Essays on Price Discovery and Volatility Dynamics in the Foreign Exchange Market

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Declaration of Authorship

I, Fei Su, clarify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text. I also clarify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Moreover, I declare that one paper titled "Global Price Discovery in the Australian Dollar Market and Its Determinants", which is drawn from Chapter 2, has been accepted for publication and is forthcoming in *the Pacific-Basin Finance Journal*. This chapter is a collaboration work with Jingjing Zhang from Nanjing Audit University, China. I contribute by developing research ideas, conducting empirical analyses, and writing up. My co-author contributes by providing constructive comments and improving the writing.

Signature_____________

Date_____________

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Table of Contents

List of Figures

List of Tables

Abstract

This dissertation consists of three independent essays that explore different aspects of price discovery and volatility dynamics in the FX market. In the first essay, I estimate daily information shares of different trading sessions (namely, Asia, Europe, and U.S.) in the global foreign exchange market, and more importantly, I examine their determinants, i.e. when and how a market contributes more to the price discovery of the exchange rates. Specifically, I study the short- and long-run price discovery in the FX market on a global basis and their determinants by taking the AUD as an example. Interestingly, I find that more favourable market states contribute to price discovery in the short-run, while the capital market openness and financial liberalization, as measured by the Chinn-Ito Index, have a strong impact on the long-run variations in price discovery. The empirical results presented in this essay provide a better understanding of the global information distribution in the FX market and contribute to the literature on the determinants of price discovery. Furthermore, I provide important policy implications regarding international financial competitiveness and market development.

In the second essay, I revisit the meteor showers and heat waves effects (namely, the inter- and intra-regional volatility spillovers) in the FX market, which have been extensively recorded and examined in the previous studies. The main methodological tools used in this essay are the heterogeneous autoregressive model (HAR) and the Shapley-Owen R^2 decomposition techniques. By examining the dynamic patterns of volatility spillover for exchange rates of AUD/USD, GBP/USD, EUR/USD, and USD/JPY spanning the period of January 1999 (January 2000 for EUR/USD) to December 2013, I confirm the presence of both meteor showers and heat waves effects, however, the meteor showers effect has been increasing steadily and predominated over heat waves effects with the trend toward global trading and correlated common shocks of the financial markets. Furthermore, I explicitly examine the role of changing market states in determining volatility spillover in the foreign exchange market. Unlike the

conventional information-based models, such as the mixture of distribution hypothesis (MDH) theory, the empirical results suggest that the volatility spillover is attributed to not only exogenous information shocks, but also endogenous information arrivals and price discovery process, which resolves uncertainty and therefore mitigates information propagation. In sum, this essay presents new evidence on the patterns and economic mechanisms of volatility spillover and contributes to the relevant literature on volatility modelling in the FX market by proposing the time-varying volatility spillovers in different regions and suggesting the segment-wise properties of FX volatility modelling.

The last essay focuses on the statistical significance and economic value of the Conditional Volatility Persistence (CVP) model as proposed in Wang and Yang (2017). Namely, the CVP model calibrates future volatility persistence base on the observed market states as captured by return and volatility. Then, I compare the economic gains of a variety of RV-based HAR models by developing a volatility-timing strategy based on the signal of predicted volatility. By applying the CVP model to the spot exchange rates of AUD/USD, GBP/USD, EUR/USD, and USD/JPY, I confirm both the statistical and economic significance of the CVP model in the FX market. Namely, the CVP model can improve the forecasting performance and generate moderate economic gains. For example, under empirically reasonable assumptions, the CVP model I use in this thesis can gain an estimated 1.26% of total wealth on an annual basis, or 0.51% of total wealth relative to a static model. Furthermore, it achieves higher Sharpe ratios, especially during the turmoil period. The gains in using CVP model remain positive and significant after controlling for the transaction costs and market microstructure noise.

Chapter 1: Introduction

It would be hard to overemphasize how important the foreign exchange market is. The average daily trading volume of the foreign exchange market reached to 5.3 trillion dollars in April 2013 (BIS, 2013). FX market plays a central role in the financial markets as it provides a way for corporates to fund foreign liabilities, for investors to hedge foreign exchange risks and construct global investment portfolios, and for policy makers to implement monetary policies. Over the last two decades, the importance of the FX market has drawn great interests of academics, policy makers, and the media (Rime and Schrimpf, 2013).

Unlike the equity market or other securities markets, a unified empirical model for the foreign exchange rate is absent. Since the seminal work of Meese and Rogoff (1983) argues that the existing model of exchange rate based on macroeconomic fundamentals could not reliably outperform the random walk forecasts for yearly changes in major currency exchange rates, the predictability of the foreign exchange rate movements has been examined extensively. However, no one has yet been able to uncover macroeconomic fundamentals that could explain a modest fraction of the changes of the exchange rate in the real world (Evans and Lyons, 2002a). Frankel and Rose (1995) describe the traditional empirical research on exchange rate as "… the case for macroeconomic determinants of exchange rates is in a sorry state".

Since the mid-1990s, with the availability of proprietary data from the large dealing banks, research on foreign exchange microstructure, or so-called "the new micro exchange rates economics", has accelerated (See, for example, Evans 2005, 2008; Evans and Lyons, 2002a, 2002b, 2003). Market microstructure refers to the study of "the process and outcomes of exchanging assets under explicit trading rules" (O'Hara, 1995), and the trading mechanisms used for financial securities (Hasbrouck, 2007). As it has been documented in the previous literature, price discovery is an essential function of the financial markets in the context of market microstructure. Price discovery has been described as "the incorporation of new information into the security price" (Hasbrouck, 1995), as well as "consisting of the efficient and timely impounding of the information implicit in investor trading into market prices" (Lehmann, 2002). According to the efficient markets hypothesis (EMH) (see, for example, Fama 1965, 1970), prices reflect all available information in a quick and accurate manner. However, how this process occurs in practice remains unclear (Arto Thurlin, 2009).

In this thesis, I study several aspects of price discovery and volatility dynamics in the Foreign Exchange (FX) market. Namely, to fully explore the price discovery and information distribution in the FX market, this thesis consists of three independent essays which examine information transmission and volatility dynamics in the FX market from different perspectives. The previous literature on price discovery has explored the issues such as the measure of information shares, the heterogeneous roles of informed and liquidity traders, and information contents of different types of orders, etc. This thesis mainly focuses on the information share and its determinants, as well as information propagation in the Foreign Exchange spot market where most of the trading and price discovery occurs (Evans, 2002). The main topics and contributions of the essays are summarized as following:

This dissertation begins with the global price discovery in the foreign exchange market. Namely, in the second chapter, I estimate daily information shares of different trading sessions (namely, Asia, Europe, and U.S.) in the global foreign exchange market, and more importantly, I examine their determinants, i.e. when and how a market contributes more to the price discovery of the spot exchange rates. To correct the shortcomings of Hasbrouck (1995)'s measure of price discovery, which aims at calculating information share for parallel markets (i.e. markets overlapping in trading hours) and utilizing the cointegration relationship for the same asset traded on different markets, I use the Two-scale Realized Variance (TSRV) ratio as a proxy for information share, which is more suitable for the FX market where the trading continues around the clock, i.e., from Asia to Europe, and then to U.S, and therefore the fundamental prices of the exchange rates will change over time.[1] For example, in Wang and Yang (2011), it is advised to use the variance ratio as a robust measure of information share for sequential markets like the FX market. With regard to the determinants of price discovery, I find that more favourable market states (i.e. higher daily return, larger trading volume, and lower bid/ask spread) contribute to price discovery in the short-run, while the capital market openness and financial liberalization, as measured by the Chinn-Ito Index, have a strong impact on the long-run variations in price discovery. Overall, in this chapter I study the short- and long-run price discovery in the FX market on a global basis and their determinants, by taking the AUD as an example. The results presented in this chapter provide a better understanding of the global information distribution in the FX market and the determinants of price discovery. Furthermore, I draw implications of the empirical evidence for policy makers about the financial market competitiveness, especially for the emerging markets.

In the third chapter, I revisit the meteor showers and heat waves effects (namely, the inter- and intra-regional volatility spillover) in the FX market, which have been extensively recorded and examined in the previous study. The main methodological tools used in this chapter are the heterogeneous autoregressive model (HAR) and Shapley-Owen R^2 decomposition techniques. In this chapter, I attempt to identify the dynamic patterns and explore the economic mechanisms of volatility spillover by taking a much broader view on the drivers and factors causing volatility spillover. Namely, this empirical study explicitly examines the role of market states, as captured by return and volatility, in explaining volatility spillovers in the foreign exchange market. By quantifying the magnitudes of volatility spillovers within the local market and across markets for the exchange rates of AUD/USD, GBP/USD, EUR/USD, and USD/JPY, I confirm the presence of both meteor showers and heat waves effects, however, the meteor showers effect has been increasing steadily and predominated over heat waves with the trend toward global trading and autocorrelated common shocks of the financial markets.

[1] The methods in measuring information share include Weighted Price Contribution (WPC), Information Share (IS), Component Share (CS), and Information Leadership Share (ILS). For a full description of the methods and their applications, please refer to a special issue of the Journal of Financial Markets (*Journal of Financial Markets*, *Issue 3, 2002*) and Talis Putnins (2015).

Furthermore, by expanding the conditional volatility persistence (CVP) model as proposed in Wang and Yang (2017) in a multi-market setting, I find that the conditional volatility persistence is the dominant channel linking each region's market states to the future volatility. Namely, unlike the classic information-based models, such as the mixture of distribution hypothesis (MDH) theory, I find that the volatility spillover is attributed to not only exogenous information shocks, but also the endogenous information arrivals and price discovery process, which mitigates information propagation and reduces volatility spillover. Besides, using the Shapley-Owen R^2 decomposition techniques, I find that the CVP is the dominant channel linking changing market states to the future volatility and its persistence. In summary, this chapter presents new evidence on the dynamic patterns and economic mechanisms of volatility spillovers and contributes to the relevant literature on volatility modelling and information propagation. The empirical results presented in this chapter also emphasize the importance of transnational intervention in the FX market, especially during the period of market stress.

The fourth chapter comprehensively investigates the role of conditional volatility persistence in predicting future volatility from both statistical and economic perspectives. Namely, different from previous studies with similar focus, I not only conduct an extensive statistical evaluation of volatility forecasting using a variant of heterogeneous autoregressive (HAR) models, but also provide new economic evidence on whether a risk-averse investor can significantly benefit from volatility timing based on the signal of predictive volatility. By developing a simple yet useful mean-variance utility framework, I examine the economic significance of the volatility timing strategy which takes advantage of the accurate volatility forecasts and the negative relationship between return and volatility. The empirical results confirm the economic value of the conditional volatility persistence model (CVP) which calibrates future volatility persistence conditional on market state variables. Namely, the models which incorporate the feature of conditional volatility persistence significantly improve the forecasting performance and therefore generate moderate economic gains. For example, the CVP model I use in this thesis can gain an estimated 0.51% of total wealth relative to a static model on an annual basis and achieve higher Sharpe ratios, especially during periods of turmoil. Furthermore, the results hold true across the major exchange rates, and are robust to market microstructure effects and transaction costs.

Conclusions and further directions are summarized in the last chapter. In summary, the three essays deepen our understanding of price discovery and volatility dynamics in one of the largest financial markets – the Foreign Exchange (FX) market. The empirical findings presented in this dissertation also provide detailed explanations of the volatility persistence and information propagation in the FX market, and shed new light on the research regarding the microstructure of the foreign exchange market.

Chapter 2: Global Price Discovery in the Foreign Exchange Market and Its determinants: Evidence from the Australian Dollar

2.1. Introduction

In recent years, the Australian Dollar (AUD) has started to play an increasingly important role in the global foreign exchange (FX) market. According to the Bank for International Settlements (BIS, 2013), the market share of the AUD in the global foreign exchange (FX) trading has steadily increased. By 2013, the AUD has become the fifth most important currency in terms of turnover.[2] The increase in the AUD trading could be attributed to a higher level of internationalization of the Australian economy (Edison, Cashin and Liang, 2003; Debelle, Gyntelberg and Plumb, 2006; Battellino and Plumb, 2011), as well as the growth in Australia's international trade, especially the increasing demand for Australia's natural resources from emerging economies, such as China.

This chapter focuses on the determinants of dynamic information shares in AUD trading. More specifically, using the intraday price quotes of AUD against the US Dollar (USD) over the period of 1999 - 2013, I firstly estimate the magnitudes of information shares of the global FX market. Then I attempt to identify the determinants of estimated information shares at two different time horizons (i.e. daily and monthly information shares).

The issue of price discovery in financial markets has been receiving more attention in recent decades due to rapid globalization of exchanges as well as the availability of high-quality trading data. For example, using data on Helsinki Stock Exchange, Booth et al. (2002) examine the roles of upstairs and downstairs markets in price discovery. Huang (2002) explores the impact of the Electronic Crossing Networks (ECNs) on price discovery of NASDAQ stocks. Hasbrouck (2003) analyses the importance of different trading venues for price discovery of the US equity indices. Wang and Yang (2011) propose a structural vector autoregressive (SVAR) model

[2] The AUD ranks fifth in the daily average turnover of foreign exchange instruments since 2010 as documented in Appendix A.

and a non-parametric approach to measure the global information distribution in the FX market and conclude that (i) the information shares of the four exchange rates considered in their paper (i.e. AUD/USD, GBP/USD, EUR/USD, and USD/JPY) are dominated by Europe and the U.S. and (ii) Asia is losing information shares in AUD trading. Chai, Lee and Wang (2015) estimate the information distribution in the over-the-counter (OTC) gold market over the period of 1996-2012, which shares a number of characteristics with the foreign exchange market. They conclude that information on the gold price is concentrated in the London/ New York overlapping trading hours.

Some existing studies have considered the determinants of information shares in different financial markets. Within the context of Euro bond futures market, Fricke and Menkhoff (2011) find that (i) order flow plays a dominant role in the price discovery process and (ii) order flow and information share of futures contracts are positively correlated. Mizrach and Neely (2008) show that a higher spread of the US bond futures contracts increases the price of incorporating non-common knowledge, which hinders the market's role in price discovery relative to the spot market. However, Patel, Putniņs and Michayluk (2014) find that the US options market makes a fairly large portion (i.e. about one third) of contribution to price discovery.

While a number of studies have considered the measures as well as the determinants of price discovery in FX market, some important issues are yet to be fully settled, especially in relation to AUD. This chapter aims to fill this gap in the existing literature. While focusing on the price discovery in the AUD market, this chapter makes some important contributions to the existing literature. First, I use a non-parametric approach to measure the global information distribution of the 24-hour AUD market, which provides an appropriate setting in the framework of sequential markets. The widely-used methodology of Hasbrouck's (1995) information share measure relies on the implicit assumption that price differentials among markets are bounded by arbitrage opportunities and hence the prices of the traded assets are cointegrated. Such price differentials can only be observed in each market when these markets are open, and studies are typically conducted for short periods, during which trading hours overlap (e.g., Grammig, Melvin and Schlag, 2005; Pascual, Pascual-Fuster and Climent, 2006). For sequential markets, like the FX market, however, the prices in different markets are not necessarily cointegrated as the fundamental prices may change over time. In order to mitigate this drawback in Hasbrouck's (1995) information share approach, I utilize a non-parametric Two-scale Realized Variance (TSRV) approach. This approach not only yields a relatively more accurate measure that can be easily applied to sequential markets but also mitigates the effect of contemporaneous correlations as documented in Hasbrouck (1995). Furthermore, the tick-by-tick data used in this study allows us to fully exploit the information and detect information-induced volatility jumps (Erdemlioglu, Laurent and Neely, 2012). Using data from January 1996 to December 2003, Wang and Yang (2011) utilize the same non-parametric approach to measuring the price discovery of four currencies including AUD. However, the market share of the AUD in the global FX trading has increased significantly after 2000, which could be attributed to Australia's closer economic ties with the emerging Asian economies, and hence a re-examination of the case of AUD, using a longer time series that includes the post-2000 period, is highly desirable.[3]

Second, this chapter attempts to identify the determinants of information shares for the AUD trading both in the short- and long-run. The conventional macroeconomic models assume that information can be reflected by exchange rates directly. However recent empirical studies on FX microstructure (e.g., Love and Payne, 2008; Evans and Lyons, 2002a, 2002b, 2008) emphasize the role of order flows. In this chpater, I argue that order flow is a crucial channel through which heterogeneous information is transmitted into the price. While taking order flows into account, I link the information shares with macroeconomic news announcements. Furthermore, I decompose the order flows into expected and

[3] The average daily transactions of the AUD in the main markets over the sample period are reported in Appendix B.

unexpected components and examine their impacts on price discovery process separately. I also contribute to the existing literature by proposing a model of long-run determinants of information shares, which evaluates the lasting impacts of market development and integration of financial centres on their roles in price discovery and providing some policy implications accordingly.

Third, in this chapter, I rely on a much broader set of macroeconomic news related to both the U.S. and Australia. In the previous studies, the most commonly used proxies of macroeconomic news are scheduled announcements on Gross Domestic Product (GDP), unemployment, interest rates, durable goods orders, and trade balance (Evans and Lyons, 2008). In this chapter, I make use of Bloomberg News, which includes both scheduled and unscheduled announcements. The dataset shows that scheduled announcements account for less than 5 percent of the total macroeconomic news. The existing studies on the AUD have mostly ignored unscheduled announcements that account for a very large proportion of macroeconomic news.[4] Therefore, I aim to examine whether the unscheduled news affects the price discovery process differently.

The remainder of this chapter is structured as follows. Section 2.2 estimates the information shares of four sequential markets (i.e. Asia, Europe, London/New York overlapping hours, and the U.S.) in the AUD trading. Section 2.3 proposes the hypotheses on the determinants of price discovery in the AUD market. Following the introduction to the dataset and the empirical specifications in Section 2.4, the empirical results and various robustness checks are reported in Section 2.5. Policy implications along with the conclusions are presented in Section 2.6.

2.2. Global information shares for the AUD trading

2.2.1. Two-scale Realized Variance

In this thesis, the approach to measuring the information share in the FX market is based on the fast-expanding literature on realized variance, where changes in

[4] The unscheduled news includes all the real-time, breaking news on the economic and financial markets of Australia and the U.S., as well as key international market-moving headlines.

the efficient price (i.e. the unobservable fundamental value) mirror the price setting behaviour of market participants, thereby reflecting the arrival of new information (Wang and Yang, 2011; Chai et al., 2015). Following Wang and Yang (2011), I divide a trading day into *n* sequential trading sessions. The existing studies suggested that the Two-scale Realized Variance (TSRV) is a consistent estimator of the integrated variance (Zhang, Mykland and Aït-Sahalia, 2005). Barndorff-Nielsen et al. (2008) show that TSRV can be expressed as a non-parametric estimator, which is based on subsampling as follows:

$$TSRV_{i,t} = \frac{1}{k}\sum_{j=1}^{k} RV_{i,t,j} - \frac{[m_i - k + 1]}{m_i k} RV_{i,t} \tag{2.1}$$

where $RV_{i,t} = \sum_{s=1}^{m} r_{i,t,s}^{2}$ is the realized variance (RV) for session *i* on day *t*, i.e., the sum of squared log-returns over the intervals *s=1, 2, …,* m. m_i is the total number of sampling intervals for session *i* and *k* is the number of sub-grids on the 1-second interval. For example, if the 1-second data is sampled at 5-minute intervals, then *k* = 5 × 60 = 300.

It is worth mentioning that TSRV estimator is, in fact, a linear combination of the standard RVs calculated at two different frequencies – a highest possible frequency and a low frequency. In this study, I take 1-second and 5-minute sampling intervals as high and low frequencies, respectively. Since the RV consistently estimates the noise variance as sampling frequency approaches infinity, the RV calculated at the highest frequency is a good approximation of the noise variance. At the low frequency, many feasible RVs may be computed (e.g., with 1-second return series, various 5-minute RVs can be constructed based on sub-sampling). Thus the linear combination of the average of the RVs calculated at low-frequencies and RV calculated at high-frequencies, which serves to correct the impact of the noise term, generates a consistent estimator of the integrated variance. Using the Two-scale estimator as a proxy for information flow, the information share can then be measured as:

$$IS_{i,t} = \frac{TSRV_{i,t}}{\sum_{j=1}^{n} TSRV_{i,t,j}} \tag{2.2}$$

where $TSRV_{i,t}$ is the two-scale estimator for trading session *i* on day *t*, and $\sum_{j=1}^{n} TSRV_{i,t,j}$ is the daily TSRV, calculated as the sum of TSRVs for *n* trading sessions on day *t*.

Following Andersen, Bollerslev and Meddahi (2005) who argue that the 5-minute sampling interval strikes a good balance between calculation accuracy and efficiency and can obtain better results of realized variance estimation, I aggregate the tick-by-tick data into 5-minute interval data.[5] The 5-minute aggregation is based on such considerations: first, the sampling frequency should be high enough to make use of the full information in estimating the realized variance; and second, the sampling frequency should be low enough to have sufficient transactions and avoid biasing the autocorrelations towards zero due to a large number of consecutive zero returns (Wang and Yang, 2011).

2.2.2. Estimated information shares for AUD trading

The intraday trading data of AUD is sourced from Thomson Reuters Tick History (TRTH) maintained by the Securities Industry Research Centre of Asia-Pacific (SIRCA). The data for the AUD/USD, spanning from 4 January 1999 to 31 December 2013, includes the time when a new quote/trade is issued rounded to the nearest millisecond, the prices of bid and ask quotes, and the trade price. Besides, I collect indicative quotes with the identification of quoting banks' names and locations from TRTH as well for further analysis[6].

In general, the trading hours span from 9 am to 4 pm local time. A 24-hour calendar day is divided into four sequential trading sessions according to trading periods and trading patterns: Asian market, European market, "London/New York" or

[5] The 5-minute sampling frequency is determined using "volatility signature plots", a practical method for determining the appropriate sampling frequency for the high frequency time series (Andersen et al., 1999).

[6] The indicative quotes collected from TRTH include the time of issuing quotes, the quoted prices, and names and locations of quoting banks, from which I can calculate the total number of quoting banks on a given day, the percentages of quotes from foreign dealers (i.e., banks headquartered elsewhere) and top dealers (i.e., top-5 most active banks) respectively.

"NYLON" market and North American market.[7] Table 2.1 shows the details of each market and local trading times relative to Greenwich Mean Time (GMT) after adjusting for the Daylight Saving Time (DST).

Table 2.1: Local Trading Time Relative to GMT

The market hours are exclusive in this table, e.g., Asia starts at 23:00:00 GMT on day t - 1 and ends at 6:59:59 GMT on day t during normal period (Non-DST). Namely, a 24-hour calendar day is divided into four trading segments: the first segment is the Asian market when major financial centres in Asia-Pacific region operate (i.e. Hong Kong SAR, Sydney, Tokyo, and Singapore), the second segment is the European market which covers most of the trading hours in London, and other major financial centres in Europe (i.e. French and German, etc.). The third segment pertains to the overlapping two (three) hours of London afternoon trading and New York early morning trading (also known as the LNY market). The last one is labelled the US market which covers trading hours in the U.S. excluding the LNY period (i.e. New York, Chicago, and San Francisco).

Time Zone	Asia	Europe	London/New York	US
Normal (Non-DST)	23:00 GMT to 7:00 GMT (+1 day)	7:00 GMT to 14:00 GMT	14:00 GMT to 16:00 GMT	16:00 GMT to 23:00 GMT
DST	23:00 GMT to 7:00 GMT (+1 day)	7:00 GMT to 13:00 GMT	13:00 GMT to 15:00 GMT	15:00 GMT to 22:00 GMT
DST (In NYC only)	23:00 GMT to 8:00 GMT (+1 day)	8:00 GMT to 13:00 GMT	13:00 GMT to 16:00 GMT	16:00 GMT to 22:00 GMT

I drop outlier observations by applying the filtering rules suggested by Barndorff-Nielsen et al. (2009).[8] The summary statistics of open-to-close returns are reported in the top panel of Table 2.2. As shown in Panel A of Table 2.2, AUD/USD exchange rate has the highest volatility in the Asian market and the lowest volatility in "NYLON" market. The returns in the four trading sessions have the same direction of skewness, i.e. all the returns are left-skewed. The Ljung-Box statistics show that the returns have strong autocorrelations at 12 lags in the Asian and North American markets, while no autocorrelation in European market. Returns in the European market are positively correlated with returns in the Asian

[7] To refer to the trading session *i*, I will use the words "market *i*" and "session *i*" interchangeably thereafter.

[8] The observations dropped include: the ones with a bid, ask or trade price equal to zero; the ones for which the quoted bid-ask spread (i.e. the bid-ask spread divided by midpoint of the bid and ask prices) is either in excess of 25% or negative; the ones for which the mid-quote (i.e. the average of the bid and ask prices) deviates by more than 10 times the mean absolute deviations from a rolling centered median of 50 observations (25 observations before and 25 after); and the ones with prices that are either above the "ask" plus the bid-ask or below the "bid" minus the bid-ask spread.

and North American markets and negatively correlated with returns in “NYLON” market.

Intraday returns at high frequency (i.e., 1-second) and low frequency (i.e., 5-minute) intervals are computed in order to calculate the TSRV as discussed in Section 2.1. I construct the mid-quote price as the average of bid and ask quotes at the end of each sampling interval or the last observation of bid and ask quotes prior to the end of an interval. The intraday return $r_{i,t}$ is then calculated as 100 times the log ratio of the mid-quotes at times *t* and *t-1*, that is, $r_{i,t} = 100 * ln(p_{i,t}/p_{i,t-1})$. Panel B of Table 2.2 reports the summary statistics of the daily information shares measured by the ratio of TSRV in market *i* to the daily TSRV on a specific day. In the four markets, Europe has the largest average information share, followed by North America, Asia, and “NYLON”. The information share in Asia has the largest standard deviation as well as the strongest autocorrelation at lag 12. Besides, all the information shares in four markets are negatively correlated.

The yearly average information share of the four markets are reported in Table 2.3. It is interesting to note that if the 24 hours are divided into three 8-hour time zones, then the European market, which includes the Europe and “NYLON” market, dominates price discovery in AUD market. The combined information shares of Europe and “NYLON” range from 44% to 54%, of which “NYLON” market (i.e. the two- to three-hour overlapping trading session) accounts for a significant proportion of price discovery in most years.

Table 2.2: Summary Statistics of Returns and Information Shares

The definitions of the four sequential sessions, namely, "Asia", "Europe", "NYLON" (London/New York), and "North America", are as given in Table 2.1. Returns are defined as $100 * \ln(price_{close}/price_{open})$. Information shares are calculated as in Section 2.2. $Q_{LB}(12)$ is the Ljung-Box Q statistic at 12 lags. The asterisk * indicates significance at the 5% level.

	Asia	Europe	London/New York	US
Panel A: Return				
Mean	0.001	0.006	-0.006	0.008
Std. Dev.	0.457	0.450	0.319	0.424
Skewness	-0.349	-0.329	-1.310	-0.078
Kurtosis	9.252	6.173	14.667	17.597
$Q_{LB}(12)$	50.163*	20.827	31.383*	57.645*
Correlation	1.000			
Europe	0.043*	1.000		
NYLON	-0.028	-0.046*	1.000	
US	0.049*	0.036*	-0.007	1.000
Panel B: Information Share				
Mean	0.269	0.332	0.141	0.259
Std. Dev.	0.136	0.111	0.074	0.119
Skewness	1.184	0.334	1.271	1.416
Kurtosis	1.857	0.605	2.967	3.353
$Q_{LB}(12)$	446.24*	315.92*	211.54*	113.25*
Correlation	1.000			
Europe	-0.447*	1.000		
NYLON	-0.415*	-0.012	1.000	
US	-0.467*	-0.413*	-0.136*	1.000

Table 2.3: Sub-period Information Share

This table reports the estimates of annual average information shares using the Two-scale Realized Variance (TSRV) approach.

	Asia	Europe	London/ New York	North America
1999	0.296	0.300	0.111	0.292
2000	0.216	0.377	0.122	0.286
2001	0.259	0.349	0.130	0.261
2002	0.268	0.343	0.125	0.264
2003	0.210	0.355	0.163	0.271
Average$^{1999\text{-}2003}$	0.250	0.345	0.130	0.275
2004	0.207	0.369	0.173	0.251
2005	0.238	0.358	0.159	0.245
2006	0.240	0.360	0.162	0.238
2007	0.286	0.349	0.129	0.235
2008	0.261	0.328	0.139	0.273
Average$^{2004\text{-}2008}$	0.247	0.353	0.152	0.248
2009	0.249	0.323	0.153	0.275
2010	0.275	0.317	0.144	0.264
2011	0.282	0.323	0.143	0.252
2012	0.303	0.315	0.135	0.246
2013	0.336	0.306	0.121	0.238
Average$^{2009\text{-}2013}$	0.289	0.317	0.139	0.255
Average$^{1999\text{-}2013}$	0.262	0.332	0.141	0.259

The estimation results show that although European market has a high and dominating share, the information share of Asia has been increasing since 2003, even with its declining share of daily transactions (see Appendix A). Table 2.3 shows that a market's information share may not be monotonically associated with its market share. For example, Europe accounted for 51.2% of the global trading for AUD in 2013, but only contributed to a 30.6% share of information flow. The determinants of information share, i.e., the percentage contribution to price discovery, will be investigated in the following sections.

2.3. Determinants of price discovery: hypothesis formulation

Following the estimation of the information shares in different markets for AUD trading, I turn to examining the determinants of price discovery in AUD market. In this section, the hypotheses on the determinants of price discovery in AUD market are discussed.

2.3.1. Market state-related variables

The existing studies have shown that information shares vary considerably across different markets and the shares are also subject to instabilities arising from different market states. The market states variables include bid-ask spread, trading volume, and volatility (see, Brandt, Kavajecz and Underwood, 2007; Mizrach and Neely, 2008), as well as the exchange rate return. Analysis of the market state variables can also help us to identify the unconditional information shares. Mizrach and Neely (2008), who are the first ones to systemically explore the roles of market state variables, show that the bid-ask spread, traded contracts, and volatility can explain the price discovery shifts between the US Treasury spot and futures markets. Fricke and Menkhoff (2011) use market state variables to examine the level of competition in price discovery among Euro bond futures with different maturities. In this chapter I use three market state variables: (i) spread, (ii) volume, and (iii) volatility. Moreover, I also consider the impact of exchange rate return on the price discovery (i.e., whether the information share of a specific market is higher on days with larger returns and vice versa).

Based on Mizrach and Neely (2008), I expect that a high bid-ask spread increases the price of incorporating the private information, which in turn impedes the price discovery process. However, Patel et al. (2014) find that higher information shares of options are associated with wider options spreads, which can be explained by the adverse selection risks faced by inter-bank market dealers (Kyle, 1985).[9] In contrast, a higher share of trading volume indicates more informed trading– or at

[9] For example, with the presence of informed traders, the dealer would widen the bid-ask spread to reduce the adverse selection costs.

least, facilitates information processing – and thus increases the information share. Besides, higher returns may help attract more trading activity, especially the speculative trading, and thereby facilitate the information flows. Finally, the impact of volatility is ambiguous: high volatility may be seen as an indicator of the presence of the noise traders in the market and hence volatility decreases the information share. However, volatility can also be a sign of heterogeneously distributed information processing, which is expected to have a positive relationship with market information share (Fricke and Menkhoff, 2011). In overall terms, the evidence suggests that market state variables are important but their expected effect on information shares is less obvious ex ante (see, for example, Fricke and Menkhoff, 2011). Based on the above discussions, the following hypothesis can be formulated:

> *Hypothesis 1:* Market state-related variables have significant impacts on the information shares for trading of AUD.

2.3.2. Macroeconomic news announcements

Among all the factors that influence price discovery, the impact of macroeconomic news announcements has received special attention. Moshirian, Nguyen and Pham (2012) argue that public information is crucial for the efficient functioning of the capital market. The earliest studies of announcement effects on the foreign exchange market constrained their consideration to the level changes of exchange rates. However, since 1990s researchers have paid more attention to the announcement effects on volatility. For example, Engle, Ito and Lin (1990) introduce the concepts of the heat waves and meteor showers effects to explore the links between intraday volatility pattern and macroeconomic news announcements in the foreign exchange market.[10] Andersen and Bollerslev (1998) conjecture that the intraday volatility patterns alter daily trading patterns and the US announcements are helpful in explaining volatility movements in Deutsche

[10] *Heat waves* refer to the idea that most important news that affects volatility and price discovery occurs during a particular session's trading hours and there is little price discovery when that market is closed. In contrast, *meteor showers* pertain to the idea that information flow spills over across sessions, i.e., from Asia to Europe, then to the U.S. (Engle, et al., 1990).

Mark (DEM)/USD spot rate. Upper and Werner (2002) show that more information is incorporated in the German bonds futures market during the announcement periods and the contribution of the spot market to the common efficient price varies in the range of 19-33%. Mizrach and Neely (2008) find that the release of macroeconomic news weakens the importance of the German bond spot prices compared to the futures prices. Andersen, Bollerslev, and Diebold (2007) detect strong but short-lived news-effects on the 5-year bond futures contracts in an international context. In the FX microstructure study, it is widely accepted that information arrival typically does increase volatility (Melvin and Yin, 2000) and news might create order flows that transmit private information to the FX market (Dominguez and Panthaki, 2006). Recently, Gau and Wu (2017) utilize the same method of TSRV ratio to study macroeconomic news announcements and price discovery in the FX markets. The empirical results suggest that the dominant role of the overlapping trading hours of LNY market in the price discovery of the EUR and JPY markets only applies on days with U.S. announcements.

In this chapter, I use a wider set of macroeconomic news types compared to the previous studies and examine whether this set of macroeconomic news affects the price discovery process differently from the previous studies. For example, Evans (2002) decompose macro news into common knowledge and non-common knowledge shocks and find that non-common knowledge shocks are of greater importance in price discovery. In the Bloomberg news dataset, most Australian macroeconomic announcements arrive during the Asian trading hours (i.e. from 23:00 GMT on day *t-1* to 1:00 GMT on day *t*), while most of the US macroeconomic announcements occur during the "NYLON" and North American markets (i.e., from 12:00 GMT to 19:00 GMT). In order to investigate whether macroeconomics news releases during the trading hours affect the specific trading session's price discovery process, I compare the average information shares of the trading sessions on announcement days versus non-announcement days. As shown in Table 2.4, on the Australian macroeconomic news announcement days, the information share of Asia increases significantly, whereas those of the European and North American markets decline. In contrast, on the US-related macroeconomic news announcement days, the information share shifts from Asia to "NYLON" and North America. Accordingly, the trading session becomes relatively more efficient in reflecting information when more macro news announcements are released during its trading hours. The gain in information share when public information is released is consistent with the findings of Jiang, Lo and Valente (2014).

Table 2.4: Information Shares on Days with and without Macroeconomic News

This table compares the average information shares for each session on the days with and without macroeconomic news. The values in the parentheses and square brackets are standard deviations and p-values respectively. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Category	Average Information Share			
	Asia	Europe	London/ NYC	North America
Days with US news	0.265	0.211	0.224	0.307
(1)	(0.120)	(0.086)	(0.110)	(0.137)
Days with Australian	0.313	0.204	0.170	0.274
news (2)	(0.135)	(0.083)	(0.101)	(0.123)
Days without news	0.272	0.201	0.183	0.270
(3)	(0.121)	(0.098)	(0.084)	(0.120)
(1) - (3)	-0.007	0.010*	0.041***	0.038***
	[0.145]	[0.000]	[0.000]	[0.000]
(2) - (3)	0.042***	-0.004	-0.013*	0.004
	[0.000]	[0.135]	[0.050]	[0.097]

There is no doubt that the announcement of macroeconomic news is among the most significant elements of price discovery process in financial markets and hence its impact on information shares in the FX market needs to be thoroughly examined. Besides, macroeconomic news can also be considered as a control variable that affects the unconditional information shares for AUD trading. Thus I propose the following hypothesis:

Hypothesis 2: The announcement of macroeconomic news has a positive impact on the information shares for trading of AUD.

2.3.3. Order flows

Order flow is a measure of the signed trades and calculated as the difference between buy- and sell-initiated trades over a particular market (assuming that buys are coded positive). It is well documented that order flow is positively related to contemporaneous returns in many financial markets.[11] This is often interpreted as an indication of order flow being the medium for incorporating information into prices. In microstructure studies, it has been argued that private information is embedded in the prices via order flows. For example, Evans and Lyons (1999) argue that order flow is a crucial determinant of the price in microstructure models that aim to explain exchange rate fluctuations. Using a microstructure model, Killeen, Lyons and Moore (2006) show that shocks to order flow induce more volatility under flexible exchange rates. Evans and Lyons (2008) confirm that up to two thirds of the level changes and volatilities in exchange rate movements are associated with order flows.

However, it has been suggested that order flow may contain elements that are not related to information. For example, in practice, the momentum trading strategy may generate a large amount of order flows that are unrelated to information. Pasquariello and Vega (2007) suggest a new approach that allows one to extract the truly informative part of order flow. They highlight a linkage between unexpected order flow and information processing in the bond market. In addition, Chai et al. (2015) examine the information distribution in the global gold market and adopt the unexpected order flow as a proxy for private information. Furthermore, Green (2004) emphasize the processing of public news via order flows. Namely, the order flow can impact price discovery and its information effect varies across the days with and without news. Based on the existing studies, the hypotheses 3.1 and 3.2 can be specified as follows:

[11] In this study, the Pearson correlations among the market state variables and order flow also suggest that order flow is significantly and positively correlated with contemporaneous returns. The results are not presented here due to space constraints, but available upon request.

Hypothesis 3.1: Order flow has a positive impact on the information shares for trading of AUD.

Hypothesis 3.2: On macroeconomic news release days, order flow has a more significantly positive impact on the information shares for trading of AUD.

2.3.4. Cross-market information flow and dynamic structure

Some relevant studies, such as Evans and Lyons (2002), suggested the possibility of the cross-market information flows, that is, the information flow of a currency could be correlated to those of other currencies. Unlike Evans and Lyons (2002) focusing on different currencies, I conjecture that the cross-market effect exists among different trading sessions of the same currency. In order to test the existence of cross-market information spillover effect, I utilize the technique of Shapley-Owen R^2 decomposition, which can explicitly examine the relative importance of each variable (i.e. the percentage contribution) in explaining the dependent variable.[12] Su and Wang (2017) measure the magnitudes of meteor shower and heat waves effects (i.e. inter-regional and intra-regional volatility spillovers respectively) in the FX market and find that the cross-market information propagation has been increasing recently. Similarly, I conduct the Shapley-Owen R^2 decomposition for the HAR-IS model and find that the cross-market effect on information spillover is significant and contributes to 58% of the total variations in daily information share, while the local-market effect constitutes the remaining portion.[13] Specifically, I extend the classic heterogeneous autoregressive model (HAR) and regress the daily information share of session *i* on the lagged daily, weekly, and monthly information shares of its own-market and other markets respectively. The sum of incremental increase in the model R^2 resulting from the addition of a predictor, or set of predictors of lagged own-market and other markets are local-market and cross-market effects

[12] For a detailed introduction to the Shapley-Owen R^2 decomposition and its applications, please refer to Lahaye and Neely (2016).

[13] The HAR-class model which examines the short-run dependence of variable of interest while controlling for the longer-run dependence (i.e. weekly and monthly dependence) was firstly proposed by Corsi (2009) and has been widely used in the relevant literature (see, for example, Bollerslev et al., 2017; Su, 2017; among many others).

respectively. The results of the Shapley-Owen R^2 decomposition are shown in Table 2.5 as below:

Table 2.5: Shapley-Owen Values for the Local- and Cross-market Spillover Effect

This table shows the Shapley-Owen proportion of the total R^2s in four trading sessions, for groups of coefficients in the HAR model in which Information Share (*IS*) is predicted by lagged *IS*. There are 2 groups of coefficients: The own-market contribution, which includes one day lagged IS, lagged weekly and monthly information shares of its own market; as well as and the cross-market contribution, which includes counterparts of lagged IS of other markets. The groups have no intersection and include all non-deterministic regressors, so the proportions for each intraday period sum to 100.

	Asia	Europe	London/NYC	North America	*Average*
local-market	0.40	0.43	0.39	0.45	**0.42**
cross-market	0.60	0.57	0.61	0.55	**0.58**

Furthermore, in order to test the possibility of self-dynamics, I plot the autocorrelation functions (ACF) of the daily and monthly information shares for each trading session respectively. As shown in Figure 2.1, there are weak autocorrelations in daily information shares, which confirms the strong daily variations of the information share as suggested in the previous section.[14]

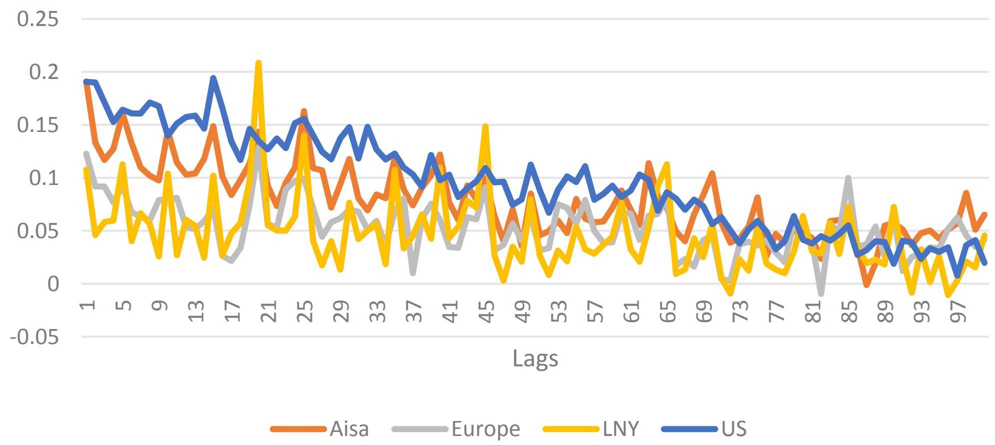

Figure 2.1: Autocorrelation Function (ACF) of Daily Information Share

[14] The Augmented Dicky-Fuller (ADF) test rejects the null hypothesis of a unit root and suggests that all the log transformations of information shares are stationary.

Slightly different results have been found for the ACF of the monthly average information share of each trading session. For example, it suggests a slow-decaying process for the monthly information share as shown in the figure below:

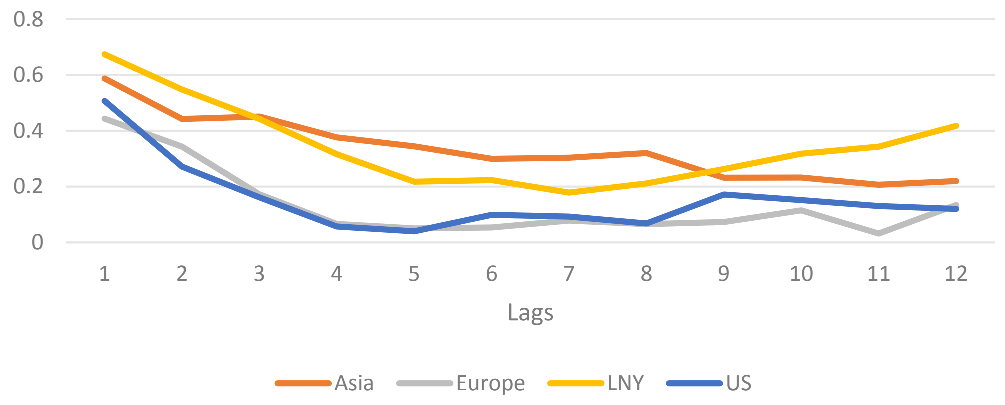

Figure 2.2: Autocorrelation Function (ACF) of Monthly Average Information Share

Based on the results of Shapley-Owen R^2 decomposition and ACF analysis, the hypotheses 4.1 and 4.2 can be proposed as follows:

> *Hypothesis 4.1:* Cross-market information flow has an impact on the information shares for trading of AUD.
>
> *Hypothesis 4.2:* Self-dependence of information flow also has an impact on the information shares for trading of AUD.

2.3.5. Long-run determinants of the information shares

The existing literature on market risks suggests that aggregate volatility is subject to shocks at different frequencies (Adrian and Rosenberg, 2008). Following this line of reasoning, I examine the determinants of information shares over a longer time horizon (i.e. on a monthly basis). Specifically, following Sassen (1999) who claim that the two most important factors in transforming a city into a global financial centre are international consolidation of financial activities (i.e., concentration of financial institutions and transactions in one location) and financial market liberalization (i.e., financial services openness and free capital flows), I make an attempt to identify the key factors in determining the "information hierarchy" in FX trading and conjecture that the financial market development and integration of a financial centre affects its price discovery capability. Specifically, in this study, I utilize pricing efficiency as an indicator of the financial market development. I also use the number of quoting banks (both local and foreign banks) and concentration of transactions (i.e., the total market share of top-5 most active quoting banks) as indicators of market consolidation, as well as the Chinn-Ito index as a proxy for the degree of capital market openness and financial market liberalization (Chinn and Ito, 2006). The last hypothesis is organized as follows:

> *Hypothesis 5:* Financial market development and integration of financial centres also have positive impacts on the information shares for the AUD trading in the long-run.

2.4. Estimation strategy and the data

Consistent with the hypotheses formulated, the empirical specifications in this chapter include market state-related variables, the announcements of macroeconomic news, order flow, as well as the financial development and market integration indicators in the AUD market. I utilize a simple Ordinary Least Square (OLS) approach to estimate the coefficients and use the Newey-West heteroscedasticity-autocorrelation-consistent (HAC) standard errors to correct the problems of heteroscedasticity and autocorrelation. Following Fricke and Menkhoff (2011), Hypothesis 1 will be tested by the following model specification:

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \beta_1 \ln(Spread_{i.t}) + \beta_2 \ln(Vol_{i.t}) + \beta_3 \ln(Ret_{i.t}) + \beta_4 \ln(Volatility_{i.t}) + \epsilon_{i,t} \tag{2.3}$$

where $i = A, E, L, and\ U$, representing the four trading sessions and $IS_{i.t}$ represents the information share of market *i* on day t. $Spread_{i,t}$, $Vol_{i,t}$, $Ret_{i.t}$, and $Volatility_{i.t}$ are the daily shares of time-weighted average quoted spread, trading volume, daily return, and standard deviation of log returns over 5-minute intervals.

Market state variables are constructed using the data from Thomson Reuters Tick History (TRTH). The summary statistics of the market state variables for the four trading sessions (i.e. Asia, Europe, London/New York, and North America) are provided in Panel A of Appendix B. The Ljung-Box Q statistics show that the volatility has strong autocorrelations in Asian, European, and North American markets, while it shows no autocorrelation for "NYLON" market. The Augmented Dicky-Fuller (ADF) tests suggest that the daily shares of all market state variables are stationary, i.e. all the series expressed as percentage shares are I(0) processes and hence simple regression can be used for hypothesis testing.

In order to test Hypothesis 2 regarding the impact of macroeconomic news on market information share, I regress the information shares on the news dummy variables as well as the control variables as specified in Eq. (2.3):

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \beta_1 \ln(Spread_{i.t}) + \beta_2 \ln\left(Vol_{i,t}\right) + \beta_3 \ln(Ret_{i.t}) + \beta_4 \ln(Volatility_{i.t})$$
$$+ \sum_{j=A}^{U} \beta_j News_{i,t}^{j} + \sum_{j=Mon}^{Thu} \beta_j WD^j + \epsilon_{i,t} \qquad (2.4)$$

where the dummy variable $News_{i,t}^{j}$, $j = A, U$, takes the value of 1 if there were news arrivals related to Australia (A) or the U.S. (U) during market *i*'s trading hours and 0 otherwise. Besides, the weekday dummy variables WD^j ($j = Monday, Tuesday, Wednesday, and\ Thursday$) captures the day-of-the-week effect, which equals 1 if it is Monday, Tuesday, Wednesday, or Thursday and 0 otherwise. I also use logarithmic transformations of the information shares to overcome any distributional problems related to limited dependent variables (Mizrach and Neely, 2008).

The US and Australian macroeconomic news announcements are sourced from the Bloomberg News service. The news dataset includes the date and time of news release, news ticker, and a short description.[15] As indicated earlier, I use a much wider set of macro news types compared to the previous studies, namely, scheduled announcement as well as the unscheduled announcements. The unscheduled news includes all the real-time news on the economic and financial

[15] The volatility and volume responses of AUD to news are mostly driven by the Australian and US related announcements, whereas the scheduled news from the Eurozone and Japan were not found to be important (Daniel, Kim and McKenzie, 2014).

markets of Australia and the U.S. as well as key international market-moving headlines.

In order to test Hypothesis 3 about the implications of order flow, I firstly regress the information shares of the four markets on their percentage share of order flows. Moreover, to distinguish the net trading effect on days with and without news, I add the news dummies and interaction terms between news dummy variables and order flow measures. The resulting empirical model is as follows:

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \beta_1 \ln(Spread_{i.t}) + \beta_2 \ln\left(Vol_{i,t}\right) + \beta_3 \ln(Ret_{i.t}) + \beta_4 \ln(Volatility_{i.t})$$
$$+\beta_5 \ln\left(OF_{i,t}\right) + \sum_{j=A}^{U} \beta_{6j} News_{i,t}^{j} + \sum_{j=A}^{U} \beta_{7j} ln(OF_{i,t}) \cdot News_{i,t}^{j} + \epsilon_{i,t} \quad (2.5)$$

where $OF_{i,t}$ represents the daily shares of order flows in market *i* on day *t*, $News^j$ $(j = A, U)$ is the news dummy variable as defined earlier.

Furthermore, in order to extract the informative element from the order flow, following Chai et al. (2015), I run a regression of the current order flow on the lagged returns and order flows, that is:

$$OF_{i,t} = \alpha + B_1(L)OF_{i,t} + B_2(L)Ret_{i,t} + v(OF_{i,t}) \quad (2.6)$$

where $OF_{i,t}$ and $Ret_{i,t}$ refer to the order flow and log return aggregated within 5-minute intervals in market *i* on day t respectively. $B_1(L)$ and $B_2(L)$ are polynomials in the lag operator. The residuals $v(OF_{i,t})$ reveal the amount of unexpected order flow in 5-minute intervals and are then summed up per market to calculate the daily unexpected order flows, which gives us a measure of private information, possibly nurtured by customer order flows (Menkveld, Sarkar and van der Wel, 2012).

In the next stage, I estimate the impacts of the expected and unexpected order flows separately by using the following model specification, where the unexpected order flow is utilized as a proxy for private information:

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \beta_1 \ln(Spread_{i.t}) + \beta_2 \ln\left(Vol_{i,t}\right) + \beta_3 \ln(Ret_{i.t}) + \beta_4 \ln(Volatility_{i.t}) + \sum_{j=E}^{U} \beta_{5j} \ln\left(OF_{i,t}^{j}\right) + \sum_{j=A}^{U} \beta_{6j} News_{i,t}^{j} + \sum_{j=E}^{U} \sum_{k=A}^{U} \beta_{7j} \ln\left(OF_{i,t}^{j}\right) \cdot News_{i,t}^{k} + \epsilon_{i,t} \quad (2.7)$$

where $OF_{i,t}^{j}$ $(j = E, U)$ represents the daily shares of expected (E) and unexpected (U) order flows in market *i* on day *t* respectively. I also include the interaction terms between news dummies and expected (unexpected) order flow variables to examine whether the expected (unexpected) order flow is the channel through which the information (i.e. the release of macroeconomic news) is incorporated into the exchange rates as documented in Evans and Lyons (2008).

In order to test Hypothesis 4 while controlling for the cross-market information spillover effect and dynamic self-dependence, I introduce the lagged dependent variables and adopt the model specification as follows:

$$\ln\left(\frac{IS_{i,t}}{1-IS_{i,t}}\right) = \alpha + \sum_{j=A}^{U} \beta_{1,j} \ln\left(\frac{IS_{j,t-1}}{1-IS_{j,t-1}}\right) + \sum_{j=E}^{U} \beta_{2j} \ln\left(OF_{i,t}^{j}\right) + \sum_{j=A}^{U} \beta_{3j} News_{i,t}^{j} + \sum_{j=E}^{U} \sum_{k=A}^{U} \beta_{4j} \ln\left(OF_{i,t}^{j}\right) \cdot News_{i,t}^{k} + \sum \beta_i ControlVariable_{i,t} + \beta_{GFC} GFC + \epsilon_{\mathrm{i,t}} \quad (2.8)$$

where $\mathrm{ControlVariable_{i,t}}$ stands for the market state variables, including spread, volume, exchange rate return, and volatility. *GFC* is a dummy variable for the 2008 Global Financial Crisis which equals 1 during the key financial crisis period of 2008:09–2009:11, and otherwise zero, with the purpose of examining the determinants of price discovery under extreme market conditions. In this equation, the information spillover is typically represented by the coefficients of one-day lagged $IS_{j,t-1}$ $(j = A, E, L, and\ U)$. Namely, the own-market spillover effect is represented here by the coefficient of its own lagged IS $\beta_{1,j}$ $(j = i)$, while the coefficients $\beta_{1,j}$ $(j \neq i)$, which measure the short-run information spillover from session *j* to session *i,* serve as a proxy for cross-market effects. Note that, here, the subscript *t-1* represents the session immediately before session *i*, which may be on the same day as session *i*. For example, when *i* = Asia, $IS_{i,t-1}$ $(i = A, E, L, and\ U)$ are *IS* from the previous day t – 1. However, when *i* = U.S., which is the last trading session on day *t*, $IS_{i,t-1}$ $(i = A, E, L)$ are from the same day *t* as

US market with only the lagged U.S. information share $IS_{i,t-1}$ $(i = U)$ from the previous day.

While the definition of Two-scale estimator pertains to the daily variance measure, the volatility over longer horizons, say, weekly or monthly, may similarly be estimated by summing the intraday squared changes of efficient price over a week or a month. Thus, from a practical perspective, the approach of realized variance parsimoniously captures the shocks at different horizons (Bollerslev et al., 2017). To estimate the long-run determinants of information shares in the FX markets, I calculate the monthly volatility as the sum of squared intraday returns over a month. Specifically, in order to test Hypothesis 5, I model the monthly information shares of the four sessions utilizing the following specification:

$$\ln\left(\frac{IS_{i.m}}{1-IS_{i.m}}\right) = \alpha + \beta_1 \ln(Eff_{i.m}) + \beta_2 \ln(NumBank_{i.m}) + \beta_3 \ln(ForeignBank_{i.m}) + \beta_4 \ln(MktCon_{i.m}) + \beta_5 \ln(ChinnIndex_{i.m}) + \epsilon_{i,t} \quad (2.9)$$

where $IS_{i,m}$ is the monthly information share of market *i* in month m. $Eff_{i,m}$ is the monthly average pricing efficiency. $NumBank_{i,m}$, $ForeignBank_{i,m}$, and $MktCon_{i,m}$ are the average number of quoting banks during market *i*'s trading hours, percentage of foreign banks identified based on their headquarters location, and degree of market concentration (i.e. the percentage of quotes issued by the top-5 most active banks). I also include the Chinn-Ito index to proxy for the degree of financial market openness, which is sourced from Chinn and Ito (2006).[16]

To further test Hypothesis 4 while controlling for the lead-lag effects, namely, the self-dependences at lag 1 and lag 12 as shown in Figure 2.2 in Section 2.3.4, I introduce the lagged terms of dependent variable as follows:

[16] The Chinn-Ito index is a comprehensive index measuring a country's degree of capital account openness. In this study, I construct the overall Market Openness Index (MOI) by using the GDP-weighted average Chinn-Ito index for the four trading sessions. For a detailed introduction to the Index, please refer to http://web.pdx.edu/~ito/Chinn-Ito_website.htm.

$$\ln\left(\frac{IS_{i,m}}{1-IS_{i,m}}\right) = \alpha + \beta_1 \ln\left(\frac{IS_{i,m-1}}{1-IS_{i,m-1}}\right) + \beta_2 \ln\left(\frac{IS_{i,m-12}}{1-IS_{i,m-12}}\right) + \beta_3 \ln(Eff_{i.m})$$
$$+\beta_4 \ln(NumBank_{i.m}) + \beta_5 \ln(ForeignBank_{i.m})$$
$$+\beta_6 \ln(MktCon_{i.m}) + \beta_7 \ln(ChinnIndex_{i.m}) + \epsilon_{i,t} \qquad (2.10)$$

with $IS_{i.m-1}$ and $IS_{i.m-12}$ representing the monthly information share for session *i* on month *m-1* and month *m-12* respectively.

In Eq. (2.9) and (2.10), $Eff_{i,m}$ strands for the monthly average pricing efficiency. As $TSRV$ can serve as a proxy for the information flow (i.e. the variance of the efficient price changes) and RV contains both the information and noise components, the ratio $TSRV/RV$ provides a measure of market-specific pricing efficiency and Table 2.6 reports the estimated yearly average pricing efficiency for the four sessions. The table shows that, for all trading sessions, the ratio $TSRV/RV$ is less than one, suggesting that RV contains considerable noise, ranging from 14% to 30%. Furthermore, it is interesting to note that the pricing efficiencies in all markets have been increasing steadily after 2003, which is consistent with Chaboud et al. (2014) who find that, with the rise of algorithmic trading, the price discovery in the FX market has been constantly improving.

Table 2.6: Sub-period Pricing Efficiency

This table reports the estimates of annual average pricing efficiency in the four trading sessions as defined in Table 2.1.

	Asia	Europe	London/New York	North America
1999	0.697	0.778	0.807	0.727
2000	0.722	0.806	0.811	0.737
2001	0.727	0.779	0.827	0.750
2002	0.766	0.786	0.820	0.777
2003	0.775	0.802	0.818	0.763
$\text{Average}^{1999\text{-}2003}$	0.737	0.791	0.816	0.751
2004	0.777	0.820	0.841	0.797
2005	0.777	0.803	0.817	0.786
2006	0.792	0.821	0.828	0.802
2007	0.807	0.819	0.847	0.803
2008	0.807	0.805	0.817	0.820
$\text{Average}^{2004\text{-}2008}$	0.792	0.813	0.830	0.802
2009	0.804	0.818	0.833	0.831
2010	0.792	0.806	0.842	0.809
2011	0.804	0.819	0.860	0.819
2012	0.801	0.819	0.829	0.796
2013	0.786	0.807	0.841	0.787
$\text{Average}^{2009\text{-}2013}$	0.797	0.814	0.841	0.808
$\text{Average}^{1999\text{-}2013}$	0.775	0.806	0.829	0.797

2.5. Estimation results

The empirical results are reported and discussed in this section. As indicated in Section 2.3, market state variables (including bid-ask spread, trading volume, volatility, and return), macroeconomic news announcements, and order flows can explain a fairly large portion of the daily variations in information shares for AUD trading, while pricing efficiency, FX market development and the integration of financial centres are the main long-run determinants of the dynamic price discovery in AUD market. Furthermore, the dynamic natures of self-dependence and cross-market information spillover help in explaining the variations of information shares both in the short- and long-run. The results of robustness testing are also presented in this section.

2.5.1. Market state variables

The estimation results regarding the market state variables are presented in Table 2.7. These results confirm that market state variables explain a significant proportion of the fluctuations in the information shares in AUD market. In overall terms, the market state-related variables perform better in explaining the shifts in the information shares of the Asian market compared to the other markets, i.e., the adjusted R-squared for Asian market is as high as 0.8. A positive change in the trading volume increases the information content of all markets. Interestingly, in general, increases in spreads alone do not indicate less information processing. The reason could be that, larger spreads are generally associated with more informed trading, which is consistent with the findings of Glosten and Milgrom (1985) who argue that the presence of informed traders leads to larger bid-ask spreads. However, it is worth noting that after controlling for volatility (i.e., the standard deviation of exchange rate returns over 5-minute intervals), the sign of *spread* changes from positive to negative except for the US market as shown in column (2) of Table 4.7. This result could be attributed to the fact that the bid/ask spread consists of three components, namely, the asymmetric information component (AIC), order processing component (OPC), and inventory holding component (IHC) (Lin, Sanger and Booth 1995). While the asymmetric information component is positively related to the information share, the order processing and inventory holding components are significantly negatively related to the information share. Thus, after controlling for the asymmetric information as proxied by the volatility, an inverse relationship between spread and information share has been documented. In addition, the estimation results confirm that higher returns have a positive effect on price discovery in the foreign exchange market.

Table 2.7: Responses of Information Shares to Market State Variables

This table mirrors the regression results of market-state variables and weekdays' dummies on daily information shares of the Asian, European, London/New York ("NYLON"), and U.S. trading session, which takes the following form:

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \beta_1 \ln(Spr_{i.t}) + \beta_2 \ln(Vol_{i.t}) + \beta_3 \ln(Ret_{i.t}) + \beta_4 \ln(Volatility_{i.t}) + \epsilon_{i,t}$$

with i representing the session, α the intercept term, Spr, Vol, Ret, and Volatility standing for individual shares of the time-weighted average quoted spread, the number of trades, return, and the standard deviation of mid-quote returns respectively on the given day. The values in the parentheses are the Newey-West standard errors. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Variable	Asia		Europe		London/New York		North America	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$Intercept$	0.038	0.529***	0.050*	1.226***	0.340***	1.222***	0.184***	1.434***
	(00027)	(0.040)	(0.027)	(0.041)	(0.042)	(0.059)	(0.023)	(0.031)
$Spread$	0.012	-0.122***	-0.011	-0.298***	0.119***	-0.140***	0.531***	0.127***
	(0.021)	(0.033)	(0.021)	(0.037)	(0.028)	(0.045)	(0.020)	(0.018)
$Volume$	0.251***	0.106***	0.419***	0.213***	0.444***	0.281***	0.226***	0.007***
	(0.020)	(0.013)	(0.024)	(0.015)	(0.027)	(0.018)	(0.014)	(0.002)
$Return$	0.006***	0.014***	0.002*	0.004**	0.003***	0.010***	0.003***	0.028***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
$Volatility$		0.684***		0.581***		0.427***		0.517***
		(0.019)		(0.024)		(0.028)		(0.025)
n	3825	3825	3824	3824	3804	3804	3816	3816
Adj_R^2	0.7902	0.8102	0.7142	0.7253	0.7001	0.7114	0.7025	0.7357

In overall terms, there is strong evidence supporting the view that market state variables are important determinants of the information shares in AUD market. More favourable market states, i.e. larger trading volume, narrower spread, and higher return, tentatively increase the information share of a certain market. However, it is not possible to make a general statement concerning the directions of the relationship (i.e., the expected signs of coefficients). For example, in some cases, an increase in the spread may hinder the market's role in price discovery, while in other cases, a relatively high spread may indicate more efficient price discovery process, thereby increasing the information share. The results in Table 2.7 suggest that a higher spread in the North American market increases the information share, but its effect is consistently negative in the Asian and European markets.

2.5.2. Macroeconomic news announcement

Table 2.8 highlights the importance of the US news on price discovery in the FX market, which is consistent with Andersen et al. (2007) and Daniel et al. (2014). The relevance of US news stems from the economic importance of the US economy as well as the fact that the price quotes used in this study are expressed as the values of the AUD against the USD. In contrast, the coefficient on the Australian news dummy does not show any clear pattern across the European and "NYLON" markets. However, we do observe a significant impact of the Australian macroeconomic news announcements on the information share of the Asian market.[17] A possible explanation for the high information share when there are macroeconomic news announcements may be that relatively more informed traders react quickly around the time of macroeconomic news releases (Evans and Lyons, 2008). Unfortunately, the signs of the estimated coefficients do not show a

[17] As indicated earlier, most Australian macroeconomic announcements arrive during the Asian trading hours (i.e. from 23:00 GMT on day t-1 to 1:00 GMT on day t), while most of the US macroeconomic announcements occur during the "NYLON" and North American markets (i.e., from 12:00 GMT to 19:00 GMT). The empirical results here support the asymmetric information hypothesis that information may be asymmetrically distributed between different regions and local traders may be better informed at the release of local macroeconomic announcements (Gau and Wu, 2017).

consistent pattern across the four markets. Furthermore, the empirical results confirm the findings of Pasquariello and Vega (2007) who argue that the importance of order flow depends on the existence of information signals.

I also consider the day-of-the-week effect by including the weekdays' dummies in the regressions. I find that the information share of Asian market tends to be higher on Mondays and that of the U.S. is higher on Thursdays and Fridays as shown in Table 2.8. A possible explanation of these results is that the information is accumulated during the weekend and incorporated into the exchange rates when the Asian market opens on Monday. While for the US market, the higher information shares on Thursdays and Fridays is consistent with the findings of Harvey and Huang (1991) who confirm that in the foreign exchange futures market, returns on Thursdays and Fridays are more volatile as many news releases related to the U.S. take place on these days.

Table 2.8: Responses of Information Shares to Macroeconomic News Announcements

This table mirrors the regression results of market-state variables and macroeconomic news announcements on daily information shares of the Asian, European, London/New York ("NYLON"), and U.S. session, which takes the following form:

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \beta_1 \ln(Spr_{i.t}) + \beta_2 \ln(Vol_{i.t}) + \beta_3 \ln(Ret_{i.t})$$
$$+ \beta_4 \ln(Volatility_{i.t}) + \sum_{j=A}^{U} \beta_{5j} News_{i,t}^{j} + \sum_{\mathrm{j=Mon}}^{\mathrm{Thu}} \beta_{6j} WD^{j} + \epsilon_{i,t}$$

The dummy variables $News^j$ $(j = A, U)$ take the value of one if the news announcement related to Australia ("A") or the U.S. ("U") occurs during session i's trading hours and zero otherwise. The dummy variable WD^j $(j = Monday, Tuesday, Wednesday, and\ Thursday)$ takes the value of one if the day is Monday, Tuesday, Wednesday, or Thursday and zero otherwise. The values in the parentheses are the Newey-West standard errors. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

	Asia	Europe	LNY	US
Intercept	1.222***	1.283***	1.434***	1.417***
	(0.059)	(0.061)	(0.031)	(0.032)
Spread	-0.140***	-0.138***	-0.127***	0.163***
	(0.045)	(0.045)	(0.018)	(0.029)
Volume	0.281***	0.250***	0.007***	0.027***
	(0.018)	(0.027)	(0.002)	(0.006)
Return	0.010***	0.010***	0.028***	0.007***
	(0.002)	(0.002)	(0.001)	(0.002)
Volatility	0.427***	0.434***	0.517***	0.513***
	(0.028)	(0.028)	(0.025)	(0.025)
$News^A$	0.064***	0.028	0.010	0.024
	(0.016)	(0.029)	(0.167)	(0.043)
$News^U$	0.017	-0.015	0.059***	0.048**
	(0.056)	(0.012)	(0.020)	(0.019)
Monday	0.054***	-0.058***	-0.038**	-0.009
	(0.019)	(0.016)	(0.019)	(0.018)
*Tue*eday	-0.042*	-0.008	-0.005	-0.067***
	(0.027)	(0.015)	(0.019)	(0.018)
Wednesdc	-0.071	-0.032**	0.001	-0.047***
	(0.070)	(0.015)	(0.018)	(0.018)
Thursday	-0.070***	-0.041***	0.007	0.044**
	(0.017)	(0.015)	(0.018)	(0.018)
n	3825	3824	3804	3816
Adj_R^2	0.7102	0.6252	0.6114	0.6358

2.5.3. Order flow

The results presented in column (1) of Table 2.9 show the relative importance of order flows in Asian and U.S. markets, i.e. the coefficients on order flows are positively and statistically significant. Column (2) of Table 2.9 reports the responses of the information shares to expected and unexpected order flows. Comparing the results shown in Table 2.9, a decomposition of order flows shows a remarkable increase in the explanatory power (i.e. the adjusted R^2 is relatively larger in column (2)). The Wald test suggests that the unexpected order flow plays a more important role in explaining the information shares.[18] The previously observed positive impact of order flow on information share vanishes after including the unexpected order flow, which confirms the elements of order flow that are unrelated to information. It is interesting to note the significances of unexpected order flow and the interactions of order flows and the news dummies, which significantly improve our understanding of information transmission in the FX market. Overall, I can argue that order flow, particularly the unexpected order flow, is a crucial determinant of the information shares. The evidence also supports the view that order flow is a medium for incorporating heterogeneous information in the FX market (Evans and Lyons, 2008). For robustness check, I also divide the sample into three sub-periods (i.e. 1999/2000 – 2006, 2007 – 2009, and 2010 – 2013). Generally, the results are consistent in all sub-periods for AUD.[19]

[18] The results of Wald statistics are not presented here due to space constraints, but available upon request.

[19] To conserve space, the results are not reported here for brevity, however, the empirical results are available upon request.

Table 2.9: Responses of Information Shares to Expected and Unexpected Order Flows

This table mirrors the regression results of market-state variables, macroeconomic news announcements, and order flows on daily information shares of the Asian, European, London/New York ("NYLON"), and U.S. session, which takes the following form:

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \sum_{j=E}^{U} \beta_{1j} \ln\left(OF_{i,t}^{j}\right) + \sum_{j=A}^{U} \beta_{2j} News_{i,t}^{j} + \sum_{j=E}^{U} \sum_{k=A}^{U} \beta_{3j} \ln\left(OF_{i,t}^{j}\right) \cdot News_{i,t}^{k} + \sum \beta_{4j} ControlVariable_{i,t} + \epsilon_{i,t}$$

where $ControlVariable_{i,t}$ stands for the market state variables, including spread, volume, open-to-close return, and volatility. Moreover, $OF_{i,t}^{J}$ $(J = E, U)$ represents the daily shares of expected ("E") and unexpected ("U") components of order flows in session i on day t respectively as defined in Section 4. The dummy variables $News^{j}$ $(j = A, U)$ is defined as in Table 2.8. The values in the parentheses are the Newey-West standard errors. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively

Variable	Asia		Europe		London/New York		North America	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$Intercept$	0.508***	0.494***	1.243***	1.242***	1.286***	1.300***	1.430***	1.426
	(0.040)	(0.041)	(0.042)	(0.043)	(0.062)	(0.064)	(0.031)	(0.032)
$Spread$	-0.119***	-0.120***	-0.304***	-0.303***	-0.136***	-0.135***	0.159***	0.160***
	(0.033)	(0.033)	(0.037)	(0.037)	(0.045)	(0.045)	(0.029)	(0.029)
$Volume$	0.252***	0.253***	0.427***	0.427***	0.461***	0.460***	0.533***	0.533***
	(0.019)	(0.020)	(0.025)	(0.025)	(0.028)	(0.028)	(0.020)	(0.020)
$Return$	0.014***	0.014***	0.004**	0.004**	0.010***	0.010***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Volatility$	0.680***	0.680***	0.588***	0.588***	0.432***	0.431***	0.514***	0.513***
	(0.019)	(0.019)	(0.025)	(0.025)	(0.028)	(0.028)	(0.025)	(0.025)

Table 2.9 (Continued)

Variable	Asia		Europe		London/New York		North America	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$News^A$	0.056***	0.079***	0.062*	-0.050	-0.090	0.132	0.020*	0.028**
	(0.011)	(0.018)	(0.043)	(0.034)	(0.097)	(0.193)	(0.012)	(0.011)
$News^U$	0.070*	-0.061	-0.016	-0.014	0.039*	0.069**	0.039	0.046***
	(0.040)	(0.070)	(0.010)	(0.014)	(0.022)	(0.029)	(0.025)	(0.015)
OF	0.014***		0.005		0.004		0.010**	
	(0.005)		(0.004)		(0.005)		(0.004)	
OF^E		0.005		0.004		0.007		0.011*
		(0.007)		(0.007)		(0.008)		(0.006)
OF^U		0.015**		0.008*		0.037***		0.013**
		(0.006)		(0.005)		(0.007)		(0.005)
$OF^E * News^A$		0.010*		-0.007		0.072		-0.011
		(0.006)		(0.018)		(0.088)		(0.021)
$OF^E * News^U$		0.039		0.001		-0.013		0.017*
		(0.029)		(0.008)		(0.010)		(0.009)
$OF^U * News^A$		0.008***		0.005		0.025		0.004
		(0.001)		(0.019)		(0.085)		(0.022)
$OF^U * News^U$		0.033		0.002		0.011*		0.009**
		(0.029)		(0.008)		(0.006)		(0.005)
n	3819	3819	3818	3818	3798	3798	3809	3809
$Adjusted\ R^2$	0.8109	0.8310	0.7250	0.7353	0.7121	0.7520	0.7352	0.7854

2.5.4. Cross-market information flow and dynamic structure

The local- and cross-market information spillover are examined, and the results are reported in Table 2.10. Reassuringly, I find that the main results in Table 2.9 remain intact. Namely, the conclusion regarding the importance of market state variables remains unchanged, besides, the unexpected order flow and its interaction with the news arrivals are most helpful in explaining the information share of each trading session. As shown in Table 2.10, the coefficients of local-market spillover effects as highlighted suggest the presence of first-order autocorrelation of the dependent variable. The cross-market effects are represented by the coefficients of lagged *IS* of other trading sessions, which suggests negative relationships between information shares of each session and a high information share of one trading session is associated with decreased share of other trading sessions. Similar results have been reported in Gau and Wu (2017). After controlling for the local- and cross-market information spillover effects, the coefficients of unexpected order flow and its interaction with news arrivals remain positive and significant.

In Table 2.10, I also include the dummy variable *GFC* in the regression which takes the value of 1 during the period of Global Financial Crisis (2008:09–2009:11), and 0 otherwise. Interestingly, the empirical results suggest that the US played more important role during the GFC period, while Europe markets became less important. Therefore, with larger information share, the U.S. became more efficient at incorporating the information into the fundamental prices related to the exchange rates during the GFC period. The results here are generally consistent with the findings in Section 2.2. For example, the US market contributes more to the price discovery during the GFC period (i.e., 2008 - 2009) as shown in Table 2.3 of the yearly average information shares.

Table 2.10: Responses of Information Shares to Order Flows and Macroeconomic News with Information Spillover

This table mirrors the regression results of own- and cross-market information spillover, market-state variables and macroeconomic news on daily information shares of the Asian, European, London/New York ("NYLON"), and U.S. market, which takes the following form:

$$\ln\left(\frac{IS_{i,t}}{1-IS_{i,t}}\right) = \alpha + \sum_{j=A}^{U} \beta_{1,j} \ln\left(\frac{IS_{j,t-1}}{1-IS_{j,t-1}}\right) + \sum_{j=E}^{U} \beta_{2j} \ln\left(OF_{i,t}^{j}\right) + \sum_{j=A}^{U} \beta_{3j} News_{i,t}^{j} + \sum_{j=E}^{U} \sum_{k=A}^{U} \beta_{4j} \ln\left(OF_{i,t}^{j}\right) \cdot News_{i,t}^{k} + \sum \beta_i ControlVariable_{i,t} + \beta_{GFC} GFC + \epsilon_{i,t}$$

where $ControlVariable$ includes all the market state variables as defined in Table 2.7, such as spread, volume, open-to-close return, and volatility. GFC is a dummy variable for the 2008 Global Financial Crisis which equals 1 for the key financial crisis months of 2008:09–2009:11, and otherwise zero. In this equation, the information spillover is typically represented by the coefficients of one-day lagged $IS_{j,t-1}$ $(j = A, E, L, and\ U)$. Namely, the own-market spillover effect is represented here by the coefficient of its own lagged IS $\beta_{1,j}$ $(j = i)$, while the coefficients $\beta_{1,j}$ $(j \neq i)$, which measure the short-run information spillover from session *j* to session i, serve as a proxy for cross-market effects. Note that the subscript *t-1* represents the session immediately before session *i*, which may be on the same day as session *i*. For example, when *i* = Asia, $IS_{i,t-1}$ $(i = A, E, L, and\ U)$ are *IS* from the previous day t – 1. However, when *i* = U.S., which is the last trading session on day *t*, $IS_{i,t-1}$ $(i = A, E, L)$ are from the same day *t* as US market with only the lagged U.S. information share $IS_{i,t-1}$ $(i = U)$ from the previous day. The values in the parentheses are the t-statistics based on Newey-West standard errors. The values highlighted in the table represents for the own-market spillover effects. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively

Variable	Asia	Europe	London/New York	North America
IS_Asia_lag	***0.0408****	-0.2216***	-0.3381***	-0.8465***
	(2.31)	(-14.93)	(-15.61)	(-13.60)
IS_Euro_lag	-0.0218	***0.0171****	-0.0548*	-0.4386***
	(-0.92)	***(1.64)***	(-2.22)	(-19.89)
IS_LNY_lag	-0.0160*	0.0005	***0.0181****	-.5557***
	(-1.64)	(0.06)	***(2.09)***	(-16.04)
IS_US_lag	-0.1247***	-0.0273***	0.0013	***0.0117****
	(-3.12)	(-2.78)	(0.13)	***(1.61)***

Table 2.10 (Continued)

Variable	Asia	Europe	London/New York	North America
OF^E	0.0062	0.0038	0.0066	0.0108*
	(0.07)	(0.07)	(0.08)	(1.64)
OF^U	0.0157**	0.0126*	0.0112**	0.0067*
	(1.82)	(2.22)	(1.98)	(1.62)
$OF^E * News^A$	0.0102*	-0.0072	0.0722	-0.0111
	(1.68)	(0.33)	(0.88)	(-0.21)
$OF^E * News^U$	0.0393	0.0014	-0.0134	0.0172*
	(1.02)	(0.22)	(-0.11)	(1.77)
$OF^U * News^A$	0.0337***	0.0053	0.0251	0.0041
	(3.11)	(1.54)	(0.85)	(0.12)
$OF^U * News^U$	0.0094	0.0021	0.0115*	0.0093**
	(0.92)	(1.33)	(1.74)	(2.08)
GFC	0.0194	-0.1059***	-0.0804***	0.1766***
	(0.74)	(-5.91)	(-4.21)	(6.77)
n	3818	3817	3797	3808
Adj_R^2	0.8455	0.7387	0.7688	0.8101

2.5.5. Market development and financial integration indicators

The estimation results of long-run determinants are reported in Table 2.11.[20] First of all, the pricing efficiency, which can be seen as an indicator of FX market development, has a positive and significant impact on price discovery. Second, with more active quoting banks in Asian trading hours, particularly with the increasing participation of foreign banks headquartered overseas, the information share of Asia increases substantially. These findings suggest that, with an increasing degree of market integration and consolidation (i.e. with more active dealing banks in the Asian market), Asia is playing an increasingly important role in the price discovery of global FX trading. Besides, the number of quoting banks has a significantly and positively effect on information shares for all markets. However, the percentage of foreign banks is not useful in explaining the information shares except for that in the Asian market, which is probably due to the fact that a larger proportion of FX trading has been conducted between counterparties located in the same place, but their headquarters could be elsewhere (BIS, 2013).

Furthermore, I consider the impact of market concentration on price discovery. There is a long-standing debate about the influences of market concentration. For example, on the one hand, the market concentration enables the top-tier banks to process greater order flow and internalize customer order flow, which helps them aggregate the dispersed information among the customers and contribute more to the price discovery (Evans, 2002; Evans and Lyons, 2002a; Rime and Schrimpf, 2013). On the other hand, the market concentration may cause erratic swings amid liquidity drought, especially during times of market stress (Yin, 2005; Hendershott and Jones, 2005). The empirical results suggest that the increasing market concentration does not have a consistent effect on the price discovery, which confirms the ambiguous effect of market concentration as documented in previous studies.

[20] Following the suggestions of the thesis examiner, I report the summary statistics of long-run determinants in Appendix C.

Finally, considering the importance of financial market infrastructure in facilitating the price discovery process, I include the GDP-weighted average Chinn-Ito Index in the regression to proxy for the degree of capital market openness and financial liberalization. The empirical results presented in Table 2.11 confirm that the overall Chinn-Ito Index have a positive effect on the information shares in all sessions. This effect is particularly high in the Asian market. In overall terms, a higher degree of FX market development and financial integration is highly desirable, particularly for Asian market.

The estimations of long-run determinants with lead-lag effects are shown in Table 2.12. The lagged term of *IS* has significantly positive effects on the monthly information share of each trading session. Furthermore, to control for seasonality as shown in Figure 2.2, I add the 12-month lagged *IS* in the regression. The results suggest the presence of seasonality and re-confirm the conclusions about the fundamental effects of the proxy variables for the degree of financial market development and integration.

Table 2.11: Responses of Information Shares to Long-run Determinant Variables

This table mirrors the regression results of market development and financial integration indicators on the monthly information shares of the Asian, European, London/New York ("NYLON"), and U.S. trading session, which takes the following form:

$$\ln\left(\frac{IS_{i.m}}{1 - IS_{i.m}}\right) = \alpha + \beta_1 \ln(Eff_{i.m}) + \beta_2 \ln(NumBank_{i.m}) + \beta_3 \ln(ForeignBank_{i.m}) + \beta_4 \ln(MktCon_{i.m}) + \beta_5 \ln(ChinnIndex_{i.m}) + \epsilon_{i,t}$$

with $IS_{i.m}$ representing the monthly information share for session i on month m, α the intercept term, *Eff*, *NumBank*, *ForeignBank*, and *MktCon* are monthly average pricing efficiency as defined in Section 2.2, the number of quoting banks during session i's trading hours, percentage of quotes posted by foreign banks identified based on their locations, and the percentage of quotes issued by the top-5 most active banks. *ChinnIndex* is the capital-weighted average Chinn-Ito index, which is sourced from Chinn and Ito (2006) and used to proxy for the degree of financial market openness. The values in the parentheses are the Newey-West standard errors. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Variable	Asia	Europe	London/New York	North America
$Intercept$	-1.8559***	-1.2400***	-1.4828***	-1.4506***
	(0.0793)	(0.0745)	(0.0595)	(0.0634)
$Efficiency$	0.4835***	0.6792***	0.4942***	0.5665***
	(0.0840)	(0.0838)	(0.0617)	(0.0758)
$Number\ of\ Banks$	0.0138***	0.0187***	0.0074***	0.0065**
	(0.0028)	(0.0067)	(0.0030)	(0.0026)
$Pct\ of\ Foreign\ Banks$	0.0383***	-0.0006	0.0089	0.0102
	(0.0178)	(0.0019)	(0.0242)	(0.0182)
$Market\ Concentration$	0.0702*	-0.0612	-0.0161	-0.0137
	(0.040)	(0.070)	(0.010)	(0.014)
$Chinn - Ito\ Index$	0.0814***	0.0456***	0.0224***	0.0280**
	(0.0050)	(0.0071)	(0.0048)	(0.0161)
n	168	168	168	168
$Adjusted\ R^2$	0.2964	0.3110	0.4551	0.4102

Table 2.12: Responses of Information Shares to Long-run Determinants with Lead-lag Effects

This table mirrors the regression results of market development and financial integration indicators on the information shares of the Asian, European, London/New York ("NYLON"), and U.S. market in the long run, while taking into account lead-lag effects, which takes the following form:

$$\ln\left(\frac{IS_{i,m}}{1-IS_{i,m}}\right) = \alpha + \beta_1 \ln\left(\frac{IS_{i,m-1}}{1-IS_{i,m-1}}\right) + \beta_2 \ln\left(\frac{IS_{i,m-12}}{1-IS_{i,m-12}}\right) + \beta_3 \ln(Eff_{i.m}) + \beta_4 \ln(NumBank_{i.m}) + \beta_5 \ln(ForeignBank_{i.m}) + \beta_6 \ln(MktCon_{i.m}) + \beta_7 \ln(ChinnIndex_{i.m}) + \epsilon_{i,t}$$

with $IS_{i.m}$ and $IS_{i.m-k}$ representing the monthly information share for session *i* on month *m and m-k* respectively, α the intercept term, *Eff*, *NumBank*, *ForeignBank*, and *MktCon* are monthly average pricing efficiency as defined in Section 2.2, the average number of quoting banks during session *i*'s trading hours, percentage of quotes posted by foreign banks identified based on their locations, and the percentage of quotes issued by the top-5 most active banks. *ChinnIndex* is the capital-weighted average Chinn-Ito index, which is sourced from Chinn and Ito (2006) and used to proxy for the degree of financial market openness. The values in the parentheses are the t-statistics based on Newey-West standard errors. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Variable	Asia	Europe	London/New York	North America
$IS\_monthly\_lag$	0.5745***	0.4648***	0.5589***	0.4114***
	(9.07)	(6.74)	(9.86)	(6.12)
$IS\_monthly\_lag12$	0.1166*	0.1230*	0.2218***	0.3018***
	(1.79)	(1.87)	(3.75)	（4.47）
$Efficiency$	0.2752***	0.2973***	0.3122***	0.3321***
	(13.14)	(18.38)	(19.21)	(27.58)
$Number\ of\ Banks$	0.0233*	0.0321***	0.0754***	0.0665***
	(1.83)	(5.67)	(7.88)	(6.12)
$Pct\ of\ Foreing\ Banks$	0.0145*	-0.0006	0.0077	0.0003
	(1.78)	(0.88)	(0.42)	(0.12)
$Market\ Concentration$	-0.0022	0.0611**	-0.0126*	0.0032
	(-1.40)	(2.32)	(-2.11)	(0.42)
$Chinn-Ito\ Index$	0.0202*	0.0356**	0.0114	0.0280*
	(1.77)	(2.11)	(1.48)	(1.65)
n	156	156	156	156
$Adjusted\ R^2$	0.3645	0.4232	0.4858	0.4380

2.5.6. Robustness test

To examine the causal relation between price discovery and market state variables, I follow Wintoki et al. (2012) by employing the GMM estimator. The GMM estimator can provide consistent and unbiased estimates when there is endogeneity and a dynamic relation between the dependent and independent variable (Frijns et al., 2015). In this case, there is an endogeneity problem induced by potential reverse causality. For example, on the one hand, I expect the various market state variables have a causal effect on price discovery and relative improvements in market quality may positively affect the contribution to price discovery of a particular region. Concurrently, the degree of price discovery may affect measures of market state or market quality. At the same time, it is expected that there is persistence in the measures of market states and price discovery. As demonstrated by Wintoki et al. (2012), the presence of simultaneity and persistence means that OLS would produce biased estimates of the causal relation between market states and price discovery, while the GMM estimator can capture the causal relation between market quality and price discovery more accurately.

Thus, I estimate the equation in Table 2.9 using the GMM techniques.[21] Namely, in Table 2.13, I report the results for the equation where I estimate the causal relation between the measures of market states and price discovery using a two-step procedure of GMM estimation as in Frijns et al. (2015). The results presented in Table 2.13 generally reconfirm the earlier findings concerning the impacts of market state variables, order flow, and macroeconomic news announcements on information shares in different trading sessions. However, the coefficients of *Volatility* become insignificant in the GMM estimation.

[21] Although the equation in Table 2.13 can be estimated directly using the GMM estimator, there are several steps to confirm the accuracy of the model specification. For example, I confirm the dynamic completeness of the model, by obtaining the correct lag structure as shown in Panel A of Appendix D where the results confirm the persistence captured by the coefficients of first three lags of dependent variable. This is desirable if lagged values of the dependent variable are to be a useful instrument in the GMM estimation (Frijns, et al., 2015). Furthermore, I test for the possible endogeneity issue in Panel B and Panel C, which suggests the simultaneity problem.

Table 2.13 Robust Regression (GMM)

This table mirrors the regression results of market-state variables, macroeconomic news announcements, and order flows on daily information shares of the Asian, European, London/New York ("NYLON"), and U.S. market, which takes the following form:

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \beta_1 \ln\left(\frac{IS_{i.t-1}}{1-IS_{i.t-1}}\right) + \beta_2 \ln(Spr_{i.t}) + \beta_3 \ln(Vol_{i.t}) + \beta_4 \ln(Ret_{i.t}) + \beta_5 \ln(Volatility_{i.t}) + \gamma Controls_{i,t} + \epsilon_{i,t}$$

with i representing the market, α the intercept term, Spr, Vol, Ret, and Volatility standing for individual shares of the time-weighted average quoted spread, the number of trades, exchange rate return, the standard deviation of mid-quote returns sampled at 5-minute interval. This Table reports results for the model that assesses the causal relation between various measures of market states and price discovery (i.e., Logit transformation of the information share). The model is estimated by a two-step GMM estimation procedure, where the measures for market states are treated as endogenous and the control variables as exogenous. It uses lags two and three as the internal instruments and employs the Windmeijer (2005) correction in the calculation of standard errors and reports t-statistics in parentheses. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

	Asia	Europe	LNY	US
$\ln\left(\frac{IS_{i.t-1}}{1-IS_{i.t-1}}\right)$	0.0924***	.0365	0.0907***	0.1018***
	(3.91)	(0.82)	(2.67)	(2.45)
$Spread$	-1.0785**	-1.2929**	-1.3647**	0.5924
	(-2.13)	(-2.08)	(-1.90)	(0.30)
$Volume$	0.7874***	0.8673***	0.5002***	0.5995**
	(2.68)	(2.28)	(2.42)	(2.28)
$Return$	0.1823***	-0.1600	-0.1043	-0.8575
	(2.26)	(-0.25)	(-0.29)	(-0.24)
$Volatility$	-0.685	-0.9152	-0.4052	-1.058
	(-0.83)	(-0.67)	(-0.66)	(-0.93)
OF^E	0.073	0.082	0.077	0.001
	(0.77)	(0.99)	(0.12)	(0.18)
OF^U	0.021**	0.002	0.034***	-0.088*
	(1.98)	(1.02)	(2.22)	(-1.67)
$News^A$	0.078***	-0.050	0.132	0.027**
	(3.55)	(0.98)	(0.11)	(2.12)
$News^U$	-0.062	-0.024	0.072***	0.049***
	(0.01)	(0.01)	(2.50)	(3.88)
$OF^E * News^A$	0.022**	0.001	-0.001	-0.000
	(1.98)	(0.33)	(-0.28)	(-0.31)
$OF^E * News^U$	0.012	0.001	0.004	0.113***
	(1.01)	(0.12)	(0.21)	(2.32)
$OF^U * News^A$	0.066***	0.010*	0.005	-0.001
	(5.13)	(1.65)	(0.98)	(-0.01)
$OF^U * News^U$	0.019	0.000	0.112***	0.010
	(1.20)	(0.03)	(5.77)	(1.10)
n	3818	3817	3797	3808
$Adjusted\ R^2$	0.4507	0.2984	0.3616	0.3970

Furthermore, I also categorize the macroeconomic news announcements into scheduled and unscheduled news and re-estimate the model of information share determination using only scheduled macroeconomic news. The estimated results, as presented in Table 2.14, shows that the coefficients of unscheduled news and its interactions with order flows are largely insignificant, suggesting that the unscheduled news has a stronger positive impact on information shares and hence should be included in relevant announcement effect analysis.

Finally, I examine the effects of market state variables using the intraday data on AUD/GBP and AUD/EUR from Jan 2000 to Dec 2013. The results of AUD/GBP are summarized in Table 2.15.[22] As we can see, the coefficients of market state variables are slightly different, for example, for AUD/GBP the variable spread has a positive effect instead of negative effect in most trading sessions. Besides, during the GFC period, both the LNY market and the U.S. market become more important in the information transmission. However, the major findings remain unchanged, which means that using different denomination currency doesn't change the main conclusions about the importance of order flow in incorporating new information into exchange rates.

[22] I omit the results of AUD/EUR for simplicity, however, the empirical findings are similar to those of AUD/GBP.

Table 2.14: Responses of Information Shares to Scheduled Macro News

This table reports the estimation results of market state variables, scheduled macroeconomic news, and order flows on daily information shares of different sessions (i.e. Asia, Europe, London/New York ("NYLON"), and the U.S.). The model specification is as follows:

$$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right) = \alpha + \sum\nolimits_{j=E}^{U} \beta_{1j} \ln\left(OF_{i,t}^{j}\right) + \beta_{2j} Sch\_News_{i,t} + \sum\nolimits_{j=E}^{U} \beta_{3j} \ln\left(OF_{i,t}^{j}\right) \cdot Sch\_News_{i,t} + \sum \beta_{4j} ControlVariable_{i,t} + \epsilon_{i,t}$$

where $ControlVariable$ includes the market state variables as defined in Table 2.7, such as spread, volume, open-to-close return, and volatility. The dummy variable *Scheduled News* takes the value of one if the scheduled news announcement related to the U.S. or Australia (including employment, Gross Domestic Product (GDP), trade balance, and durable goods orders for the US and the equivalent news variables for Australia) occurs during session *i*'s trading hours and zero otherwise. The values in the parentheses are the Newey-West standard errors. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Variable	Asia		Europe		London/New York		North America	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$Intercept$	0.513***	0.822***	1.225***	1.406***	1.221***	1.325***	1.432***	1.551***
	(0.040)	(0.041)	(0.042)	(0.041)	(0.016)	(0.054)	(0.031)	(0.030)
$Spread$	-0.124***	-0.098***	-0.304***	-0.015***	-0.137***	-0.132***	0.152***	0.309***
	(0.033)	(0.034)	(0.037)	(0.038)	(0.045)	(0.045)	(0.028)	(0.028)
$Volume$	0.248***	0.366***	0.418***	0.509***	0.443***	0.550***	0.530***	0.531***
	(0.020)	(0.016)	(0.024)	(0.019)	(0.027)	(0.021)	(0.020)	(0.016)
$Return$	0.014***	0.010***	0.004**	0.003**	0.010***	0.008***	0.007***	0.005***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$Volatility$	0.681***	0.581***	0.584***	0.473***	0.426***	0.267***	0.518***	0.441***
	(0.019)	(0.018)	(0.024)	(0.023)	(0.028)	(0.026)	(0.025)	(0.024)

Table 2.14 (Continued)

Variable	Asia		Europe		London/New York		North America	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$Scheduled\ News$	0.039*	0.025	0.013	0.004	0.041	-0.002	0.072**	0.017
	(0.021)	(0.020)	(0.008)	(0.012)	(0.043)	(0.038)	(0.038)	(0.363)
OF^E		0.006		0.006		-0.006		-0.002
		(0.004)		(0.004)		(0.005)		(0.004)
OF^U		0.006		0.006		0.013***		0.004
		(0.004)		(0.004)		(0.005)		(0.004)
$OF^E * Sch\_News$		0.004		0.010		-0.003		-0.077
		(0.012)		(0.008)		(0.021)		(0.197)
$OF^U * Sch\_News$		0.012		0.004		0.004		0.017**
		(0.014)		(0.022)		(0.022)		(0.010)
n	3825	3819	3824	3818	3804	3798	3809	3807
$Adjusted\ R^2$	0.8091	0.8254	0.7048	0.7205	0.7107	0.7391	0.7258	0.7558

Table 2.15: Responses of Information Shares to Market State Variables for AUD/GBP

This table mirrors the regression results of market-state variables and macroeconomic news announcements on daily information shares of the Asian, European, London/New York ("NYLON"), and U.S. market for AUD/GBP, which takes the following form:

$$\ln\left(\frac{IS_{i,t-1}}{1-IS_{i,t-1}}\right) = \alpha + \sum_{j=A}^{U} \beta_{1,j} \ln\left(\frac{IS_{j,t-1}}{1-IS_{j,t-1}}\right) + \sum_{j=E}^{U} \beta_{2j} \ln\left(OF_{i,t}^{j}\right) + \sum_{j=A}^{U} \beta_{3j} News_{i,t}^{j} + \sum_{j=E}^{U} \sum_{k=A}^{U} \beta_{4j} \ln\left(OF_{i,t}^{j}\right) \cdot News_{i,t}^{k} + \sum \beta_5 ControlVarialbe_{i,t} + \beta_{GFC} GFC + \epsilon_{i,t} \ ,$$

with i representing the market, α the intercept term. $OF_{i,t}^{J}$ $(J = E, U)$ represents the daily shares of expected (E) and unexpected (U) order flows in session i on day t respectively. $ControlVariable_{i,t}$ includes all the market state variables as defined in Table 2.7, such as spread, volume, and open-to-close return. GFC is a dummy variable for the 2008 Global Financial Crisis which equals to 1 for the key financial crisis months 2008:09–2009:11, and otherwise zero. The values highlighted in the table represents for the own-market spillover effects and the values in the parentheses are the t-statistics calculated based on Newey-West standard errors. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Variable	Asia	Europe	London/New York	North America
IS_Asia_lag	**-0.0361**	-0.1444***	-0.2648***	-0.4856***
	(-1.38)	(-8.72)	(-14.71)	(-14.70)
IS_Euro_lag	-0.0703***	**-0.0099**	-0.1847***	-0.4423***
	(-2.25)	**(-0.82)**	(-7.55)	(-10.54)
IS_LNY_lag	-0.0951***	-0.0096	**0.0186****	-0.4683***
	(-3.34)	(-0.92)	**(2.18)**	(-16.64)
IS_US_lag	-0.0083	-0.0109	-0.0154	**0.0004**
	(-0.38)	(-1.22)	(-1.54)	**(1.04)**

Table 2.15 (Continued)

Variable	Asia	Europe	London/New York	North America
$Spread$	0.2894***	0.3931***	0.1538***	-0.1202***
	(10.48)	(14.15)	(13.11)	(-11.75)
$Volume$	0.1489***	0.3099***	0.1709***	0.3493***
	(10.18)	(12.88)	(16.27)	(10.37)
$Return$	0.0118***	0.0055***	0.0033	0.0048**
	(3.29)	(2.89)	(1.25)	(2.06)
OF^E	0.0121	0.0211*	0.0011	0.0072
	(1.22)	(1.64)	(0.08)	(1.04)
OF^U	0.0157**	0.0022	0.0428***	0.0677*
	(1.82)	(1.02)	(2.02)	(1.62)
$OF^E * News^A$	0.0221**	0.0008	-0.0072	-0.0001
	(1.99)	(0.58)	(-0.18)	(-0.21)
$OF^E * News^U$	0.0118	0.0001	0.0033	0.1832**
	(1.33)	(0.22)	(0.11)	(2.01)
$OF^U * News^A$	0.0662***	0.0098*	0.0052	-0.0009
	(5.11)	(1.64)	(0.58)	(-0.02)
$OF^U * News^U$	0.0189	0.0002	0.1112***	0.0101
	(1.21)	(0.33)	(11.74)	(1.08)
GFC	-0.0116	-0.0212	0.0555***	0.1444***
	(-0.43)	(-1.31)	(3.42)	(7.33)
n	3824	3824	3804	3816
Adj_R^2	0.7911	0.6677	0.7156	0.7484

2.6. Conclusions and policy implications

With rapid growth in emerging economies, such as China and India, the demand for Australia's natural resources has increased substantially. As a result, the role of the Australian dollar (AUD) in the global financial markets has become more important (McCauley, 2006). Using firm quotes and trading data from January 1999 to December 2013, this chapter estimates the global information distribution of AUD trading in the Asian, European, and North American markets. Specifically, using the price quotes of AUD against the US dollar over a relatively long period (i.e. 15 years in total), I employ a non-parametric price discovery methodology, i.e., Two-scale Realized Variance (TSRV) ratio, to estimate the information shares of global AUD trading. I find that the European market and U.S. market, particularly the overlapping trading session of London and New York, dominate in price discovery process in AUD market, but Asia is rapidly gaining information shares even with its declining market share of daily transactions.

After estimating the information share, I focus on its short- and long-run determinants in each market. Namely, I consider the effects of macroeconomic news, order flow measures, market state variables while taking into account cross-market effects and dynamic completeness of information shares in each trading session. The empirical analysis shows that more favourable market states and more unexpected order flows, particularly on macroeconomic announcement days, make a significantly positive contribution to price discovery in all trading sessions for AUD trading. Meanwhile, there are strong information spillover effects in the FX market, and high information share of one trading session is associated with increased information share in the future, while decreased information share of other trading sessions. The empirical results also confirm that a higher degree of market integration and international consolidation contributes to price discovery in the long-run.

The distinguishing feature of this chapter is that I consider the impact of a broader set of news announcements on information shares, which includes both scheduled and unscheduled news announcements. Besides, I show that the decomposition of order flows into an expectation-related and an innovation term can significantly improve our understanding of the dealer behaviour responding to different types of information arrival. This chapter also contribute to the literature on price discovery by considering the long-run determinants of information shares. Specifically, I attempt to explore the relationship between the price discovery, market integration, and the development of financial markets. The empircal results are generally consistent with Sassen (1999) who claims that the two most important factors in transforming a city into a global financial centre are international consolidation of financial activities and financial market liberalization.

This study on price discovery in AUD market has some important policy implications, especially for financial centres in the Asia-Pacific region. For example, the empirical results suggest that the financial market openness and liberalization have a strong impact on the long-run trends in price discovery. To better compete with the leading financial centres in North America and Europe, the Asian financial centres need to be more open to international investors and adopt global principles of financial market regulations. Furthermore, the findings of inter- and intra-regional information spillover effects suggest that price discovery is sticky and persistent. Hence the improvement of price discovery in Asia can gain a competitive edge over other regions in the long-run.

The research presented in this chapter can also be extended in several directions. For example, how to accurately measure the information shares in the financial markets is one question that is yet to be fully answered. Furthermore, additional research is required to consider the generalizability of these results. This will involve considering price discovery of other major currencies and emerging currencies. Last but not least, the issue of how to identify volatility jumps associated with macroeconomic news announcements deserves further study, which will definitely improve the measure of information shares and extend our understanding in economic intuition of price discovery in the foreign exchange market.

Chapter 3: Meteor Showers and Heat Waves Effects in the Foreign Exchange Market: Some New Evidence

3.1. Introduction

The development of estimators of volatility based on high-frequency information has led to large improvements in measuring financial market volatility. The investigation into volatility spillovers across geographical regions is an import topic, which contributes to our knowledge about global financial interconnectedness. The phenomenon of volatility spillover occurs when volatility in one market triggers volatility in other markets. This effect can be particularly visible during periods of turmoil which diminishes the benefits of international portfolio diversification for investors. It is further amplified by the recent technological advances, such as the rise of electronic trading and algorithm trading, which have undoubtedly facilitated information flows. Besides, with the dominance of cross-market effects in a wide range of financial markets, the financial instruments become more temporally correlated across markets, which raises concerns from regulators about global financial instability and contagion effects. The international information transmission across markets through volatility have a wide range of practical implications as well. For example, models incorporating these features significantly improve volatility and these statistical improvements can be translated into significant economic gains (Su, 2018).

In this paper, I mainly focus on the Foreign Exchange (FX) market which is the largest financial market in the world, with a daily trading volume of about five trillion U.S. dollars (Bank for International Settlements, 2013). Also, the FX market is fairly opaque and decentralized because of its two-tier market structure when compared to, for example, the major equity markets.[23] Besides, unlike the equity markets, the Foreign Exchange markets operate continuously from Asia to Europe, then to America throughout the day. In sum, the size, sophistication, global

[23] For a thorough introduction to the market structure and its evolution in the Foreign Exchange market, please refer to King, Osler, and Rime (2011).

perspective, and relative continuity of trading in the FX market make it an ideal candidate for the study of volatility spillover and information propagation effects.

With the decentralised market structure, the question naturally arises: what drives volatility spillovers in the FX market? This paper addresses several related questions that arise in this market setting. First, I provide new evidence to the debate on the patterns of volatility spillovers as documented in the previous study and find evidence of both meteor shower (i.e. intra-regional volatility spillover) and heat waves effects (i.e. inter-regional volatility spillover) in the FX market, while the meteor shower effect has been increasing and predominated over heat waves effect with the trend toward global trading in the financial markets. Second, I take a broad view on the economic mechanism of volatility spillover and identify the key factors contributing to the time-varying volatility spillover, which sheds light on the economic explanations of volatility persistence and improves our understanding of contagion risk in the financial markets. Third, I explicitly quantify the contributions of market state variables (i.e. return and volatility) to the volatility spillover, which sheds light on studies about microstructure of the FX market and contributes to the existing literature on volatility modelling. Namely, I empirically examine the magnitudes and determinants of volatility persistence in local market (i.e., heat waves effect) and volatility spillovers to other regions (i.e., meteor showers effect) for AUD, GBP, EUR, and JPY, all against USD, spanning from January 1999 (January 2000 for EUR) to December 2013.[24]

In this chapter, I use the Heterogeneous Autoregressive (HAR) model proposed in Corsi (2009) and utilize the technique of the Shapley-Owen decomposition of the R-squared, which proves to be more efficient in measuring the relative importance of the meteor shower and heat waves effects (Lahaye and Neely, 2016). Unsurprisingly, I confirm the presence of both effects. However, unlike Lahaye and Neely (2016), I find that the importance of meteor shower effect has been increasing rapidly. By now, the volatility spillover has been dominated by the

[24] For EUR, the tick-by-tick data has not been available until January 2000. All the intraday data used in this paper is sourced from Thomson Reuters Tick History (TRTH) maintained by SIRCA.

meteor showers effect, which is probably attributed to the increasingly interconnected and interdependent financial markets with the rise of information technology and algorithmic trading. Specifically, Lahaye and Neely (2016) quantify the relative importance of meteor showers and heat waves effects in the FX market by utilizing the Shapley-Owen R^2 measures, which shows that meteor showers account for around 60% of the volatility spillover effects in the EUR/USD and USD/JPY markets, while the heat waves constitutes the remaining 40%. In this chapter, I use the same method to quantify the explanatory power of the meteor showers and heat waves in predicting future volatility for the AUD/USD, GBP/USD, EUR/USD, and USD/JPY markets. The empirical results suggest that the meteor showers effects (i.e. inter-regional spillover effects) have been increasing rapidly and accounted for around 70% of total volatility spillover effects during the whole period, while the heat waves effects contribute to the remaining portion. In fact, it seems unsurprising that meteor showers should predominate over heat waves with the trend toward global trading and correlated common shocks across countries (Erdemlioglu, Laurent, and Neely, 2012).

The economic explanations in this chapter of volatility persistence is closely related to earlier theories on information propagation, such as the theory of Mixture of Distribution Hypothesis (MDH) developed by Clark (1973) and Tauchen and Pitts (1983) and extended by Andersen (1996). The key prediction of the MDH is that daily returns and trading volume are jointly determined by a latent information variable that measures the daily rate of information flow to the market. If the daily number of information arrivals is positively correlated across days, then the model predicts positive serial correlation in the squared daily returns. In other words, the MDH implies that the persistence in the variance forecasts mimics the persistence in the information flow. However, while conceptually appealing, the number of information arrivals are often unobservable, meaning empirical tests of these mechanisms are "inherently difficult" (Wang and Yang, 2017). Besides, the MDH as an empirical explanation for volatility persistence finds mixed support (See Andersen, 1996; Liesenfeld, 2001; Fleming and Kirby, 2011; He and Velu, 2014; among others). In this study, different from the classic MDH, I find that volatility spillover is not solely determined by exogenous information arrivals, but also by the price discovery process of absorbing shocks and resolving uncertainty. Namely, a faster process of price discovery within a period reduces information persistence to future periods and therefore mitigates volatility spillover. The explanation here is generally consistent with the findings of Wang and Yang (2017) which suggest that, for a given information shock, a high daily realized variance implies more information being priced today, and less spillovers of unpriced information to other markets in the future. The explanation is also closely related to Berger et al. (2009) who claim the volatility persistence varies with investors' sensitivity to information as proxied by the price impact of orders. However, in this study, I utilize several market state variables (i.e. return, volatility, and information share) and focus on the lead-lag relationship rather than the contemporaneous effects.

To sum up, this empirical study contributes to the existing literature on volatility modelling by utilizing the technique of realized volatility to examine the magnitudes and economic mechanisms of volatility spillover effects in the global FX market. It also contributes to the literature on information propagation by providing information-based explanations of volatility spillovers and bridging the gap in the literature between news-related and trading-based explanations. The remainder of this chapter proceeds as follows: Section 3.2 reviews the literature. Section 3.3 describes the data and introduces relevant variables. An empirical investigation into the patterns of meteor showers and heat waves effects is presented in Section 3.4, while Section 3.5 proposes the model of conditional volatility persistence and presents the main findings on the determinants of volatility spillover. Section 3.6 conducts the robustness analysis and compares the forecasting performances with other volatility models. Summaries and directions for future research are provided in Section 3.7.

3.2. Literature Review

A vast amount of literature has focused on how the volatility is transmitted in the foreign exchange market since Engle, Ito and Lin (1990) propose the concepts of “meteor showers” and “heat waves”. Heat waves refer to the idea that geography determines volatility. Namely, volatility has only location-specific autocorrelation such that a heat wave might raise volatility in New York trading on consecutive days, i.e., from Monday to Tuesday, but not in Tokyo on Tuesday. In contrast, meteor showers refer to temporally correlated volatility that spills over from one trading centre to another so that high volatility in New York trading on Monday is likely to be followed by a volatile day in Tokyo on Tuesday morning. In Engle et al. (1990), the authors examine the short- and long-run volatility spillover effects for daily volatility using GARCH models and find that meteor showers predominated, while Melvin and Peiers Melvin (2003) reinvestigate the question with a VAR model for realized volatility and argue that heat waves were more important. Furthermore, Baillie and Bollerslev (1991) find evidence of both the meteor shower and heat wave patterns. To explicitly calculate the portion of each effect, Ito, Engle and Lin (1992) propose a Forecast Error Variance Decomposition (FEVD) method and confirm that the magnitude of meteor shower effect is relatively larger. Lahaye and Neely (2016) re-examine the meteor showers and heat waves effects by decomposing the daily realized variance into the continuous and jump components. They find evidence of both meteor shower and heat waves effects in the integrated volatility, while the meteor shower effects are more influential than heat waves. Thus, different approaches to volatility measurement lead to different conclusions.

In examining the local- and cross-market volatility spillovers, I show a time-varying pattern of meteor showers and heat waves effects in each regional market, which highlights the complex geographical nature of the FX market. Namely, these results argue in favour of modelling FX volatility dynamics segment-wise, rather than in the more traditional approach of assuming a homogeneous process (Dacorogna et al., 1993). For example, Dacorogna, et al. (1993) identify the intraday periodicity in the FX market using geographical models, and Andersen and Bollerslev (1997) demonstrate that intraday seasonality in FX volatility contains a geographic component reflecting the timing of business activity in the major geographical trading zones. In this study, I confirm the “information dominance" that the FX microstructure literature has highlighted (Su and Zhang, 2018). Namely, some regions are more important sources of volatility shocks than others. Besides, the increasing magnitude of meteor showers effect reflects the fact that the global financial market becomes increasingly interdependent and interconnected with the rise of advanced information technology which facilitates electronic trading and information processing. Whether the relative importance of meteor showers and heat waves can be utilized to measure the degree of currency internationalization deserves further study. For example, Wang (2014) quantify the degree of the internationalization of Korean won by checking the relative importance of overnight market in price discovery and find a strong uptrend in overnight price discovery in recent years associated with greater internationalization of Korean won. Similarly, we would expect the meteor shower effect to be increasingly dominant in the process of currency internationalization with the incremental impacts from other regions.

Regarding the mechanism of volatility spillover in the FX market, one strand of relevant studies attempts to explain the meteor showers and heat waves effects by focusing on the news arrivals. Specifically, since most news of relevance to financial markets occurs during each region's business hours, a regular global pattern of intra-daily seasonality in the news arrival process in each region would seem to give rise to the "heat waves" effect of regionally-specific autocorrelation in volatility. For example, the results of Melvin and Peiers Melvin (2003) support the sources of FX volatility being primarily local: a volatility spike in one region today is generally related to higher-than-normal volatility in the same region tomorrow. In the same vein, Lahaye and Neely (2016) argue that heat waves are more likely to occur if most important news that affects volatility occurs during a particular country's business day, while meteor showers will tend to predominate if autocorrelated international news is more important. Furthermore, Hogan and Melvin (1994) provide empirical explanations to meteor showers effect. Namely, the authors examine the role of institutional investors' heterogeneous expectations in the volatility spillover of exchange rates. By measuring different opinions of money managers on U.S. leading macroeconomic indicators, which are shown to have a significant and persisting effect on the exchange rate and its conditional variance, the authors find that the degree to which U.S. news affects other geographical markets is functionally related to heterogeneous priors. Furthermore, a vast amount of trading-related explanations has been proposed in the literature, including but not limited to: (1) models of optimal trading strategy that generates a positive relationship between heterogeneity of expectations, trading volume, and the time required for price to fully reflect information (Kyle, 1985; Admati and Pfleiderer, 1988); (2) models of different trading horizons of institution investors (Müller et al., 1997); For instance, FX dealers are usually concerned with extremely short trading horizons while corporate treasurers or central bankers generally consider longer horizons. Müller et al. (1997) then utilize the different trading horizons of heterogeneous institution investors to explain their empirical findings that volatility calculated at lower sampling frequencies predicts those calculated at higher sampling frequencies significantly better than the converse. (3) models of incorporating private information via order flow (Ito, Lyons and Melvin, 1998); For example, position-taking that is based on informational advantages may result in a rippling of trades and generate autocorrelated volatility across regions. In the context of information-based explanations, Berger et al. (2009) propose empirical specifications of volatility that links volatility to the information flow, as well as the price sensitivity to that information. Their empirical analysis suggests that the time variation in the market's sensitivity to information plays a similar role in explaining the persistence of volatility as the rate of information arrival itself.

However, how to empirically explore the sources of volatility spillover in the FX market remains unclear. As pointed out by Goodhart and O'Hara (1997), "the underlying question of why such volatility persistence endures remains unanswered." The literature on the economic origins of volatility persistence remains relatively small and diverse. For example, with the high-frequency and short-periodicity of the foreign exchange market, one might expect that the market reaction to new information would tend to be contained within the region with the news release (Hogan and Melvin, 1994). Besides, the scenario in Melvin and Peiers Melvin (2003) does not explain why volatility would persist within the markets for a relatively long period (i.e., over a week). In this chapter, I offer a new explanation for volatility persistence based on the main findings of Wang and Yang (2017) who attribute the time-varying volatility persistence to the changing overall state of the market, as captured by daily return and volatility.[25] Specifically, unlike the previous literature which focuses mainly on the exogenous information arrivals (i.e. the release of macroeconomic announcements) which result in a rippling of trading activity and autocorrelated volatility, I explore the volatility persistence based on information flows and provide new explanations of the economic mechanisms of volatility spillover. For example, on the one hand, large information shocks can draw investors' attention, invoke information searching, and trigger strategic trading, which is consistent with the previous trading-related explanations of volatility spillover. On the other hand, I take a much broader view on the volatility spillovers, namely, a large information shock may take a few days to be priced in, leading to spillover effects across markets even in the absence of new information, while a market with more efficient price discovery absorbs the information shocks quickly and generates less information spillover to other regions, resulting in low volatility spillover. In this chapter, I extend the conditional volatility persistence (CVP) model as proposed in Wang and Yang (2017) in a multi-market setting. Then I explore the role of market state variables in explaining the meteor shower and heat waves effects by utilizing the concept of conditional volatility persistence which is also closely related to the GARCH-family models (Engle, 1982; Bollerslev, 1986), and therefore provide a deeper understanding of the mechanisms underlying volatility persistence. Interestingly, I find that the CVP is the dominant channel linking each region's market conditions to the future volatility.

In sum, I tackle the question whether the volatility spillover in the FX market is better described as "meteor showers" or "heat waves" effect using intraday data

[25] For example, Wang and Yang (2017) propose three potential mechanisms that would probably lead to volatility persistence, including the endogenous/exogeneous information flow, the persistence of information processing, and uninformed trading, such as portfolio adjustments in response to information shocks.

for AUD, GBP, EUR and JPY, all against USD, covering a relatively long period of January 1999 (January 2000 for EUR) to December 2013. Compared with earlier studies, this chapter extends their analyses by reconsidering the economic mechanism of volatility spillovers in the foreign exchange market (i.e. meteor showers and heat waves effects). To my best knowledge, this is the first comprehensive study on the mechanisms of volatility spillover effects, which sheds light on the volatility forecasting based on time-varying volatility persistence. I also fill the gap between the literature on news-related and trading-based explanations of volatility spillover by emphasizing the role of conditional volatility persistence in relating each region's market states to future volatility persistence. Interestingly, I find that volatility persistence varies daily with market state variables and higher return is generally associated with greater volatility persistence, while higher volatility leads to less volatility persistence. Furthermore, considering the fact that daily volatility often has an information flow interpretation (Andersen, 1996), I utilize the variance ratio as a measure of price discovery (Su and Zhang, 2018; Gau and Wu, 2017), and find that the price discovery plays a key role in determining future volatility persistence. The model has practical implications as well. For example, models incorporating these features significantly improve volatility forecasts and generate moderate economic gains accordingly (Su, 2017). The major findings can be summarized as following:

(i) I confirm the presence of meteor showers and heat waves effects, while the magnitude of meteor showers effects has been increasing rapidly. By now, the relative importance of meteor showers effect has predominated over that of heat waves (for example, 70% and 30% on average for meteor shower and heat waves effects respectively).

(ii) I find that volatility spillover (i.e. meteor showers and heat waves effects) increases with information shocks as proxied by positive and negative returns, while decreases with daily information flows measured by realized variance and/or the variance ratio.

(iii) By utilizing the Shapley-Owen R^2 decomposition approach in the HAR-based CVP model, I find that estimated CVP explains large portions of the variations in future volatility. Namely, the Shapley value of the group of market state variables accounts for around 60% of the total R^2 on average for the exchange rates of AUD/USD, GBP/USD, EUR/USD, and USD/JPY. Therefore, the CVP is the dominant channel linking changing market states of each region to future volatility, to which similar results have been obtained in Wang and Yang (2017). Furthermore, the CVP model which calibrates future volatility persistence conditionally on changing market states achieves better forecasting performance with regards to loss values.

3.3. Data description and variable construction

3.3.1. Data Description

The primary data source is Thomson Reuters Tick History (TRTH) maintained by the Securities Industry Research Centre of Asia-Pacific (SIRCA), a leading financial services research hub in Australia. The intraday data for AUD/USD, GBP/USD and USD/JPY spans from 1 January 1999 to 31 December 2013, while the data for EUR/ USD isn't available until 1 January 2000.[26] The four currencies I use in this chapter are among the most actively traded currencies and account for more than 50% of the globe FX trading (Bank for International Settlements, 2013). The dataset includes firm quotes (i.e. bid and ask prices), rather than the indicative quotes as used in the previous studies (i.e. Melvin and Peiers Melvin, 2003), the time when a new quote is posted, trading prices, and the time of trading rounded to the millisecond. Following other studies such as Bollerslev and Domowitz (1993), I exclude weekends, because of thin and inconsistent trading. I define weekends as extending from 22:00 GMT Friday evening (the end of day trading in New York) until 22:00 GMT Sunday evening (the commencement of morning trading session in Sydney). In consistent with Wang and Yang (2011), I remove days with large time gaps (i.e. over four hours) in quote arrival, which could be the result of technical issues or public holidays. To mitigate the impact of extremely high

[26] To remove erroneous data, I use the dataset for EUR starting from January 2001 in our robustness analysis.

volatility on volatility dependence, I also winsorize the data and replace the highest 1% of the realized variances with their nearest observations.

To examine the cross-region volatility spillovers, I divide a 24-hour trading day into 4 non-overlapping trading sessions in the same way as in Table 2.1 of Chapter 2. Namely, a 24-hour calendar day is divided into four trading segments: the first segment is the Asian market when major financial centres in Asia-Pacific operate (i.e. Sydney, Tokyo, Hong Kong SAR, and Singapore), the second segment is the European market which covers most of the trading hours in London, and other major financial cities in Europe (i.e. Frankfurt, Amsterdam, Oslo, and Zurich, etc.). The third segment pertains to the overlapping two to three hours of London afternoon trading and New York early morning trading (also known as the LNY market). The last one is labelled the US market which covers trading hours in the U.S. excluding the LNY period. In general, the trading hours span from 9 am to 4 pm local time, while the opening and closing times of the local market will be shifted by one hour ahead immediately following the implementation of DST.

3.3.2. Integrated variance

The main approach to measuring volatility in this thesis is based on the fast-expanding literature on integrated variance as introduced in Chapter 2. Namely, the search for an adequate framework for the estimation and prediction of the conditional variance of financial asset returns has led to the analysis of high frequency intraday data. For example, Merton (1980) note that the variance over a fixed interval can be estimated arbitrarily, although accurately, as the sum of squared realizations, provided that the data are available at a sufficiently high sampling frequency. More recently, Andersen and Bollerslev (1998) show that ex post daily exchange rate volatility is best measured by aggregating 288 squared five-minute returns (see McAleer and Medeiros (2008) for a very useful survey on this issue). Following the work of Andersen and Bolleslev (1998), Andersen et al. (2001) introduce the concept of realised volatility which is the technique that uses the intra-day high frequency asset price data to construct the model-free estimates of daily asset price volatility. Namely, I propose the observed price $P_{i,t}$ of market *i* on day *t* as follows:

$$P_{i,t} = X_{i,t} + \varepsilon_{i,t} \tag{3.1}$$

where $X_{i,t}$ is a latent (unobservable) true price process, and $\varepsilon_{i,t}$ are independent noise around the true price process.

Note that the realised volatility is approximately free of measurement error only under certain conditions and a vast amount of empirical studies suggests that the realized volatility estimator is not robust when the sampling interval is too small.[27] The main explanation for this phenomenon is a vast array of issues collectively known as market microstructure, including the existence of the bid–ask bounce, non-synchronous trading, price discreteness, etc. (Zhang et al., 2015). Since the efficient price and the noise term components in the integrated variance are not observable, the existing studies have proposed alternative approaches to reducing the impact of the noise term on the estimation of the integrated variance (see, for example, Ait-Sahalia, Mykland and Zhang, 2005; Bandi and Russell, 2008; Barndorff-Nielsen et al., 2008). Among the alternative measures, the Two-scale Realized Variance (TSRV) estimator as introduced in Section 2.2 of Chapter 2 proves to be the first consistent estimator of the integrated variance (Zhang et al., 2005; Barndorff-Nielsen et al., 2008).

Specifically, a trading session *i* is divided into *n* sampling intervals. For each interval, I assume a Brownian semi-martingale process for the log-price $P_{i,t}$ of market *i* on day *t*:

$$dP_{i,t} = \mu_{i,t}dt + \sigma_{i,t}dB_t \tag{3.2}$$

where B_t is a standard Brownian motion process, $\sigma_{i,t}$ is the spot stochastic volatility, and $\mu_{i,t}$ is the drift coefficient.

[27] Several issues such as large bias in the estimate and non-robustness to changes in the sampling interval have been reported in a series of studies (see, e.g., Brown 1990; Hansen and Lunde, 2004; Zhang et al., 2005; Bandi and Russell, 2004).

Here, I am interested in estimating the sum of diffusion variation (i.e., integrated variance). The realized variance $\mathrm{RV}_{\mathrm{i,t}} = \sum_{\mathrm{s=1}}^{\mathrm{m}} \mathrm{r}_{\mathrm{i,t,s}}^{2}$ is calculated as the sum of squared log returns sampled over high-frequency intervals *s* = 1, 2, …, m. Following Andersen et al. (2005), I aggregate tick-by-tick data to 5-minute intervals which strikes a trade-off between sampling at a high enough frequency to exploit the full information, but low enough to have sufficiently many transactions to avoid biasing the autocorrelations towards zero due to a large number of consecutive zero returns (Wang and Yang, 2011).

To reduce or remove the impact of the bias induced by microstructure noise (i.e. bid/ask bounce, non-synchronous trading, price discreteness, etc.) on the estimation of integrated variance, Zhang et al. (2005) show that the TSRV appears to be an efficient estimator of the integrated variance. Furthermore, Barndorff-Nielsen et al. (2008) show that TSRV estimator can be expressed as a non-parametric estimator based on averaging and subsampling as follows:

$$\mathrm{TSRV}_{\mathrm{i,t}} = \frac{1}{\mathrm{k}} \sum_{\mathrm{j=1}}^{\mathrm{k}} \mathrm{RV}_{\mathrm{i,t,j}} - \frac{[\mathrm{m_i - k + 1}]}{\mathrm{m_i k}} \mathrm{RV}_{\mathrm{i,t}} \tag{3.3}$$

where $\mathrm{RV}_{\mathrm{i,t}}$ is the realized variance for market *i* on day *t* calculated from intraday data sampled at high frequency (i.e. 1-second interval). m_i is the total number of sampling intervals during the trading hours of market *i* and *k* is the number of sub-grids at 1-second intervals. For example, k equals 300 if the 1-second time series are sampled at 5-minute intervals.

Following Hasbrouck (1995) who claims that the information flow can be measured by the variation in the efficient price, Wang and Yang (2011) modify that the information share of a particular region can be calculated as its share of the total variance of the efficient price in a trading day. That is,

$$IS_{\ i,t} = \frac{Var(\Delta m_{i,t})}{Var(\Delta m_t)} = \frac{Var(\Delta m_{i,t})}{\sum_{i=1}^{4} Var(\Delta m_{i,t})} \tag{3.4}$$

where $\Delta m_{i,t} = m_{i,t} - m_{i-1,t}$ is the change in the efficient price in market i (for i = Asia, Europe, LNY, and US). Andersen and Benzoni (2008) show that the conditional variance of the efficient price over a period can be measured by the integrated variance when the efficient price is treated as a continuous time process, that is, when the sampling interval $M_i \rightarrow \infty$, the sum of squared $\Delta m_{i,t}$ converges to the integrated variance in market i on day t. However, if we use the usual formula of realized variance $RV_{i,t} = \sum_{s=1}^{M_i} r_{i,t,s}^2$ to estimate the variance of $\Delta m_{i,t}$, we will obtain a biased and inconsistent estimator for the integrated variance in the presence of noise term, better known as the microstructure noise.

To remove the impact of noise term on the estimation of the integrated variance, many alternative realized variance measures have been proposed. Among these approaches, the two-scale realized variance (TSRV) of Zhang et al. (2005) is the first consistent estimator of the integrated variance (Gau and Wu, 2017). With its popularity and simplicity, I also adopt the TSRV estimator to proxy for information flow as in Wang and Yang (2011), Chai, Lee, and Wang (2015), and Gau and Wu (2017).

In fact, there is a large number of variants of RVs, for example, the threshold bipower variance (BPV) as proposed by Corsi et al. (2010) which corrects for volatility jumps, among many others.[28] For the robustness checks, I calculate the BPVs for the exchange rates of AUD, GBP, EUR, and JPY. The empirical results suggest that these measures of variance (i.e. RV, TSRV, and BPV) are highly correlated, the correlation coefficient centres around 0.93 – 0.97. The table below presents the correlation coefficients of RVs using different realized variance measures. Based on the TSRV and BPV, I re-estimate the benchmark HAR model. The empirical results are omitted here for the sake of brevity. However, it suggests that these changes do not affect the main conclusions of long-memory in volatility

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[28] More specifically, the realized Bipower Variation (BPV) was originally proposed by Andersen, et al. (2007) which approximates the continuous component of realized variance as following:

$$\mathrm{BPV}_{i,t} = \mu_1^{-2} \sum_{j=2}^{m_i} |r_{i,t,j}||r_{i,t,j-1}|$$

where m_i is the total number of intraday sampling intervals in market *i*, $|r_{i,t,j}|$ and $|r_{i,t,j-1}|$ are the absolute values of intraday returns over the adjacent sampling intervals *j* and *j-1*. $\mu_1^{-2} \equiv \sqrt{2/\pi} \approx 0.79788$, which denotes the mean of the absolute value of the standard normally distributed random variable *Z*. Barndorff-Nielsen and Shephard (2004) show that when sampled at high frequency, i.e. $m \rightarrow \infty$, the realized Bipower Variation (BPV) converges to the continuous component of the continuous-time jump-diffusion process.

and the dominant role of market state variables in determining volatility persistence.

Table 3.1: Correlations among Different RV Measures

RV, BPV, and TSRV refer to realized variance, bipower variation, and two-scale realized variance respectively. Corr is the correlation coefficient between corresponding variables. The asterisk ***indicates significance at the 1% level.

	Corr(RV, BPV)	Corr(RV, TSRV)	Corr(BPV, TSRV)
Realized Variance	0.968***	0.961***	0.927***

3.3.3. Summary statistics of relevant variables

The daily RV for AUD, GBP, EUR, and JPY are plotted in Figure 3.1. As shown in the figure below, there is strong evidence of commonality in volatility among the four currencies. The volatility spikes during the period of global financial crisis of 2008 – 2009. Besides, the volatility of GBP and EUR surges during the European sovereign debt crisis around late 2010. The results here are generally consistent with Bollerslev et al. (2017) who calculate the daily volatility for nine currencies spanning from January 2000 to September 2014 and confirm that the AUD has the highest daily RV on average (11.8%), while GBP has the smallest (8.3%).

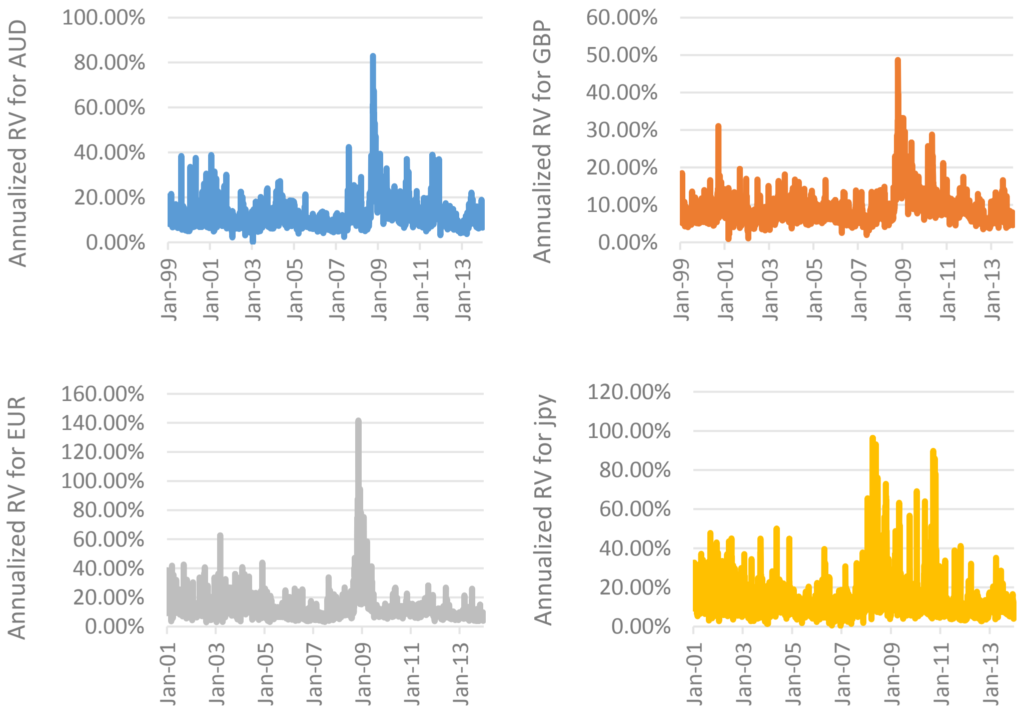

Figure 3.1: Daily RV of AUD, GBP, EUR, and JPY

Table 3.2 reports the summary statistics of the realized variance and return. The annualized RV is 11.8% for AUD, 8.8% for GBP, 9.8% for EUR, and 10.6% for JPY, among which the GBP has the lowest volatility, while the AUD and JPY have higher volatilities and weaker autocorrelations than the other currencies. For the JPY and EUR which are mostly traded on another electronic trading platform – EBS (the Electronic Broking Services), they exhibit more frequent volatility jumps on the TRTH platform where the data is sourced, particularly during periods of turmoil, and therefore leads to reduced autocorrelations. The medians of RV are much lower than means due to a small number of high RV days. Compared to returns, the realized variance has much stronger autocorrelations, which is consistent with the previous literature on long-memory in volatility (Engle, 1982; Andersen and Bollerslev, 1998; Fleming and Kirby, 2011; among many others). In the last column, it reports the daily correlations across relevant variables which suggest that RV is negatively correlated with contemporaneous return.

Table 3.2: Summary Statistics

Q_{LB} (5) is the Ljung-Box Q statistic at 5 lags. Corr is the correlation coefficient between Return and RV. The asterisk * indicates significance at the 5% level.

	Mean	Median	St Dev	Skew	Kurt	Min	Max	$Q_{LB}(5)$	Corr
AUD									
Return	.0002	.0003	.0082	-.3572	7.213	-.0733	.0737	2.399	-.0667*
RV	.7076	.4648	.8265	4.001	19.48	.1063	5.946	9,800*	
GBP									
Return	.0002	.0002	.0057	-.2158	2.190	-.0350	.0299	2.461	-.0419*
RV	.3683	.2658	.3635	3.535	14.51	.0666	2.428	9,364*	
EUR									
Return	.0002	.0002	.0065	.4678	5.938	-.0305	.0693	2.214	-.0442*
RV	.9537	.4900	1.486	4.493	24.41	.0793	11.23	5,029*	
JPY									
Return	-.0001	.0000	.0066	-.3655	4.132	-.0488	.0365	3.888	-.0621*
RV	1.346	.5892	2.486	4.561	23.84	.0522	17.85	2,259*	

3.4. Volatility spillover in the FX market

3.4.1. Meteor showers and heat waves effects

To capture the volatility impacts from heterogeneous investors with different trading horizons, Corsi (2009) argues that investors can be broadly classified as trading at daily, weekly, and monthly frequencies and proposes a heterogeneous autoregressive (HAR) model that examines differential role of three volatility components: the daily volatility $\mathrm{RV}_{t,D}$, weekly volatility $\mathrm{RV}_{t,W}$, and monthly volatility $\mathrm{RV}_{t,M}$ respectively. The HAR model has been applied extensively to different financial markets, such as equity market (Andersen, Bollerslev, and Diebold, 2007; Forsberg and Ghysels, 2007; Bollerslev et al., 2017), gold market (Chai et al., 2015), and foreign exchange market (Wang and Yang, 2009; Wang and Yang, 2017). In fact, Bollerslev et al. (2017) comments that the HAR model has become "somewhat of a benchmark in the financial econometrics literature for judging other RV–based forecasting procedures." In this chapter, I utilize a modified heterogeneous autoregressive (HAR) model to capture the dynamic patterns of volatility spillovers in four trading segments as I defined earlier.

To simplify the notations, I denote $RV_{\mathrm{i,t}}$ by $V_{\mathrm{i,t}}$ for i = A (Asia), E (Europe), L (London/New York) and U (US). Because volatilities are persistent, lagged volatilities beyond one day are represented by weekly heat waves effect, that is, the average volatility of market *i* over lagged 2 to 5 days, $\mathrm{HW}_{W,t-1} = \frac{1}{4}\sum_{\mathrm{k=2}}^{5} \mathrm{V}_{\mathrm{i,t-k}}$ and monthly heat waves effect, i.e. average volatility of market *i* over lagged 6 to 22 days, $\mathrm{HW}_{M,t-1} = \frac{1}{17}\sum_{\mathrm{k=6}}^{22} \mathrm{V}_{\mathrm{i,t-k}}$. The weekly and monthly meteor showers effects can be defined similarly, which are average volatility of market *j* ($j \neq i$) over lagged 2 to 5 days, $\mathrm{MS}_{W,t-1} = \frac{1}{4}\sum_{\mathrm{k=2}}^{5} \mathrm{V}_{\mathrm{j,t-k}}$, and over lagged 6 to 22 days, $\mathrm{MS}_{M,t-1} = \frac{1}{17}\sum_{\mathrm{k=6}}^{22} \mathrm{V}_{\mathrm{j,t-k}}$, respectively. Thus, the dynamic volatility spillover model can be written as follows:

$$\mathrm{V}_{i,t} = \alpha_{i,t} + \beta_{\mathrm{i,D}}^{\mathrm{HW}} V_{i,t-1} + \sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta_{\mathrm{i,j,D}}^{\mathrm{MS}} \mathrm{V}_{\mathrm{j,t-1}}$$

$$+ \beta_{\mathrm{i,W}}^{\mathrm{HW}} \mathrm{HW}_{i,t-1,W} + \sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta_{\mathrm{i,j,W}}^{\mathrm{MS}} \mathrm{MS}_{i,t-1,W}$$

$$+ \beta_{\mathrm{i,M}}^{\mathrm{HW}} \mathrm{HW}_{i,t-1,M} + \sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta_{\mathrm{i,j,M}}^{\mathrm{MS}} \mathrm{MS}_{i,t-1,M} + \varepsilon_{i,t}$$

(3.5)

where $V_{i,t}$ is a proxy for the integrated variance for market *i* on day *t*. The coefficients $\beta_{i,W}^{HW}$, $\beta_{i,M}^{HW}$, $\beta_{i,W}^{MS}$, and $\beta_{i,M}^{MS}$ capture the long-run dependence (i.e. weekly and monthly) of volatility on its own lags and lagged RVs of other regions respectively, while the short-run dependence is typically represented by the coefficients of one-day lagged volatility $V_{i,t-1}$ $(i = A, E, L, and\ U)$. The heat waves effect is represented here by the coefficient of its own lagged daily volatility $\beta_{\mathrm{i,D}}^{\mathrm{HW}}$, while the coefficients $\beta_{\mathrm{i,j,D}}^{\mathrm{MS}}$, which measure the short-run volatility spillover from market *j* to market *i*, serving as a proxy for meteor shower effects. Note that the subscript $\mathrm{t} - 1$ represents the markets immediately before market *i*, which may be on the same day as market *i*. For example, when *i* = Asia, $V_{i,t-1}$ $(i = A, E, L, and\ U)$ are volatilities from the previous day. However, when *i* = U.S., which is the last trading session on day *t*, $V_{i,t-1}$ $(i = A, E, L)$ are from the same day *t* as US market with only the lagged U.S. volatility $V_{i,t-1}$ $(i = U)$ from the previous day. This model is useful for modelling the short-run volatility spillover effects while taking account of long memory in volatility. The error term is assumed to be normally distributed and the model is estimated by OLS with the Newey-West robust standard errors (Chai et al., 2015).

Since I define the four trading sessions such that they open and close sequentially, the information set available at the open of one trading session contains all the trading information revealed during the previous sessions. Therefore, some markets may possess more information simply because of its long trading hours. To control for the different trading hours, the realized variances are normalized by dividing them by the squared root of the number of 5-minute intervals in each session. All the results are robust to the time intervals I use, and the volatility measures I utilize. Figure 3.2 plots the sample autocorrelation function (ACF) of daily realized variances by trading sessions for AUD/USD, GBP/USD, EUR/USD, and USD/JPY. It suggests that the realized volatilities in all markets are highly persistent except for JPY which exhibits frequent volatility jumps and reduces autocorrelations of realized variance.

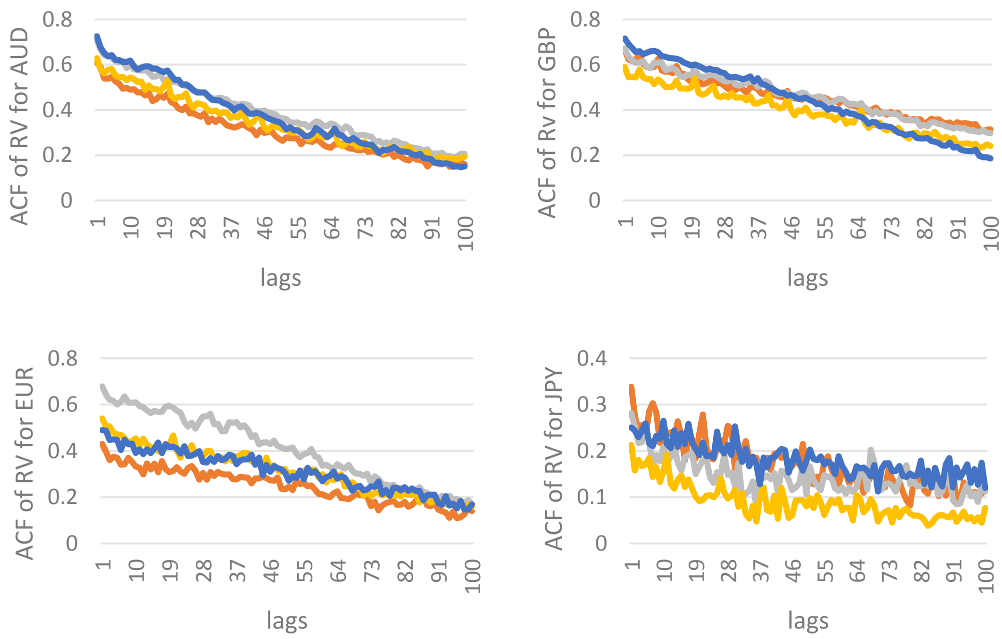

Figure 3.2: Autocorrelation of RVs by Trading Sessions

Table 3.3 reports coefficients and accompanying heteroskedasticity- and autocorrelation- consistent (HAC) standard errors. Namely, for each session, the coefficient of spillover effects from lagged own market (i.e., the heat waves effects, HW) come first, followed by the sum of coefficients representing spillover effects from other segments (i.e., the meteor showers effects, MS). The null hypothesis for the heat wave effect is that each regional proxy for information (i.e. realized variance) depends on its own past proxy for information, while the null hypothesis for the meteor showers effect is that each regional proxy for information depends on other regions' past proxies (Cai, Howorka and Wongswan, 2008). All of the coefficients are significantly different from zero, suggesting the presence of both heat waves and meteor showers effects. However, because the regressors are highly correlated, individual coefficients are often estimated imprecisely, so it should be interpreted with caution (Lahaye and Neely, 2016).

Interestingly, as shown in Appendix E of sub-period analysis, the adjusted R^2 increases for the regressions over the GFC period, to what a similar pattern has been found in Wang and Yang (2017). Besides, the magnitudes of the meteor shower and heat waves effects become larger during the global financial crisis period (2007 - 2009). For example, the coefficients of meteor showers and heat waves effects are significantly larger than those estimated in other periods.

The findings of increased volatility spillovers during the GFC period is consistent with the Conditional Volatility Persistence (CVP) model where the future volatility and its spillover varies with the market states. For example, a potential channel of risk contagion is through the more fundamental parameters among market participants, including changes in risk aversion and herding behaviour (Dungey et al., 2006; W. Xiong, 2012), and the findings of increased volatility spillover during GFC period could be attributed to the deteriorating market state (i.e. extremely high volatility and negative returns) as a result of large exogenous information shocks, increased risk aversion, and the herding behaviour of investors.

Table 3.3: Heat Waves and Meteor Showers: Full Sample

This table reports the daily persistence coefficients of the following model:

$$\mathrm{V}_{i,t} = \alpha_{i,t} + \beta^{\mathrm{HW}}_{\mathrm{i,D}} V_{i,t-1} + \sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,D}} \mathrm{V}_{\mathrm{j,t-1}} + \beta^{\mathrm{HW}}_{\mathrm{i,W}} \mathrm{HW}_{i,t-1,W} + \sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,W}} \mathrm{MS}_{i,t-1,W} + \beta^{\mathrm{HW}}_{\mathrm{i,M}} \mathrm{HW}_{i,t-1,M} + \sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,M}} \mathrm{MS}_{i,t-1,M}$$

where i = Asia (A), Europe (E), London/NYC (L), and US (U). *HW* stands for daily heat waves effect as proxied by $\beta^{\mathrm{HW}}_{\mathrm{i,D}}$, while *MS* stands for meteor shower effect $\sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,D}}$ (i.e., the sum of volatility spillover effects from all other trading sessions). $\beta^{\mathrm{HW}}_{\mathrm{i,W}}$, $\beta^{\mathrm{HW}}_{\mathrm{i,M}}$ are weekly and monthly heat waves effects, while $\beta^{\mathrm{MS}}_{\mathrm{i,j,W}}$, $\beta^{\mathrm{MS}}_{\mathrm{i,j,M}}$ are the weekly and monthly meteor shower effects respectively. The t-statistics are calculated based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. The asterisks ***, **, * indicate significance at 1%, 5%, and 10% respectively.

	Asia		Europe		London/NYC		US	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
AUD								
HW	0.1544***	6.14	0.1116***	4.64	0.0783***	3.57	0.1733***	5.73
MS	0.4920***	9.44	0.3687***	12.47	0.5206***	13.39	0.5338***	9.13
$\bar{R}^2$	.5625		.6678		.6089		.6782	
GBP								
HW	0.2220***	6.18	0.1326***	5.72	0.0865***	4.41	0.1517***	4.51
MS	0.4777***	8.98	0.4506***	10.02	0.3471***	11.14	0.3354***	10.25
$\bar{R}^2$	.6447		.6327		.5490		.6697	
EUR								
HW	0.0983***	2.74	0.1628***	3.61	0.1136***	3.82	0.0806**	2.40
MS	0.7856***	4.27	0.1642***	4.14	0.3365***	8.34	0.8066***	8.06
$\bar{R}^2$	.3823		.6090		.4911		.4579	
JPY								
HW	0.1179***	2.63	0.0876**	2.52	0.0705**	2.09	0.0614*	1.74
MS	0.4533***	3.33	0.0913***	3.08	0.3014***	8.88	0.5623***	6.93
$\bar{R}^2$	.2360		.2518		.2568		.2983	

3.4.2. Shapley – Owen R^2 decomposition techniques

The magnitudes of the coefficients of meteor shower and heat waves effects as shown in Table 3.3 don't explicitly suggest the relative importance of the corresponding effects (Lahaye and Neely, 2016). For example, the individual coefficient estimates will be conditionally marginal effects that depend on the effects of correlated regressors, not unconditional effects. Therefore, I seek to evaluate the importance of heat waves and meteor showers effects by adopting other methods. In this chapter, I use the Shapley-Owen R^2 measure which has its roots in game theory, Lindeman, Merenda and Gold (1980) then apply the same concepts to decompose goodness-of-fit among regressors and coalitions of regressors in econometrics. In Lahaye and Neely (2016), the authors investigate on the meteor shower and heat waves effects in the EUR and JPY spot rates by utilizing the same method. Namely, the Shapley-Owen R^2 measure of a group of regressors is the average incremental improvement in R^2s for each regressor (or coalition) over all possible permutations of regressors or coalitions of regressors.[29]

The results of Shapley-Owen R^2 values as shown in Table 3.4 suggest that the meteor showers effect contributes more to the total variations in future volatility compared to heat waves over daily, weekly, and monthly horizons respectively, which is consistent with Lahaye and Neely (2014) who investigate on the EUR and JPY spot rates and find that the meteor shower contributes 60% to the total variations in volatility persistence, while heat waves account for the remaining portion. Besides, the heat waves effects are relatively weaker in the LNY market compared to other segments, which is probably due to the fact that the LNY market is more efficient at information incorporation and contributes more to the price discovery with large trading volume and the presence of informed traders, resulting in low volatility spillovers to the future in the local market (Su and Zhang, 2018).

Furthermore, I conduct a subperiod analysis to examine the presence of meteor showers and heat waves effects in different sub-periods using the same techniques of Shapley-Owen R^2 values as before. The adjusted R^2 increases for the regressions over the GFC period, to what a similar pattern has been found in Wang and Yang (2017). Interestingly, I find that the relative importance of meteor showers effect has been increasing rapidly and has surpassed that of heat waves effect as shown in Table 3.5. For example, during the period of 2007 - 2009, the meteor showers effect dominates the volatility spillovers and contributes to around 70% of the total R^2 for AUD, GBP, and EUR respectively. One possible explanation for the dominant meteor showers effect is that the financial markets

[29] For an in-detail demonstration of the Shapley-Owen R^2 method, please refer to Appendix A-2 of Lahaye and Neely (2016).

are becoming increasingly interdependent and interconnected with financial liberalization and market openness. On the other hand, the increasing meteor showers effect can be seen as an indicator of the speeded-up information flow in the FX market and the internationalization of currencies. For example, Evans and Lyons (2002) find strong evidence of a high degree of informational integration in international money markets.

The potential adverse effects of volatility spillover on financial stability, particularly during periods of high uncertainty, is a subject of great importance in the current context of increasing financial integration (Boucher et al., 2016). Interestingly, the results in Table 3.5 suggest that the meteor shower effects become particularly strong on high volatility days (i.e. during the GFC period). High volatility reflects high uncertainty which takes longer to be resolved, while high volatility is generally associated with greater volatility spillovers across regions, an interesting question that is worth exploring in the future.

Table 3.4: Shapley-Owen R^2 Values: Full Sample

This table shows the Shapley-Owen proportion of the total R^2s in four trading sessions (Asia, Europe, LNY, and US). The calculation is based on Eq. (3.5). Namely, there are 2 groups of coefficients: the heat wave (*HW*) contribution, which includes the daily, weekly, and monthly own lags of RV, and the meteor shower (*MS*) counterparts. Normal and High stands for the days with normal and extreme volatilities respectively as defined in Section 3.4.2. The groups have no intersection and include all non-deterministic regressors, so the proportions for each intraday period sum to one.

		Asia	Europe	LNY	US	Average
AUD						
Daily	HW	0.10	0.09	0.08	0.10	0.09
	MS	0.26	0.25	0.27	0.24	0.26
Weekly	HW	0.14	0.13	0.16	0.10	0.13
	MS	0.23	0.22	0.22	0.23	0.22
Monthly	HW	0.09	0.10	0.09	0.10	0.09
	MS	0.19	0.21	0.19	0.22	0.20
Total	HW	0.32	0.32	0.22	0.31	0.32
	MS	0.68	0.68	0.78	0.69	0.68
GBP						
Daily	HW	0.12	0.08	0.07	0.10	0.09
	MS	0.25	0.23	0.25	0.25	0.24
Weekly	HW	0.12	0.11	0.10	0.09	0.11
	MS	0.24	0.24	0.25	0.25	0.25
Monthly	HW	0.07	0.09	0.09	0.08	0.08
	MS	0.21	0.24	0.24	0.23	0.23
Total	HW	0.30	0.29	0.26	0.27	0.28
	MS	0.70	0.71	0.74	0.73	0.72
EUR						
Daily	HW	0.08	0.11	0.09	0.07	0.09
	MS	0.24	0.26	0.25	0.25	0.25
Weekly	HW	0.16	0.06	0.17	0.10	0.12
	MS	0.22	0.29	0.21	0.24	0.24
Monthly	HW	0.04	0.04	0.06	0.10	0.06
	MS	0.25	0.25	0.22	0.24	0.24
Total	HW	0.28	0.21	0.22	0.27	0.27
	MS	0.72	0.79	0.78	0.73	0.73
JPY						
Daily	HW	0.13	0.07	0.04	0.03	0.07
	MS	0.24	0.19	0.12	0.30	0.21
Weekly	HW	0.12	0.34	0.51	0.20	0.30
	MS	0.26	0.20	0.12	0.23	0.20
Monthly	HW	0.02	0.04	0.11	0.06	0.06
	MS	0.24	0.15	0.10	0.18	0.17
Total	HW	0.26	0.46	0.33	0.29	0.42
	MS	0.74	0.54	0.67	0.71	0.58

Table 3.5: Shapley-Owen R^2 Values: Sub-periods

This table shows the Shapley-Owen proportion of the total R^2s in four trading sessions (i.e., Asia, Europe, LNY, and US), for groups of coefficients in the HAR model where RV is predicted by lagged RVs, in different sub-periods. There are 2 groups of coefficients: the heat waves (*HW*) contribution, which includes the daily, weekly, and monthly components of own lags of RV, and the meteor shower (*MS*) counterparts. The groups have no intersection and include all non-deterministic regressors, so the proportions of HW and MS effects for each trading session sum to one.

	Asia	Europe	London/NYC	US	Average
AUD					
1999 – 2006					
HW	0.49	0.47	0.40	0.54	0.48
MS	0.51	0.53	0.60	0.46	0.52
2007 – 2009					
HW	0.34	0.34	0.33	0.30	0.33
MS	0.66	0.66	0.67	0.70	0.67
2010 – 2013					
HW	0.31	0.25	0.38	0.50	0.36
MS	0.69	0.75	0.62	0.50	0.64
GBP					
1999 – 2006					
HW	0.35	0.42	0.27	0.47	0.38
MS	0.65	0.58	0.73	0.53	0.62
2007 – 2009					
HW	0.35	0.29	0.27	0.27	0.30
MS	0.65	0.71	0.73	0.73	0.70
2010 – 2013					
HW	0.37	0.39	0.34	0.36	0.37
MS	0.63	0.61	0.66	0.64	0.63
EUR					
2000 - 2006					
HW	0.42	0.37	0.49	0.42	0.43
MS	0.58	0.63	0.51	0.58	0.57
2007 – 2009					
HW	0.29	0.22	0.30	0.26	0.27
MS	0.71	0.78	0.70	0.74	0.73
2010 - 2013					
HW	0.30	0.25	0.40	0.39	0.34
MS	0.70	0.75	0.60	0.61	0.66
JPY					
1999 - 2006					
HW	0.72	0.57	0.68	0.34	0.58
MS	0.28	0.43	0.32	0.66	0.42
2007 – 2009					
HW	0.17	0.63	0.71	0.61	0.53
MS	0.83	0.37	0.29	0.39	0.47
2010 - 2013					
HW	0.22	0.53	0.69	0.18	0.40
MS	0.78	0.47	0.31	0.82	0.60

3.5. Determinants of Volatility Spillover

3.5.1. Conditional Volatility Persistence Model (CVP)

As stated earlier, I propose that volatility persistence is driven by the nature, precision, and volume of both exogenous and endogenous information arrivals. It is also driven by uninformed trading such as portfolio adjustments to lagged information shocks. Collectively these mechanisms determine the state of the market, and in turn, volatility persistence. Through the above-mentioned channels, I introduce the Conditional Volatility Persistence (CVP) model as proposed in Wang and Yang (2017), which captures the long memory in volatility while controlling for conditional variables (i.e., return, volatility, and other proxies for trading activities).

Namely, to examine the determinants of volatility spillover, I incorporate time-varying volatility persistence into the HAR model, i.e., the HAR-CVP model. Here, considering that the negative returns are generally associated with greater volatility than positive returns in the equity market (Patton and Sheppard, 2006), and in the FX market (Wang and Yang, 2009), I decompose exchange rate returns into positive and negative returns, and examine their volatility impacts separately. Specifically, I extend the HAR model in a multi-market setting and examine the heterogeneous effects of market state variables in different FX trading sessions as follows:

$$\begin{aligned} RV_{i,t} = {} & \alpha_{i,t} + \beta^{e}_{A,t} RV_{A,t-1} + \beta^{e}_{E,t} RV_{E,t-1} + \beta^{e}_{L,t} RV_{L,t-1} + \beta^{e}_{U,t} RV_{U,t-1} + \beta^{HW}_{i,W} \overline{RV}_{i,t-1,W} + \\ & \textstyle\sum_{j\neq i, j=A}^{U} \beta^{MS}_{i,j,W} \overline{RV}_{j,t-1,W} + \beta^{HW}_{i,M} \overline{RV}_{i,t-1,M} + \sum_{j\neq i, j=A}^{U} \beta^{MS}_{i,j,M} \overline{RV}_{j,t-1,M} + \varepsilon_{i,t} \end{aligned} \tag{3.6}$$

where $RV_{i,t}$ stands for the realized variance (RV) for market *i* on day *t*. The coefficients of $\beta^{HW}_{i,W}$, $\beta^{HW}_{i,M}$, $\beta^{MS}_{i,j,W}$, and $\beta^{MS}_{i,j,M}$ capture the long-run dependence of volatility on its own lagged market and other markets respectively. Here, the short-run dependence is represented by the time-varying coefficients of one-day lagged volatility $\beta^{e}_{j,t}(i = A, E, L, and\ U)$, namely, $\beta^{e}_{j,t} = \beta + \beta^{-} r^{-}_{j,t-1} + \beta^{+} r^{+}_{j,t-1} + \beta^{RV} RV_{j,t-1}$ $(j = A, E, L, and\ U)$ is the conditional volatility spillover from market *j* to market *i* , which depends on the lagged market state variables as defined earlier. The meteor shower effects are defined as the volatility spillovers from other segments $\beta^e_{j,t}$ $(j \neq i)$, while heat waves effects are represented by the volatility persistence within the local segment $\beta^e_{j,t}$ $(j = i)$. The use of return and volatility as the state variables is in the same spirit as Campbell and Hentschel (1992) and Wu (2001) who use dividend shock and dividend volatility as the state variables to explain the asymmetric return impact on volatility. I also test the impacts of other market state variables on volatility persistence, e.g. liquidity, trading volume, etc., in the robustness section.

Furthermore, to relate the volatility spillovers model to the information-based explanations, I explore the impacts of price discovery on the volatility spillover. Namely, considering the fact that daily volatility often has an information flow interpretation (Andersen, 1996) and a popular measure for price discovery is the variance of the random-walk return component (Hasbrouck, 1995), I utilize the information share (i.e. realized variance ratio) as a measure of price discovery (Gau and Wu, 2017; Su and Zhang, 2018).[30] The empirical results in Wang and Yang (2017) suggest that the price discovery plays a key role in determining the time-varying volatility persistence, and more price discovery increases the information content of quoted price and reduces the spillovers of uncertainty over time. Thus, I utilize the information share as a proxy for price discovery process and explicitly explore its role in volatility spillovers in different trading sessions. In fact, the information interpretation of daily volatility is supported by the MDH theory, e.g. Andersen (1996), and the microstructure literature where price discovery is measured as the variance of the random walk component of return, e.g. Hasbrouck (1995). The summary statistics of information share as shown in Appendix G suggest that the European market contributes the most to the price discovery, while the LNY market dominates the price discovery process on a per hour basis.[31]

[30] Using volatility to proxy for information has some advantages over using returns (Cai, et al., 2008). Firstly, the volatility is more persistent and therefore inherently easier to forecast. Furthermore, volatility is more closely related to information. For example, Wang and Yang (2017) argue that even though the absolute return has been used in many studies as a proxy for return standard deviation, the absolute return is not a robust measure of return uncertainty.

[31] The high information share of the LNY market is also possibly attributed to the timing of release of macroeconomic news announcements on the U.S. economy as the market becomes relatively

To conserve space, I don't report all the coefficient estimates from the four-market equations. Instead I present the Wald statistics and the corresponding p-values. As reported in Column (1) of Panel A of Table 3.6, the null hypotheses that $\beta^{-} = \beta^{+} = \beta^{RV} = 0$ are resoundingly rejected at the 5% significance level, which confirm the explanatory power of market state variable in explaining volatility spillovers. Furthermore, the null hypotheses that $\beta^{-} = \beta^{+} = \beta^{RV} = \beta^{IS} = 0$ are examined by adding the information share as one of market state variables in the conditional volatility persistence $\beta_{j,t}^{e}$ as documented in Eq. (3.6). The empirical results in Panel A of Table 3.6 can be interpreted as following: Firstly, comparing the overall explanatory power of models as shown in Table 3.3 and Table 3.6, the adjusted R-squared are in favour of the extended HAR model specification over the regular one which ignores the role of changing market states in explaining volatility persistence. Secondly, the inclusion of variance ratio increases the model performance and deepens our understanding of the economic mechanisms of volatility spillovers in the FX market (i.e. either the adjusted R-squared or the Wald-statistics suggests the superior performance when including the information share). Furthermore, I report a summary of the sign and significance of CVP variables. Namely, Panel B of Table 3.6 reports the number of significantly positive (negative) coefficients of market state variables (i.e., including the constant, positive\negative return, volatility, and information share) which presents evidence on individual coefficients without reporting all coefficients. The result suggests that most of the coefficients of negative (positive) return are negatively (positively) significant, which is consistent with the previous findings on asymmetric effect, while the coefficients of RV are generally negatively significant, suggesting a reduction in volatility spillover on days of high volatility. Furthermore, most of the coefficients of information share are negatively significant, suggesting that the price discovery has a dampening effect on the volatility spillover. With high information shares, the market contributes more to the price discovery process, which helps in reducing the uncertainty and mitigating the propagation

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more efficient in reflecting information when more macro news announcements are released during its trading hours (Su and Zhang, 2018). The gain in information share when public information is released is also consistent with the findings of Jiang, et al. (2014).

of volatility. Besides, including information share as the market state variable slightly weakens the statistical significance of other market state variable and decreases the volatility persistence as measured by the coefficient β_j^0. Overall, the inclusion of information share significantly improves the model performance and provides information-based explanations by relating the time-varying volatility spillovers in the FX market to the price discovery process.

Furthermore, I explore the differential role of market state variables in predicting the future volatility by utilizing the Shapley-Owen R^2 Decomposition techniques. Namely, I assess the importance of conditional volatility persistence (CVP) by computing the Shapley-Owen values in the HAR-CVP models. Panel C of Table 3.6 reports the Shapley-Owen values of each market state variable in explaining the inter- and intra-regional volatility spillover (i.e. meteor showers and heat waves effects) which confirms the relatively important role of market state variable in predicting the future volatility in different regions. For example, the ratio of Shapley-Owen value of β_0 to the CVP ranges from 39% to 44%, indicating that the conventional measure of volatility persistence in each region, as proxied by β_0, decreases substantially after controlling for the market state variables, while the groups of market state variables contribute to more than half of the explanatory powers in conditional volatility spillover. Overall, the CVP variable has the highest Shapley-Owen R^2 values across all explanatory variables. The Shapley-Owen R^2 values of market state variables sum to around 0.6, suggesting that roughly 60% of the explanatory power of RV_t in the traditional HAR model comes from the omitted CVP variables. Furthermore, the negative return, positive return, volatility, and information share explains around 8%, 7%, 23%, and 20% of the total variations in conditional volatility persistence respectively, among which the volatility and variance ratio explains most of the total variations in time-varying volatility spillover. Besides, negative return plays a slightly more important role than positive return, confirming the weak asymmetric effects as documented earlier. However, for each market state variable, I don’t find their differential roles in explaining the meteor showers and heat waves effects. Overall, the consideration of market state variables significantly depends our understanding of the economic mechanisms of volatility spillover and shed new lights on mathematical techniques for volatility modelling and forecasting.

For robustness check, I also divide the sample into three sub-periods (i.e. 1999/2000 – 2006, 2007 – 2009, and 2010 – 2013). Generally, the coefficients of negative returns are comparable to or slightly larger than those of positive returns in all sub-periods for AUD, GBP, and JPY, while for EUR, the coefficients of negative returns are significantly smaller than the coefficients of positive returns. The coefficients of *RV* and *IS* are mostly negative and significant in the sub-periods, suggesting a reduction in volatility persistence on days of extreme volatility and/or high price discovery.[32] Furthermore, the negative return has played a more important role in determining volatility spillover during the GFC period as most of the coefficients of negative return become significant in the sub-period of 2007 – 2009, which confirms the conjecture of Patton and Sheppard (2015) that persistence comes mostly from the "bad volatility" associated with negative returns. Overall, the empirical results presented suggest the possibility of informational linkages across regions through more fundamental channels such as the endogenous information arrivals and price discovery as the exchange rates incorporating the new information sequentially. For example, Andersen et al. (2003) show that exchange rates incorporate news within 5 minutes, while the exchange rate volatilities increase for a much longer period. In this chapter, I find that the volatility can persist for a relatively long period. However, after controlling for the market state variables including information share, the persistence of volatility within most markets decreases substantially as shown in Panel C of Table 3.6.

[32] For the sake of brevity, I only report a brief summary of the coefficient estimates for the sub-period analysis in Appendix F, however, more detailed results are available from the author upon request.

Table 3.6: Determinants of Conditional Volatility Spillover

This table reports the Wald statistics of the joint significance test for the daily conditioning variables (i.e., negative return, positive return, volatility, and variance ratio) of the following model:

$$RV_{i,t} = \alpha_{i,t} + \beta_{A,t}^{e} RV_{A,t-1} + \beta_{E,t}^{e} RV_{E,t-1} + \beta_{L,t}^{e} RV_{L,t-1} + \beta_{U,t}^{e} RV_{U,t-1} + \beta_{i,W}^{HW} \overline{RV}_{i,t-1,W} + \sum_{j\neq i,j=A}^{U} \beta_{i,j,W}^{MS} \overline{RV}_{j,t-1,W} + \beta_{i,M}^{HW} \overline{RV}_{i,t-1,M} + \sum_{j\neq i,j=A}^{U} \beta_{i,j,M}^{MS} \overline{RV}_{j,t-1,M} + \varepsilon_{i,t}$$

where i = Asia (A), Europe (E), London/New York (L), and US (U) and $\beta_{j,t}^{e} = \beta_j^0 + \beta_j^- r_{j,t-1}^- + \beta_j^+ r_{j,t-1}^+ + \beta_j^{RV} RV_{j,t-1} + \beta_j^{IS} IS_{j,t-1}$. The null hypothesis in Column (1) of Panel A is $H_{0,j}: \beta_j^- = \beta_j^+ = \beta_j^{RV} = 0$, against the alternative hypothesis $H_{1,j}: \beta_j^- \neq 0, \beta_j^+ \neq 0, \beta_j^{RV} \neq 0$. While the null hypothesis in Column (2) is $H_{0,j}: \beta_j^- = \beta_j^+ = \beta_j^{RV} = \beta_j^{IS} = 0$, against the alternative hypothesis $H_{1,j}: \beta_j^- \neq 0, \beta_j^+ \neq 0, \beta_j^{RV} \neq 0, \beta_j^{IS} \neq 0$. The asterisks ***, **, * indicate significance at 1%, 5%, and 10% level respectively. The t-statistics are based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. In Panel B, Sig+ and Sig- present the total number of positively and negatively significant coefficients of each market state variables at 5% significance level respectively. For example, if all the coefficients of positive return r_{t-1}^+ are positively significant in $\beta_{A,t}^{e}$, then sig+ equals 4 for β_r^+ in Asia. In Panel C, it reports the Shapley-Owen values of each market state variable in explaining the inter-regional volatility spillover (i.e. meteor showers effects) and intra-regional volatility spillover (i.e. heat waves effects). In the last column, it reports the ratios of Shapley-Owen values of each market state variables to the total CVP of $\beta_{j,t}^{e}$ (j = A, E, L, U).

Panel A

Wald-test	Asia		Europe		London/New York		US	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
AUD								
H_A	4.26***	3.85***	3.56**	7.30***	2.47*	7.32***	2.57*	1.30
H_E	2.39***	6.66***	15.11***	225.0***	7.32***	53.64***	1.19	50.83***
H_L	5.40***	7.48***	4.83***	3.16**	5.56***	100.1***	16.48***	59.95***
H_U	3.66**	4.17***	11.99***	11.21***	9.27***	5.52***	6.54***	86.06***
R^2_Adj	.5661	.5769	.6832	.7440	.6138	.6915	.6933	.7524
GBP								
H_A	11.69***	7.09***	3.20**	4.38***	7.13***	8.07***	1.67	2.19*
H_E	12.56***	8.84***	15.63***	129.1***	1.56	86.15***	8.01***	21.45***
H_L	6.62***	10.32***	9.68***	11.98***	9.39***	66.91***	0.83	60.83***
H_U	7.91***	7.06***	3.98***	4.84***	5.63***	6.83***	7.12***	48.04***
R^2_Adj	.6577	.6614	.6409	.7050	5543	.6494	.6758	.7195
EUR								
H_A	1.55	1.45	18.23***	32.62***	0.89	4.39***	6.82***	10.12***
H_E	13.10***	8.17***	0.92	141.2***	2.95**	27.95***	13.42***	47.17***
H_L	2.43*	1.72	1.16	2.56**	3.56**	44.30***	29.08***	76.50***
H_U	3.67**	3.03**	7.80***	7.44***	0.74	1.90*	11.45***	146.3***
R^2_Adj	.3930	.3933	.6155	.6759	.4885	.5300	.4809	.6070
JPY								
H_A	10.93***	9.05***	5.00***	8.02***	3.74**	2.68**	5.13***	3.66***
H_E	15.76***	17.73***	17.65***	114.9***	1.16	31.17***	6.53***	27.23***
H_L	7.85***	4.49***	3.52**	0.76	14.33***	65.28***	1.86	16.33***
H_U	5.43***	4.64***	1.63	1.46	5.35***	4.38***	6.80***	208.6***
R^2_Adj	.2682	.2758	.2721	.3619	2669	.3564	.3055	.4794

Panel B

	Asia				Europe				London/New York				US			
	(1)		(2)		(1)		(2)		(1)		(2)		(1)		(2)	
	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-
AUD																
β_0	3	0	3	0	3	0	3	0	3	0	3	0	4	0	4	0
β_r^+	1	0	1	0	2	0	2	0	1	0	1	0	3	0	0	2
β_r^-	0	3	0	1	0	3	0	3	0	3	0	3	0	3	0	2
β_{RV}	0	1	0	1	0	2	0	2	0	1	0	2	0	2	2	1
β_{IS}			0	3			0	3			0	3			0	4
GBP																
β_0	4	0	3	0	3	0	3	0	4	0	3	0	3	0	3	0
β_r^+	2	0	1	0	3	0	2	0	2	0	0	0	2	0	1	1
β_r^-	0	3	0	3	0	3	0	3	0	3	1	2	1	1	0	1
β_{RV}	1	2	1	1	0	2	0	2	1	2	0	1	0	1	0	1
β_{IS}			0	3			0	3			0	4			0	4
EUR																
β_0	3	0	2	0	3	0	3	0	3	0	3	0	3	0	3	0
β_r^+	1	0	0	0	0	1	0	2	1	0	0	1	0	1	2	0
β_r^-	0	1	0	1	0	1	0	1	0	1	0	1	1	0	3	0
β_{RV}	0	1	0	1	0	1	0	1	0	1	0	2	0	2	0	1
β_{IS}			0	1			0	3			0	4			0	3
JPY																
β_0	4	0	2	0	2	0	2	0	4	0	2	0	2	0	2	0
β_r^+	1	0	1	0	0	0	0	0	1	0	0	1	0	1	0	0
β_r^-	0	2	0	2	0	1	1	1	0	2	0	2	0	0	0	1
β_{RV}	0	2	0	3	0	2	0	2	0	2	0	0	0	2	0	1
β_{IS}			0	1			0	1			0	4			0	3

Panel C

		Asia	Europe	LNY	US	β_i/CVP
AUD						
β_r^-	HW	0.02	0.01	0.02	0.02	9.34%
	MS	0.06	0.07	0.06	0.05	
β_r^+	HW	0.02	0.01	0.01	0.01	6.33%
	MS	0.04	0.03	0.05	0.04	
β_{RV}	HW	0.05	0.05	0.04	0.06	26.20%
	MS	0.18	0.15	0.16	0.18	
β_{IS}	HW	0.04	0.02	0.02	0.03	17.47%
	MS	0.09	0.12	0.14	0.12	
β_0	HW	0.07	0.08	0.06	0.08	40.66%
	MS	0.26	0.27	0.29	0.24	
GBP						
β_r^-	HW	0.02	0.02	0.01	0.01	8.72%
	MS	0.06	0.06	0.05	0.05	
β_r^+	HW	0.02	0.01	0.01	0.02	7.48%
	MS	0.04	0.05	0.05	0.04	
β_{RV}	HW	0.06	0.05	0.04	0.06	27.41%
	MS	0.17	0.16	0.16	0.18	
β_{IS}	HW	0.05	0.03	0.02	0.03	17.76%
	MS	0.08	0.11	0.14	0.11	
β_0	HW	0.09	0.08	0.06	0.07	38.63%
	MS	0.21	0.24	0.27	0.22	
EUR						
β_r^-	HW	0.01	0.02	0.01	0.01	6.25%
	MS	0.03	0.04	0.04	0.03	
β_r^+	HW	0.02	0.01	0.01	0.01	8.55%
	MS	0.06	0.04	0.04	0.07	
β_{RV}	HW	0.04	0.06	0.05	0.03	23.03%
	MS	0.12	0.12	0.14	0.14	
β_{IS}	HW	0.04	0.04	0.02	0.02	20.07%
	MS	0.10	0.09	0.12	0.18	
β_0	HW	0.08	0.10	0.08	0.05	42.11%
	MS	0.24	0.19	0.27	0.27	
JPY						
β_r^-	HW	0.04	0.01	0.01	0.01	7.59%
	MS	0.08	0.02	0.04	0.03	
β_r^+	HW	0.01	0.01	0.01	0.01	5.70%
	MS	0.03	0.03	0.04	0.04	
β_{RV}	HW	0.05	0.02	0.01	0.01	16.77%
	MS	0.07	0.09	0.16	0.12	
β_{IS}	HW	0.06	0.02	0.01	0.01	25.95%
	MS	0.08	0.19	0.20	0.25	
β_0	HW	0.08	0.05	0.02	0.02	43.99%
	MS	0.13	0.35	0.41	0.33	

To sum up, the empirical results suggest the dominant role of conditional volatility persistence in linking changing market states to future volatility and its spillover. Importantly, this study makes several contributions to the literature on volatility spillover and information propagation. For example, I confirm that it is not only the exogeneous information arrival (i.e. release of macroeconomic news) that can cause the volatility spillover, but also the endogenous information arrival and information propagation, which probably involves information searching, price discovery, and strategic trading. For a big information shock, it may take a few days, even a few weeks to be fully incorporated into the price, which is capable to induce volatility spillovers even without new incoming information, that is, a significant departure from the previous literature which essentially ignore the role of endogenous information arrival and price discovery in volatility spillover. Last but not least, this study has important practical implications as well. For example, volatility model which explicitly takes into account the characteristics of conditional volatility persistence can achieve superior forecasting performance and therefore generate moderate economic gains (Su, 2017).

3.5.2. Intraday pattern of volatility spillover

In this section, I calculate the magnitudes of daily conditional volatility spillovers as follows: $\widehat{CVP}_{i,t} = \hat{\beta}_0 + \hat{\beta}^{-} r_t^{-} + \hat{\beta}^{+} r_t^{+} + \hat{\beta}^{RV} RV_t + \hat{\beta}^{IS} IS_t$ $(\mathrm{i} = Asia, Europe, LNY, and\ US)$ for different trading sessions. $\widehat{CVP}$ are very high in all markets, particularly during the financial crisis in the second half of 2008. There are a few $\widehat{CVP}$, either larger than one or smaller than 0. The mean and standard deviation of the estimated $\widehat{CVP}$ for each trading session of AUD, GBP, EUR, and JPY are reported in Table 3.7. The values on the diagonal in each panel reports the summary statistics of local-market effect (i.e., heat waves effect), while the off-diagonal elements of each panel represent the cross-market effects (i.e., meteor showers effect). Overall, there is considerable support for the presence of meteor showers and heat waves effects since most of the values are statistically different from zero. The findings of Table 3.7 also confirm the "information dominance" that the FX microstructure literature has highlighted: information shocks from some regions are more important than others (Evans and Lyons, 2001). The evidence indicates that volatility from Europe is an important source of volatility shocks for LNY market, while the volatility from LNY spills over to all other markets. Besides, volatility emanating from Asia is more relevant for JPY than for AUD.

I also report the correlations of $\widehat{CVP}$ with other variables in Table 4.6 of Chapter 4. $\widehat{CVP}$ is significantly and negatively correlated with return, which is consistent with the large impacts from negative returns. Besides, the unconditional correlation between $\widehat{CVP}$ and RV is positive. Furthermore, $\widehat{CVP}$ is highly persistent (i.e. the Ljung-Box statistics are all statistically significant at the 5% significance level) but is less persistent than RV as indicated by the Ljung-Box statistics.

Besides, under the model specification of HAR-CVP model, to measure the relative importance of volatility spillover effects from different trading sessions in predicting future volatility, I utilize the techniques of Shapley-Owen R^2 values, which proves to be a more efficient estimator as stated earlier. Interestingly, the results as shown in Table 3.8 suggest that the meteor shower effect, especially the volatility spillover effect from the preceding market, contributes most to the total variations in future volatility, which is in accordance with the results of Table 3.7. However, the volatility from Asia contributes a significant proportion of the total variations in the time-varying volatility persistence for AUD, which is consistent with the findings of Su and Zhang (2018) which suggest that the Asia contributes more to the price discovery for AUD trading even with its declining market shares compared to Europe and U.S.

Table 3.7: **Characteristics of Time-varying Volatility Spillover**

This table reports the means and standard deviations of estimated CVP. Specifically, I estimate the equation as shown in Table 3.6. Then I calculate the estimated CVP in different sessions as $\widehat{CVP}_{i,t} = \beta + \beta^{-} r_{i,t}^{-} + \beta^{+} r_{i,t}^{+} + \beta^{RV} RV_{i,t} + \beta^{IS} IS_{i,t}$ $(i = A, E, L, and\ U)$, The bold numbers on the diagonal for each panel stand for one-day lagged heat waves effect, while the italic numbers stand for the highest values in each row, suggesting the sources of largest volatility impacts. The values in the parentheses are standard deviations of estimated CVP. The asterisks ***, **, * indicate that the values are statistically different from zero at 1%, 5%, and 10% respectively.

	Asia	Europe	London/NYC	US
AUD				
Asian Market	**0.037**	0.248***	*0.371****	0.280***
	(0.035)	(0.041)	*(0.050)*	(0.057)
European Market	*0.279****	**0.200*** **	0.053	0.088***
	(0.072)	**(0.035)**	(0.041)	(0.011)
LNY Market	0.133*	*0.748****	**0.053**	0.025*
	(0.071)	*(0.103)*	**(0.075)**	(0.014)
US Market	0.064	0.424***	*0.542****	**-0.072**
	(0.090)	(0.125)	(0.137)	**(0.057)**
GBP				
Asian Market	**0.078*** **	0.189***	*0.279****	0.156***
	(0.018)	(0.050)	*(0.062)*	(0.024)
European Market	*0.398****	**0.104** **	0.224***	0.101***
	(0.044)	**(0.055)**	(0.060)	(0.026)
LNY Market	0.111**	*0.647****	**0.099**	0.001
	(0.050)	*(0.109)*	**(0.077)**	(0.031)
US Market	0.086	*0.355****	0.295***	**-0.117**
	(0.063)	*(0.108)*	(0.056)	**(0.061)**
EUR				
Asian Market	**0.150*** **	0.452***	0.280**	*0.668****
	(0.016)	(0.118)	(0.140)	*(0.094)*
European Market	0.119***	***0.315**** **	0.084*	-0.037
	(0.038)	***(0.051)***	(0.047)	(0.030)
LNY Market	0.059***	*0.513****	**-0.007**	0.187***
	(0.021)	*(0.054)*	**(0.018)**	(0.069)
US Market	0.280***	*0.661****	0.641**	**-0.015**
	(0.115)	*(0.269)*	(0.317)	**(0.022)**
JPY				
Asian Market	**0.129*** **	0.437***	*0.575****	0.439***
	(0.025)	(0.048)	*(0.144)*	(0.176)
European Market	*0.212****	**0.170*** **	0.072***	0.006
	(0.063)	**(0.032)**	(0.029)	(0.009)
LNY Market	0.113***	*0.533****	**0.005**	0.017
	(0.050)	*(0.098)*	**(0.010)**	(0.044)
US Market	0.308*	0.396***	*0.418***	**0.019**
	0.169	(0.130)	*(0.207)*	**(0.022)**

Table 3.8: Shapley-Owen Values of Volatility Spillover

This table shows the Shapley-Owen proportion of the total R^2s for groups of CVP coefficients in the HAR-CVP model where RV_t is predicted by lagged RVs:

$$RV_{i,t} = \alpha_{i,t} + \beta^e_{A,t} RV_{A,t-1} + \beta^e_{E,t} RV_{E,t-1} + \beta^e_{L,t} RV_{L,t-1} + \beta^e_{U,t} RV_{U,t-1} + \beta^{HW}_{i,W} \overline{RV}_{i,t-1,W} + \sum_{j\neq i, j=A}^{U} \beta^{MS}_{i,j,W} \overline{RV}_{j,t-1,W} + \beta^{HW}_{i,M} \overline{RV}_{i,t-1,M} + \sum_{j\neq i, j=A}^{U} \beta^{MS}_{i,j,M} \overline{RV}_{j,t-1,M} + \varepsilon_{i,t}$$

where i = Asia (A), Europe (E), London/New York (L), and US (U) and $\beta^e_{j,t} = \beta^0_j + \beta^-_j r^-_{j,t-1} + \beta^+_j r^+_{j,t-1} + \beta^{RV}_j RV_{j,t-1} + \beta^{IS}_j IS_{j,t-1}$. There are 4 components: $\beta^e_{j,t}$ $(j = A, E, L, U)$, which proxy for daily volatility spillover effects from lagged local market (i.e. heat waves effect when $j = i$) and from other regional markets (i.e. meteor showers effect when $j \neq i$). The bold numbers on the diagonal for each panel stand for the proportion of Shapley-Owen value of one-day lagged heat waves effect, while the italic numbers suggest the largest proportion of Shapley-Owen values in predicting the future volatility for each trading session.

	Asia	Europe	London/NYC	US
AUD				
Asian Market	**0.196**	0.199	0.203	*0.218*
European Market	*0.309*	**0.171**	0.175	0.170
LNY Market	*0.264*	0.244	**0.167**	0.166
US Market	*0.224*	0.218	0.215	**0.169**
GBP				
Asian Market	***0.206***	0.196	0.195	0.190
European Market	*0.280*	**0.182**	0.175	0.166
LNY Market	0.237	*0.260*	**0.169**	0.153
US Market	0.202	*0.223*	0.204	**0.164**
EUR				
Asian Market	**0.183**	0.154	0.159	*0.239*
European Market	*0.252*	**0.195**	0.177	0.108
LNY Market	0.231	*0.268*	**0.177**	0.112
US Market	*0.286*	0.204	0.229	**0.110**
JPY				
Asian Market	***0.220***	0.109	0.080	0.217
European Market	*0.588*	**0.100**	0.064	0.054
LNY Market	0.380	*0.424*	**0.053**	0.040
US Market	0.268	0.133	*0.391*	**0.055**

3.6. Robustness Analysis

3.6.1. Additional Conditioning Variables

Existing studies have shown that information share varies considerably over time and is subject to the market conditions. For example, the market contributes more to the price discovery with more favourable market states (i.e. large trading volume, low volatility, and narrow bid/ask spread). In this chapter, I propose that volatility persistence is driven by the characteristics of both exogenous and endogenous information arrivals and strategic trading such as portfolio adjustments to lagged information shocks. Collectively these mechanisms determine the state of the market, and in turn, impact volatility persistence. The use of market state variables (i.e., number of trades, illiquidity, and order imbalance) as the additional conditioning variables is in the same spirit as Wang and Yang (2017) who examine whether daily volatility persistence is affected by volatility jumps (VJ), number of trades (NT), illiquidity (IL), and the imbalance of buyer- and seller-initiated trades (TI) in the stock market. Namely, the market state variables include return, trading volume, illiquidity, order imbalance, and volatility (see, Brandt et al., 2007; Mizrach and Neely, 2008; Frijns, Lehnert and Zwinkels, 2010; Su and Zhang, 2018).

The market state variables for each segment are constructed as follows: trading volume is defined as the number of trades aggregated over 5-minute intervals; daily illiquidity is measured by the Amihud (2002)'s illiquidity measure, which is defined as $IL_t = |r_t|/NT_t$ where NT_t is the number of trades and $|r_t|$ is the absolute value of return over 5-minute intervals. For the order imbalance, following Wang and Yang (2017), I use the method of "bulk volume" classification (BVC) of Easley, de Prado and O'Hara (2012) to partition the number of trades into buyer- and seller-initiated portions sampled at 5-minute intervals. Then the difference between these two portions is termed the order imbalance (OI_t). Recently, Chakrabarty, Pascual, and Shkilko (2015) prove that *BVC* is better linked to proxies of information-based trading, compared to Lee and Ready (1991)'s trade classification algorithm.

The summary statistics of market state variables (including return, volatility, information share, number of trade, illiquidity, and order imbalance) by trading sessions are reported in Appendix G. As shown in Panel A of Appendix G, AUD/USD has the highest volatility during the Asian market, while the lowest volatility in LNY market. The returns in the four markets have the same direction of skewness, i.e. the distributions of returns are left skewed, or negatively skewed. The Ljung-Box statistics show that the returns have weak autocorrelations at 5 lags in the Asian and North American markets, while there is little or no autocorrelation in European market. The transactions concentrate in the Europe and LNY markets, particularly for GBP and EUR. Besides, the order imbalances are not statistically different from zero in all trading sessions, which confirms earlier works on FX microstructure suggesting that dealers generally tend to "hold positions for very short time horizons, typically under a day, and have zero inventory overnight" (King et al., 2011). Appendix G also presents the summary statistics of the daily information shares measured as the *TSRV* ratio in four trading sessions, among which Europe has the largest estimated information share, followed by the U.S., Asia, and "LNY" market. The information share of Asia has the largest standard deviation, while the strongest autocorrelations at lag 12. Besides, the information shares in four markets are negatively correlated, suggesting increased information shares of one trading session is associated with decreased information shares for other sessions.

This section presents a robustness analysis where volatility spillovers (namely, meteor showers and heat waves effects) are regressed on exchange rate returns, volatility, and other additional variables. Namely, in addition to daily return and RV, I examine whether daily volatility spillovers are affected by other conditioning variables, including Amihud's illiquidity measure (IL), number of trades (NT), and order imbalance (OI). Let Y_{t-1} be one of these variables on day $t-1$. To assess the impacts of these variables on volatility persistence, I extend the model in Eq. (5.1) to include Y_{t-1} and its interaction with RV_t. However, I don't find any consistent effects of the additional market state variables in explaining the conditional volatility persistence.[33] Besides, I also attempt to examine the impacts of investors' sensitivity to information on volatility persistence as documented in Berger et al. (2009), however, these effects are insignificant under most circumstances. One of the possible reasons is that I focus on the lead-lag effects rather than the contemporaneous relationships as documented in the earlier literature. Overall,

[33] The results of additional conditioning variables are not presented here for the sake of brevity, however, which are available upon request.

these empirical findings are consistent with those of Wang and Yang (2017) who examine the volatility persistence in the equity markets and find no effects of the additional market state variables. The results are also consistent with those of Gillemot, Farmer, and Lillo (2006), who conclude that "the long-memory of volatility is dominated by factors other than transaction frequency or total trading volume".

3.6.2. Out-of-sample forecasting performance

In this robustness analysis sub-section, I compare the ex-post out-of-sample forecasting performances of various volatility models. Namely, if the daily volatility persistence varies as a function of the observed market condition, the model which calibrates RV dynamics conditional on market state variables should provide superior forecast performance. To examine the forecasting performances, I first estimate the model parameters using the first 5 years of observations as the in-sample period, and then use the rest of the sample as the out-of-sample period. All forecasts are generated using rolling WLS regressions and parameter estimates are updated daily. Forecasting performance is evaluated based on two loss functions: the negative quasi-likelihood function $\mathrm{QLIKE}\left(\mathrm{RV}_t, \widehat{\mathrm{RV}}_t\right) = \frac{\mathrm{RV}_t}{\widehat{\mathrm{RV}}_t} - \ln\left(\frac{\mathrm{RV}_t}{\widehat{\mathrm{RV}}_t}\right) - 1$ and the logarithmic mean-squared errors $\mathrm{LMSE}\left(\mathrm{RV}_t, \widehat{\mathrm{RV}}_t\right) = (\ln(\mathrm{RV}_t) - \ln(\widehat{\mathrm{RV}}_t))^2$, where $\widehat{\mathrm{RV}}_t$ is the forecasted value of RV_t. Patton (2012) shows that QLIKE is robust to the noise in the empirical volatility measures. Patton and Sheppard (2009) show that QLIKE has the best size-adjusted power among robust loss functions. The usual mean-squared error (MSE) is often affected by a few extreme observations. Therefore, I use the logarithmic MSE to mitigate this problem. Furthermore, forecast performance is examined by the Diebold-Mariano (1995)'s test (i.e., DM statistics). Specifically, taking the HAR model as the benchmark, a negative DM statistic indicates a reduction in loss value by other volatility models relative to HAR. While HAR is nested in CVP model, Giacomini and White (2006) show that the DM test remains asymptotically valid when the estimation period is finite.

In this section, I compare the pseudo out-of-sample volatility forecasts based on the benchmark HAR model (HAR) against the extended Conditional Volatility Persistence model (CVP). If the dynamic volatility persistence indeed varies with return and volatility as suggested in the preceding analysis, the CVP model should achieve superior out-of-sample forecasting performance and therefore lead to significant economic gains. Table 3.9 provides a summary of QLIKE and LMSE values. For both loss functions, CVP has the lowest mean and median loss values, and the reduction in loss value of CVP is substantial for all currencies as suggested by the DM tests.

Table 3.9: Out-of-sample Forecasting Performance

This table reports the average, median, and standard deviation of the loss functions QLIKE and LMSE for the HAR model and the conditional HAR model (CVP) using the exchange rates of AUD, GBP, EUR, and JPY, all against USD. DM stat is the Diebold-Mariano (1995)'s test for the equality of forecast accuracy of two forecasts. Here, taking the HAR model as the benchmark, a negative DM statistic indicates a reduction in loss value relative to HAR.

	HAR		CVP	
	QLIKE	LMSE	QLIKE	LMSE
AUD				
Average	0.2129	0.1243	0.2083	0.1222
Median	0.0779	0.0395	0.0752	0.0382
St Dev	0.4127	0.3302	0.4040	0.3188
DM Stat	-	-	-8.26***	-4.13***
GBP				
Average	0.1478	0.0801	0.1429	0.0800
Median	0.0597	0.0159	0.0525	0.0128
St Dev	0.2147	0.2302	0.2040	0.2266
DM Stat	-	-	-1.82*	-1.72*
EUR				
Average	0.5206	0.3345	0.4920	0.3210
Median	0.2385	0.1265	0.2179	0.1140
St Dev	0.7937	0.7310	0.8088	0.7562
DM Stat	-	-	-2.78**	-1.76*
JPY				
Average	1.0115	0.8968	0.9633	0.8359
Median	0.4907	0.2671	0.4561	0.2449
St Dev	1.4504	2.2453	1.4449	2.2282
DM Stat	-	-	-1.54	-1.66*

3.7. Conclusions and Implications

In this chapter, I revisit the meteor shower and heat wave effects for AUD/USD, GBP/USD, EUR/USD, and USD/JPY spanning from January 1999 (January 2000 for EUR) to December 2013. Utilizing the volatility measures based on high-frequency data, I find evidence of both meteor showers and heat waves effects in the four trading segments of global FX market, which is consistent with Lahaye and Neely (2016) who divide a calendar day into five segments and confirm the presence of meteor shower and heat waves effect in each segment. However, unlike Lahaye and Neely (2016), I find that the relative importance of meteor shower effect has been increasing rapidly and has predominated over heat waves effects in the intra-daily volatility spillovers, which emphasizes the increasing interdependence and interconnectedness in the global FX market, and highlights the potential contagion risks posed by financial liberalization and market openness.

By investigating the pattern and economic mechanism of meteor showers and heat waves effects, I contribute to the literature regarding volatility spillover in the financial markets. Specifically, I identify the key factors contributing to volatility spillovers in different trading sessions of the FX market. The empirical results also highlight the complex geographical nature of the FX market. That is, the spillover effect of volatility depends on where the information shocks arise. This study has modelling implications for the FX market as well. For example, these results argue in favour of modelling FX volatility dynamics segment-wise, rather than in the more traditional approach of assuming a homogeneous process.

In this study, I also contribute to the growing literature on information propagation in the foreign exchange market. By exploring the economic mechanism of volatility spillover in the exchange rates, the findings presented in this study highlight the impacts of changing market states on the volatility spillovers, which could be the results of exogeneous and endogenous information arrivals, the persistence of characteristics of information propagation process, and uninformed trading in response to lagged information shocks, etc. The analysis in this chapter builds upon ideas contained in the literature on mixture of distributions hypothesis (MDH) (Liesenfeld, 2001). However, this particular volatility model is based on relationships introduced in the market microstructure literature, and the estimation relies on the availability of a long time-series of trading data at very high frequency. Besides, different from the conventional MDH, I find that volatility spillover is not solely determined by exogenous information arrivals, but also by the process of absorbing information shocks and resolving uncertainty. Namely, a faster process of price discovery within a period reduces information persistence to future periods and mitigates volatility spillover to other markets.

However, additional research is required to consider how generalizable the results presented in this chapter are to other major currencies and emerging market currencies. Besides, how to identify the institutional sources of long-memory in volatility (i.e. institution- and market-wide characteristics) deserves further study, which will definitely improve the understanding of volatility spillover and extend our economic intuition of risk contagion in the financial markets. Also, if there is a common component in conditional volatility, should provide more evidence on the factors driving the variations in exchange rate returns. Another possible direction is to assess the usefulness and economic values of conditional volatility persistence in concrete financial applications such as portfolio management and volatility timing strategy as in Fleming et al. (2003).

Chapter 4: Conditional Volatility Persistence and Volatility Timing in the Foreign Exchange Market

4.1. Introduction

The phenomenon of volatility, i.e., up-and-down movements of the market, plays a central role in derivatives pricing, risk management, and optimal portfolio. It draws great attention to academics, practitioners, and regulators, and motivates a vast amount of literature on volatility modelling. Starting from Engle (1982), a variety of autoregressive conditional heteroskedasticity (ARCH), generalized ARCH (GARCH), and stochastic volatility (SV) models have been fit to asset returns. However, starting with Andersen and Bollerslev (1998) and Andersen et al. (2003), the literature has been increasingly focused on so-called realized volatility (RV) models with the availability of quality high-frequency data (see, for example, Bollerslev, Chou and Kroner, 1992; Bollerslev, Engle and Nelson, 1994; Diebold and Lopez, 1995; and recently, Bollerslev et al., 2017). The empirical evidence on volatility is generally consistent across a wide range of assets and econometric specifications, which overwhelmingly suggests that volatility is predictable to a great extent. These literature, however, has been exclusively focused on evaluating the statistical performance of volatility models rather than the economic significance of predictive volatility. Following Fleming, Kirby, and Ostdiek (2001, 2003) and Bollerslev et al. (2017), I focus on the latter. Namely, I not only conduct an extensive statistical evaluation of volatility forecasting using a variant of heterogeneous autoregressive (HAR) models, but also provide new economic evidence on whether a risk-averse investor can significantly benefit from volatility-timing based on mean-variance analysis. Furthermore, I explore the economic mechanisms of the conditional volatility persistence, which help in achieving superior forecasting performance and potential economic gains.

Volatility persistence is a well-documented phenomenon across a broad range of financial markets, including the Foreign Exchange market. This suggests that standard volatility models deliver reasonably accurate forecasts, but the question of whether volatility timing has economic value still remains unanswered, particularly when forecasting using the model which incorporates the features of volatility asymmetry and persistence. In short, the economic value of volatility timing is the utility gain compared with a static strategy. For an investor with a mean-variance utility, the major concern is to estimate the fee she is willing to pay for a new volatility model rather than a static one. In this chapter, I apply the conditional volatility persistence model as proposed in Wang and Yang (2017) to the FX market, and examine the presence of volatility persistence in the exchange rates and its determinants by taking a much broader view on the economic mechanisms of the volatility persistence. In addition, I adopt an optimal rebalancing strategy in volatility targeting solutions and utilize the technique of backtesting to examine the ex-post performance of optimal portfolio holdings.

This approach has several advantages over existing studies. First, instead of measuring the benefits of predictability via ex-ante calibration (Balduzzi and Lynch, 1999; Campbell and Viceira, 1999; and Campbell, Chan and Viceira, 2002), I measure economic benefits through the ex-post performance of the optimal portfolio with predictable volatility. More importantly, considering that there is little evidence for any out-of-sample expected return predictability (Bossaerts and Hillion, 1999), I focus exclusively on the prediction of realized variance, which eliminates the noise form random return realizations and provides a practical evaluation of the economic benefits. Second, ignoring estimation risk or parameter learning (i.e., the dynamic counterpart of estimation risk) that arises when estimating parameters would typically lead to misleading allocations (Brennan, 1998; Stambaugh, 1999; Barberis, 2000). By utilizing a non-parametric “realized utility” technique as proposed in Bollerslev et al. (2017), I solve the single-period asset allocation problem while accounting for estimation risk and parameter learning, since “the multi-period portfolio problem with time-varying expected returns or volatility in the presence of estimation risk or parameter learning is computationally intractable” (Johannes et al. 2002). The main difference between the single- and multi-period asset allocation problems is intertemporal hedging demands. However, recent evidence suggests that ignoring hedging demands would not be a major concern, since they are typically only a small component of asset demands (see Brandt, 1999; Ait-Sahalia and Brandt, 2001).

This chapter contributes to the extant literature on the economic value of volatility timing in several different ways. Firstly, previous studies demonstrate that volatility timing strategy can be enhanced by using high frequency data, optimal sampling, optimal rebalancing frequencies, and noise- and jump-robust volatility measures (See, for example, Fleming et al., 2001, 2003; Bandi and Russell, 2006; Bandi, Russell, and Zhu, 2008; Nolte and Xu, 2015). I extend the previous studies by considering the economic value of conditional volatility persistence model, which explicitly links the changing overall market conditions to the future volatility and far surpasses the benchmark models with regard to the forecasting performance. Besides, although more sophisticated utility functions can be utilized, I stick to a simple mean-variance utility because the major concern is to examine whether statistical improvements in volatility forecasting by taking the time-varying volatility persistence into consideration can be translated into economic gains. Furthermore, to concentrate on the impacts of volatility timing, I assume only one risky asset in each portfolio to avoid covariance matrix forecasting in a multivariate setting and control for information spillover across different assets. I also assume that the investor is myopic, and she does not consider the hedging demand when constructing the optimal portfolio. I make this assumption for both simplicity and consistency. Namely, without loss of generality, the volatility forecasting results generated can be easily translated into certainty equivalent performance fees and directly compared with those documented in the existing literature on the economic value of volatility timing. In summary, I conclude the main findings as follows:

(1) Utilizing the conditional volatility persistence (CVP) model as proposed in Wang and Yang (2017), I find that the conditional volatility persistence increases with information shocks as proxied by negative and positive returns, while decreases with information flows as proxied by realized variance. Taking into

account conditional volatility persistence improves volatility forecasting performance both in-sample and out-of-sample. For example, by utilizing the Shapley decomposition techniques, I find that the conditional volatility persistence explains large portions of the variations in future volatility and is the dominant channel linking changing market conditions to future volatility. However, I provide mixed evidence on asymmetric effects in the FX market, to which similar results have been found in Wang and Yang (2009).

(2) Under conservative assumptions about the Sharpe ratio and the investor's risk aversion, having a Heterogeneous Autoregressive (HAR) - based model which takes the conditional volatility persistence into consideration is worth about 0.51% of total wealth per year relative to the static risk model (i.e., using in-sample average volatility). And the utility gains are even larger during the crisis period or under the assumption of higher Sharpe ratio and/or lower risk aversion. Besides, the gains in using the conditional volatility persistence model remain positive and significant after accounting for transaction costs and market microstructure noise.

(3) The volatility targeting approach which utilizes dynamic asset allocation based on accurate volatility forecasting can take advantage of the negative relationship between volatility and return and the properties of volatility persistence, and achieves a stable level of volatility in all market environments. The economic gains of volatility targeting are significant (i.e., the Sharpe ratio of volatility timing strategy using CVP model is as high as 1.23, compared to 0.83 for that without volatility timing).

The rest of this chapter is structured as follows. Section 4.2 introduces the data and construction of relevant variables. Section 4.3 presents the model specifications including the classic Heterogeneous Autoregressive model (HAR), the semi-variance Heterogeneous Autoregressive model (SHAR), and the Conditional Volatility Persistence model (CVP). A simple utility-based framework for quantifying the economic gains of the new risk models is given in this section as well. Section 4.4 compares the forecasting performances of various risk models and discusses the utility benefits under different scenarios. Section 4.5 performs a robustness check, while Section 4.6 concludes with further research directions.

4.2. Variable Construction and Summary Statistics

4.2.1. Data Description

The data source is Thomson Reuters Tick History (TRTH) supplied by the Securities Industry Research Centre of Asia-Pacific (SIRCA). The intraday data for AUD/USD, GBP/USD and USD/JPY spans from 1 January 1999 to 31 December 2013, while the data for EUR/USD isn't available until 1 January 2000. The four currencies I am using in this chapter are among top-5 most actively traded currencies and account for more than 50% of the globe FX trading (Bank for International Settlements, 2013). The dataset includes the time rounded to the nearest millisecond whenever a new quote is posted, prices of firm bid/ask quotes, trading time, and trading prices. Following other studies such as Bollerslev and Domowitz (1993), I exclude weekends, because of thin and inconsistent trading. I define weekends as extending from 22:00 GMT Friday evening (i.e., the end of day trading session in New York) until 22:00 GMT Sunday evening (i.e., the commencement of morning trading session in Sydney). In consistent with Wang and Yang (2011), I remove days with large time gaps (i.e. over four hours) in quote arrivals, which could be the result of holidays in major financial centres, system halts, or other technical issues. I also exclude observations which deviate by more than 10 times standard deviations from a rolling sample of 50 observations. Last but not least, to mitigate the potential impacts of extremely large values, I winsorize the daily realized variance at the 99^{th} percentile.

4.2.2. Integrated Variance

In recent years, there has been a renewed interest in obtaining improved daily volatility estimates by constructing daily "realized" or "integrated" volatility with the availability of quality high-frequency data (Thomakos and Wang, 2010). The most popular estimator is realized volatility, see Andersen et al. (2003) for a review. Namely, daily realized volatility can be obtained as the sum of intraday squared returns. Using the theory of quadratic variation, Andersen and Bollerslev (1998) and Barndorff-Nielsen and Shephard (2002) show that the realized volatility estimator is a model-free estimator of the true but latent volatility.

In this chapter, I utilize the Realized Variance (RV) as a proxy for the integrated variance. Specifically, I am interested in estimating the sum of diffusion variation (i.e., integrated variance) and the realized variance $\mathrm{RV_t} = \sum_{s=1}^{m} r_{s,t}^2$, i.e. the sum of squared log returns over appropriate sampling intervals *s* = 1, 2, …, m, proves to be a consistent estimator under certain conditions.[34] Following Andersen et al. (2005), I construct the "volatility signature plots" as presented in Figure 4.1 which suggest the usage of 5-minute interval when estimating the realized variance. In fact, Liu, Patton, and Sheppard (2015) compare several hundred different RV estimators across multiple assets and conclude that "it is difficult to significantly beat 5-minute RV"). Therefore, I aggregate the tick-by-tick data into 5-minute intervals and calculate the 5-minute realized variance accordingly.

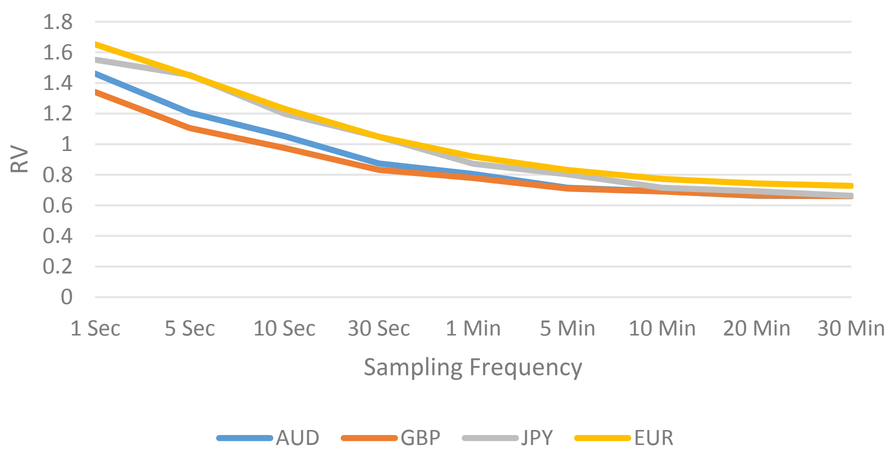

Figure 4.1: Signature Plots for AUD, GBP, EUR, and JPY

In the robustness section, I also report the relevant empirical results using a noise-robust volatility estimator to control for market microstructure noise, namely, the two-scale realized variance estimator of Zhang et al., (2005). This estimator can be constructed easily using sub-sampling and averaging (Wang and Yang, 2011; Su and Zhang, 2018). Namely, the two-scale estimator is a linear combination of RVs calculated at two different frequencies, i.e. the highest possible frequency and a lower frequency, which serves to eliminate the noise variance. Barndorff-Nielsen

[34] A vast amount of literature suggests that the realized volatility estimator is not robust when the sampling interval is too small due to microstructure effects (see, e.g., Brown 1990; Hansen and Lunde, 2004; Zhang, Mykland, and Ait-Sahalia, 2005; Bandi and Russell, 2004).

et al. (2008) find that the two-scale RV is the first consistent estimator for integrated variance.

4.2.3. Summary statistics of relevant variables

Intraday returns are sampled at various frequencies (i.e., 1-second to 30-minute) to calculate the realized variance of different sampling intervals and construct the volatility "signature plots" as discussed above. Table 4.1 reports the summary statistics of the realized variance and market state variables. Namely, the market state variables include trading volume, illiquidity, order imbalance, and volatility (see Brandt et al., 2007; Mizrach and Neely, 2008; Frijns et al., 2010). Trading volume NT_t is defined as the number of trades aggregated over 5-minute intervals; daily illiquidity is measured by the Amihud (2002)'s illiquidity measure, which is defined as $IL_t = |r_t|/NT_t$ where NT_t is the number of trades and $|r_t|$ is the absolute value of return over 5-minute intervals. Then the number of trades is partitioned into buyer- and seller-initiated portions using the method of bulk volume classification (BVC) of Easley et al. (2012) and the difference between these two portions is termed the order imbalance OI_t.

As shown in Panel A of Table 4.1, the annualized average RV is 11.8% for AUD, 8.8% for GBP, 9.8% for EUR, and 10.6% for JPY, among which the GBP has the lowest volatility. The AUD and JPY have higher volatilities, while weaker autocorrelations than the other two currencies. For the JPY and EUR which are mostly traded on another electronic trading platform – EBS (Electronic Broking Services), they display more frequent volatility jumps, particularly during periods of turmoil, which leads to reduced autocorrelations. The medians of RV are much lower than means due to a small number of high RV days. Overall, the AUD has the highest volatility, which is consistent with Bollerslev et al. (2017) who calculate the daily volatility for 9 major currency pairs spanning from January 2000 to September 2014 and confirm that the AUD has the highest average daily RV (11.8%), while GBP has the smallest volatility (8.3%). Besides, the AUD and GBP have larger daily trading volumes than the EUR and JPY since the "commodity currencies" (i.e., AUD, GBP, and CAD) are mostly traded on Reuters where the data is sourced, while EBS dominates interbank trading for the EUR and JPY.[35] With regard to liquidity, GBP has the highest liquidity, followed by AUD, EUR, and JPY. Interestingly, the order imbalance of all currencies is not significantly different from zero, which is generally consistent with earlier works on FX microstructure which highlights that dealers generally tend to "hold positions for very short time horizons, typically under a day", and prefer to have zero inventory overnight (King, Osler, and Rime, 2011).

The daily correlations across market state variables are reported in Panel B of Table 4.1. Most correlations are consistent with those documented in the literature. For example, RV is negatively correlated with contemporaneous return, while positively correlated with number of trades and illiquidity. Besides, there is a significant positive correlation between return and order imbalance, which is consistent with the literature on FX microstructure which emphasize the role of order imbalance in determining the exchange rates (Evans and Lyons, 2002a, 2002b, 2005).

[35] The interdealer trading is largely carried out through electronic brokerages nowadays. However, due to network externalities, liquidity is naturally concentrated on one platform for each currency (King, Osler, and Rime, 2011).

Table 4.1: Summary Statistics

This table reports the summary statistics of market state variables. IL, NT, and OI stand for illiquidity, number of trades, and order imbalance respectively. $Q_{LB}(5)$ is the Ljung-Box test statistic at 5 lags. The numbers in the square brackets are the corresponding P-values. The asterisks ***, **, * indicate that the values are statistically different from zero at 1%, 5%, and 10% respectively.

Panel A: Summary statistics of market state variables

	Mean	Median	St Dev	Skew	Kurt	Min	Max	$Q_{LB}(5)$
AUD								
Return	.0002	.0003	.0082	-.3572	7.213	-.0733	.0737	24.39*
RV	.7076	.4648	.8265	4.001	19.48	.1063	5.946	9,800*
IL	2.995	2.534	.1.279	1.016	.7014	1.191	9.767	16,216*
NT	8.441	5.994	6.746	1.183	1.509	.0540	48.86	9,358*
OI	-.0330	-.0077	.3782	-.5142	5.483	-2.334	2.091	53.49*
GBP								
Return	.0002	.0002	.0057	-.2158	2.190	-.0350	.0299	2.461
RV	.3683	.2658	.3635	3.535	14.51	.0666	2.428	11,364*
IL	1.936	1.820	.6356	2.031	7.235	.8892	6.887	13,404*
NT	7.120	6.693	3.405	.5934	.1704	.0330	26.82	9,155*
OI	-.0200	-.0100	.3516	-.2010	2.462	-2.217	1.785	10.05
EUR								
Return	.0002	.0002	.0065	.4678	5.938	-.0305	.0693	2.214
RV	.9537	.4900	1.486	4.493	24.41	.0793	11.23	5,029*
IL	4.247	3.307	2.651	1.794	4.018	1.255	18.22	11,505*
NT	1.703	1.583	.9124	.6024	.0886	.0010	5.864	4,067*
OI	.0090	.0010	.1334	.2987	1.505	-.5160	.8520	21.11*
JPY								
Return	-.0001	.0000	.0066	-.3655	4.132	-.0488	.0365	3.888
RV	1.346	.5892	2.486	4.561	23.84	.0522	17.85	2,259*
IL	8.108	7.681	3.500	.4655	-.4295	1.899	23.19	8,870*
NT	.1720	.1410	.1291	2.104	9.002	.0000	1.657	1,833*
OI	-.0020	-.0010	.0013	-2.102	9.018	-.6570	.7770	6.44

Panel B: Correlations

	Return	RV	NT	OI	IL
AUD					
RV	-.0667*** [.0000]	1.000			
NT	-.0671*** [.0000]	.2838*** [.0000]	1.000		
OI	.7083*** [.0000]	-.0703*** [.0000]	-.1643*** [.0000]	1.000	
IL	-.0522*** [.0013]	.4703*** [.0000]	-.3453*** [.0000]	.0088 [.5894]	1.000
GBP					
RV	-.0442*** [.0061]	1.000			
NT	-.0180 [.2674]	.4105*** [.0000]	1.000		
OI	.8071*** [.0000]	-.0354** [.0285]	-.0419*** [.0094]	1.000	
IL	-.0212 [.1887]	.5306*** [.0000]	-.1773*** [.0000]	-.0077 [.6358]	1.000
EUR					
RV	-.0419* [.1004]	1.000			
NT	.0184 [.2871]	.0914*** [.0000]	1.000		
OI	.5733*** [.0000]	.0046 [.5861]	.0546*** [.0014]	1.000	
IL	-.0230 [.1459]	.6144*** [.0000]	-.1737*** [.0000]	.0006 [.9743]	1.000
JPY					
RV	-.0621*** [.0009]	1.000			
NT	-.0119 [.5219]	.1465*** [.0000]	1.000		
OI	.7719 [.0000]	.0012 [.9122]	-.0012 [.1221]	1.000	
IL	-.0432** [.0204]	.5598*** [.0000]	-.1064* [.0716]	.0002 [.9879]	1.000

4.3. Model Specification

4.3.1. HAR Model

In this chapter, I employ variants of the heterogeneous autoregressive (HAR) models, which takes into account the heterogeneous impacts of investors at different trading horizons (i.e., daily, weekly, and monthly horizon respectively), while capturing the property of long-memory in volatility. The HAR model was firstly proposed in Corsi (2009), which is based on the concept of the Heterogeneous Market Hypothesis of Muller et al. (1997), and has been employed in several applications, such as for equity markets (Andersen, Bollerslev, and

Diebold, 2007; Forsberg and Ghysels, 2007; Bollerslev et al., 2017; Wang and Yang, 2017), gold market (Chai, Lee, and Wang, 2015), and foreign exchange market (Wang and Yang, 2009).

With its popularity, Bollerslev et al. (2017) comment that the HAR model has become "somewhat of a benchmark in the financial econometrics literature for judging other RV–based forecasting procedures". For further analysis, I firstly calculate daily realized variance as $RV_{\mathrm{i,t}}$ for i = AUD, GBP, EUR, and JPY. Because variances are persistent, lagged variances beyond one day are represented by non-overlapping long-run variances, such as weekly variance, that is, average volatility over lagged 2 to 5 days, $\mathrm{RV_{i,t,W}} = \frac{1}{4}\sum_{\mathrm{k=2}}^{5} \mathrm{RV_{i,t-k}}$ and monthly variance, i.e. average volatility over lagged 6 to 22 days, $\mathrm{RV_{i,t,M}} = \frac{1}{17}\sum_{\mathrm{k=6}}^{22} \mathrm{RV_{i,t-k}}$. Thus, the HAR model is specified as follows:

$$RV_{i,t+1} = \alpha_{i,t+1} + \beta_{i,D}RV_{i,t} + \beta_{i,W}RV_{i,t,W} + \beta_{i,M}RV_{i,t,M} + \varepsilon_{i,t+1} \qquad (4.1)$$

where $RV_{i,t}$ is the realized variation for currency *i* on day t ($i = AUD, GBP, EUR, and\ JPY$). The coefficients $\beta_{i,W}$ and $\beta_{i,M}$ capture the long-run (i.e. weekly and monthly) dependence of volatility, while the short-run dependence is represented by the coefficient of one-day lagged volatility $\beta_{i,D}$. This model is useful for modelling the short-run volatility persistence effect while taking account of the long memory in volatility and has been widely used in the relevant literature (See, for example, Bollerslev et al. (2017) and references therein). The error term is assumed to be normally distributed and the model is estimated via OLS with Newey-West covariance correction for heteroscedasticity and autocorrelation as documented in previous studies (Chai et al., 2015; Wang and Yang, 2017). Besides, although the model is written with one-day lag, nothing precludes more lags. In the robustness analysis, I re-estimate the model using more lags (i.e. 1- to 4-day lagged realized variance), and the alternative specifications do not change the conclusions about the presence of volatility persistence.

Another feature of the HAR model is that the original HAR model can be directly geared to forecasting longer-run volatility, say, over weekly or monthly horizons, by simply replacing the daily variance $\mathrm{RV}_{i,t+1}$ on the left-hand-side in Eq. (4.1) with the realized variance $\mathrm{RV}_{i,t+h}$ over the forecast horizon *h* of interest. For example, with a 22-day forecast horizon, I estimate the following predictive model specification with *h* = 22:

$$RV_{i,t+h}^{h} = \alpha_{i,t+h} + \beta_{i,D}^{h} RV_{i,t} + \beta_{i,W}^{h} RV_{i,t,W} + \beta_{i,M}^{h} RV_{i,t,M} + \varepsilon_{i,t+h} \tag{4.2}$$

Again, this “monthly” model is straightforward to estimate by standard OLS with the Newey-West robust standard errors. The beta coefficients, which dictate the importance of the different factors, will obviously depend on the forecast horizon, as explicitly indicated by the superscripts “*h*” for the coefficients in Eq. (4.2).

The estimation results in Table 4.2 are generally consistent with findings documented in the previous literature. For example, when $\mathrm{h} = 1$ (i.e., the one-day-ahead forecast of RV), it shows that there is substantial evidence of volatility persistence in the FX market, with the sum of $\beta_{i,D}$, $\beta_{i,W}$, and $\beta_{i,M}$ close to one. While the predictive power of recent information captured by $\beta_{i,D}$ dominates the weekly and monthly dependence (i.e., $\beta_{i,W}$ and $\beta_{i,M}$), it diminishes as the forecasting horizon increases, which reflects the gradual information diffusion of the fundamental prices of exchange rates. Interestingly, the impact of daily volatility decreases with the forecasting horizon of future volatility, while the impact of weekly volatility increases, and achieves the largest magnitude of coefficient when $\mathrm{h} = 5$.

Table 4.2: Heterogeneous Autoregressive (HAR) Model

This table reports the coefficients of the following regression:

$$RV_{i,t+h}^{h} = \alpha_{i,t+h} + \beta_{i,D}^{h} RV_{i,t} + \beta_{i,W}^{h} RV_{i,t,W} + \beta_{i,M}^{h} RV_{i,t,M} + \varepsilon_{i,t+h}$$

where RV_t are the realized variances of exchange rates for AUD, GBP, EUR, and JPY, all against USD. h stands for the forecasting horizon. The t-statistics are based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. The asterisks ***, **, * indicate significance at 1%, 5%, and 10% respectively.

		β	β_W	β_M	$\bar{R}^2$
AUD	$h = 1$	.4068*** (8.43)	.3044*** (6.01)	.2445*** (5.45)	.6865
	$h = 5$	.1891*** (4.64)	.3697*** (5.35)	.3393*** (4.22)	.5749
	$h = 22$	.2155*** (3.85)	.3697*** (3.54)	.1561** (2.35)	.4084
	$h = 44$	.1644*** (3.26)	.3011*** (2.98)	.1007 (0.89)	.2398
GBP	$h = 1$	.3772*** (12.16)	.3271*** (7.65)	.2660*** (6.10)	.7344
	$h = 5$	.2010*** (4.58)	.4496*** (7.24)	.2876*** (4.31)	.7021
	$h = 22$	.1578*** (3.35)	.4445*** (4.74)	.2447** (2.49)	.5725
	$h = 44$	.1691*** (3.42)	.3803*** (3.65)	.1741 (1.53)	.4202
EUR	$h = 1$	.4966*** (6.39)	.2670*** (4.43)	.2567*** (5.98)	.5207
	$h = 5$	.4186*** (6.23)	.3561*** (5.47)	.0506 (1.30)	.4665
	$h = 22$	.3780*** (4.47)	.3185*** (3.68)	.1111*** (2.87)	.3854
	$h = 44$	.2801*** (2.91)	.2754*** (3.50)	.1046** (2.56)	.2630
JPY	$h = 1$	.2244*** (5.56)	.1701*** (3.22)	.4800*** (7.53)	.2847
	$h = 5$	.1008*** (2.72)	.2320*** (3.89)	.4803*** (6.09)	.2323
	$h = 22$	.0356 (1.02)	.1931*** (3.13)	.4582*** (6.00)	.1658
	$h = 44$	.0141 (0.59)	.1884*** (3.53)	.3710*** (4.68)	.1166

4.3.2. Semi-variance HAR

It is a well-established empirical regularity in the finance literature that negative returns generally lead to higher future volatility than positive returns. While the facts on the asymmetric effects are well-known in the equity markets (see, for example, Andersen et al., 2007; Patton and Sheppard, 2015; Lahaye and Neely, 2016; Wang and Yang, 2017), the relevant studies present mixed results in the foreign exchange market. For example, in contrast to equity markets, foreign exchange market usually exhibits symmetric volatility, that is, the volatility impacts of past positive and negative shocks are of similar magnitudes (Diebold and Nerlove, 1989; Andersen et al., 2001; Hansen and Lunde, 2005; and Laurent et al., 2011). However, in Wang and Yang (2009), the authors confirm the presence of asymmetric volatility in the exchange rates, while the realized volatility of EUR appears to be symmetric.

A key contribution of the recent econometric advances in modelling RV dynamics is the improved volatility forecast performance. Corsi (2009) shows that the HAR model generates more accurate forecasts than a true long-memory model with fractional cointegration, while Patton and Sheppard (2015) show that the semi-variance HAR model has better RV forecasts than the standard HAR and a RV-based GJR-GARCH model.[36] Therefore, I utilize the same concepts of "good volatility" and "bad volatility" as in Patton and Sheppard (2015), to explicitly test for the presence of asymmetric effects in the FX market. Specifically, Barndorff-Nielsen, Kinnebrock and Shephard (2010) introduce estimators that can capture the variations only due to negative or positive returns using the realized semi-variance (RS) estimator, which is defined as $RS_t^+ = \sum_{s=1}^{m} r_{s,t}^2 I\{r_{s,t} > 0\}$ and $RS_t^- = \sum_{s=1}^{m} r_{s,t}^2 I\{r_{s,t} < 0\}$ and I is the indicator function. These estimators provide a complete decomposition of RV_t, in that $\mathrm{RV}_t = RS_t^+ + RS_t^-$, which holds exactly for any sampling interval *m*, as well as in the limit (Patton and Sheppard, 2015). I adopt this technique of volatility decomposition for the following empirical analysis and

[36] However, Bollerslev, Patton, and Quaedvlieg (2016) show that the HAR model with realized quarticity outperforms a range of models including the semi-variance HAR.

propose the semi-variance Heterogeneous Autoregressive model (SHAR) as follows:

$$RV_{i,t+1} = \alpha_{i,t+1} + \beta_{i,D}^{+} RS_{i,t}^{+} + \beta_{i,D}^{-} RS_{i,t}^{-} + \beta_{i,W} RV_{i,t,W} + \beta_{i,M} RV_{i,t,M} + \varepsilon_{i,t+1} \qquad (4.3)$$

where $RS_{i,t}^{+}$ and $RS_{i,t}^{-}$ are the realized semi-variances of market *i* on day *t* due to positive and negative returns respectively. Note that if the decomposition of RV into RS^{+} and RS^{-} added no information, we would expect to find $\beta_D^{+} = \beta_D^{-} = \beta_D$. Interestingly, as shown in Table 4.3, I find that the coefficients of semi-variances are positively significant, and the semi-variance model explains more variations of future volatility than the regular one with realized variance. Furthermore, for the effect of lagged daily RV which can be inferred as $(\beta_D^{+} + \beta_D^{-})/2$ in this model specification, it is similar in magnitude to the coefficient found in the benchmark HAR model. Thus, the models which include only lagged RV, are essentially averaging the different effects of positive and negative returns. However, in striking contrast to other currencies, there is no evidence of asymmetric volatility in EUR market where the positive return has a larger effect on future volatility than negative return.

Table 4.3: Semi-variance Heterogeneous Autoregressive (SHAR) Model

This table reports the coefficients of the following regression:

$$RV_{i,t+1} = \alpha_{i,t+1} + \beta_{i,D}^{+} RS_{i,t}^{+} + \beta_{i,D}^{-} RS_{i,t}^{-} + \beta_{i,W} RV_{i,t,W} + \beta_{i,M} RV_{i,t,M} + \varepsilon_{i,t+1}$$

where $RV_{i,t}$, $RS_{i,t}^{+}$, and $RS_{i,t}^{-}$ are the realized variance, the realized semi-variances due to positive and negative returns respectively for currency *i* (i = AUD, GBP, EUR, and JPY). The t-statistics are based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. The asterisks ***, **, * indicate significance at 1%, 5%, and 10% respectively.

	β^{+}	β^{-}	β_W	β_M	$\bar{R}^2$
AUD	.2621***	.5983***	.2721***	.2466***	.6941
	(4.15)	(6.65)	(5.64)	(5.70)	
GBP	.2961***	.4801***	.3105***	.2679***	.7694
	(4.96)	(6.86)	(7.47)	(6.34)	
EUR	.4177***	.0810	.3212***	.2672***	.5216
	(2.64)	(0.47)	(6.47)	(4.48)	
JPY	.0549	.3959***	.1719***	.4786***	.2871
	(0.37)	(2.83)	(3.27)	(7.53)	

Figure 4.2 presents the point estimates of β_D, β_D^{-}, and β_D^{+} from Eq. (4.2) and Eq. (4.3) respectively for forecast horizons ranging between 1 and 66 days. For all

currencies, the effects of negative and positive semi-variance are significant and positive for one-day-ahead forecasting, while the coefficients decline and the magnitudes diminish rapidly as the forecasting horizon increases. Besides, the magnitudes of the coefficients of positive semi-variance are vastly different from those of negative semi-variance which suggest the presence of asymmetric effect in the FX market and confirm the suitability of using the semi-variance HAR (SHAR) model in modelling FX volatility. However, the positive return of EUR leads to larger future volatility than negative returns, an interesting phenomenon that warrants further investigation. For example, Wang and Yang (2009) also document a stronger response of volatility to positive shocks than to negative shocks for EUR.

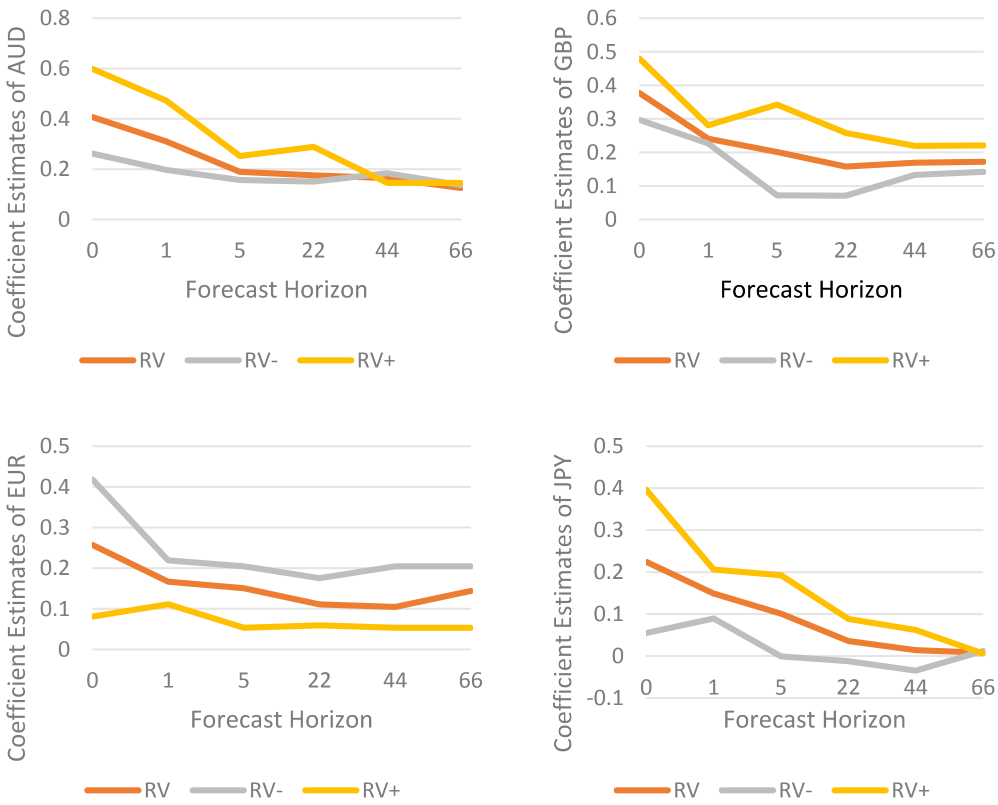

Figure 4.2: Estimated Coefficients of Short-run Volatility Dependence

4.3.3. Conditional Volatility Persistence (CVP) Model

The question of the economic origins of volatility persistence remains unanswered to a large extent (Goodhart and O'Hara, 1997). Potential explanations include the clustering of release of macroeconomic news (Melvin and Peiers Melvin, 2003; Lahaye and Neely, 2016), institutional investors' heterogeneous expectation on macroeconomic indicators (Hogan and Melvin, 1994) and heterogeneous trading horizons (Müller et al., 1997), the incorporation of private information via trading (Kyle, 1985; Admati and Pfleiderer, 1988; Ito et al., 1998), information flow and market's sensitivity to that information (Berger et al., 2009), the theory of Mixture of Distribution Hypothesis (MDH) (Clark, 1973; Tauchen and Pitts, 1983; Andersen, 1996), and the conditional volatility persistence model which attributes the time-varying volatility persistence into the changing market conditions, as captured by daily return and volatility (Wang and Yang, 2017).[37]

In this section, I introduce the Conditional Volatility Persistence (CVP) model as proposed in Wang and Yang (2017), which captures the long memory in volatility while controlling for conditional variables. Specifically, I estimate a new empirical model of the expected volatility persistence conditional on a set of observed variables (i.e., return, volatility, and other proxy measures of trading activity), then I calibrate and examine the volatility forecasting performance based on conditional volatility persistence.

Namely, following Wang and Yang (2017) who attribute the time-varying volatility persistence to the changing states of the market as captured by daily return and volatility, I incorporate conditional volatility persistence into the HAR model similarly. Here, considering that the negative returns are generally associated with greater volatility than positive returns within a wide range of finance markets (Patton and Sheppard, 2015; Wang and Yang, 2017), I decompose the exchange rate returns into positive and negative returns, and examine their volatility impacts separately. Then the modified HAR model which incorporates the conditional volatility persistence can be written as follows:

[37] Wang and Yang (2017) propose several dynamical mechanisms of volatility persistence, such as exogenous and endogenous information arrivals, the persistence of characteristics of price discovery, and uninformed trading, such as portfolio adjustments to lagged information shocks.

$$RV_{i,t+1} = \alpha_{i,t+1} + \beta_{i,t}^{e} RV_{i,t} + \beta_{i,\mathrm{W}} RV_{i,t,W} + \beta_{i,M} RV_{i,t,M}$$

$$+\theta_{i,t} r_{i,t} + \theta_{i,W} r_{i,t,W} + \theta_{i,M} r_{i,t,M} + \varepsilon_{i,t+1} \tag{4.4}$$

where $\beta_{i,t}^{e} = \beta_{i}^{0} + \beta_{i}^{-} r_{i,t}^{-} + \beta_{i}^{+} r_{i,t}^{+} + \beta_{i}^{RV} RV_{i,t}$ is called the conditional volatility persistence (CVP) as defined earlier. The weekly and monthly realized variance are calculated as $\mathrm{RV}_{\mathrm{i,t,W}} = \frac{1}{4} \sum_{\mathrm{k=2}}^{5} \mathrm{RV}_{\mathrm{i,t-k}}$ and $\mathrm{RV}_{\mathrm{i,t,M}} = \frac{1}{17} \sum_{\mathrm{k=6}}^{22} \mathrm{RV}_{\mathrm{i,t-k}}$ respectively. $\mathrm{r}_{\mathrm{i,t,W}}$ and $\mathrm{r}_{\mathrm{i,t,M}}$ are weekly and monthly return, which are defined similarly and utilized to capture the heterogeneous return impacts.

By incorporating time-varying conditional volatility persistence into the HAR model, I can examine the dynamic "leverage effect" while capturing long memory in volatility (Wang and Yang, 2017). In Table 4.4, I find that the proposed CVP model reduces the sizes of all coefficients in HAR model, therefore, reducing the estimated long-run dependence of volatility as documented earlier. While not reported here, the Wald-statistics resoundingly reject the null hypothesis of $\beta^{-} = \beta^{+} = \beta^{RV} = 0$; both the adjusted R-squared and information criteria (i.e., AIC and BIC) are in favour of the conditional HAR model, namely, the CVP model, over the regular one. While the stylized facts on the asymmetric effects are well-documented in the equity market, the relevant studies present mixed results in the foreign exchange market. The results presented in Table 4.4 suggest that there is mixed evidence on asymmetric effects in the FX market, i.e. the volatility impact of negative return is stronger than that of positive return for AUD, GBP, and JPY, while for EUR, it responds more strongly to past positive shocks.[38]

[38] As stated earlier in Section 4.3.2, similar results have been documented in Wang and Yang (2009).

Table 4.4: Conditional Volatility Persistence (CVP) Model

This table reports the daily persistence coefficients of the following model:

$$RV_{i,t+1} = \alpha_{i,t+1} + (\beta_i^0 + \beta_i^- r_{i,t}^- + \beta_i^+ r_{i,t}^+ + \beta_i^{RV} RV_{i,t})RV_{i,t} + \beta_{i,\mathrm{W}} RV_{i,t,W} + \beta_{i,M} RV_{i,t,M} + \theta_{i,t} r_{i,t} + \theta_{i,W} r_{i,t,W} + \theta_{i,M} r_{i,t,M} + \varepsilon_{i,t+1}$$

The t-statistics are based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. The asterisks ***, **, * indicate significance at 1%, 5%, and 10% respectively.

	β^0	β^-	β^+	β^{RV}	$\beta_{RV,W}$	$\beta_{RV,M}$	θ_r	$\theta_{r,W}$	$\theta_{r,M}$	$\bar{R}^2$
AUD	.3162***	-.0676***	.0248*	-.0183**	.3014***	.2546***	-.0795***	-.0900***	-.0781	.7606
	(6.83)	(-4.53)	(1.65)	(-2.36)	(5.16)	(6.43)	(-5.59)	(-2.68)	(-1.38)	
GBP	.3137***	-.0603***	.0237	-.0205	.3223***	.2770***	-.0142	-.0324**	-.0451	.7851
	(5.92)	(-2.91)	(1.13)	(-1.49)	(7.49)	(6.31)	(-1.39)	(-1.95)	(-1.46)	
EUR	.3208***	-.0574	.1329***	-.0220**	.3134***	.3565***	-.0987**	-.0376	-.0833**	.5890
	(4.13)	(-1.60)	(3.23)	(-2.35)	(4.70)	(5.22)	(-2.52)	(-0.54)	(-2.54)	
JPY	.2114***	-.0837*	.0405	-.0173***	.1971***	.3257***	-.2788***	-.2642*	.0477	.2998
	(5.29)	(-1.94)	(0.73)	(-2.80)	(3.14)	(4.60)	(-3.05)	(-1.80)	(-0.16)	

For robustness check, I divide the sample into three sub-periods (i.e. 1999/2000 – 2006, 2007 – 2009, and 2010 – 2013) and report the relevant results in Appendix H. Interestingly, the CVP model achieves the highest adjusted-R^2 during the financial crisis period (i.e., 2007 to 2009) which is probably because negative returns would be most helpful for explaining the conditional volatility persistence during volatile periods and the model which incorporates this feature will significantly improve estimation performance. Generally, the coefficients of negative returns are comparable to or larger than those of positive returns in all sub-periods for AUD, GBP, and JPY, while for EUR, the coefficients of the positive returns appear significantly larger than those of negative returns. Besides, the coefficients of RV are negatively significant in most sub-periods, suggesting a reduction in volatility persistence on days of extreme volatility.

4.3.3.1. Characteristics of the estimated CVP

In this section, I calculate the daily CVP of market i as $\widehat{CVP}_{i,t} = \widehat{\beta_i^0} + \widehat{\beta_i^-} r_{i,t}^- + \widehat{\beta_i^+} r_{i,t}^+ + \widehat{\beta_i^{RV}} RV_{i,t}$. Figure 4.2 depicts the time series of the estimated daily CVP. As we can see, the CVP ranges from 0.1 to 0.8, suggesting large variations in volatility persistence. It is particularly high during the height of the financial crisis in October 2008 due to large and mostly negative daily returns. Table 4.5 reports the summary statistics of the estimated daily CVP. The mean values are statistically significantly different from zero at 1% level. Medians are below the means, indicating some large CVP values. The distribution of CVP is skewed to the right as the skewness is positive, except for JPY. Although the coefficient of RV is negative (i.e., $\beta^{RV} < 0$), the correlations between CVP and RV measures are significantly positive which is consistent with the findings of Ning, Xu and Wirjanto (2015). This is due to negative correlations between CVP and the return and negative correlations between the return and RV. Besides, Ljung-Box statistics indicate that CVP is autocorrelated to some extent.

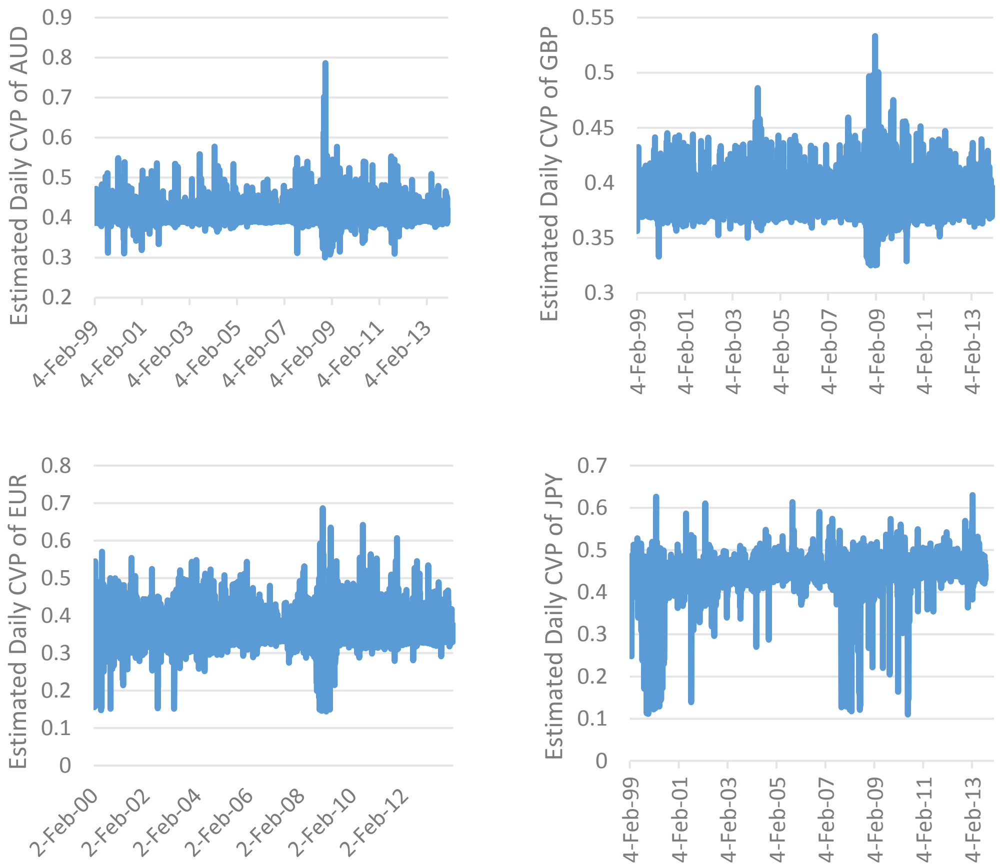

Figure 4.2: Estimated Daily CVP for AUD, GBP, EUR, and JPY

Table 4.5: Characteristics of the Estimated CVP

This table reports summary statistics of the estimated CVP and its correlations with *Return* and *RV*. Specifically, I estimate the equation as shown in Table 4.4. Then I calculate the estimated CVP as $\widehat{CVP}_t = \beta^0 + \beta^- r_t^- + \beta^+ r_t^+ + \beta^{RV} RV_t$, The asterisks ***, **, * indicate significance at 1%, 5%, and 10% level respectively.

	Summary Statistics								Correlations	
	Mean	Median	Std. Dev.	Skew	Kurt	Min	Max	$Q_{LB}(5)$	Return	*RV*
AUD	.4068	.4002	.0281	2.588	18.34	.3004	.7862	16.60*	-.071*	.127***
GBP	.3825	.3780	.0173	1.877	7.140	.3249	.5332	10.83*	-.079*	.272***
EUR	.3512	.3342	.0510	.8322	3.839	.1444	.6866	87.81***	-.053*	.122***
JPY	.4375	.4411	.0459	-3.24	18.29	.1099	.6303	169.9***	-.012	.223***

To further examine return impacts on future volatility, I utilize the Shapley-Owen R^2 decomposition technique. Namely, the Shapley-Owen R^2 measure of regressors is the average incremental improvement in R-squared for each regressor (or coalition) over all possible permutations of regressors or coalitions of regressors (Lahaye and Neely, 2016). Table 4.6 shows that the Shapley-Owen R^2 of RV_t in the CVP model is lower by around 30% on average than that in the HAR model.[39] In other words, roughly 30% of the explanatory power of RV_t in the HAR model comes from the omitted CVP variables. Furthermore, the Shapley value in the last column of Table 4.6 suggests that the CVP explains 20% - 30% of the total variations in future volatility. Overall, Table 4.6 shows that the CVP is the dominant channel linking market conditions to future volatility. Unsurprisingly, Wang and Yang (2017) apply the CVP model to the US stock markets and obtain similar results.

Table 4.6: Shapley-Owen Values of Explanatory Variables in HAR and CVP Models

This table reports the Shapley-Owen decomposition of regression R^2. CVP_t includes $r_t^- RV_t$, $r_t^+ RV_t$, and RV_t^2. Δ% is the percentage change of the contribution in the HAR-CVP model in Table 4.4 relative to the contribution in the baseline HAR model in Table 4.2.

	RV_t	CVP_t	$RV_{t,W} + RV_{t,M}$	$r_{t,W} + r_{t,M}$	R^2	CVP_t/R^2
AUD						
HAR	0.238		0.422	0.027	0.697	
CVP	0.156	0.205	0.313	0.018	0.761	**29.21%**
Δ%	**-34.35%**					
GBP						
HAR	0.258		0.494	0.012	0.754	
CVP	0.170	0.230	0.355	0.008	0.785	**30.08%**
Δ%	**-34.24%**					
EUR						
HAR	0.157		0.361	0.004	0.524	
CVP	0.109	0.132	0.291	0.004	0.589	**24.61%**
Δ%	**-30.85%**					
JPY						
HAR	0.087		0.193	0.005	0.292	
CVP	0.065	0.059	0.168	0.004	0.301	**19.43%**
Δ%	**-25.35%**					

[39] Corsi and Reno (2012) demonstrate that the return impact on future volatility is also highly persistent and propose a HAR structure for returns to capture their heterogeneous effects. Accordingly, in Table 4.7, the lagged weekly ($r_{i,t,W}$) and monthly ($r_{i,t,M}$) returns are added to the benchmark HAR model, which are similarly defined as $RV_{i,t,W}$ and $RV_{i,t,M}$ in Section 4.3.1.

4.3.3.2. Additional conditioning variables

Furthermore, I attempt to test if adding trading activities as proxies for private information to the empirical volatility specification reduces the persistence of past volatility, then it may be reasonable to assume that the volatility clustering phenomena are related to trading activities. This section presents a simple empirical investigation where volatility persistence is regressed on exchange rate returns, volatility, and other additional variables. Namely, in addition to return and RV, I examine whether daily volatility persistence is affected by other conditioning variables, including Amihud's illiquidity measure (IL), number of trades (NT), and order imbalance (OI). The constructions and statistical descriptions of these variables are given in Section 3.6.1. of Chapter 3 and Table 4.1 respectively. Let Y_t be one of these variables on day t. To assess the impacts of these variables on volatility persistence, I extend the model in Eq. (4.4) to include Y_t and its interaction with RV_t.[40]

Table 4.7 reports the impacts of the additional conditioning variables. Even though I find that the realized volatility is highly contemporaneously correlated with the number of trades, illiquidity, and the order imbalance as shown in Panel B of Table 4.1, which is consistent with the Mixture of Distribution Hypothesis (MDH) theory suggesting that a latent information variable causes variabilities in trading activities and volatility simultaneously, none of the additional conditioning variable has a consistently significant impact on volatility persistence after the seasonal adjustments. For example, volume, illiquidity, and order flow have no consistently positive and significant effect on volatility persistence in the CVP model, and the significant effects of return and RV as shown in Table 4.7 remain intact.

[40] To adjust for seasonality, I regress the market state variables on their own lagged values, time dummies (i.e., weekdays and months), linear and quadratic time trends, and then use the residuals as the seasonally-adjusted series in the following regressions.

Table 4.7: CVP Model with Additional Conditioning Variables

This table reports the daily persistence coefficients of the following model:

$$RV_{i,t+1} = \alpha_{i,t+1} + (\beta_i^0 + \beta_i^- r_{i,t}^- + \beta_i^+ r_{i,t}^+ + \beta_i^{RV} RV_{i,t} + \beta_i^Y Y_{i,t}) RV_{i,t} + \beta_{i,\mathrm{W}} RV_{i,t,W} + \beta_{i,M} RV_{i,t,M} + \theta_{i,t} r_{i,t} + \theta_{i,W} r_{i,t,W} + \theta_{i,M} r_{i,t,M} + \varepsilon_{i,t+1}$$

where $Y_{i,t}$ denotes additional conditioning variables, including Amihud (2002)'s illiquidity measure (IL), the number of trades (NT), and order imbalance (OI). All the market state variables are detrended, namely, I regress the time series of market state variables on their own lagged values, weekday and month dummies, linear and quadratic time trends, and then define the residuals as the corresponding detrended data. The t-statistics are based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. The asterisks ***, **, * indicate significance at 1%, 5%, and 10% respectively.

	β^0	β^-	β^+	β^{RV}	β^{OI}	β^{NT}	β^{IL}	$\bar{R}^2$
	.3780***	-.0466*	.0797**	-.0153	-.1514			.7594
	(6.50)	(-1.74)	(2.02)	(-1.60)	(-1.56)			
AUD	.2106***	-.0595**	.0551	-.0186**		.0142*		.7594
	(3.05)	(-2.02)	(1.56)	(-2.06)		(1.70)		
	.3476***	-.0352***	.0472***	-.0229*			.0063	.7640
	(7.01)	(-2.25)	(3.13)	(-1.65)			(0.41)	
	.3355***	-.0327	.0752	-.0024	-.1363*			.7600
	(5.58)	(-0.70)	(1.41)	(-0.24)	(-1.75)			
GBP	.2115**	-.0519	.0375	-.0032		.0192**		.7645
	(2.26)	(-1.33)	(0.85)	(-0.29)		(2.49)		
	.2730***	-.0652***	.0602**	-.0076			.0203	.7853
	(5.49)	(-2.87)	(2.50)	(-0.34)			(0.56)	
	.3780***	-.0466*	.0797**	-.0153	-.2514***			.4212
	(6.50)	(-1.74)	(2.02)	(-1.60)	(-3.56)			
EUR	.2106***	-.0595**	.0551	-.0186**		.0142*		.4987
	(3.05)	(-2.02)	(1.56)	(-2.06)		(1.70)		
	.3065***	-.0661*	.1706***	-.0301***			.0114	.5915
	(4.06)	(-1.69)	(6.24)	(-2.62)			(1.40)	
	.3355***	-.0327	.0752	-.0024	-.1363*			.1898
	(5.58)	(-0.70)	(1.41)	(-0.24)	(-1.75)			
JPY	.2115**	-.0519	.0375	-.0032		.0018		.2133
	(2.26)	(-1.33)	(0.85)	(-0.29)		(0.49)		
	.2730***	-.0652***	.0602**	-.0076			.0203	.2034
	(5.49)	(-2.87)	(2.50)	(-0.34)			(0.56)	

4.3.4. Economic Value of Volatility Timing

In this section, I estimate the economic benefits of volatility forecasting models using a number of evaluation metrics. First, in terms of economic gains, I compute the realized utility that a given volatility model generates over that from the static one. Namely, the main purpose is to estimate the fee that an investor would be willing to pay for switching from a static risk model. Second, I examine the ex-post performance of optimal portfolio with predictive volatility (i.e. average portfolio returns, volatility, and the Sharpe ratio). If the dynamic volatility models generate more accurate volatility forecasts, then the investor would gain from dynamically rebalancing the optimal portfolio based on the signal of the predicted volatility.

To compare the realized utility across risk models, I consider the simplest possible utility-based framework, namely, an investor with mean-variance preferences investing in an asset with time-varying volatility and a constant Sharpe ratio.41 The major advantages of this "realized utility" approach lie in the fact that by assuming a constant Sharpe ratio, I don't have to predict future exchange rate movements, which is difficult if possible at all, given the fact that exchange rates generally follow a random walk process (Meese and Rogoff, 1983). Furthermore, the "realized utility" approach is based on the daily estimates of volatility and is very easy to implement. Last but not least, this non-parametric approach also mitigates the impact of estimation risk or parameter learning which would probably lead to misleading allocations.

To empirically conduct the economic evaluations of volatility forecasting models, I consider a risk-averse investor with mean-variance preferences, who allocates her wealth into one risky asset (i.e., a single currency pair) and one risk-free asset (i.e. the US treasury bond). The specification of one risk asset in the portfolio is similar to Nolte and Xu (2005) and Bollerslev et al. (2017), which avoids covariance forecasting in multivariate settings and controls for information spillovers across

[41] However, as explained in Bollerslev et al. (2017), the same setup readily extends to allow for time-varying Sharpe ratios as long as the temporal variation of Sharpe ratio is independent of the conditional risk.

different assets. The economic explanation behind this strategy is intuitive: given the expected return, when the volatility level is high (low), the investor allocates less (more) wealth into the risky asset and yields higher risk-adjusted return. If taking account of the conditional volatility persistence leads to more accurate volatility forecasting, then the investor would improve her portfolio performance by dynamically rebalancing the portfolio based on the signal of the predicted volatility. Different from existing studies which compare dynamic and static strategies (Fleming et al., 2001), dynamic strategies based on returns sampled at high frequency and daily frequency (Fleming et al., 2003), dynamic strategies utilizing the conventional realized variance and jump-robust realized variance measures (Nolte and Xu, 2015), the analysis in this chapter compares the performances of variants of HAR models all of which use high frequency information and build upon dynamic structure. Generally, this study is closely related to Bollerslev et al. (2017) which compares multiple RV-based HAR models. However, I confirm that the CVP model, which explicitly links market conditions to future volatility persistence, beats other RV-based HAR models in terms of statistical significance and economic value.

Namely, I consider an investor with mean-variance preferences that trades a risky asset with a constant Sharpe ratio, so the investor's optimal portfolio naturally adjusts the position size to keep a constant volatility (which will also depend on the investor's risk aversion). For concreteness and simplicity, I take the Sharpe ratio to be SR = 0.3 and the risk aversion to be $\gamma = 3$, which results in a specified target volatility of 0.1 or 10%.[42] Hence, risk models that help the investor achieve more accurate forecasts of future volatilities are associated with higher levels of utility. Here, I empirically evaluate the average realized utility per unit of wealth (*UoW*) for each risk model by summing the corresponding realized expressions

[42] In fact, the number of 10% volatility level is in the right ballpark for many target volatility funds, according to Bollerslev et al. (2017).

over the same rolling out-of-sample forecasts (For short, we can simply call this the "realized utility" as in Bollerslev et al. (2017).):[43]

$$UoW^{\theta} = \frac{1}{T}\sum_{t=1}^{T}\left(3\%\frac{\sqrt{RV_{t+1}}}{\sqrt{E_t^{\theta}(RV_{t+1})}} - 1.5\%\frac{RV_{t+1}}{E_t^{\theta}(RV_{t+1})}\right) \tag{4.5}$$

where RV_{t+1} and $E_t(RV_{t+1})$ are the observed and predicted realized variance on day *t+1* respectively. Mathematically, a perfect risk prediction model would lead to 1.50% utility according to Eq. (4.5). The realized utility obviously depends on the specific risk model θ, since each risk model gives rise to different predictions $E_t^{\theta}(RV_{t+1})$, therefore leading to different position sizes. Since the expected return has been substituted, this measure of realized utility only depends on each risk model's ability to correctly target volatility. Importantly, this approach eliminates the noise from random return realizations, allowing us to meaningfully compare different risk models based only on the actual realized volatilities for different assets (Bollerslev et al., 2017).

4.4. Empirical Results

4.4.1. Out-of-sample Forecasting Performance

I firstly estimate the model parameters using the first 5 years of observations as the in-sample period, and then use the rest of the sample as the out-of-sample period. All of the forecasts are generated using rolling WLS regressions and parameter estimates are updated daily. Namely, forecasts are based on 5-year rolling windows, starting from January 1999 for AUD, GBP, and JPY, while from January 2000 for EUR, resulting in more than 2,000 daily observations as the forecasting subsample. No restrictions on the parameters are imposed and therefore forecasts are occasionally negative.[44] Forecasting performance is evaluated based on two loss functions: the quasi-likelihood function $\mathrm{QLIKE}(\mathrm{RV}_t, \widehat{\mathrm{RV}}_t) = \frac{\mathrm{RV}_t}{\widehat{\mathrm{RV}}_t} - \ln\left(\frac{\mathrm{RV}_t}{\widehat{\mathrm{RV}}_t}\right) - 1$ and the logarithmic mean-squared errors

[43] For a more detailed introduction to the derivation of the expression of average realized utility per unit of wealth (*UoW*), please refer to Section 6 of quantifying the utility benefit of risk models in Bollerslev et al. (2017).

[44] Following Wang and Yang (2017), an "insanity filter" is used to replace a negative RV forecast with the lowest RV in the rolling window.

$\mathrm{LMSE}\big(\mathrm{RV}_t, \widehat{\mathrm{RV}}_t\big) = (\ln(\mathrm{RV}_t) - \ln(\widehat{\mathrm{RV}}_t))^2$, where $\widehat{\mathrm{RV}}_t$ is the forecasted value of RV_t. Patton (2012) shows that QLIKE is robust to the noise in the empirical volatility measures, and Patton and Sheppard (2009) suggest that QLIKE has the best size-adjusted power among robust loss functions. The usual mean-squared error (MSE) is often affected by a few extreme observations. Therefore, I use the logarithmic MSE to mitigate this problem. Furthermore, forecast performance is examined by the Diebold-Mariano (1995)'s test of equal forecast accuracy. Specifically, taking the HAR model as the benchmark, a negative DM statistic indicates a reduction in loss value by other volatility models relative to HAR. While HAR is nested in CVP model, Giacomini and White (2006) show that the DM test remains asymptotically valid when the estimation period is finite.

To compare the performance of volatility models and provide further evidence on the importance of the conditional volatility persistence, I compare the pseudo out-of-sample volatility forecasts based on the benchmark HAR model (HAR) against those based on the semi-variance HAR (SHAR) and conditional HAR model (CVP). In volatility forecasts, model parameters are estimated using a rolling window. Therefore, even in models with constant volatility persistence, the coefficient of persistence is re-estimated every day. If the dynamic volatility persistence indeed varies with return and volatility as suggested in the preceding analysis, the CVP model should achieve superior out-of-sample forecasting performance and therefore lead to significant economic gains. Table 4.8 provides a summary of QLIKE and LMSE values. For both loss functions, CVP has the lowest mean and median loss values, and the reduction in loss value of CVP is substantial for most currencies as suggested by the DM tests. Besides, SHAR has relatively lower values of loss functions compared to benchmark HAR model, which justify the usage of asymmetric volatility models in the FX market.

Table 4.8: Forecasting Performance Evaluation

This table reports the average, median, and standard deviation of the loss functions QLIKE and LMSE for the HAR model, the semi-variance HAR model (SHAR), and the conditional HAR model (CVP) using the exchange rates of AUD, GBP, EUR, and JPY, all against USD. DM stat is the Diebold-Mariano (1995)'s test for the equality of forecast accuracy of two forecasts. Here, taking the HAR model as the benchmark, a negative DM statistic indicates a reduction in loss value relative to HAR.

	HAR		SHAR		CVP	
	QLIKE	LMSE	QLIKE	LMSE	QLIKE	LMSE
AUD						
Average	0.2129	0.1243	0.2111	0.1234	0.2083	0.1222
Median	0.0779	0.0395	0.0768	0.0390	0.0752	0.0382
St Dev	0.4127	0.3302	0.4092	0.3256	0.4040	0.3188
DM Stat	0	0	-4.33***	-3.18***	-8.26***	-4.13***
GBP						
Average	0.1478	0.0804	0.1458	0.0801	0.1429	0.0800
Median	0.0597	0.0159	0.0568	0.0147	0.0525	0.0128
St Dev	0.2147	0.2302	0.2104	0.2288	0.2040	0.2266
DM Stat	0	0	-1.77*	-1.72*	-1.82*	-1.83*
EUR						
Average	0.5392	0.3491	0.5206	0.3345	0.4920	0.3210
Median	0.2402	0.1415	0.2385	0.1265	0.2179	0.1140
St Dev	0.7997	0.7411	0.7937	0.7310	0.8088	0.7562
DM Stat	0	0	-1.78*	-1.56	-2.78**	-1.76*
JPY						
Average	1.0115	0.8968	0.9633	0.8724	0.9922	0.8359
Median	0.4907	0.2671	0.4561	0.2582	0.4769	0.2449
St Dev	1.4504	2.2453	1.4449	2.2385	1.4482	2.2282
DM Stat	0	0	-1.62*	-1.48	-1.54	-1.66*

4.4.2. Realized Utility of Volatility Timing

Firstly, I investigate the utility benefits of the different risk models in the absence of transaction costs by calculating the realized utilities as given directly by Eq. (3.5). I then incorporate reasonable transaction cost estimates into the analysis, along with noise-robust realized variance measures in the robustness analysis section. The results rely on the same rolling estimates for the different risk models underlying the daily predictive out-of-sample forecasts. For comparison purposes, I also include the results for additional simple benchmark models.

Specifically, the first column on the top of Table 4.9 (i.e., the full sample) reports the realized utilities from using static risk models, namely, the in-sample mean of volatility. Doing so achieves a realized utility of 0.75% on average across all currencies, half the 1.50% maximum utility for the perfectly targeted daily positions. Meanwhile, as the second column shows, even a simple dynamic risk targeting strategy based on the 21-day rolling average of realized variance generates quite substantial gains vis-à-vis the static position reported in the first column. The third to fifth columns report the realized utilities obtained from using the predicted realized variances based on classic HAR model, semi-variance HAR (SHAR) model, and conditional HAR (CVP) model respectively. As previously noted, perfectly targeting the daily volatility would result in a realized utility of 1.50%. By comparison, a risk model that takes the conditional volatility persistence into account would result in an average realized utility of 1.26%. This latter number, of course, is quite close to the utilities obtained from each of the practically feasible RV-based risk models.

Table 4.9: Realized Utility for Volatility Targeted Positions

This table reports average utilities of holding a volatility-targeted asset, where dynamics positions are based on volatility predictions from various risk models. Simple Average, Moving Average, HAR, SHAR, and CVP stands for in-sample average volatility, expanding mean volatility (i.e., simple moving average with a rolling 21-day window), heterogeneous autoregressive model, semi-variance heterogeneous autoregressive model, and conditional volatility persistence model respectively. GFC stands for the global financial crisis period of July 1, 2008 to June 30, 2009. Here I assume zero transactions costs for all utility calculations, and all assets trade completely to their target positions at the end of each trading day.

	Simple Average	Moving Average	HAR	SHAR	CVP
Full Sample					
AUD	0.7593%	1.1052%	1.2278%	1.2292%	1.2307%
GBP	0.7965%	1.1590%	1.2473%	1.2477%	1.2483%
EUR	0.7554%	1.0994%	1.2761%	1.2763%	1.3337%
JPY	0.6890%	1.0028%	1.2122%	1.2234%	1.2241%
Average	0.7521%	1.0916%	1.2409%	1.2442%	1.2592%
GFC					
AUD	0.2024%	0.4145%	1.2310%	1.2368%	1.4398%
GBP	0.2313%	0.4736%	1.2521%	1.2563%	1.4578%
EUR	0.2439%	0.4994%	1.1649%	1.1667%	1.1720%
JPY	0.2024%	0.4144%	1.4368%	1.4377%	1.4398%
Average	0.2212%	0.4505%	1.2712%	1.2744%	1.3774%

To put these numbers further in perspective, consider the 1.26% utility of the conditional volatility persistence (CVP) model relative to the 0.75% utility of the static risk model. These two numbers imply that the risk-targeting investor would give up 0.51% of wealth annually to use the CVP model rather than a static risk model. This shows the non-trivial importance of risk modelling more generally. It also illustrates that the value of a good risk model can account for a substantial fraction of typical asset management fees.

Furthermore, I conduct a subperiod analysis to examine whether the CVP performs better during the high volatile periods (i.e. the GFC period). Namely, I investigate whether the relative performance of the CVP model improves or deteriorates under extreme market conditions. Then I calculate the values of realized utility for the GFC period and compare economic performances under different market conditions. The bottom panel of Table 4.9 reports the realized utility during the global financial crisis period of July 1, 2008 to June 30, 2009. Consistent with the results as shown in the top panel of Table 4.9, the CVP model leads to the largest realized utility for all currencies during the GFC period. However, the static risk models (i.e., in-sample average and simple moving average of historical volatility) generate significantly smaller utility during the GFC period, while the dynamic volatility models, particularly the CVP model, perform better under stressed market environments. The average increase in the realized utility for the CVP model is around 0.12% (i.e., from 1.26% to 1.38%), which is quite large relatively to the benchmark HAR model (e.g., from 1.24% to 1.27%), suggesting that the CVP achieves significantly better performance under extreme market conditions. Besides, the CVP still outperforms the HAR and SHAR models during the GFC period and the improved performance of the CVP model highlights the benefits of using market conditions to calibrate volatility prediction during high volatile periods.

The 0.51% utility gain for the CVP model is obtained under the assumption of a Sharpe ratio of 0.3 and a risk aversion coefficient of 3, or equivalently an optimal risk target of 10% together with a Sharpe ratio of 0.3. Furthermore, Table 4.10 reports the utility gains of the CVP model that would result in under alternative assumptions. Clearly, the utility benefits of the CVP model are substantially larger if the SR and/or risk target are bigger. For instance, if the SR is 0.4 and the annualized risk target is 15% (corresponding to a risk aversion of 2.7), then the utility benefits increase to 1.01% per year.

Table 4.10: Utility Benefits of CVP Model Relative to Static Risk Model

This table shows the average utility benefit of positions based on fitted values from the CVP model relative to a static volatility model (i.e., in-sample average volatility) as the assumed Sharpe ratio and optimal risk target vary. I assume zero transactions costs for all utility calculations, and all assets trade completely to their target positions at the close of each business day.

		Risk Target				
		5%	10%	15%	20%	25%
Annualized Sharpe Ratio	0.1	0.08%	0.17%	0.25%	0.34%	0.42%
	0.2	0.17%	0.34%	0.51%	0.68%	0.85%
	0.3	0.25%	0.51%	0.76%	1.01%	1.27%
	0.4	0.34%	0.68%	1.01%	1.35%	1.69%
	0.5	0.42%	0.85%	1.27%	1.69%	2.11%
	0.6	0.51%	1.01%	1.52%	2.03%	2.54%
	0.7	0.59%	1.18%	1.77%	2.37%	2.96%
	0.8	0.68%	1.35%	2.03%	2.70%	3.38%

However, the previous comparisons ignore the trading cost of implementing the strategy based on predictions from the different risk models. In practice, of course, trading is costly. Since the realized utility in Eq. (4.5) is effectively expressed in units of returns, it is easy to incorporate the effect of transaction costs by simply subtracting the simulated costs of implementing the different risk models. For simplicity, I will assume that the costs of trading are linear in the absolute magnitude of the change in the positions, $\left|x_t^\theta - x_{t-1}^\theta\right|$. I use the median spread for each of the currencies over the last six months of the forecasting period as the benchmark estimate for the cost of trading. However, I also consider both lower (one-half times the typical spreads) and higher (two-and-a-half times the typical spreads) transaction costs. The resulting realized utilities net of costs are reported in Table 4.11. All of the utilities (aside from the utilities for the constant positions based on the static risk model in the first column) are obviously lower than the corresponding numbers reported under the previous zero-cost assumption. Explicitly incorporating transaction costs also tends to slightly magnify the utility differences among the different risk models, and more so the higher the transaction costs.

Interestingly, the conditional volatility persistence (CVP) volatility model reported in the last column is now quite inferior and far from the 1.50% maximum utility, particularly when the transaction cost is 5 times half-spread, as the costs of (too much) trading far outstrip the benefits. At a more general level, this highlights the trade-off that exists between a more accurate risk model and the cost associated with the implementation of such a model. It also indirectly suggests that faced with high(er) transaction costs it may be better to not trade all the way to the target, but instead only adjust the positions partially.

Table 4.11: Realized Utility for Volatility Targeted Positions with Transaction Costs

This table reports average utilities of holding a volatility-targeted asset, where dynamics positions are based on volatility predictions from various risk models. Simple Average, HAR, SHAR, and CVP stands for in-sample average volatility, heterogeneous autoregressive model, semi-variance heterogeneous autoregressive model, and conditional volatility persistence model respectively. Transactions costs are 1, 2, or 5 times the median of half-spread over the last six months of the forecasting period for each currency.

		Simple Average	HAR	SHAR	CVP
AUD	1*Half-Spread	0.7593%	1.1783%	1.1785%	1.1873%
	2*Half-Spread	0.7593%	1.1157%	1.1128%	1.1154%
	5*Half-Spread	0.7593%	0.9279%	0.9157%	0.8997%
GBP	1*Half-Spread	0.7965%	1.1939%	1.1925%	1.2033%
	2*Half-Spread	0.7965%	1.1405%	1.1373%	1.1482%
	5*Half-Spread	0.7965%	0.9803%	0.9717%	0.9831%
EUR	1*Half-Spread	0.7554%	1.2065%	1.2036%	1.2045%
	2*Half-Spread	0.7554%	1.1370%	1.1311%	1.1353%
	5*Half-Spread	0.7554%	0.9285%	0.9138%	0.9178%
JPY	1*Half-Spread	0.6890%	1.1311%	1.1300%	1.1312%
	2*Half-Spread	0.6890%	1.0528%	1.0533%	1.0687%
	5*Half-Spread	0.6890%	0.8133%	0.8078%	0.8983%
Average	1*Half-Spread	0.7501%	1.1775%	1.1762%	1.1816%
	2*Half-Spread	0.7501%	1.1115%	1.1086%	1.1169%
	5*Half-Spread	0.7501%	0.9125%	0.9023%	0.9247%

4.4.3. Alternative Measure of Economic Gains of Volatility Timing

Around 0.51% annualized average performance fee looks small in magnitude, and I therefore assess the statistical significance of the economic value generated. In this section, I utilize the volatility targeting strategy, which dynamically rebalances the portfolio daily based on the one-day ahead prediction of realized variance, to construct a portfolio with a target annualized volatility of 10%.[45] This increasingly popular strategy simply utilizes dynamic asset allocation by selling (buying) assets when their risk-adjusted expected return is falling (rising), while their volatility is rising (falling), and thereby investors can increase risk-adjusted returns and smooth the overall volatility profile of the allocation by maintaining a targeted level of risk. Then I perform a simple backtesting analysis and report the portfolio return, volatility, and the Sharpe ratio to examine the ex-post portfolio performances of volatility targeting strategies based on various risk models.[46] Namely, for each currency, I calculate the annualized mean realized return μ, the annualized standard deviation σ, and the realized Sharpe ratio SR in Table 4.12. The sample period is January 3, 2008 through December 31, 2013. Averaging across the currencies, the static strategy (i.e., the strategy without volatility timing) produces a mean Sharpe ratio of 0.83, compared to 1.13, 1.12, and 1.23 for the dynamic volatility targeting strategies using HAR, SHAR, and CVP model respectively. Although these differences do not seem large, they can translate into sizable performance fees (Fleming et al., 2001). Overall, the CVP model can achieve superior performance relative to other dynamic volatility models in terms of forecasting performance and economic value. Besides, during the GFC period, the CVP model achieves a Sharpe ratio as high as 1.55, which significantly outperforms its counterparts and proves to be an essential risk management tool to deliver sizable profits.

[45] I also calculate the Sharpe ratio under the assumption of the target annualized volatility ranging from 5% to 30%. The empirical results suggest that the CVP model achieves the highest Sharpe ratio, followed by SHAR and HAR model, under all possible scenarios.

[46] The Sharpe ratio, a measure of the expected return per unit of risk, was originally proposed to measure the performance of mutual funds by William Sharpe (Sharpe, 1966). Since then, it has been extensively applied in financial practices to evaluate the investment performance due to its simplicity and popularity.

Table 4.12: Sharpe Ratios of Volatility Timing Strategy

This table reports the mean realized return μ, standard deviation σ, and Sharpe ratio SR of various volatility models. Simple Average stands for the static portfolio without volatility timing, while HAR, SHAR, and CVP stands for dynamic portfolio rebalancing based on the one-day-ahead volatility forecasting using heterogeneous autoregressive model, semi-variance heterogeneous autoregressive model, and conditional volatility persistence model respectively. Here I assume zero transactions costs for all calculations, and all assets trade completely to their target positions at the end of each trading day.

	No Volatility Timing			Volatility Timing Strategy								
	Simple Average			HAR			SHAR			CVP		
	μ	σ	SR	μ	σ	SR	μ	σ	SR	μ	σ	SR
AUD	1.166	0.935	**1.247**	1.271	0.849	**1.497**	1.271	0.851	**1.494**	1.290	0.825	**1.564**
GBP	1.192	0.770	**1.548**	1.197	0.652	**1.836**	1.196	0.650	**1.840**	1.206	0.637	**1.893**
EUR	1.613	2.705	**0.596**	1.615	1.902	**0.849**	1.613	1.903	**0.848**	1.632	1.945	**0.839**
JPY	1.160	1.814	**0.639**	1.267	1.321	**0.959**	1.249	1.335	**0.936**	1.424	1.116	**1.276**
Average	1.283	1.556	**0.825**	1.338	1.181	**1.133**	1.332	1.185	**1.124**	1.388	1.131	**1.227**

The most important result in this section is that the volatility targeting strategy, based on conditional volatility persistence model, uniformly dominates the static strategy as well as dynamic strategies based on other volatility models. This is measured by the realized utility and out-of-sample returns to optimal portfolios and holds for a range of plausible risk aversions and are robust to market microstructure noise and transaction costs. [47] I am aware that a portfolio consisting of only one currency pair is unlikely to be a realistic portfolio managed by a currency manager, however, a larger portfolio would expand the opportunity set and likely perform much better (King, Sarno and Sojli, 2010). Hence, I can achieve the objective of measuring the economic value of the predictive content of conditional volatility persistence in the context of a single currency pair, which provides a plausible test of the volatility-timing ability of Conditional Volatility Persistence model. Furthermore, considering commonality in foreign exchange

[47] Furthermore, I calculate the Information Ratio (IR) of optimal portfolios based on different risk models. The optimal portfolio based on the CVP model achieves the highest IR as well, particularly during the GFC period (i.e. July 2008 to June 2009). These results are not reported here for brevity, which are however available upon request.

volatility and liquidity, the generality of these empirical results can be grounded to a large extent.

4.5. Robustness Analysis

In this section, I conduct a robustness analysis to examine the relative performance of the CVP model by using noise-robust realized variance measures as suggested in Section 4.2.2. Namely, I re-estimate the variant HAR models and compare their performances by using the Two-scale Realized Variance (TSRV) estimator which proves to be an efficient and robust-sound realized variance measure. Interestingly, the results of the forecasting comparisons (i.e., the values of loss functions of QLIKE and LMSE) suggest that the CVP model can still generates better forecasting performance when using noise-robust variance measures.[48] Instead I report the realized utilities calculated when forecasting using TSRV as shown in Table 4.13. Interestingly, the results of economic gains are comparable to those calculated by using RV. Overall, I can conclude that the conditional volatility persistence which links market state variables to future volatility is helpful in explaining the asymmetry and long memory in volatility even after controlling for market microstructure noise. The model which incorporates the feature of conditional volatility persistence can outperform other dynamic volatility models with regard to forecasting performance and economic value.

[48] For the sake of brevity, I do not present those results, which are available upon request.

Table 4.13: Realized Utility for Volatility Targeted Positions using TSRV

This table reports average utilities of holding a volatility-targeted asset, where dynamics positions are based on volatility predictions from various risk models. Simple Average, Moving Average, HAR, SHAR, and CVP stands for in-sample average volatility, expanding mean volatility (i.e., simple moving average with a rolling 21-day window), heterogeneous autoregressive model, semi-variance heterogeneous autoregressive model, and conditional volatility persistence model respectively. RV and TSRV stands for using the realized variance and two-scale realized variance respectively when estimating the RV-based HAR models. Here, I assume zero transactions costs for all utility calculations, and all assets trade completely to their target positions at the end of each trading day.

	Simple Average	Moving Average	HAR	SHAR	CVP
RV					
AUD	0.7593%	1.1052%	1.2278%	1.2292%	1.2307%
GBP	0.7965%	1.1590%	1.2473%	1.2477%	1.2483%
EUR	0.7554%	1.0994%	1.2761%	1.2763%	1.3337%
JPY	0.6890%	1.0028%	1.2122%	1.2234%	1.2241%
Average	0.7521%	1.0916%	1.2409%	1.2442%	1.2592%
TSRV					
AUD	0.7605%	1.1040%	1.2290%	1.2280%	1.2319%
GBP	0.7953%	1.1578%	1.2485%	1.2465%	1.2495%
EUR	0.7566%	1.0982%	1.2773%	1.2751%	1.3349%
JPY	0.6878%	1.0040%	1.2110%	1.2246%	1.2229%
Average	0.7501%	1.0910%	1.2415%	1.2435%	1.2598%

4.6. Concluding Remarks

In this chapter, I extend the conditional volatility persistence (CVP) model to the FX market and present a simple utility-based approach to evaluating the economic gains of volatility timing strategy which has been widely implemented into financial practices (i.e. the ever-growing market share of target volatility funds). A convenient feature of this timing strategy is that it requires only daily estimates of the second moment of exchange rate returns. For example, I utilize the forecasting techniques of the realized variance estimators in the empirical analysis above and prove the significant economic value of the CVP model which incorporates the feature of time-varying volatility persistence and explicitly links the changing market conditions to the future volatility.

Considering the profitability of accurate volatility forecasts and volatility timing in optimal portfolio construction, there are several possible directions for further study. Firstly, it would be interesting to investigate whether more sophisticated estimation techniques can lead to significant benefits, such as increased economic gains of volatility forecasting; secondly, all of the forecasting models implemented in this chapter are univariate. However, most practical questions related to risk measurement and management are intrinsically multivariate in nature, requiring the forecasts of both asset return variances and covariances. Whether the CVP model can be applied to the portfolio construction in the multivariate context deserves further study.

Chapter 5: Conclusions

This dissertation consists of three independent essays that explore different aspects of price discovery and volatility dynamics in the FX market. The main findings of each chapter can be summarised as follows:

I estimate the magnitudes and determinants of global information distribution of AUD trading in the Asian, European, and North American markets in the second chapter. Specifically, using the firm quotes of AUD against the US dollar from January 1999 to December 2013, and employing a non-parametric methodology of price discovery measures, i.e., the Two-scale Realized Variance (TSRV) ratio, I estimate the information shares of global AUD trading. I find that the European market and US market, particularly the overlapping trading session of London and New York, dominate the price discovery process in AUD market, but Asia is rapidly gaining information shares even with its declining market share of daily transactions. After estimating the information shares, I focus on the short- and long-run determinants in each market. The empirical analysis shows that after controlling for spillover effects and dynamic natures of information shares, more favourable market states and more unexpected order flows on macroeconomic announcement days make a significantly positive contribution to price discovery for AUD trading in the short-run, while a higher degree of market integration and capital market openness, as proxied by the Chinn-Ito Index, contributes to price discovery in the long-run.

In the third chapter, I revisit the meteor showers and heat waves effects for AUD/USD, GBP/USD, EUR/USD, and USD/JPY spanning from January 1999 (January 2000 for EUR) to December 2013. Utilizing the volatility measures based on high-frequency data, I find evidence of both meteor showers and heat waves effects in the four trading segments of global FX market, which is consistent with Lahaye and Neely (2016) who divide a calendar day into five segments and confirm the presence of meteor shower and heat waves effect in each segment. However, unlike Lahaye and Neely (2016), I find that the relative importance of meteor shower effect has been increasing rapidly and has predominated over heat waves effects in the intra-daily volatility spillovers, which emphasizes the increasing interdependence and interconnectedness in the global FX market. By investigating the patterns and economic mechanisms of meteor showers and heat waves effects, I contribute to the literature regarding volatility spillover in the financial markets. Specifically, I identify the key factors causing volatility spillovers in different trading sessions, which highlight the complex geographical nature of the FX market. Namely, the conditional volatility persistence is the fundamental channel linking each region's market states to the future volatility. These empirical results argue in favour of modelling FX volatility dynamics segment-wise, rather than in the more traditional approach of assuming a homogeneous process.

In the fourth chapter, I comprehensively investigate the role of conditional volatility persistence in predicting future volatility from both statistical and economic perspectives. I show that taking into account conditional volatility persistence improves volatility forecasts both in-sample and out-of-sample. For example, by utilizing the Shapley decomposition techniques, I find that the conditional volatility persistence explains large portions of the variations in future volatility and is the dominant channel linking market states to future volatility. Moreover, I show that these statistical improvements can be translated into economic values. By developing a simple yet accurate utility framework based on mean-variance analysis, I show that under empirically realistic assumptions, the CVP model is worth at least 0.51% of wealth per year relative to a static risk model, and can achieve higher Sharpe ratios, particularly during the turmoil period. The results hold true across the major exchange rates and are robust to market microstructure effects and transaction costs.

In sum, the empirical findings presented in this dissertation provide a thorough analysis of the information distribution and propagation in one of the largest financial markets – the Foreign Exchange (FX) market. The empirical studies discussed in this thesis also deepen our understanding of the microstructure of the FX market. Besides, the evidence presented in this thesis could be of great interest to academics, practitioners, and regulators, and can potentially aid policy development of the FX market which remains opaque to a great extent (Rime and Schrimpf, 2013). The empirical evidences presented in this dissertation will provide important policy implications, especially for emerging markets, which are still in the process of currency internationalization. For example, with the increasing interdependence and interconnectedness in the global FX market, the authorities in emerging markets have to strike a balance between maintaining exchange rate stability and internationalizing their currency in the face of growing international capital flows.

There are several possible directions for further study. For example, how to accurately measure the price discovery in the financial markets is one question that is yet to be fully answered and better understood. Furthermore, additional research is required to consider the generalizability of these results. This will involve considering price discovery and volatility dynamics in other major currencies, as well as in emerging market currencies. Besides, how to identify the institutional sources of long-memory in volatility and its spillovers deserves further study, which will definitely improve our understanding of volatility transmission and extend our economic intuition of risk contagion in the financial markets. Another possible direction is to assess the economic values of volatility timing in more concrete financial applications such as multi-period portfolio management in the multivariate context as in Fleming et al. (2001, 2003). Lastly, the intraday relationship between markets can be affected by microstructure differences such as institutional features, heterogeneous investors, or different trading rules. Therefore, more investigation on the effects of microstructure over volatility dynamics mechanisms would be highly desirable.

Appendices

Appendix A: Turnover of foreign exchange instruments, by currency

This table reports the average daily turnover of top-5 most traded currencies from April 2010 to April 2016. It is based on the triennial central bank surveys conducted by the Bank for International Settlements (BIS, 2010, 2013, and 2016). Amount includes spot, outright forward, and swap transactions which is measured in billions of USD and percentage share. The percentage shares sum to 200% because two currencies are involved in each transaction.

	2010		2013		2016	
	Amount	Percent	Amount	Percent	Amount	Percent
USD	3,371	84.91	4,662	87.02	4,438	87.26
EUR	1,551	39.02	1,790	33.43	1,591	31.43
JPY	754	19.01	1,235	23.06	1,096	21.65
GBP	512	12.94	633	11.86	649	12.86
AUD	301	7.63	463	8.62	348	6.92
Global Total	3,973	200.00	5,357	200.00	5,067	200.00

Appendix B: Average daily transactions of AUD

This table reports the average daily transactions for AUD against USD from April 2007 to April 2013 in the top-10 foreign exchange markets. It is based on a series of triennial central bank surveys conducted by the Bank for International Settlements (BIS, 2007, 2010, and 2013). Volumes include spot, outright forward, and swap transactions and are measured in billion USD.

AUD	2007		2010		2013	
	Value	Precent	Value	Precent	Value	Precent
Australia	76.70	33.41	75.50	23.09	80.50	17.30
Denmark	0.46	0.20	1.40	0.43	2.31	0.50
France	5.89	2.57	6.25	1.91	9.00	1.93
Germany	1.25	0.54	2.11	0.65	3.08	0.66
Hong Kong	14.00	6.10	24.64	7.54	20.81	4.47
Japan	10.60	4.62	8.16	2.50	18.11	3.89
Singapore	15.70	6.84	27.57	8.43	37.19	7.99
Switzerland	6.12	2.67	10.08	3.08	8.12	1.75
United Kingdom	55.90	24.35	102.00	31.19	181.80	39.08
United States	30.90	13.46	56.06	17.14	82.39	17.71
Asia in Top 10	117.00	50.96	135.87	41.55	156.61	33.67
Europe in Top 10	69.60	30.31	121.84	37.26	204.31	43.92
America in Top 10	30.90	13.46	56.06	17.14	82.39	17.71
Top 10	217.50	94.73	313.77	95.95	443.31	95.29
Global Total	229.60	100.00	327.00	100.00	465.20	100.00

Appendix C: Summary statistics of long-run determinants

The definitions of the four sequential sessions, namely, “Asia”, “Europe”, “NYLON” (London/New York), and “North America”, are as given in Table 2.1. QLB (12) is the Ljung-Box Q statistic at 12 lags. The asterisk * indicates significance at the 5% level.

	Asia	Europe	London/New York	US
Number of Banks				
Mean	40.00	34.00	30.00	33.00
Std. Dev.	15.73	15.52	16.04	14.44
Skewness	0.521	0.067	-0.077	-0.192
Kurtosis	0.201	-0.334	-0.441	-0.170
$Q_{LB}(5)$	454.9*	403.7*	476.1*	354.5*
Pct. of Foreign Banks				
Mean	21.42	26.65	40.18	47.63
Std. Dev.	12.31	15.95	17.32	13.60
Skewness	-0.283	0.147	0.406	1.054
Kurtosis	-0.805	-1.340	-1.217	0.995
$Q_{LB}(5)$	568.0*	701.3*	687.7*	795.2*
Market Concentration				
Mean	63.40	60.49	58.40	62.93
Std. Dev.	11.76	15.83	15.49	14.76
Skewness	0.544	0.508	0.726	0.573
Kurtosis	-0.582	-1.037	-0.682	-1.019
$Q_{LB}(5)$	684.6*	727.5*	734.1*	558.2*

Appendix D: Dynamic structure and endogeneity test

This Table reports various tests for the endogenous relation between price discovery and various measures of market states. Panel A tests for the dynamic completeness of dependent variable. Panel B examines the relation between current measures of market states and lagged information share. Panel C presents a test for strict exogeneity by regressing current values of information share on future values of market state variables. All models are estimated by OLS and the values in the parentheses are the t-statistics calculated based on Newey-West standard errors.

	Asia	Europe	LNY	US
Panel A: Dynamic structure of dependent variable				
Dependent Variable	$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right)$			
$\ln\left(\frac{IS_{i.t-1}}{1-IS_{i.t-1}}\right)$	0.085***	0.042***	0.080***	0.117***
	(4.90)	（2.50）	(4.62)	（6.80）
$\ln\left(\frac{IS_{i.t-2}}{1-IS_{i.t-2}}\right)$	0.083***	0.040**	0.063***	0.095***
	(4.82)	(2.36)	(3.73)	(5.58)
$\ln\left(\frac{IS_{i.t-3}}{1-IS_{i.t-3}}\right)$	0.037**	0.009	0.041**	0.0432**
	(2.08)	(0.60)	(2.54)	(2.43)
R^2	0.1592	0.0706	0.1191	0.2708
Panel B: Relation between market state variables and lagged Information Share				
Dependent Variable	$\text{Spread}_{i,t}$			
$\ln\left(\frac{IS_{i.t-1}}{1-IS_{i.t-1}}\right)$	0.042***	0.022*	0.011*	0.064***
	(6.15)	(1.70)	(1.73)	（5.60）
$Spread_{i,t-1}$	-0.001	-0.043***	-0.037***	-0.136***
	(-1.01)	(-3.20)	(-3.10)	(-11.32)
$Volume_{i,t-1}$	-0.077***	-0.030**	-0.054***	-0.143***
	(-6.33)	(-1.97)	(-3.91)	（-9.90）
$Return_{i,t-1}$	-0.002*	-0.001	0.003*	-0.003
	(-1.76)	(-0.15)	(1.65)	（-1.24）
$Volatility_{i,t-1}$	0.074***	0.112***	0.101***	0.072***
	(4.06)	(5.19)	(4.93)	（3.21）
R^2	0.2007	0.1809	0.1006	0.1094
Dependent Variable	$Volume_{i,t}$			
$\ln\left(\frac{IS_{i.t-1}}{1-IS_{i.t-1}}\right)$	-0.045***	-0.018**	-0.028***	-0.141***
	(-4.18)	(-1.85)	(-2.36)	（9.50）
$Spread_{i,t-1}$	-0.033	-0.084***	-0.050*	-0.053**
	(-1.01)	(-2.87)	(-1.68)	（-1.94）
$Volume_{i,t-1}$	0.295***	0.133***	0.256***	0.327***
	(12.20)	(5.52)	(9.68)	(11.05)
$Return_{i,t-1}$	-0.006***	-0.001	0.001	-0.002
	(-2.56)	(-0.62)	(0.16)	（-0.46）
$Volatility_{i,t-1}$	-0.152***	-0.047*	0.122***	-0.083**
	(-3.41)	(-1.71)	(2.89)	（-2.18）
R^2	0.2012	0.1502	0.1604	0.2442

Appendix D (Continued)

	Asia	Europe	LNY	US
Panel B: Relation between market state variables and lagged Information Share				
Dependent Variable		$Return_{i,t}$		
$\ln\left(\frac{IS_{i.t-1}}{1-IS_{i.t-1}}\right)$	-0.002 (-0.03)	-0.046 (-0.38)	-0.133 (-1.17)	0.004 （0.06）
$Spread_{i,t-1}$	-0.692*** (-3.24)	0.287 (1.05)	-0.071 (-0.37)	-0.004 （-0.04）
$Volume_{i,t-1}$	-0.192 (-1.41)	-0.220 (-1.06)	0.078 (0.37)	-0.066 （-0.62）
$Return_{i,t-1}$	0.016 (0.51)	-0.019** (-2.39)	0.006 (0.83)	0.021 (0.73)
$Volatility_{i,t-1}$	0.262 (1.40)	0.004 (1.01)	0.383 (1.26)	0.222 （1.40）
R^2	0.0032	0.0005	0.0005	0.0003
Dependent Variable		$Volatility_{i,t}$		
$\ln\left(\frac{IS_{i.t-1}}{1-IS_{i.t-1}}\right)$	0.053*** (7.48)	-0.028*** (-3.86)	-0.032*** (-4.47)	0.043*** （4.86）
$Spread_{i,t-1}$	-0.143*** (-5.90)	0.143*** (8.51)	0.180*** (10.34)	-0.066*** （-5.19）
$Volume_{i,t-1}$	-0.076*** (-5.61)	0.010 (0.69)	0.044*** (3.43)	-0.098*** （-7.31）
$Return_{i,t-1}$	-0.001 (-0.77)	0.001 (0.28)	-0.002 (-1.13)	-0.002 （-1.11）
$Volatility_{i,t-1}$	0.110*** (4.31)	0.295*** (11.35)	0.281*** (11.02)	0.195*** (7.34)
R^2	0.2089	0.2027	0.2454	0.2085
Panel C: Strict Exogeneity Test				
Dependent Variable		$\ln\left(\frac{IS_{i.t}}{1-IS_{i.t}}\right)$		
$Spread_{i,t}$	0.155*** (3.08)	0.052 (1.42)	0.024 (0.62)	0.138*** (4.40)
$Volume_{i,t}$	0.588*** (20.42)	0.622*** (21.57)	0.701** (25.40)	0.440*** (22.93)
$Return_{i,t}$	0.009*** (2.69)	0.002 (0.78)	0.004* (1.65)	0.007** (2.16)
$Volatility_{i,t}$	0.469*** (11.90)	0.266*** (10.84)	0.783*** (13.70)	0.481*** (9.94)
$Spread_{i,t+1}$	0.092*** (2.65)	0.105*** (3.77)	0.066** (2.17)	0.074*** (3.24)
$Volume_{i,t+1}$	-0.111*** (-4.67)	-0.041** (-2.14)	-0.071*** (-3.75)	-0.115*** (-6.04)
$Return_{i,t+1}$	-0.001 (-0.31)	0.001 (0.22)	-0.001 (-0.47)	0.001 (0.14)
$Volatility_{i,t+1}$	0.137*** (3.10)	-0.192*** (-4.34)	-0.154*** (-3.72)	-0.012 (-0.33)
R^2	0.4892	0.5257	0.6229	0.4876

Appendix E: Heat waves and meteor showers: Sub-periods

This table reports the daily persistence coefficients of the following model:

$$\mathrm{V}_{i,t} = \alpha_{i,t} + \beta^{\mathrm{HW}}_{\mathrm{i,D}} V_{i,t-1} + \sum\nolimits_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,D}} \mathrm{V}_{\mathrm{j,t-1}} + \beta^{\mathrm{HW}}_{\mathrm{i,W}} \mathrm{HW}_{i,t-1,W} + \sum\nolimits_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,W}} \mathrm{MS}_{i,t-1,W}$$
$$+ \beta^{\mathrm{HW}}_{\mathrm{i,M}} \mathrm{HW}_{i,t-1,M} + \sum\nolimits_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,M}} \mathrm{MS}_{i,t-1,M}$$

where i = Asia (A), Europe (E), London/NYC (L), and US (U). *HW* stands for daily heat waves effect as proxied by $\beta^{\mathrm{HW}}_{\mathrm{i,D}}$, while *MS* stands for meteor shower effect $\sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,D}}$ (i.e., the sum of volatility spillover effects from all other trading sessions). $\beta^{\mathrm{HW}}_{\mathrm{i,W}}, \beta^{\mathrm{HW}}_{\mathrm{i,M}}$ are weekly and monthly heat waves effects, while $\beta^{\mathrm{MS}}_{\mathrm{i,j,W}}, \beta^{\mathrm{MS}}_{\mathrm{i,j,M}}$ are the weekly and monthly meteor shower effects respectively. The t-statistics are based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. The asterisks ***, **, * indicate significance at 1%, 5%, and 10% respectively.

	Asia		Europe		London/NYC		US	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
AUD								
1999 – 2006								
HW	.1000***	3.43	.0688**	2.39	.0445**	2.09	.0749***	2.73
MS	.3065***	5.27	.2886***	6.27	.3469***	6.19	.3957***	5.98
N	2024		2024		2022		2024	
$\bar{R}^2$	.2118		.2656		.2113		.1436	
2007 – 2009								
HW	.1967***	3.76	.1066**	2.32	.0926*	1.75	.1759***	2.59
MS	.5431***	6.35	.4542***	9.20	.6143***	9.92	.8571***	6.99
N	765		765		765		765	
$\bar{R}^2$	**.7169**		**.7978**		**.7714**		**.8060**	
2010 – 2013								
HW	.1049***	2.62	.1799***	4.00	.0682**	1.96	.0424	1.15
MS	.6575***	4.79	.2774***	7.63	.6304***	7.51	1.189***	5.53
N	1026		1026		1026		1026	
$\bar{R}^2$	.4251		.5591		.4209		.6153	
GBP								
1999 – 2006								
HW	.1487***	4.18	.1240***	4.18	.0643***	3.08	.0891***	4.11
MS	.1991***	6.03	.3114***	6.27	.2154***	4.97	.4697***	6.67
N	2025		2024		2024		2024	
$\bar{R}^2$	.1863		.1672		.1071		.1604	
2007 – 2009								
HW	.3400***	6.13	.1560***	3.18	.1142**	2.32	.1311***	2.86
MS	.3321***	6.23	.5447***	7.22	.4048***	7.02	.5379***	6.48
N	765		765		765		765	
$\bar{R}^2$	**.7903**		**.7582**		**.7517**		**.7326**	
2010 – 2013								
HW	.2499***	4.60	.0801**	2.32	.1057***	2.86	.0103	0.44
MS	.2314***	3.59	.4685***	5.08	.4133***	7.30	.5982***	6.41
N	1026		1026		1026		1026	
$\bar{R}^2$	.6223		.3360		.3263		.2247	

Appendix E (Continued)

	Asia		Europe		London/NYC		US	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
EUR								
2000 – 2006								
HW	.0892**	2.16	.1468***	3.64	.0873**	2.30	.0105	0.37
MS	1.263***	3.24	.0633***	3.07	.2552***	5.03	1.789***	8.15
N	1759		1759		1759		1759	
$\bar{R}^2$	.1639		.2612		.1353		.2117	
2007 – 2009								
HW	.0816	1.18	.1304*	1.84	.1142*	1.81	.0473	0.78
MS	.8610**	2.57	.2595***	3.34	.3533***	5.51	1.212***	4.79
N	762		765		765		765	
$\bar{R}^2$	**.5300**		**.6726**		**.6629**		**.5708**	
2010 – 2013								
HW	.0491*	1.84	.2600***	6.60	.1329***	2.77	.0732	1.60
MS	.5613***	4.22	.1733***	4.54	.5117***	8.07	.7253***	7.20
N	1023		1023		1026		1026	
$\bar{R}^2$	.2131		.4629		.2778		.1682	
JPY								
1999 – 2006								
HW	.1097*	1.81	.0545**	1.96	.0519*	1.64	.0691	1.38
MS	.5170**	2.40	.0960***	3.17	.2699***	6.01	.5163***	4.67
N	1986		1989		1940		1965	
$\bar{R}^2$	.2802		.1619		.1625		.3103	
2007 – 2009								
HW	.0165	0.23	.1126**	2.03	.0069	0.18	.0959**	1.95
MS	.5416**	2.53	.1623***	2.28	.3104***	5.46	.8199***	5.12
N	611		723		749		724	
$\bar{R}^2$	**.3552**		**.2102**		**.2829**		**.3320**	
2010 – 2013								
HW	.0335	0.46	.0438	1.44	.1312	1.22	-.0773	-1.15
MS	.6517*	1.64	.0072	0.21	.6657***	8.30	.9870**	2.03
N	1018		1022		1022		969	
$\bar{R}^2$	.2232		.1670		.3318		.2727	

Appendix F: Determinants of Conditional Volatility Spillover: Sub-periods

This table reports the summary of the estimates of the daily conditioning variables (including the constant, negative return, positive return, volatility, and variance ratio) for the following equation in different sub-periods:

$$RV_{i,t} = \alpha_{i,t} + \beta^{e}_{A,t}RV_{A,t-1} + \beta^{e}_{E,t}RV_{E,t-1} + \beta^{e}_{L,t}RV_{L,t-1} + \beta^{e}_{U,t}RV_{U,t-1} + \beta^{\mathrm{HW}}_{\mathrm{i,W}}\overline{\mathrm{RV}}_{\mathrm{i,t-1,W}} + \sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,W}}\overline{\mathrm{RV}}_{\mathrm{j,t-1,W}} + \beta^{\mathrm{HW}}_{\mathrm{i,M}}\overline{\mathrm{RV}}_{\mathrm{i,t-1,M}} + \sum_{\mathrm{j\neq i,j=A}}^{\mathrm{U}} \beta^{\mathrm{MS}}_{\mathrm{i,j,M}}\overline{\mathrm{RV}}_{\mathrm{j,t-1,M}} + \varepsilon_{i,t}$$

where i = Asia (A), Europe (E), London/New York (L), and US (U) and $\beta^{e}_{j,t} = \beta^{0}_{j} + \beta^{-}_{j} r^{-}_{j,t-1} + \beta^{+}_{j} r^{+}_{j,t-1} + \beta^{\mathrm{RV}}_{j} RV_{j,t-1} + \beta^{\mathrm{IS}}_{j} IS_{j,t-1}$. Sig+ and Sig- present the total number of positively and negatively significant coefficients of each market state variables at 5% significance level respectively. For example, if all the coefficients of positive return r^{+}_{t-1} are positively significant in $\beta^{e}_{A,t}$, then sig+ equals 4 for β^{+}_{r} in Asia.

	Asia		Europe		LNY		US	
	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-
				1999-2006				
AUD								
β_0	2	0	2	0	3	0	3	0
β_r^+	2	0	1	2	1	0	2	0
β_r^-	0	2	0	2	1	2	0	1
β_{RV}	1	2	1	1	0	1	2	0
β_{IS}	0	1	0	3	0	4	0	4
GBP								
β_0	2	0	3	0	3	0	3	0
β_r^+	2	0	2	0	2	0	1	1
β_r^-	0	2	0	1	1	0	2	0
β_{RV}	0	1	0	2	0	1	2	0
β_{IS}	0	2	0	2	0	4	0	4
EUR								
β_0	2	0	3	0	3	0	3	0
β_r^+	2	1	0	0	0	1	2	1
β_r^-	0	0	0	0	0	0	0	2
β_{RV}	1	0	2	1	0	1	2	1
β_{IS}	0	1	0	3	0	3	0	4
JPY								
β_0	2	0	2	0	3	0	3	0
β_r^+	1	1	1	0	0	0	3	0
β_r^-	0	3	1	1	1	1	0	2
β_{RV}	0	2	0	1	0	1	1	2
β_{IS}	0	1	0	1	0	3	0	3

Appendix F (Continued)

	Asia		Europe		LNY		US	
	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-
2007-2009								
AUD								
β_0	2	0	2	0	3	0	3	0
β_r^+	0	0	1	0	2	0	0	2
β_r^-	0	3	0	2	0	3	0	2
β_{RV}	1	1	0	2	0	1	1	1
β_{IS}	0	2	0	3	0	3	0	4
GBP								
β_0	1	0	2	0	3	0	3	0
β_r^+	1	0	1	0	1	0	0	1
β_r^-	0	3	0	2	1	2	0	1
β_{RV}	0	1	0	2	0	2	1	1
β_{IS}	1	1	1	3	0	4	0	4
EUR								
β_0	1	0	2	0	3	0	3	0
β_r^+	1	0	2	1	2	0	2	0
β_r^-	1	1	0	3	0	0	1	0
β_{RV}	0	2	1	2	0	1	0	1
β_{IS}	0	2	0	2	0	3	0	3
JPY								
β_0	1	0	2	0	2	0	3	0
β_r^+	2	0	2	0	0	0	0	0
β_r^-	0	3	0	1	1	2	1	2
β_{RV}	0	1	0	2	0	1	0	1
β_{IS}	0	1	0	2	0	3	0	3

Appendix F (Continued)

	Asia		Europe		LNY		US	
	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-
				2010-2013				
AUD								
β_0	2	0	2	0	3	0	2	0
β_r^+	1	1	0	0	0	1	0	1
β_r^-	0	3	0	1	1	1	1	2
β_{RV}	0	1	1	1	1	1	1	2
β_{IS}	0	2	0	2	0	3	0	4
GBP								
β_0	2	0	2	0	3	0	3	0
β_r^+	0	1	1	1	1	0	2	0
β_r^-	0	1	1	0	0	1	1	2
β_{RV}	1	0	0	1	1	1	1	1
β_{IS}	0	1	0	2	0	3	0	4
EUR								
β_0	1	0	4	0	2	0	2	0
β_r^+	0	2	1	1	0	1	0	1
β_r^-	0	0	1	1	0	2	1	0
β_{RV}	1	1	0	1	1	1	2	1
β_{IS}	0	1	0	3	0	3	0	4
JPY								
β_0	2	0	2	0	3	0	2	0
β_r^+	1	1	2	0	2	1	1	0
β_r^-	0	3	0	2	0	0	1	1
β_{RV}	0	1	2	1	0	2	1	2
β_{IS}	1	2	0	1	0	3	0	3

Appendix G: Summary statistics of market state variables

The definitions of the four sessions, namely, Asia, Europe, London/New York (NYLON), and North America, are as given in Table 2.1. Information share and market state variables (return, volatility, number of trades, illiquidity, and order flow) are defined as in Section 3.3. $Q_{LB}(5)$ is the Ljung-Box Q statistics for 5 lags. The asterisk * indicates significance at 5% level.

	Mean	Median	St Dev	Skew	Ex Kurt	Min	Max	$Q_{LB}(5)$
Panel A: AUD								
Asia								
Return	.0001	.0002	.0047	-.2597	10.66	-.0477	.0525	35.64*
RV	.2051	.1260	.2452	3.608	15.91	.0257	1.667	6,993*
IS	.3784	.3629	.1506	.5296	.1086	.0161	.9522	96.96*
# of Trade	2,821	2,023	2,261	1.389	2.752	33.00	21,030	6,999*
Illiquidity	2.767	2.443	1.231	1.752	5.237	1.341	13.77	7,818*
Order	26.02	28.00	196.3	-.1517	2.702	-1,021	1,108	24.13*
Europe								
Return	.0000	.0000	.0036	-.2024	8.534	-.0379	.0311	2.315
RV	.1350	.0847	.1624	3.848	18.45	.0139	1.162	8,277*
IS	.2039	.1935	.0887	.9832	2.472	.0102	.9462	48.85*
# of Trade	1,962	1,438	1,576	1.400	2.622	8.000	12,638	9,873*
Illiquidity	2.828	2.408	1.301	1.785	6.233	1.103	14.33	8,765*
Order	2.005	7.000	145.8	−. 2886	3.819	-952.0	744.0	22.62*
LNY								
Return	.0000	.0000	.0037	-.2991	6.583	-.0372	.0238	13.39*
RV	**.1500**	.0916	.1854	3.628	15.91	.0108	1.244	6,612*
IS	.2237	.2048	.1130	1.278	2.522	.0068	.8371	114.7*
# of Trade	2,282	1,773	1,883	1.432	2.940	15.00	14,018	8,962*
Illiquidity	2.869	2.370	1.342	1.268	1.534	.3384	10.75	7,765*
Order	-1.522	11.00	168.5	-.4561	3.722	-1,161	852.0	32.52*
US								
Return	.0001	.0002	.0041	-.0218	17.01	-.0452	.0450	36.89*
RV	.2053	.1094	.3322	4.757	26.44	.0158	**2.483**	7,213*
IS	.1940	.1728	.1060	1.749	5.318	.0177	.9084	137.6*
# of Trade	1,530	1,117	1,377	1.954	6.556	18.00	13,339	7,833*
Illiquidity	3.292	2.530	1.872	1.454	2.229	1.277	14.91	7,998*
Order	4.764	10.00	134.9	-.5683	6.645	-839.0	795.0	22.34*

Appendix G (Continued)

	Mean	Median	St Dev	Skew	Ex Kurt	Min	Max	$Q_{LB}(5)$
Panel B: GBP								
Asia								
Return	-.0001	.0000	.0027	-.4954	7.641	-.0280	.0168	5.923
RV	.0821	.0525	.0937	3.310	13.00	.0101	.6091	10,194*
IS	.2613	.2445	.1226	.9823	1.646	.0052	.9333	409.3*
# of Trade	1,231	1,071	746.2	1.351	3.147	33.00	7,487	7,834*
Illiquidity	2.081	1.943	.7954	3.000	17.47	.9549	10.24	9,948*
Order Fl	10.10	11.00	119.0	-.1200	5.098	-767.0	1,023	48.60*
Europe								
Return	-.0001	-.0001	.0032	-.0689	3.372	-.0208	.0177	1.299
RV	.1009	.0713	.1054	3.345	13.43	.0111	.6937	7244*
IS	.2914	.2817	.1132	.7053	1.074	.0035	.8600	175.1*
# of Trade	2,436	2,194	1,280	1.057	1.754	19.00	10,844	5,532*
Illiquidity	1.631	1.519	.6178	8.837	19.15	.8475	18.32	5,827*
Order Fl	6.539	8.000	173.6	.0148	4.102	-928.0	1,268	12.51
LNY								
Return	.0001	.0000	.0030	.1368	4.034	-.0192	.0238	5.951
RV	**.0857**	.0591	.0867	2.963	10.44	.0087	.5399	5785*
IS	.2555	.2341	.1174	1.298	2.686	.0097	.9840	131.1*
# of Trade	2,357	2,194	1,121	.7381	.5144	45.00	7,761	5,071*
Illiquidity	1.556	1.463	.4814	2.374	14.08	.8058	7.773	26.12*
Order Fl	14.02	16.00	153.7	.1008	3.300	-908.0	813.0	8,997*
US								
Return	.0002	.0002	.0027	.0759	10.61	-.0195	.0272	15.44*
RV	.0931	.0576	.1224	3.980	18.53	.0091	**.8486**	6571*
IS	.1918	.1703	.1028	1.524	3.924	.0073	.9111	580.1*
# of Trade	1,382	1,216	803.8	1.279	2.339	26.00	6,606	5,675*
Illiquidity	1.877	1.643	.7436	1.600	4.299	.9016	8.436	12.45
Order Fl	13.10	14.00	103.9	-.0333	3.826	-699.0	613.0	7,776*

Appendix G (Continued)

	Mean	Median	St Dev	Skew	Ex Kurt	Min	Max	$Q_{LB}(5)$
Panel C: EUR								
Asia								
Return	.0002	.0001	.0038	1.507	40.59	-.0355	.0726	7.895
RV	**.3973**	.1183	.7853	3.975	17.68	.0137	**5.124**	2753*
IS	.3773	.3347	.2000	.6977	-.1937	.0025	.9980	476.2*
# of Trade	240.0	198.0	166.9	1.330	2.026	2.000	1,172	9,006*
Illiquidity	6.625	3.883	12.69	9.379	11.50*	1.062	22.26	5,665*
Order Fl	.4587	0.000	39.70	.1032	4.726	-302.0	301.0	13.82*
Europe								
Return	-.0002	-.0002	.0032	.1258	5.183	-.0224	.0301	6.316
RV	.1080	.0665	.1579	5.058	30.33	.0112	1.246	7277*
IS	.1829	.1694	.1089	.8449	.8407	.0006	.7294	1285*
# of Trade	710.1	625.0	424.8	.9253	.7874	5.000	2,905	9,987*
Illiquidity	2.625	1.850	4.408	9.286	12.93*	.0690	95.21	9,888*
Order Fl	-.4660	0.000	82.56	.1667	3.343	-461.0	570.0	53.6*
LNY								
Return	.0001	.0000	.0034	-.0018	2.422	-.0169	.0187	2.897
RV	.1239	.0800	.1504	3.792	17.84	.0081	1.059	4283*
IS	.2170	.1908	.1370	1.257	2.191	.0006	.9110	662.8
# of Trade	629.0	574.0	365.1	.8190	.7059	4.000	2,634	8,108*
Illiquidity	3.136	2.007	5.563	7.518	72.08	.0279	93.24	9,898*
Order Fl	8.049	4.000	76.77	.3918	2.101	-332.0	355.0	78.95*
US								
Return	.0001	.0001	.0029	.0578	6.304	-.0221	.0218	12.56*
RV	.3220	.1305	.5404	3.743	16.30	.0087	3.538	3367*
IS	.2229	.1865	.1495	1.293	1.713	.0002	.9312	170.2*
# of Trade	157.0	123.0	116.9	1.612	3.835	1.000	1,030	6,494*
Illiquidity	7.859	3.729	15.17	7.296	76.97	1.102	25.87	9,111*
Order Fl	.6969	0.000	29.12	-.0635	4.463	-230.0	184.0	6.58

Appendix G (Continued)

	Mean	Median	St Dev	Skew	Ex Kurt	Min	Max	$Q_{LB}(5)$
Panel D: JPY								
Asia								
Return	-.0002	-.0001	.0047	-.0172	9.854	-.0476	.0382	8.122
RV	**.5799**	.1773	1.393	5.354	32.25	.0044	**10.66**	1365*
IS	.4032	.3791	.2156	.3931	-.5131	.0003	.9989	159.5*
# of Trade	56.00	45.00	47.47	1.500	3.844	1.000	420.0	7,079*
Illiquidity	16.45	9.477	30.13	18.36	62.40	.9309	115.2	1,098*
Order Flow	.4587	0.000	39.70	.1032	4.726	-302.0	301.0	13.82*
Europe								
Return	.0001	.0001	.0033	-.8416	20.71	-.0494	.0327	7.640
RV	.2054	.0927	.3484	4.192	20.49	.0045	2.439	965.6*
IS	.2005	.1709	.1396	1.333	2.398	.0003	.8915	380.2*
# of Trade	44.00	32.00	38.90	2.132	6.514	1.000	322.0	7,611*
Illiquidity	11.85	5.627	16.05	5.833	66.38	.8551	29.31	3,473*
Order Flow	-.4660	0.000	82.56	.1667	3.343	-461.0	570.0	53.6*
LNY								
Return	.0000	.0000	.0032	.2383	4.540	-.0185	.0223	10.76
RV	.1856	.0963	.3017	4.456	24.02	.0034	2.226	586.2*
IS	.2054	.1760	.1477	1.304	2.122	.0003	.9420	208.6*
# of Trade	40.00	29.00	38.15	2.758	17.68	1.000	587.0	3,928*
Illiquidity	13.30	5.58	16.49	4.369	45.80	1.296	28.80	3,323*
Order Flow	8.049	4.000	76.77	.3918	2.101	-332.0	355.0	78.95*
US								
Return	.0000	.0000	.0029	-.2749	5.668	-.0207	.0187	8.112
RV	.3519	.0970	.7874	4.683	25.20	.0001	5.686	1198*
IS	.1909	.1449	.1690	1.506	2.342	.0001	.9867	461.2*
# of Trade	22.00	12.00	28.70	3.137	14.79	1.000	318.0	4,265*
Illiquidity	23.09	9.013	43.65	9.285	14.17	1.043	96.96	1,607*
Order Flow	.6969	0.000	29.12	-.0635	4.463	-230.0	184.0	6.58

Appendix H: Conditional Volatility Persistence (CVP) model: Sub-periods

This table reports the daily persistence coefficients of the following model in three sub-periods (i.e., 1999/2000 – 2006, 2007 – 2009, 2010 – 2013):

$$RV_{i,t+1} = \alpha_{i,t+1} + (\beta_i^0 + \beta_i^- r_{i,t}^- + \beta_i^+ r_{i,t}^+ + \beta_i^{RV} RV_{i,t})RV_{i,t} + \beta_{i,\mathrm{W}} RV_{i,t,W} + \beta_{i,M} RV_{i,t,M} + \theta_{i,t} r_{i,t} + \theta_{i,W} r_{i,t,W} + \theta_{i,M} r_{i,t,M} + \varepsilon_{i,t+1}$$

The t-statistics are based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. The asterisks ***, **, * indicate significance at 1%, 5%, and 10% respectively.

	β_0	β^-	β^+	β^{RV}	$\beta_{RV,W}$	$\beta_{RV,M}$	θ_r	$\theta_{r,W}$	$\theta_{r,M}$	$\bar{R}^2$
1999 - 2006										
AUD	.3372***	-.0646**	.0299	-.0647***	.3188***	.2831***	-.0566**	-.0123	-.0507	.3785
	(4.42)	(-2.12)	(0.75)	(-6.10)	(4.28)	(4.25)	(-2.38)	(-0.35)	(-0.79)	
GBP	.2469***	-.1777***	.0934	-.1262*	.3367***	.2526***	.0085	-.0029	-.0972**	.2621
	(2.61)	(-3.03)	(1.45)	(-1.86)	(5.66)	(4.35)	(0.48)	(-0.15)	(-2.35)	
EUR	.3217***	-.0528	.0257	-.0267**	.2170***	.3137***	-.0189	.1194	-.3880**	.1616
	(4.28)	(-0.84)	(0.27)	(-2.16)	(3.60)	(5.38)	(-0.32)	(1.50)	(-2.17)	
JPY	.3267***	-.0343	.2096***	-.0132***	.2308***	.3392***	.0353	-.0483	-.0144	.1676
	(4.25)	(-0.55)	(3.01)	(-3.39)	(4.30)	(6.01)	(0.55)	(-0.48)	(-0.07)	
2007 - 2009										
AUD	.5818***	-.0230*	.0473***	-.0217	.1876**	.2192***	-.0867**	-.0646	-.2604**	**.8440**
	(6.35)	(-1.70)	(2.78)	(-1.41)	(2.17)	(4.03)	(-2.35)	(-0.95)	(-2.12)	
GBP	.4832***	-.0648***	.0382*	-.0268	.2091***	.2777***	.0182	-.0329	-.1383*	**.8707**
	(5.01)	(-2.76)	(1.69)	(-0.85)	(3.26)	(4.34)	(0.81)	(-1.00)	(-1.82)	
EUR	.5146***	-.0608	.1709***	-.0388**	.2534***	.3364***	-.0251	.0455	-1.403***	**.6994**
	(2.75)	(-1.36)	(5.86)	(-2.52)	(2.75)	(3.14)	(-0.23)	(0.24)	(-3.08)	
JPY	.3465***	-.0006	.0593	-.0185*	.2898***	.3113***	-.3126*	-.4499	-.6409	**.1836**
	(2.53)	(-0.01)	(0.46)	(-1.89)	(2.69)	(2.58)	(-1.68)	(-1.35)	(-1.08)	

Appendix H (Continued)

	β_0	β^-	β^+	β^{RV}	$\beta_{RV,W}$	$\beta_{RV,M}$	θ_r	$\theta_{r,W}$	$\theta_{r,M}$	$\bar{R}^2$
2010 - 2013										
AUD	.4326***	-.1884***	.0070	-.0474**	.2382***	.1959***	-.0384	-.1078**	-.1069	.5404
	(3.92)	(-5.12)	(0.12)	(-2.14)	(4.14)	(3.82)	(-1.47)	(-2.21)	(-1.23)	
GBP	.3954***	-.1701	.0211	-.1255**	.3536***	.2129***	.0012	-.0833***	-.1195**	.4840
	(4.47)	(-1.27)	(0.31)	(-2.21)	(4.73)	(3.09)	(0.04)	(-3.17)	(-2.47)	
EUR	.5255***	-.0087	.0461***	-.0906**	.3140***	.1523***	-.0611**	-.0326	-.0718	.4330
	(5.07)	(-0.08)	(2.00)	(-2.36)	(5.84)	(2.92)	(-2.17)	(-0.96)	(-1.10)	
JPY	.8664***	.1201**	-.1420*	-.0311**	.0158	.2326**	-.1335	-.2740**	-.1910	.2254
	(4.71)	(2.01)	(-1.76)	(-2.36)	(0.28)	(2.16)	(-1.38)	(-2.21)	(-0.73)	

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