-1.961	(3.582)	-2.553	(3.604)
New home sales	0.840	(2.728)	1.669	(2.473)
Durable goods orders	0.084	(2.387)	1.240	(2.567)
Factory orders	1.353	(1.650)	-1.471	(1.607)
Business inventories	3.646	(2.673)	1.781	(2.277)
Trade balance	0.175	(3.476)	-2.756	(2.406)
Producer price index	-2.826	(3.080)	-2.867	(2.720)
Consumer price index	-1.654	(4.822)	-0.687	(4.003)
Consumer confidence index	2.241	(3.747)	0.317	(3.788)
NAPM index	2.181	(1.975)	-0.096	(2.271)
Housing starts	-0.040	(2.218)	-0.703	(2.123)
Index of leading indicators	-2.248	(7.118)	-0.775	(4.959)
Japanese Announcements	Coef.	S.E.	Coef.	S.E.
Trade balance	-5.553*	(2.857)	-5.452**	(2.796)
Current account	-1.648	(1.782)	-0.632	(1.760)
Leading economic index	2.220	(1.982)	0.752	(1.626)
Consumer confidence index	3.660**	(1.865)	3.517*	(1.859)
TANKAN large manufacturing index	0.317	(3.915)	4.810	(3.647)
TANKAN non-manufacturing index	2.639	(5.011)	-2.026	(3.856)
Monetary base	-2.744	(4.125)	-2.265	(4.115)
Capacity utilization	-7.503	(13.797)	-5.090	(9.934)
GDP (quarterly)	-2.258	(3.118)	-3.249	(2.366)
Large retail sales	-5.532	(3.595)	-5.086	(3.388)
Construction orders	-0.019	(1.150)	1.326	(1.858)
Industrial production	0.434	(2.123)	1.683	(2.367)
Retail trade	0.386	(3.218)	0.097	(3.309)
Consumer price index	-3.304	(2.229)	0.158	(2.951)
Overall household spending	5.738**	(2.485)	5.558***	(1.530)
Exchange rate			5.239***	(1.256)
Interest rate differential			-0.067*	(0.041)
Lag dependent variable	0.008	(0.052)	0.003	(0.044)
R-squared	0.033		0.211	
Durbin-Watson	1.814		2.085	
Akaike info criterion	-2.402		-2.600	

Notes: 3/18/2004 12/29/2006 sample, 715 observations. Standard errors in parentheses; *, **, and *** indicate coefficients significant at 10%, 5%, and 1% level respectively. Constant and day of the week omitted because of insignificant coefficient.

Table 5.3: Regression results of risk reversals on LARGE macroeconomic announcement surprises

LARGE Macro Surprises	Baseline(2)				ARMA(4,4)			
	Narrow Bounds		Wide Bounds		Narrow Bounds		Wide Bounds	
U S Announcements	Coef	S E	Coef	S E	Coef	S E	Coef	S E
GDP	-4 219**	(1 747)	-3 557*	(2 043)	-4 327**	(1 841)	-3 959**	(1 982)
Nonfarm payroll empl	0 661	(2 317)	1 663	(2 388)	0 583	(2 110)	1 567	(2 214)
Industrial production	-2 744	(3 166)	0 354	(5 383)	-2 517	(3 244)	0 897	(5 315)
Capacity utilization	-1 784	(3 024)	-3 847	(5 701)	-1 289	(3 041)	-3 186	(5 544)
Personal income	1 658	(1 293)	1 082**	(0 421)	1 569	(1 168)	1 211***	(0 374)
Consumer credit	-4 873*	(2 635)	-6 478*	(3 441)	-5 518**	(2 726)	-7 033**	(3 567)
Consumer spending	-2 522	(3 603)	-2 284	(4 088)	-2 289	(3 257)	-2 430	(3 688)
New home sales	1 620	(2 481)	2 850	(2 617)	0 666	(2 539)	2 717	(2 582)
Durable goods orders	1 190	(2 576)	1 221	(1 842)	0 788	(2 485)	1 511	(1 751)
Factory orders	-1 488	(1 612)	-1 512	(1 567)	-0 900	(1 509)	-0 762	(1 461)
Business inventories	1 786	(2 278)	1 949	(2 844)	1 613	(2 245)	1 781	(2 788)
Trade balance	-2 850	(2 396)	-1 254	(2 825)	-1 924	(2 379)	-0 069	(2 867)
Producer price index	-3 049	(2 771)	-0 751	(1 060)	-2 227	(2 164)	-0 659	(1 010)
Consumer price index	-0 717	(4 008)	1 308	(3 540)	-0 263	(4 031)	1 826	(3 593)
Consumer confidence index	0 406	(3 800)	1 052	(4 317)	1 149	(3 635)	0 139	(4 335)
NAPM index	-0 064	(2 263)	-0 456	(2 179)	0 163	(2 169)	-0 399	(2 067)
Housing starts	-0 612	(2 127)	0 602	(2 020)	-0 936	(2 262)	0 244	(2 179)
Index of leading indicators	-0 774	(4 958)	-4 849	(3 602)	-2 628	(3 934)	-5 116	(3 891)
Japanese Announcements	Coef	S E	Coef	S E	Coef	S E	Coef	S E
Trade balance	-5 526**	(2 793)	-6 396*	(3 448)	-5 620**	(2 788)	-6 436*	(3 512)
Current account	-0 622	(1 774)	-0 762	(1 951)	-0 696	(1 716)	-0 868	(1 916)
Leading economic index	0 758	(1 634)	0 393	(1 753)	0 303	(1 723)	-0 322	(1 762)
Consumer confidence index	3 513*	(1 855)	1 812	(1 569)	3 538*	(1 939)	1 680	(1 765)
TANKAN large manuf index	4 823	(3 650)	4 440	(4 463)	3 874	(3 346)	3 640	(3 857)
TANKAN non-manuf index	-1 946	(3 904)	-3 702*	(2 100)	-2 765	(3 764)	-3 017*	(1 658)
Monetary base	-2 209	(4 111)	-2 144	(4 271)	-1 551	(3 607)	-1 062	(3 776)
Capacity utilization	-4 751	(9 922)	-6 452	(8 678)	-7 923	(10 476)	-10 506	(9 524)
GDP (quarterly)	-3 205	(2 355)	-3 261	(2 410)	-2 948	(2 396)	-2 828	(2 480)
Large retail sales	-5 197	(3 399)	-5 197	(3 495)	-4 110	(3 578)	-4 798	(3 739)
Construction orders	1 365	(1 898)	0 736	(2 112)	1 321	(1 698)	1 007	(2 126)
Industrial production	1 565	(2 379)	0 987	(2 583)	0 726	(2 205)	0 648	(2 576)
Retail trade	0 064	(3 353)	1 833	(3 692)	-0 102	(3 277)	1 304	(3 672)
Consumer price index	0 114	(2 972)	2 747	(3 460)	0 644	(2 616)	2 765	(2 995)
Overall household spending	5 583***	(1 478)	4 389***	(0 928)	5 903***	(1 948)	4 794***	(1 573)
Exchange rate	5 237***	(1 256)	5 193***	(1 249)	4 593***	(0 705)	4 539***	(0 691)
Interest rate differential	-0 068*	(0 041)	-0 065	(0 041)	-0 076**	(0 037)	-0 074**	(0 037)
Lag dependent variable	0 003	(0 044)	0 002	(0 045)				
AR(4)					-0 658***	(0 164)	-0 653***	(0 169)
MA(4)					0 726***	(0 148)	0 724***	(0 152)
R-squared	0 212		0 211		0 286		0 286	
Durbin-Watson	2 084		2 078		2 129		2 126	
Akaike info criterion	-2 600		-2 599		-2 696		-2 696	

Notes 3/18/2004 12/29/2006 sample, 715 observations Standard errors in parentheses, *, **, and *** indicate coefficients significant at 10%, 5%, and 1% level respectively Constant and day of the week omitted because of insignificant coefficient

Table 5.4: Impact of significant news surprises on the value of 1-year risk reversals

Subsample Period:	01/07/2005-03/13/2006 Falling yen appreciation risk		04/12/2006-05/17/2006 Rising yen appreciation risk	
Surprise Announcement	Narrow Bands	Wide Bands	Narrow Bands	Wide Bands
US GDP	0.096	0.070	0.000	0.000
US Personal income	0.000	0.014	0.000	0.000
US Consumer credit	0.198	0.143	0.009	0.000
JP Trade balance	0.091	0.106	-0.058	-0.058
JP Consumer confidence index	-0.012	0.000	-0.009	0.000
TANKAN non-manufacturing index	0.000	-0.016	0.000	0.000
JP Overall household spending	0.000	0.000	-0.029	-0.024
Total	0.373	0.317	-0.088	-0.081
% of Change in 1-Year Risk Reversal	29.84%	25.34%	9.24%	8.56%

Note: The impact is calculated by multiplying the standardized value of the news surprise component relative to the Bloomberg survey of market expectation by the regression coefficient. The bottom row reports the cumulative impact of news surprises during each subsample period as a percentage of change in the value of 1-year risk reversal during the same time period.

Table 5.5: Cumulative impact of significant news surprises on net non-commercial yen short positions

	Baseline				Controlling for exchange rate			
	1-lag		2-lag		1-lag		2-lag	
	RRs cause NCMS	NCMS cause RRs	RRs cause NCMS	NCMS cause RRs	RRs cause NCMS	NCMS cause RRs	RRs cause NCMS	NCMS cause RRs
	1-Month Risk Reversals							
F-Statistic	3.837**	0.483	8.832***	2.213	4.326**	0.362	8.374***	1.409
Probability	0.052	0.488	0.000	0.113	0.039	0.548	0.000	0.248
Coeff. Sum	6.042	0.002	21.439	0.000	7.683	0.002	24.116	0.004
Obs.	146		143		146		143	
	1-Year Risk Reversals							
F-Statistic	9.023***	0.521	9.611***	2.570*	7.720***	0.022	6.924***	1.798
Probability	0.003	0.471	0.000	0.080	0.006	0.882	0.001	0.169
Coeff. Sum	14.491	0.001	29.964	-0.003	15.495	0.000	30.388	-0.005
Obs.	151		150		151		150	

Note: *, **, and *** indicate the null hypothesis of no Granger-causality is rejected at significant at 10%, 5%, and 1% level respectively.

Table 5 6· Granger causality tests between risk-reversals and net non-commercial short positions (% O.I.)

Subsample Penod	01/07/2005-03/13/2006 Fallıng yen appreciatıon rısk		04/12/2006-05/17/2006 Rısıng yen appreciatıon rısk	
Calculatıon Method	Wıde Bounds 1-Lag Coeff	Narrow Bounds 2-Lag Coeff	Wıde Bounds 1-Lag Coeff	Narrow Bounds 2-Lag Coeff
Surprıse Announcement	$\Delta NCMS(\%O\ I)$	$\Delta NCMS(\%O\ I)$	$\Delta NCMS(\%O\ I)$	$\Delta NCMS(\%O\ I)$
US GDP	1 08	2 92	0 00	0 00
US Personal ıncome	0 22	0 00	0 00	0 00
US Consumer credıt	2 22	6 01	0 00	0 27
JP Trade balance	1 64	2 76	-0 89	-1 77
JP Consumer confidence ındex	0 00	-0 37	0 00	-0 28
TANKAN non-manufac ındex	-0 25	0 00	0 00	0 00
JP Overall house spend	0 00	0 00	-0 37	-0 89
Total	4 91	11 33	-1 26	-2 67
% of Total $\Delta NCMS(\%O\ I\ )$	16 47%	38 03%	4 79%	10 14%

Note The table shows the estımated cumulatıve ımpact over the sample perıod of macroeconomıc news surprıses on net non-commercıal short posıtıons (NCMS) as a percentage of total open ınterest (% O I) on the Chıcago Mercantıle Exchange (CME) The ımpact ıs calculated by multıplyıng the cumulatıve ımpact of news surprıses on rısk-reversals by the Granger-causalıty coefficıents of rısk-reversals on NCMS (% O I)

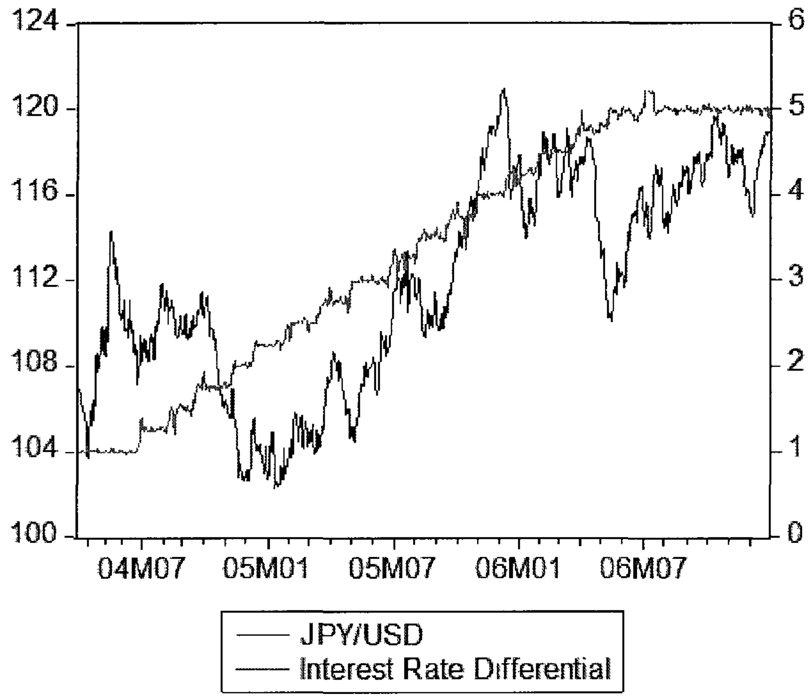

Figure 5.1: U.S.-Japan interest rate differential and JPY/USD exchange rate.

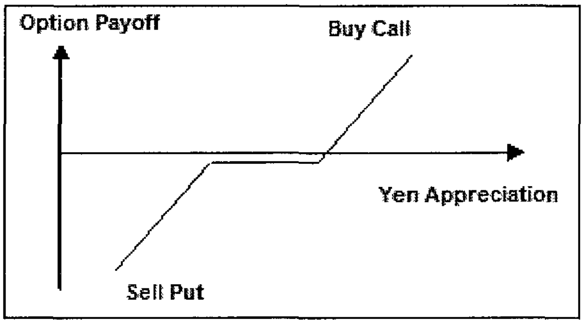

Figure 5.2: Risk reversal payoff diagram.

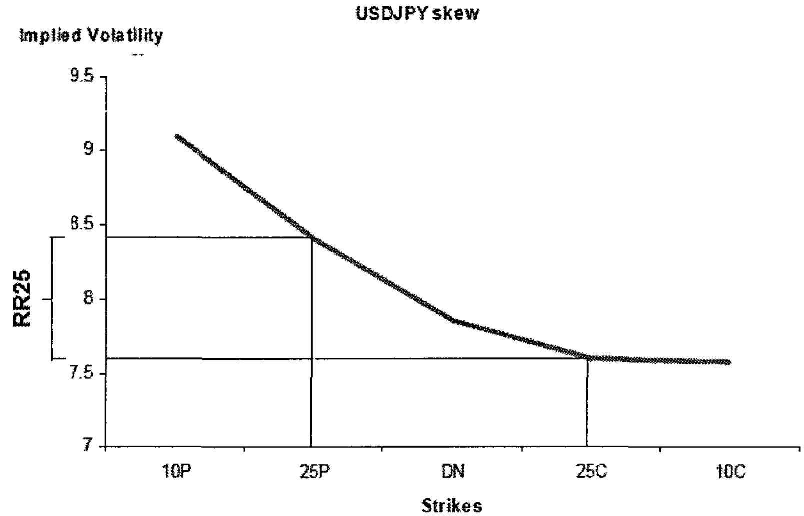

Figure 5.3: JPY/USD implied volatility smirk means yen calls/dollar puts are more expensive. (Source: Bloomberg, DB FX Research and authors' edits)

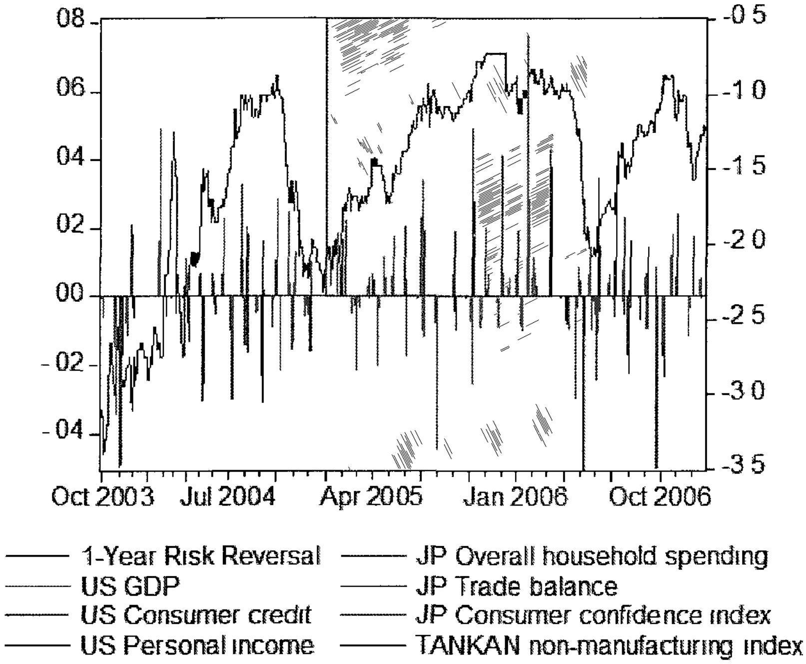

Figure 5.4: Impact of macroeconomic surprises (1 s d. bounds) on the risk premium of yen appreciation.

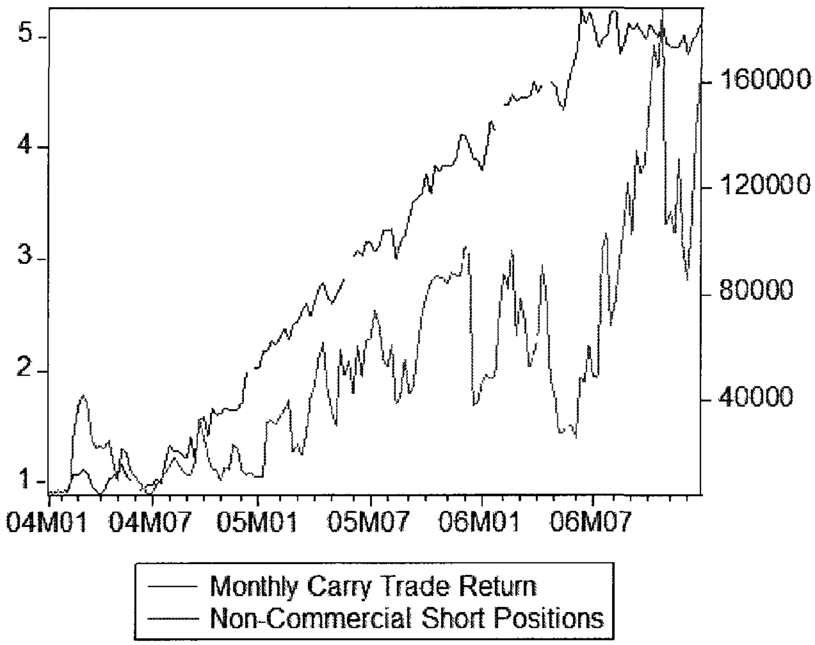

Figure 5.5: Carry trade return and total CME non-commercial short positions.

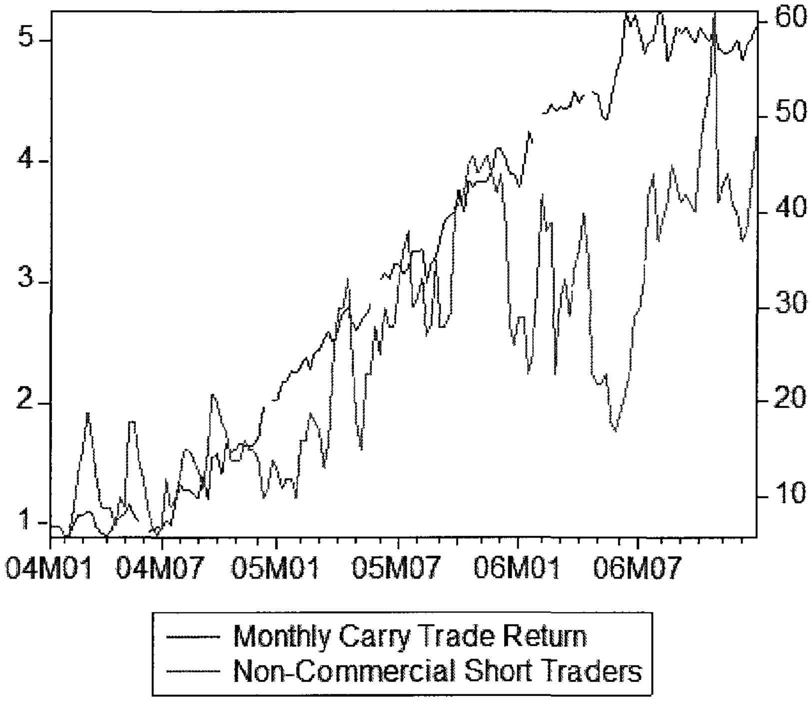

Figure 5.6: Carry trade return and total CME non-commercial short traders.

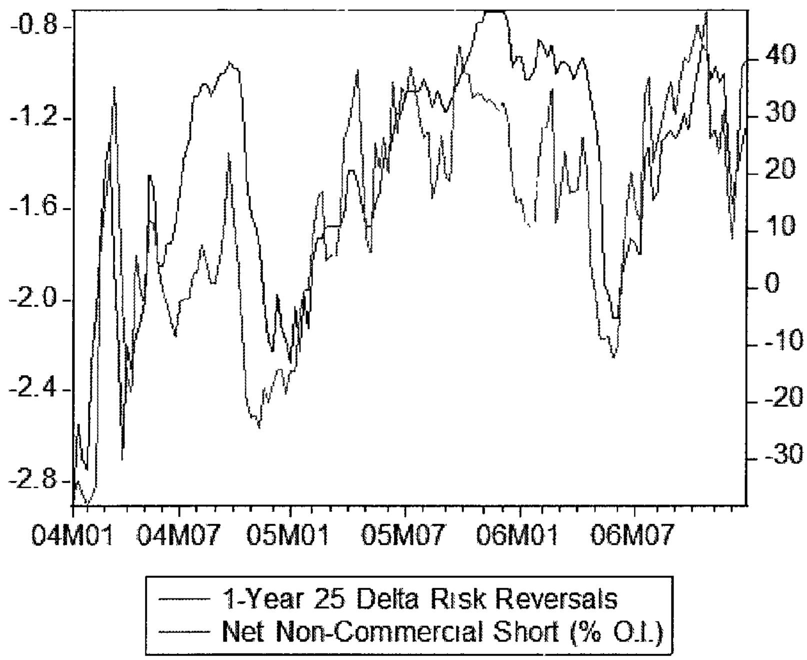

Figure 5.7: Risk reversals and CME net non-commercial Yen short futures positions.

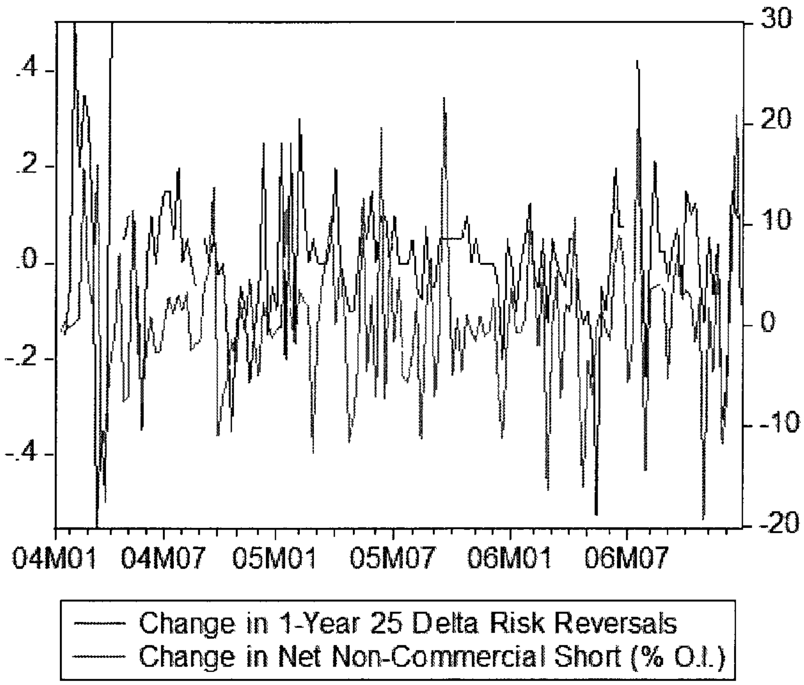

Figure 5.8: Changes in risk reversals and CME net non-commercial Yen short futures positions.

Appendix A

Chapter 2 Statistical Methodology

The autocorrelation coefficient on institutional demand, $\rho_\imath$, has two components. First. the positive correlation from institutional demand this quarter and last quarter could result from institutions following each other in and out of the same securities. Second, the positive correlation could come from the institution reinforcing its own portfolio over adjacent quarters. In order to distinguish between the two effects. we follow Sias's methodology in decomposing $\rho_\imath$ into the two components:

$$\begin{aligned}
\rho_\imath &= \frac{cov(\Delta_{\imath,k,t}, \Delta_{\imath,k,t-1})}{\sigma^2(\Delta_{\imath,k,t-1})} \\
&= \frac{\frac{1}{K-1}\sum_{k=1}^{K} \Delta_{\imath,k,t}\Delta_{\imath,k,t-1}}{\sigma^2(\Delta_{\imath,k,t-1})} \\
&= \frac{1}{K-1}\sum_{k=1}^{K} \Delta_{\imath,k,t}\Delta_{\imath,k,t-1}
\end{aligned} \tag{A.1}$$

where $\sigma^2(\Delta_{\imath,k,t-1})$ is one because it is the covariance between standardized data. Also. using dummy variable. $D_{m,\imath,k,t}$ that equals one (zero) if investor m of type $\imath$ buys (sells) security k at time t. we can rewrite the standardized fraction of institutions buying a given security during current quarter as:

$$\Delta_{\imath,k,t} = \frac{Buy\Delta_{\imath,k,t} - Bu\bar{y}\Delta_{\imath,t}}{\sigma(Buy\Delta_{\imath,k,t})} = \frac{\left[\sum_{n=1}^{N_{\imath,k,t}} \frac{D_{\imath,k,t}}{N_{\imath,k,t}}\right] - Bu\bar{y}\Delta_{\imath,t}}{\sigma(Buy\Delta_{\imath,k,t})} \tag{A.2}$$

Substituting (A.2) into (A.3) the slope coefficient becomes:

$$\begin{aligned} \rho_\imath &= \left[\frac{1}{(K-1)\sigma(Buy\Delta_{\imath,k,t})\sigma(Buy\Delta_{\imath,k,t-1})}\right] \\ &\times \sum_{k=1}^{K}\left[\left(\sum_{n=1}^{N_{\imath,k,t}} \frac{D_{\imath,k,t} - Bu\bar{y}\Delta_{\imath,t}}{N_{\imath,k,t}}\right)\left(\sum_{n=1}^{N_{\imath,k,t-1}} \frac{D_{\imath,k,t-1} - Buy\bar{\Delta}_{\imath,t-1}}{N_{\imath,k,t-1}}\right)\right] \\ &= \left[\frac{1}{(K-1)\sigma(Buy\Delta_{\imath,k,t})\sigma(Buy\Delta_{\imath,k,t-1})}\right] \\ &\times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{\imath,k,t}} \frac{\left(D_{\imath,k,t} - Bu\bar{y}\Delta_{\imath,t}\right)\left(D_{\imath,k,t-1} - Buy\bar{\Delta}_{\imath,t-1}\right)}{N_{\imath,k,t}N_{\imath,k,t-1}}\right] \\ &+ \left[\frac{1}{(K-1)\sigma(Buy\Delta_{\imath,k,t})\sigma(Buy\Delta_{\imath,k,t-1})}\right] \\ &\times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{\imath,k,t}} \sum_{n=1,n\neq m}^{N_{\imath,k,t-1}} \frac{\left(D_{\imath,k,t} - Bu\bar{y}\Delta_{\imath,t}\right)\left(D_{\imath,k,t-1} - Buy\bar{\Delta}_{\imath,t-1}\right)}{N_{\imath,k,t}N_{\imath,k,t-1}}\right] \end{aligned} \tag{A.3}$$

$$(A.5)$$

The first term on the right hand side is the portion of correlation that results from investors following themselves into and out of the same real estate stocks and the second term is the portion of correlation that results from investors investors of particular type following each other in and out of the same real estate stocks. This second portion corresponds to herding.

Appendix B

Chapter 3 Model Derivations

B.1 Proof of Proposition 4

First. we show that $\delta(\bar{x}, a)$ is increasing in a for a fixed value of $\bar{x}$. By completing the square on θ we obtain:

$$e^{-\frac{(x_i-\theta)^2}{2\sigma_e^2}} e^{-\frac{(\theta-\theta_0)^2}{2\sigma_0^2}} = e^{-\frac{\theta-\mu_\theta(x_i)}{2\sigma_\theta^2}} \xi(x_i) \tag{B.1}$$

where.

$$\mu_\theta(x_i) \equiv \frac{x_i/\sigma_e^2 + \theta_0/\sigma_0^2}{1/\sigma_e^2 + 1/\sigma_0^2} \tag{B.2}$$

$$\sigma_\theta^2 \equiv (1/\sigma_e^2 + 1/\sigma_0^2)^{-1} \tag{B.3}$$

$$\xi(x_i) \equiv \frac{\mu_\theta(x_i)^2}{2\sigma_\theta^2} - \frac{x_i^2}{2\sigma_e^2} - \frac{\theta_0^2}{2\sigma_0^2}. \tag{B.4}$$

Then we have:

$$\delta(x_i, a) = \frac{\int^{\alpha} e^{-\frac{(x_i-\theta)^2}{2\sigma_e^2}} e^{-\frac{(\theta-\theta_0)^2}{2\sigma_0^2}} d\theta}{\int_{\alpha} e^{-\frac{(x_i-\theta)^2}{2\sigma_e^2}} e^{-\frac{(\theta-\theta_0)^2}{2\sigma_0^2}} d\theta} = \frac{\Phi(\alpha; x_i)}{1-\Phi(\alpha; x_i)} \tag{B.5}$$

where $\Phi(\cdot; x_i)$ denotes the cumulative distribution function for a normal distribution with mean $\mu_\theta(x_i)$ and variance σ_θ^2. When a is increased. the numerator rises and the denominator falls. and thus $\delta(x_i, a)$ increases.

Next we show that $A(\bar{x}, a)$ and $B(\bar{x}(k), a)$ increase in a for a fixed $\bar{x}$ and $k < a$. We start by showing that $G(\bar{x}, a)$ is increasing in the second argument:

$$\begin{aligned}
\frac{\partial G(\bar{x}, a)}{\partial a} &= \frac{\partial}{\partial a}\left(\frac{\Pr(x_j > \bar{x}, \theta < a/N)}{\Pr(\theta < a/N)}\right) && \text{(B.6)}\\
&= \frac{\Pr(x_j > \bar{x}, \theta = a/N)\Pr(\theta < a/N)}{\Pr(\theta < a/N)^2} && \text{(B.7)}\\
&- \frac{\Pr(x_j > \bar{x}, \theta < a/N)\Pr(\theta = a/N)}{\Pr(\theta < a/N)^2}\\
&= \frac{\Pr(\theta = a/N)}{\Pr(\theta < a/N)}\left(\frac{\Pr(x_j > \bar{x}, \theta = a/N)}{\Pr(\theta = a/N)} - \frac{\Pr(x_j > \bar{x}, \theta < a/N)}{\Pr(\theta < a/N)}\right) && \text{(B.8)}\\
&= \frac{\Pr(\theta = a/N)}{\Pr(\theta < a/N)}\left(\Pr(x_j > \bar{x} \mid \theta = a/N) - \Pr(x_j > \bar{x} \mid \theta < a/N)\right) && \text{(B.9)}\\
&> 0 && \text{(B.10)}
\end{aligned}$$

where "Pr" denotes likelihood functions. The last inequality holds by the property (3.14). We show likewise that $F(\bar{x}, a)$ is decreasing in a. Since $A(\bar{x}, a) = G(\bar{x}, a)/F(\bar{x}, a)$. we obtain that A is increasing in the second argument (a).

Finally, when a is increased by one, one trader switches sides from A to B. and this increases the right hand side of (3.13) because $A < B$. In sum. the right hand side increases in a for a fixed $\bar{x}$. Thus, if A is decreasing in $\bar{x}$, $\bar{x}(a)$ must be greater than $\bar{x}(a-1)$ in order to satisfy the equation (3.13).

Now we show that $\partial A/\partial \bar{x} < 0$. Define F_1 and G_1 as the derivatives of F and G with respect to the first argument $\bar{x}$. respectively. Then:

$$\frac{\partial A(\bar{x},a)}{\partial \bar{x}} = \frac{F_1(\bar{x},a)}{F(\bar{x},a)}\left(\frac{G_1(\bar{x},a)}{F_1(\bar{x},a)} - A\right). \tag{B.11}$$

G_1/F_1 can be rewritten as:

$$\frac{G_1(\bar{x},a)}{F_1(\bar{x},a)} = \frac{\Phi(\alpha;\bar{x})}{1-\Phi(\alpha;\bar{x})}\frac{\Pr(\theta \geq \alpha)}{\Pr(\theta < \alpha)} \tag{B.12}$$

A and B are written as:

$$\begin{aligned} A(\bar{x},a) &= \frac{\int_{\bar{x}}\int^{\alpha} e^{-\frac{(x_\imath-\theta)^2}{2\sigma_e^2}} e^{-\frac{(\theta-\theta_0)^2}{2\sigma_0^2}}\, d\theta dx_\imath}{\int_{\bar{x}}\int_{\alpha} e^{-\frac{(x_\imath-\theta)^2}{2\sigma_e^2}} e^{-\frac{(\theta-\theta_0)^2}{2\sigma_0^2}}\, d\theta dx_\imath} \frac{\Pr(\theta \geq \alpha)}{\Pr(\theta < \alpha)} \\ &= \frac{\int_{\bar{x}} \Phi(\alpha;x_\imath)\xi(x_\imath)dx_\imath}{\int_{\bar{x}}(1-\Phi(\alpha;x_\imath))\xi(x_\imath)dx_\imath}\frac{\Pr(\theta \geq \alpha)}{\Pr(\theta < \alpha)} \qquad \text{(B.13)} \\ B(\bar{x}(k),a) &= \frac{\int^{\bar{x}(k)}\int^{\alpha} e^{-\frac{(x_\imath-\theta)^2}{2\sigma_e^2}} e^{-\frac{(\theta-\theta_0)^2}{2\sigma_0^2}}\, d\theta dx_\imath}{\int^{x(k)}\int_{\alpha} e^{-\frac{(x_\imath-\theta)^2}{2\sigma_e^2}} e^{-\frac{(\theta-\theta_0)^2}{2\sigma_0^2}}\, d\theta dx_\imath} \frac{\Pr(\theta \geq \alpha)}{\Pr(\theta < \alpha)} \\ &= \frac{\int^{\bar{x}(k)} \Phi(\alpha;x_\imath)\xi(x_\imath)dx_\imath}{\int^{\bar{x}(k)}(1-\Phi(\alpha;x_\imath))\xi(x_\imath)dx_\imath}\frac{\Pr(\theta \geq \alpha)}{\Pr(\theta < \alpha)} \qquad \text{(B.14)} \end{aligned}$$

Then.

$$\frac{A}{G_1/F_1} = \int_x \frac{\Phi(\alpha;x_\imath)}{\Phi(\alpha,\bar{x})}\xi(x_\imath)dx_\imath \bigg/ \int_x \frac{1-\Phi(\alpha;x_\imath)}{1-\Phi(\alpha;\bar{x})}\xi(x_\imath)dx_\imath. < 1 \tag{B.15}$$

where the inequality obtains by that $\Phi(\alpha; x_i) < \Phi(\alpha; \bar{x})$ for any $x_i > \bar{x}$. Noting that $F_1 < 0$, we obtain from (B.11) that $\partial A(\bar{x}, a)/\partial \bar{x} < 0$.

B.2 Proof of Proposition B.2

By taking logarithm of (3.13) for a and $a+1$ and subtracting each side, we obtain:

$$\begin{aligned} 0 \;=\; & \log \delta(\bar{x}(a+1), a+1) - \log \delta(\bar{x}(a), a) \\ & + (N-1-a)(\log A(\bar{x}(a+1), a+1) - \log A(\bar{x}(a), a)) \\ & + \sum_{k=0}^{a-1} (\log B(\bar{x}(k), a+1) - \log B(\bar{x}(k), a)) \\ & + \log B(\bar{x}(a), a+1) - \log A(\bar{x}(a+1), a+1) \end{aligned} \tag{B.16}$$

The second argument a in δ and B affects the functions through $\alpha = a/N$ as in (B.5,B.14), and thus the direct effects of a' on δ and B are of order $1/N$. Also, as we show shortly, the difference $\bar{x}(a+1) - \bar{x}(a)$ is of order $1/N$, and so are a's effects through $\bar{x}$ on δ and B. Hence, the difference terms in (B.16) on $\log \delta$ and $\log B$ are of order $1/N$ and tends to zero as N goes to infinity.

The difference term in $\log A$ is broken down as:

$$\begin{aligned} & \frac{\log A(\bar{x}(a+1), a+1) - \log A(\bar{x}(a), a)}{1/N} \\ & \sim_{N\to\infty} \frac{\partial \log A(\bar{x}(a), a)}{\partial \bar{x}} \frac{\bar{x}(a+1) - \bar{x}(a)}{1/N} \\ & + \frac{\partial \log A(\bar{x}(a), a)}{\partial a(1/N)} \end{aligned} \tag{B.17}$$

Thus, as $N \to \infty$ for a fixed finite a we have

$$(N-1-a)\left(\bar{x}(a+1)-\bar{x}(a)\right) \to \frac{\log B(\bar{x},a)-\log A(\bar{x},a)+\partial \log A(\bar{x}(a),a)/\partial\alpha}{-\partial \log A(\bar{x},a)/\partial\bar{x}} \tag{B 18}$$

The right hand side is of order N^0 and hence it is shown that $\bar{x}(a+1)-\bar{x}(a)$ is of order $1/N$

Appendix C

Chapter 4 Model Derivations and Estimation Details

C.1 Proof of Proposition 4

By taking a partial derivative with respect to m for a fixed $\bar{x}$, we have:

$$\frac{\partial}{\partial m} \log \frac{\Pr(\text{High} \mid x_i = \bar{x}, m)}{\Pr(\text{Low} \mid x_i = \bar{x}, m)} = \log \frac{F(\bar{x})}{G(\bar{x})} - \log \frac{1 - F(\bar{x})}{1 - G(\bar{x})} \tag{C.1}$$

$$< 0 \tag{C.2}$$

where the inequality obtains because of $F/G < f/g < (1-F)/(1-G)$ since f/g is increasing. Thanks to the MLRP, we also have the following properties:

$$\frac{\partial}{\partial \bar{x}} \log \frac{f(\bar{x})}{g(\bar{x})} > 0 \tag{C.3}$$

$$\frac{\partial}{\partial \bar{x}} \log \frac{F(\bar{x})}{G(\bar{x})} = \frac{g(\bar{x})}{F(\bar{x})} \left(\frac{f(\bar{x})}{g(\bar{x})} - \frac{F(\bar{x})}{G(\bar{x})} \right) > 0 \tag{C.4}$$

$$\frac{\partial}{\partial \bar{x}} \log \frac{1-F(\bar{x})}{1-G(\bar{x})} = -\frac{g(\bar{x})}{1-F(\bar{x})} \left(\frac{f(\bar{x})}{g(\bar{x})} - \frac{1-F(\bar{x})}{1-G(\bar{x})} \right) > 0 \tag{C.5}$$

Then, the partial derivative of the left-hand side of (4.3) with respect to $\bar{x}$ becomes:

$$\begin{aligned} \frac{\partial}{\partial \bar{x}} \log \frac{\Pr(\text{High} \mid x_i = \bar{x}, m)}{\Pr(\text{Low} \mid x_i = \bar{x}, m)} &= \frac{\partial}{\partial \bar{x}} \log \frac{f(\bar{x})}{g(\bar{x})} + m \frac{\partial}{\partial \bar{x}} \log \frac{F(\bar{x})}{G(\bar{x})} \\ &+ (N-1-m) \frac{\partial}{\partial \bar{x}} \log \frac{1-F(\bar{x})}{1-G(\bar{x})} \\ &> 0 \end{aligned} \tag{C.6}$$

The partial derivative of the right-hand side of (4.3) is:

$$\frac{\partial}{\partial m} \log \frac{-\Delta s_L - \delta}{\Delta s_H + \delta} = \frac{(\Delta s_L - \Delta s_H)(k-1)\Delta s'}{-(\Delta s_H + \delta)(\Delta s_L + \delta)} \tag{C.7}$$

$$> 0 \tag{C.8}$$

Collecting terms, we obtain:

$$\frac{d\bar{x}}{dm} = \frac{-\log\frac{F(\bar{x})}{G(\bar{x})} + \log\frac{1-F(\bar{x})}{1-G(\bar{x})} + \frac{(\Delta s_L - \Delta s_H)(k-1)\Delta s'}{-(\Delta s_H+\delta)(\Delta s_L+\delta)}}{\frac{\partial}{\partial \bar{x}}\log\frac{f(\bar{x})}{g(\bar{x})} + m\frac{\partial}{\partial \bar{x}}\log\frac{F(\bar{x})}{G(\bar{x})} + (N-1-m)\frac{\partial}{\partial \bar{x}}\log\frac{1-F(\bar{x})}{1-G(\bar{x})}} \tag{C.9}$$

$$= \frac{-\log\frac{F(\bar{x})}{G(\bar{x})} + \log\frac{1-F(\bar{x})}{1-G(\bar{x})} + \frac{(\Delta s_L - \Delta s_H)(k-1)\Delta s'}{-(\Delta s_H+\delta)(\Delta s_L+\delta)}}{\frac{f'(\bar{x})-g'(\bar{x})}{f(\bar{x})/g(\bar{x})} + m\left(\frac{f(\bar{x})}{F(\bar{x}))} - \frac{g(\bar{x})}{G(\bar{x})}\right) + (N-1-m)\left(\frac{g(\bar{x})}{1-G(\bar{x})} - \frac{f(\bar{x})}{1-F(\bar{x})}\right)} \tag{C.10}$$

which is strictly positive by the inequalities shown above.

C.2 Empirical Methodology

C.2.1 Jump component

In the limit (as $\Delta \to 0$) realized daily volatility approaches the continuously aggregated sum of square returns:

$$RV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(s)ds + \sum_{t<s\leq t+1} \kappa^2(s) \tag{C.11}$$

and $BV_t(\Delta)$ is defined as the sum of the product of adjacent absolute intraday returns standardized by a constant:

$$BV_t(\Delta) \equiv \mu^{-2}\sum_{j=2}^{1/\Delta} |r_{t+j\Delta,\Delta}||r_{t+(j-1)\Delta,\Delta}| \tag{C.12}$$

where $\mu \equiv (2/\pi)^2$ is the mean of the absolute value of standard normally distributed random variable. Since returns from two adjacent time periods share the persistent volatility but not the sporadic jumps, it follows from (C.12) that bi-power variation provides a reasonable proxy for the persistent component of the volatility. Barndorff-Nielsen et al. (2006) show that:

$$BV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(s)ds \tag{C.13}$$

as $\Delta \to 0$.

Since realized volatility. $RV_{t+1}(\Delta)$. and bi-power volatility. $BV_{t+1}(\Delta)$. can be directly calculated from the observed asset prices. it follows that the jump component can be approximated as the difference of the two:

$$RV_{t+1}(\Delta) - BV_{t+1}(\Delta) \to \sum_{t<s\leq t+1} \kappa^2(s) \tag{C.14}$$

Because of a finite sample the estimate of the squared jump process might be negative so Beine et al. (2007) truncate the measurement at zero to get:

$$\kappa_{t+1}(\Delta) \equiv max[RV_{t+1}(\Delta) - BV_{t+1}(\Delta), 0] \tag{C.15}$$

We select only significant jumps while discounting smaller jumps as a part of continuous process or noise. Andersen et al. (2007) derive an asymptotically standard-normally distributed test statistic based on the fourth moment of the jump-diffusion process:

$$Z_{t+1}(\Delta) \equiv \Delta^{1/2} \frac{[RV_{t+1}(\Delta) - BV_{t+1}(\Delta)]RV_{t+1}(\Delta)^{-1}}{[(\mu^4 + 2\mu^2 - 5)max\,\{1, TQ_{t+1}(\Delta)BV_{t+1}(\Delta)^{-2}\}]^{1/2}} \tag{C.16}$$

where,

$$
\begin{aligned}
TQ_{t+1}(\Delta) &\equiv \Delta^{-1}\nu^{-3}\sum_{j=3}^{1/\Delta}|r_{t+j\Delta,\Delta}|^{4/3}|r_{t+(j-1)\Delta,\Delta}|^{4/3}|r_{t+(j-2)\Delta,\Delta}|^{4/3} \quad \text{(C.17)} \\
\nu &\equiv 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1} \quad \text{(C.18)}
\end{aligned}
$$

so that $TQ_{t+1}(\Delta) \to \int_t^{t+1} \sigma^4(s)ds$ as $\Delta \to 0$.

Hence, choosing to estimate fewer but larger jumps amounts to choosing a smaller significance level α associated with critical value Φ_α to compute:

$$\kappa_{t+1,\alpha}(\Delta) = I[Z_{t+1}(\Delta) > \Phi_\alpha] \cdot [RV_{t+1}(\Delta) - BV_{t+1}(\Delta)] \quad \text{(C.19)}$$

In addition to reporting all jumps, we report jumps estimated with $\alpha = 0.05$ and $\alpha = 0.01$. As a final step of implementing (C.19) Andersen et al. (2007) tackle first order autocorrelation due to microstructure noise by dividing $BV_{t+1}(\Delta)$ and $TQ_{t+1}(\Delta)$ by $(1 - 2\Delta)$ and $(1 - 4\Delta)$ respectively and adjusting the lags on returns.

C.2.2 Bayesian Markov Chain - Monte Carlo (MCMC) Estimation of ζ and ϕ

Under the assumption of exponentially dampened power-law for $\kappa_j \geq \kappa_{min}$ using equation (4.4.6) the joint likelihood is:

$$f(\kappa_1, \kappa_2, .., \kappa_J) \propto \prod_{j=1}^{J} \kappa_j^{-\zeta} exp\{-\phi\kappa_j\} \tag{C.20}$$

The conjugate prior families for the power exponent and exponential decay parameter are Gamma families[1]: $\zeta \sim$ Gamma $(\alpha_\zeta, \beta_\zeta)$ and $\phi \sim$ Gamma $(\alpha_\phi, \beta_\phi)$. Combining prior parameter densities with equation (C.20) and assuming ζ and ϕ are orthogonal we obtain the joint posterior:

$$f(\zeta, \phi|\kappa_1, \kappa_2, .., \kappa_J) \propto \left[\prod_{j=1}^{J} \kappa_j^{-\zeta}\right] \zeta^{\alpha_\zeta - 1} exp\{-\beta_\zeta\zeta\} \left[exp\left\{-(\sum_{j=1}^{J} \kappa_j + \beta_\phi)\phi\right\}\right] \phi^{\alpha_\phi - 1} \tag{C.21}$$

From (C.21) we obtain complete parameter conditionals:

$$f(\zeta|\kappa_1, \kappa_2, .., \kappa_J) \propto \zeta^{\alpha_\zeta - 1} exp\left\{-(\beta_\zeta + \sum_{j=1}^{J} ln(\kappa_j))\zeta\right\} \tag{C.22}$$

and

$$f(\phi|\kappa_1, \kappa_2, .., \kappa_J) \propto \phi^{\alpha_\phi - 1} exp\left\{-(\beta_\phi + \sum_{j=1}^{J} \kappa_j)\phi\right\} \tag{C.23}$$

[1]See Arnold and Press (1983) for the detailed discussion on the Bayesian techniques to estimate parameters in the power-law distribution

From (C.22) and (C.23)it follows that we can apply the Gibbs step in the MCMC algorithm to sample the power exponent and the exponential decay parameter from the following distributions respectively:

$$\zeta|\kappa_1, \kappa_2, .., \kappa_J \sim \text{Gamma } (\alpha_\zeta,\, \beta_\zeta + \textstyle\sum_{j=1}^{J} ln(\kappa_j)) \tag{C.24}$$

$$\phi|\kappa_1, \kappa_2, .., \kappa_J \sim \text{Gamma } (\alpha_\phi,\, \beta_\phi + J\bar{\kappa}) \tag{C.25}$$

For each jump sample we have a strong prior for the parameters based on preliminary MLE results, therefore we chose prior parameters such that $\alpha_\zeta/\beta_\zeta = \hat{\zeta}_{MLE}$ and $\alpha_\phi/\beta_\phi = \hat{\phi}_{MLE}$.

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