Essays on Price Discovery and Volatility Dynamics in Emerging Market Currencies

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By

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Declaration of Authorship

I, Ran Xiao, 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. This research is supported by the Australian Government Research Training Program.

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I would like to dedicate this thesis to the two most important people in my life: my aunt Shuzhen Wang and my husband Hang Wang. My aunt raised me and she is the person I respect the most. No matter what hardships or challenges I have encountered in my life, she has always been there to support, direct and encourage me. I met my husband at the end of 2014. He brings so much fun to my life. He is not only my husband, but also a friend, father, and life mentor.

Abstract

This thesis investigates the price discovery and volatility dynamics in spot foreign exchange (FX) markets of emerging countries by using nearly 20 years of high frequency data. It includes three independent essays.

The first essay depicts comprehensive information distribution of emerging market currencies (EMCs) by employing microstructure methods. We separate the 24-hour FX market into two sequential trading periods: daytime and overnight, and then we further divide the active daytime session into onshore and offshore markets. We find that overnight investors have contributed more to pricing EMCs in recent years. The key reason is that price discovery capacity to macro news of overnight investors have improved. Moreover, the onshore dealer information advantage to local news is decreasing, as offshore dealers become more informed in pricing EMCs. This suggests that EMCs are more market-determined, and international FX trading hubs now have more information and are providing more liquidity for them. However, it also suggests that EMCs are harder for central banks to manage and they are more fragile to the impact of one or two crucial dealers withdrawing supply of liquidity.

In the second essay, we focus on two crucial statistical features of volatility: volatility persistence and return asymmetric effect. By using the heterogeneous autoregressive realized volatility model (HAR-RV model) and its variants, we provide new empirical evidence that EMCs have lower volatility persistence and larger asymmetric return effect than the major currencies (MCs). Furthermore, we find that the daily volatility persistence and asymmetric effect change over time: the former decreases with information flow inconsistency and the latter increases with market illiquidity. The stronger negative impact of news inconsistency and the lower market liquidity level cause EMCs to have lower daily volatility persistence and higher asymmetric

volatility than MCs. The essay compares two stylized features of volatility between MCs and EMCs for the first time and suggests that information arrival pattern and market state are crucial determinants.

The third chapter investigates the source of long memory in FX volatility. Inspired by Berger et al. (2009) and Patton and Sheppard (2015), we propose a new empirical specification that links volatility to good and bad news, measured as the order imbalance in the market, and to traders' sensitivity to that news. We estimate the time-varying daily market sensitivity to good or bad news from high-frequency data. We find the explanatory power of bad market sensitivity to volatility is similar to that of good market sensitivity. This finding is different from Patton and Sheppard (2015), who find that bad volatility drives volatility persistence. Furthermore, we use Koenker and Bassett's (1978) quantile regression model to estimate traders' time-varying sensitivity to information across the quantiles of the conditional distribution. The empirical results also do not show a different influence on the long memory of volatility between the market sensitivity to extreme good or bad news. However, we find that sensitivity to extreme events has stronger explanatory power than that to other news, which emphasizes the importance of volatility tail persistence. Overall, this chapter expands on Berger et al. (2009) and Patton and Sheppard (2015) and finds the interesting result that price sensitivity to (extreme) good and bad news has similar importance in explaining the long memory of volatility.

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Chapter 1: Introduction

Deepening financial market liberalization has led to more foreign investment in emerging countries, driving up transactions of and hedging demands for emerging market currencies (EMCs). The 2016 BIS (Bank for International Settlements) triennial foreign exchange (FX) market survey shows that total FX trading turnover reached an average of $5.1 trillion per day. EMCs turnover share rose to around 20% in 2016 compared with almost zero in the 1990s. Interestingly, the volume geographical distribution changed dramatically. In the early 1990s, EMCs trading mostly involved local counterparties on at least one side of the transaction (e.g., McCauley and Scatigna, 2011). Now, the trading of EMCs is conducted increasingly offshore and the offshore trading share is approaching the level of major currencies (MCs). Even though the volume and offshore trading share of EMCs have increased sharply, EMCs are still characterized as having low liquidity and high volatility compared with MCs. The unique evolution and features of EMCs have attracted increasing attention from both policymakers and market participants (Ma and Villar, 2014). However, there are limited studies exploring either price discovery or volatility dynamics in EMCs.

Prior to the 1990s, macroeconomists were the biggest players in currency pricing. However, Meese and Rogoff (1983) find that there is a big gap between the way a currency market works, and the stories revealed by macro-based exchange rate models.[1] Later on, this disconnect between exchange rates and macro fundamentals is entangled by the market microstructure theory. Kyle (1985) and Glosten and Milgrom (1985) build seminal information-based models with realistic assumptions. Their models assume the market participants are no longer homogeneous. This means that investors can hold private information, and thereby, market makers adjust price according to

[1] Meese and Rogoff (1983) find that no macro-based model outperforms the random walk model. Furthermore, the failure does not change over time. Cheung et al. (2005) draw the same conclusion by using more recent and longer sample period.

information conveyed by the order flow from investors.[2] Unsurprisingly, micro-structure currency models are supported by empirical works. Evans et al. (2002) show that order flow explains daily FX changes with R^2 ranging from 40% to 60%, and order flow reflects institutional research on macro fundamentals long before announcements (e.g., Peiers, 1997).

One advantage of these information-based models is that they allow for the examination of market dynamics and, hence, provide insights into the adjustment process of prices (O'Hara, 1995). With the development of microstructure theory in the 1990s, the focus of price discovery has shifted to the dynamic process of incorporating the implicit information from investor trading into market prices in an efficient and timely manner (Lehmann, 2002). Hence, it is worthwhile investigating which group of dealers holds more private information or contribute more to pricing assets in a currency market. Any of the following issues can be determinants of price discovery share or capacity: market institutional setting (transparency), telecommunication infrastructures, market design, algorithm trading/high frequency trading, and so on. Overall, the existence of private information motivates us to investigate information distribution in currency markets.

Additionally, high volatility is one stylized fact of EMCs after the adoption of floating regimes, especially during a crisis period. Volatility is a good measurement of risk, which is important for asset allocation, asset pricing, and risk management. After seminal studies conducted by Engle (1982) and Bollerslev (1986), many variants of the generalized autoregressive conditional heteroscedasticity (GARCH) model have been built to capture FX statistical features. Among the features, two stylized facts of exchange rate draw significant attention: daily volatility persistence/long memory and asymmetric volatility. Researchers have focused on the volatility dynamics of MCs for over 40 years, since the inception of the floating rates regime in 1973.[3] Even

[2] Order flow is the net of buyer-initiated orders and seller-initiated orders.
[3] The Bretton Woods Conference of 1944 established an international fixed exchange rate system based on the gold

though more emerging countries have adopted a floating currency regime since the 1990s, researchers have not fully documented or explored the dynamics of volatility in EMCs.

This study uses high frequency exchange rate data to investigate the price discovery and volatility dynamics in the spot exchange rates of EMCs. This thesis consists of three independent essays, which examine information distribution, volatility dynamics, and the source of volatility long memory in the FX market from different perspectives. The main topics and contributions of the essays are summarized below.

In the first essay, we aim to present the comprehensive location-related information distribution of six EMCs: the Brazilian real (BRL), the Indian rupee (INR), the South Korean won (KRW), the Mexican peso (MXN), the Philippine peso (PHP), and the South African rand (ZAR), which are all against the United States dollar (USD) from 1999 to 2017. We apply the following empirical methodology. We first separate the 24-hour market into two sequential trading sessions, daytime and overnight, and then further divide the daytime period into onshore and offshore markets. Using the two-scaled variance ratio (Wang and Yang, 2011) and information leadership shares, or ILS (Yan and Zivot, 2010; Putniņš, 2013), we estimate the information shares (IS) of the two sequential trading sessions and the two parallel markets. We find that overnight IS increases from 40% to 50% and offshore market IS jumps from 20% to 40% over the sample period. Furthermore, to investigate the determinants of the overnight and offshore IS trends, we regress IS on macro news while controlling market state variables. We find that the enhanced price discovery capacity of overnight investors to macro news can explain the trend of increased IS in the overnight period and we find that the increased ability of offshore investors to collect and interpret emerging

exchange standard, in which currencies were pegged to the United States dollar, itself convertible into gold at \$35/ounce. The Smithsonian Agreement in 1973 created a new dollar standard whereby the major currencies of the most highly industrialized nations were pegged to the US dollar at central rates, with the currencies being allowed to fluctuate by 2.25%.

countries' macro news contributes to the offshore IS growth. Our findings suggest that where there is increased liberalization of emerging financial markets, the growing transaction and hedging demands of EMCs lead to an information distribution shift from inside to outside the issuers' borders, while non-local investors' abilities to collect and interpret information from macro news have been largely enhanced in recent years.

In the second essay, we focus on the volatility dynamics of EMCs. Volatility persistence and return asymmetric effect are two crucial statistical features. Although these features are well-documented and examined for MCs, they are rarely investigated for EMCs. Therefore, we aim to compare the two features for MCs and EMCs, and to further investigate the determinants of the differences. For MCs, we include the Australian dollar (AUD), the Canadian dollar (CAD), the Euro (EUR), and the Great British pound (GBP), and for EMCs, we use the same six currencies mentioned in the first essay. All rates are against USD and the sample period is from January 2000 to December 2017. We use both restricted (AR-RV-R model) and unrestricted (HAR-RV-R model) autoregressive models to provide new and robust empirical evidence that EMCs have lower volatility persistence and a larger asymmetric return effect than MCs. Then, we examine the determinants of the differences. With respect to volatility persistence, the mixture of distribution hypothesis (MDH) theory suggests that the persistence of exogenous information flow is the source. To test this hypothesis, we build a conditional volatility persistence model with information flow inconsistency (CVP-IIC model) inspired by the CVP model in Wang and Yang (2017). We find that daily volatility persistence decreases with inconsistency of information flow, and the stronger negative impact causes EMCs to have lower volatility persistence than MCs. For the return asymmetric effect, we expect higher market illiquidity associated with a higher asymmetric effect, considering the positive relationship between illiquidity level and return. To test this hypothesis, we build conditional asymmetric effect model with quoted spread (CAE-Qspd model) allowing return direct impact to be time-varying. Our findings show that return asymmetry increases with illiquidity level and can partly explain why EMCs have higher asymmetric volatility than MCs. This essay provides new evidence in the comparison of the volatility dynamics of MCs and EMCs. The findings are totally opposite to that of the equity market: emerging equity markets have higher volatility persistence and lower asymmetric effect. Our findings confirm the uniqueness of the FX market and its volatility dynamics and calls for more work to be conducted on it in the future.

In the last essay, we investigate the source of long memory in FX volatility. Inspired by Berger et al. (2009) and Patton and Sheppard (2015), we propose a new empirical specification that links volatility to good and bad news, measured as the order imbalance in the market, and to traders' sensitivity to that news. We estimate the time-varying daily market sensitivity to good or bad news from high-frequency data. We find the explanatory power of bad market sensitivity to volatility is similar to that of good market sensitivity. This finding is different from Patton and Sheppard (2015), who find that bad volatility drives volatility persistence. Furthermore, we use Koenker and Bassett's (1978) quantile regression model to estimate traders' time-varying sensitivity to information across the quantiles of the conditional distribution. The empirical results also do not show a different influence on the long memory of volatility between the market sensitivity to extreme good or bad news. However, we find that sensitivity to extreme events has stronger explanatory power than that to other news, which emphasizes the importance of volatility tail persistence. Overall, this chapter expands on Berger et al. (2009) and Patton and Sheppard (2015) and finds the interesting result that price sensitivity to (extreme) good and bad news has similar importance in explaining the long memory of volatility.

Chapter 2: Global Price Discovery in Emerging FX Markets and its Determinants

2.1 Introduction

The emerging financial markets have become more liberalized since the 1990s.[4] Offshore investors gained access to and became more active in trading emerging market financial assets, driving up the transaction and hedging demand for EMCs. The BIS 2016 FX market triennial survey shows that total FX trading turnover reached an average of $5.1 trillion per day. EMCs turnover share rose to around 20% in 2016 compared with only 8% in 2001. In contrast, the trading volume share of MCs showed a mildly decreasing trend (Fig 2.1).[5] This significant volume increase places EMCs into the spotlight. More importantly, when we look at FX volume geographic distribution, it is noteworthy that the offshore turnover share of MCs continued to wave around 60%, while the share of EMCs rose from less than 40% to over 55%, thereby approaching the average level of MCs (Fig 2.2).[6] This substantial trading location shift motivates us to raise the following questions: does the expansion in offshore transactions make a significant impact on where the EMC price discovery takes place, and do local investors still play a dominant role in pricing EMCs?

[4] Levine and Zervos (1998) for the equity market and Chinn and Ito (2002) for the equity and bond market, among others.

[5] As two currencies are involved in each transaction, the sum of the shares of individual currencies will total 200%. For details, please check the BIS "net net" basis volume calculation methods. For figures 2.1 and 2.2, we include USD, EUR, JPY, GBP, AUD, CAD, and NZD as major currencies; BRL, CNY, CZK, HKD, HUF, IDR, INR, KRW, MXN, PHP, PLN, RUB, SGD, THB, TRY, TWD, and ZAR are included as emerging market currencies.

[6] Taking the Brazilian real as an example, its offshore trading share was less than 10% in 2001 and rocketed to more than 60% in 2013, reaching $41 billion.

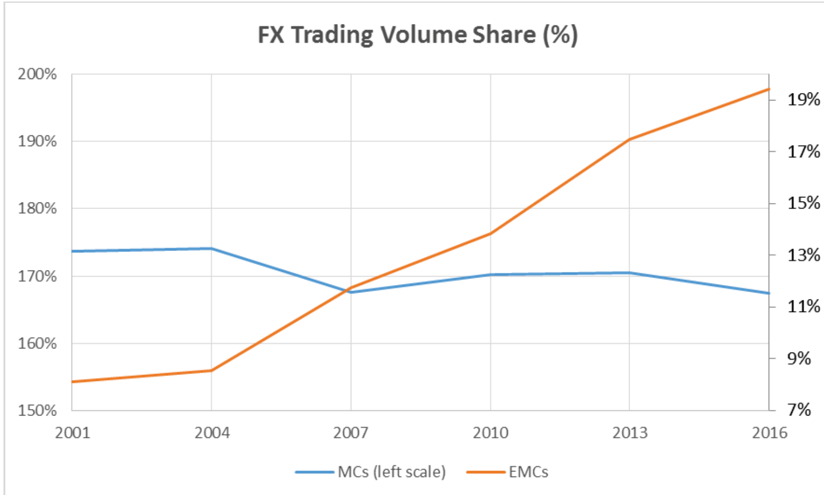


Figure 2.1. Trading volume share (%) of MCs and EMCs
Data Source: Author's calculations using BIS FX market triennial survey

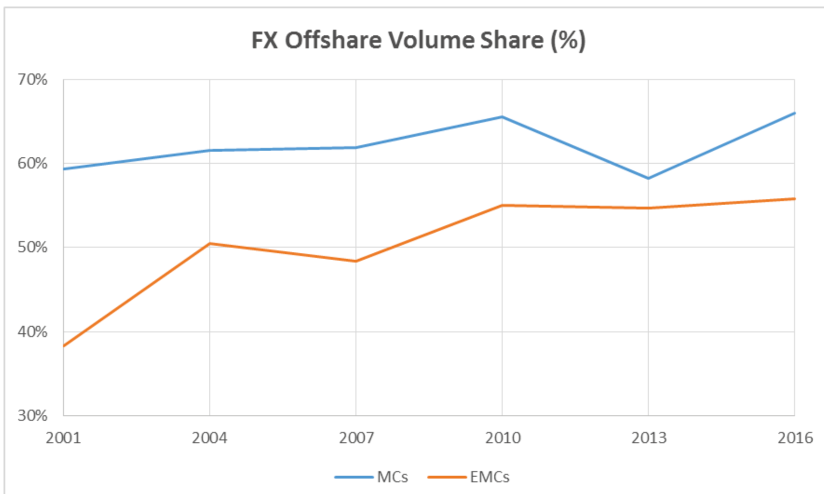


Figure 2.2. Offshore volume share (%) of MCs and EMCs
Data Source: Author's calculations using BIS FX market triennial survey

In this study, we first depict a comprehensive information distribution for six spot exchange rates of emerging countries during the sample period from 1999 to 2017. The currency pairs we investigate include three Asian currencies: the INR, the KRW and the PHP; two Latin American currencies: the BRL and the MXN; and one African currency: the ZAR, with all rates against the USD. All rates data, intraday indicative quoting data, are obtained from the Thomson Reuters Tick History (TRTH) database provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA).

We first separate the 24-hour market into two sequential trading sessions, daytime and overnight and then further divide the daytime period into onshore and offshore markets. By estimating the Wang and Yang (2011) IS for daytime and overnight periods, we test our hypothesis that overnight investors play an increasing role in pricing EMCs during our sample period. The daytime onshore- and offshore-dealer price discovery shares are gauged by the ILS in Yan and Zivot (2010) and Putniņš (2013). We conjecture that offshore dealers have become more informed in pricing EMCs in recent years. The two methods we employed here are both developed in the market microstructure literature. [7]

We further investigate the determinants of the price discovery share evolution. Here, we mainly look at macro fundamentals. We start with the definition of price discovery which is the efficient and timely incorporation of the information implicit in investor trading into market prices (Lehmann, 2002). In fact, the currency market is not always efficient at incorporating news. For

[7] The well-known disconnect in macro-based models proposed by Meese-Rogoff (1983) shows that macro fundamentals have limited explanatory and predictive power for exchange rate movement of low-frequency data. Microstructure theories shed light on this puzzle. The underlying reason why a specific group of dealers has an information advantage is because macro activities are not realized at a macro level, but rather first as a dispersed micro realization. In particular, order flows are the critical conduit between exchange rate changes and economic fundamentals (e.g. Evans and Lyons, 2002, 2005, 2008, 2012). Papers prove that order flows from financial institutions have greater information content than other investors (e.g., Fan and Lyons, 2003; Carpenter and Wang, 2007; Bjønnes et al., 2008).

example, if the exchange rate is hard pegged to the USD or another major currency, the market loses all price discovery function. According to the International Monetary Fund (IMF) Annual Report on Exchange Arrangements and Exchange Restrictions, since the 1990s, an increasing number of emerging market central banks have announced the adoption of floating rather than pegged currency regimes. However, does this the change imply that, after adopting a floating currency regime, EMCs can immediately perform timely and efficiently news absorption? Studies suggest that the de jure floating regime is not equivalent to the de facto floating regime (Calvo and Reinhart, 2002), but an increasing percentage of EMCs have become de facto floating regimes in recent years (Bleaney and Tian, 2014). Therefore, by regressing the IS on the respective period's number of macro announcements collected from Bloomberg macro announcement calendar, while controlling the market state variables, we test the following two conjectures. The first is that the increasing overnight price discovery share can be attributed to the enhanced news incorporation capacity of overnight investors; the second is that the decreasing onshore IS is resulting of diminishing local information advantage.

Our study has two distinct features that distinguish it from existing literature. First, the geographic link between investment and performance has been extensively proved in equity and money markets using the local information advantage hypothesis (e.g., Hau, 2001; Choe, Kho and Stulz, 2005; Bae et al., 2008; Ferreira et al., 2017). However, in FX literature, there is a limited number of papers investigating location-related price discovery share and its evolution (Peiers, 1997; Covrig and Melvin, 2002; Menkhoff and Schmeling, 2008; Wang and Yang, 2011). For the first time, our study presents comprehensive information distribution across emerging countries' 24-hour spot FX markets, that is, we separate the market into two sequential markets, daytime and overnight, and further separate the daytime period into two parallel markets, onshore and offshore.

Second, the impact of macro announcements on price discovery evolution in spot FX markets, especially EMCs, has yet to be adequately discussed in existing literature (Anderson et al., 2003; Phylaktis and Chen, 2010; Gau and Wu, 2017). Based on previous studies, we examine the impact of macro announcements on daytime/overnight and daytime onshore/offshore dealers' IS over time. Instead of focusing on the impact of news transparency (Eichengreen et al., 2017) and telecommunication infrastructure (Michaelides et al., 2017) improvements on FX price discovery, our study provides evidence showing that macro news is one important determinant of the shift in EMCs price discovery share during the sample period.

Our analysis presents several interesting findings. We find that overnight investors play an increasing role in the pricing of EMCs. Their IS increased from about 40% in 1999 to 50% in 2017. However, the pricing contribution from overnight investors is still lower than that of internationalized currencies. Taking the AUD as an example, its overnight IS remained around 70% from 1999 to 2013 (Wang and Yang, 2011; Su and Zhang, 2018). Moreover, we investigate the IS between onshore and offshore dealers during the daytime period. An increasing IS trend is detected in the offshore market. The average offshore IS jumped from 20% to 40% over the sample period. The estimated IS show local dealers are still better informed when pricing EMCs than offshore dealers during daytime period. However, we observe that the local information advantage is diminishing. Offshore dealers of some EMCs, such as the ZAR and PHP, recently even became price leaders. The trend for increases in the IS of overnight and offshore investors are consistent with the aggregated offshore volume share upsurge reported by BIS.

As in many previous studies, we employ macro news as an information flow proxy to investigate the determinants of IS. Unlike other studies, we expect macro news impact to help explain the IS shift of EMCs. For the overnight period, we find that US macro fundamentals have had a stronger and more significant impact on price discovery share in recent years. Taking Asian currencies as an example, we find that in recent years, the overnight period price discovery share has increased by 2.5% on US news days compared with non-news days. However, in the early years of our sample, there was no significant IS change on US news days. Therefore, we argue that an improving price discovery capacity is one crucial reason for the trend of increased overnight period IS.

For the offshore market, we find local macro news had a significant impact on price discovery share in the early years, but the impact has disappeared in recent years. Taking BRL as an example, we find that, in the early years, daytime onshore dealers tended to incorporate local news before the offshore market; onshore dealers had a 27% IS increase on local news days compared to non-news days. However, the IS increase diminished and ultimately disappeared in recent years. Hence, we argue that the decreasing local information advantage, resulting in offshore dealers becoming more agile to local news, is one crucial reason behind the trend of increased offshore IS.

2.2 Literature Review

Our study relates to two strands of literature, namely studies focusing on geographic price discovery distribution and studies investigating the impact of macro news on price discovery share.

Information, along with its presumed asymmetric distribution, is an important aspect of financial market theory. It is commonplace to assume heterogeneity of agents in microstructure models. However, there is natural doubt about who is "informed". Empirical studies have found that, in the presence of a local information advantage, there is a geographic link between investment and performance. Using data from the German Security Exchange, Hau (2001) found that traders located in Germany earn higher trading profit. Similarly, Choe, Kho and Stulz (2005) using Korean data, Dvorak (2005) using Indonesian data, Teo (2009) using Asian data and Ivkovic and Weisbenner (2005) and Ferreira et al. (2017) using US data proved that local investors realize higher profits than foreign investors. Local information advantage can also be detected between local and foreign analysts. Bae et al. (2008) found that local analysts are able to make more precise earnings forecasts for firms than non-resident analysts. Moreover, local proximity can provide an information advantage. Papers show that US money managers and analysts who are geographically closer to the headquarters of a firm have an information advantage (Coval and Moskowitz, 2001; Malloy, 2005; Baik et al., 2010). Rather than checking the performance of local investors, Anand et al. (2011) directly investigated the relative price discovery share between market makers located close to the firm headquarters and those located further away. They found that the former possesses superior information about the firm's stock than the latter.

The FX spot market is decentralized and opaque (King et al., 2011) and customer order flows are proven to convey private information, which are absorbed into the price via market dealers (e.g., Fan and Lyons, 2003; Carpenter and Wang, 2007; Bjønnes, 2008; Phylaktis and Chen, 2008). These characteristics make spot FX markets perfect for testing the local information advantage hypothesis. However, only a limited number of papers examine this aspect. Ito, Lyons, and Melvin (1998) and Covrig and Melvin (2002) analyzed an analogous experiment in the Tokyo FX market. On December 1994, restriction on trading over a lunch period (from 12 noon to 1:30 pm local time) was lifted in Tokyo. Ito, Lyons and Melvin (1998) found that the U-shaped volatility of Japanese yen/US dollar (JPY/USD) exchange rate returns in the Tokyo morning session disappeared after the lifting of the restriction. According to models using private information, informed traders are forced to reveal their informational advantage before the market closes due to time limitations that causes higher volatility than in other normal periods. Hence, they argue that this disappearance proves the existence of informed traders in the Tokyo FX market. However, they cannot discard the possibility that the U-shaped volatility is caused by dealers' inventory control behavior. Covrig and Melvin (2002) used the same natural experiment but more direct tests to prove that Tokyo-based traders know more about the JPY. They found that Japanese quotes led non-Japanese quotes in the late-morning period before the lifting of the restriction. However, no quote dominated the market in any other period, including the late-morning period after the lifting of the restriction. Peiers (1997) and Sapp (2002) found that Deutsche Bank has an advantage over other banks in detecting and interpreting interventions from the German Central Bank. More recently, by using spot Russian ruble/US dollar (RUB/USD) interbank transaction data at the Moscow Interbank Currency Exchange (MICEX), a Russian local trading venue, Menkhoff and Schmeling (2008) argued that order flows from Russian political and financial centers have a higher permanent price impact than order flows from other rural areas. These papers support local proximity as a reason behind information asymmetry among dealers in FX markets.

In contrast to studies that decompose the currency market into a few parallel markets, Wang and Yang (2011) sequentially separate the market into four regional trading sessions, that is, Asia, Europe, NYLON,[8] and the United States. They propose a structural vector autoregressive (SVAR) model and a non-parametric approach to measuring global information distribution. They conclude that for the four currency pairs they investigate, that is, AUD, JPY, EUR, and GBP against the USD, the Europe and US trading sessions contribute most to the price discovery process and the contribution from Asia is decreasing. The price discovery contribution methods in the sequential market setting inspired Wang (2014) to apply it as a measurement of the level of currency internationalization. He argues that when the offshore trading of a currency pair is active, it allows

[8] Overlapping London and New York trading hours.

the currency to incorporate information into price in a timely fashion, so that price discovery is enhanced in the overnight period. By separating a trading day into daytime and overnight periods, Wang found that KRW/USD became more internationalized than before. The overnight period IS increased from less than 10% in 1999–2000 to above 50% in 2011–2012.

Based on the existing literature, our study is the first to present a comprehensive price discovery distribution of EMCs between two sequential trading sessions, daytime and overnight, and between two parallel markets, onshore and offshore trading locations, during local business hours.

As for the determinants of local information advantage, which is considered to explain the equity investment home bias puzzle, studies mainly look at information transparency. Gelos and Wei (2005) found that both government and corporate information transparency matters. International funds prefer to hold more assets in more transparent markets. Papers like Bradshaw et al. (2004) and Khurana and Michas (2011) prove that US investors allocate more weight to foreign stocks that adopt familiar or the same accounting methods, as this reduces information processing costs and increases financial information comparability (Hail and Leuz, 2009; Barth et al., 2011).

Regarding the currency market, Michaelides et al. (2017) looked at the information leakage ahead of public sovereign debt downgrade announcements. They observed that the effect is stronger in currency pairs with lower institutional quality. Therefore, we argue that private information does exist in FX markets and lower institutional quality may emphasize the asymmetry of information. Eichengreen et al. (2017) used the point-to-point fiber optic submarine cable connections as a proxy for geographic proximity between the currency issuer country and the United States. They found that the fewer cable connections make the exchange rate react less to both local and US news, especially for currencies that mainly trade onshore. The underlying reason, they argue, is that the cable connection can reduce the informational disadvantage of poorly informed investors, so that they do not need to trade according to observed prices, which causes trend-following behavior.

Complementary to determinants like information transparency, institutional quality, and telecommunications infrastructure improvement, our study directly employs macro fundamentals from both the United States and the issuer's country as a proxy for information flow. The macro fundamentals are the most critical news to exchange rate fluctuations, and we examine their impact on the price discovery share of EMCs over time. Microstructure literature has found that there is a significant linkage between exchange rate dynamics and macro news. Anderson et al. (2003) focused on the impact of United States and German macro news on five major currency exchange rates. Using Reuters Money-Market Headline News, Melvin and Yin (2000) found that all types of news related to the United States and issuer countries increase quoting activity and volatility for JPY/USD and DEM/USD (Deutsche mark/US dollar). Dominguez and Panthaki (2006) extended the news categories and argued that non-fundamental news is also an exchange rate determinant.

Moreover, numerous papers have investigated the change in price discovery contribution during macro news announcements. Using GBP/USD data, Phylaktis and Chen (2010) investigated the price discovery of the top 10 active quoting banks during macro news announcements. They found that their information advantage became prevalent and their IS increased during a news release period. Chen and Gau (2010) found evidence that FX futures rates contribute more to price discovery than FX spot price around the point of a macroeconomic announcement. Frijns et al. (2015) compared the price discovery shares of 38 cross-listed Canadian companies on the Toronto Stock Exchange (TSX) and the New York Stock Exchange (NYSE).

They found the NYSE became more important for price discovery with both US and Canadian macro news. The empirical results of Gau and Wu (2017) suggest that, exclusively on days with US announcements, the overlapping trading hours between London and New York play a dominant role in the price discovery of the EUR and JPY markets. In this study, we examine the impact of macro news on location-related price discovery share in spot FX markets of emerging countries, whether overnight investors have enhanced capacity to help US news to be incorporated into price in a more timely fashion than previously and whether the information advantage of local investors becomes less prominent when local news arrives during the daytime period.

2.3 Hypotheses formation

2.3.1 Overnight IS

Hypothesis One: Overnight investors play an increasing role in pricing EMCs.

FX markets are open 24 hours a day, 7 days a week. The ebb and flow of daily turnover naturally separates the market into three main regional trading sessions, that is, Asia, Europe and the United States. However, most EMCs are still in their infancy, meaning that trading is mainly concentrated in local business hours, especially in the early years (for details, please check section 2.5.). Therefore, we first separate the 24-hour market into two sequential sessions, daytime and overnight.

During their early stages, due to strict currency and capital controls, EMCs convertibility was effectively prohibited on capital account transactions, so that foreign investors held and traded limited EMC-denominated financial assets or instruments. At that time, local investors must have been the main contributors to the pricing of EMCs. However, with the liberalization of local currencies and financial markets, capital mobility was boosted (e.g., Levine and Zervos, 1998 for the equity market; Chinn and Ito, 2002 for the equity and bond markets). Overnight investors gained access to and became much more active in trading emerging market financial assets, driving up the transaction and hedging demands of EMCs (Tsuyuguchi, 2008). Therefore, we expect that an increase in offshore trading facilitates the timely incorporation of overnight releases of news and events into price, so that overnight IS trends upward.

2.3.2 Offshore IS

Hypothesis Two: In the recent years, daytime offshore markets have become more informed in pricing EMCs.

We research local business hours by separating them into two parallel markets, onshore and offshore. Papers prove that the quantity and quality of customer order flows identify how informed a market or a group of dealers are. Onshore dealers are located in or nearby the decision-making center of the issuer's country. This allows onshore dealers to receive and gather higher-quality customer order flows that convey private information about local economic fundamentals. Consequently, onshore dealers possess superior information for pricing EMCs due to location advantage (e.g., Peiers, 1998; Covrig and Melvin, 2007; Menkhoff et al., 2010).

Recent studies show that better institutional quality and telecommunications infrastructure can lead to a decrease in local information advantage in pricing currencies. Higher institutional quality can lower information leakage before the announcement of important rates (Michaelides et al., 2017), which supports the argument that information asymmetry can be resolved through improved data transparency. [9] Moreover, telecommunications infrastructure development is important, as it helps poorly informed offshore investors to gain faster access to news from the

[9] Aimed at helping countries access international capital markets through the dissemination of economic and financial data to the public, the IMF established the Special Data Dissemination Standard (SDDS) in 1996. SDDS Plus began in 2012, with the goal of improving SDDS. Some of emerging countries are subscribers to this standard and make a commitment to observing the standard and to providing timely information. According to statistical capacity indicators, which gauge countries abilities to adhere to international standards and methods, emerging countries' data transparency and quality have improved in recent years.

issuer's country and related analysis produced by informed local dealers, banks, consultancies, and research firms (Eichengreen et al., 2017). In conclusion, based on the institutional quality and telecommunications infrastructure improvements, we expect dealers, especially in FX trading hubs like London and New York,[10] to have become more informed in pricing EMCs in recent years.

2.3.3 Impact of macro news on IS

Based on the MDH (e.g., Clark, 1973), if exchange rates walk randomly and if the number of steps depends positively on the number of information events, then exchange rate volatility over a given period should increase with the number of information events in that period. Empirical studies have found that macro fundamentals do have an impact on exchange rate volatility. Papers like Ederington and Lee (1993), Andersen and Bollerslev (1998), and Andersen et al. (2003) concluded that, from an intra-day perspective, the impact of macro announcements on price is short lived, lasting for only a few minutes, and influence on volatility is lengthier lasting for around a few hours.

Studies also investigated the impact of macro fundamentals on price discovery contribution for parallel or sequential markets. Where a market is divided into sequential segments, Gau and Wu (2017) argued that on days with US announcements, the overlapping trading hours between London and New York play the dominant role in the price discovery of the EUR and JPY markets. Su and Zhang (2018) show that in AUD/USD market, on days with Australian macro news, the price discovery share of Asia increases significantly; on days with US macro news, the IS of New York + London[11] and North America trading sessions rise. Where a market is separated into parallel markets, Frijns et al. (2015) examined 38 cross-listed Canadian firms listed on the TSX and NYSE showing that the US market becomes more dominant in terms of price discovery,

[10] These two biggest FX trading hubs intermediated over half of all FX transactions in 2016 (BIS triennial survey).
[11] The overlapping trading session between New York and London.

regardless of the news country of origin. Mizrach and Neely (2008) found that the release of macro news weakens the importance of German bond spot prices compared to futures prices. Chen and Gau (2010) found evidence that FX futures rates contribute more to price discovery than spot price in the time surrounding the release of a macro announcement.

2.3.3.1 Impact of macro news on overnight IS

Hypothesis Three: Higher price discovery capacity of overnight investors to US macro news causes overnight IS to trend upward.

As discussed in Hypothesis One, more active overnight trading helps news and events to be incorporated into price more efficiently. Other than that, the higher flexibility of an exchange rate is also a crucial determinant of price discovery capacity. Based on the previous literature, it is reasonable to expect that daytime/overnight IS increase with macro news releases during the daytime/overnight. However, in the early years, due to the limited flexibility of the exchange rate and frequent central bank interventions, [12] it is possible that information arrivals did not determine the return variance. In other words, the arrival of news may not have increased price discovery in the market. In the recent years, EMCs have become more market-determined (Bleaney and Tian, 2014),[13] which makes it possible for FX participants to incorporate information into price. At the same time, offshore EMCs markets have become more active in recent years, which facilitates overnight news and event absorption. Therefore, by testing the overnight IS changes associated with US news releases we can prove whether enhanced news incorporation capacity leads to the increased overnight IS. Additionally, countries release most of

[12] For surveys of central bank intervention in emerging country currency markets, please see Kriljenko (2004), Menkhoff (2010) and others.

[13] Bleaney and Tian (2014) proved that an increasing percentage of EMCs has become a de facto floater, from 40% in the 1990s to over 60% in recent years.

their macro news during local business hours.[14] Due to regional time zone patterns, Asian people are asleep when US people are at work. Therefore, Asian currencies represent the perfect opportunity to test Hypothesis Three.

2.3.3.2 Impact of macro news on offshore IS

Hypothesis Four: In recent years, decreasing local information advantage has made offshore investors more agile to local macro news.

By gauging IS between onshore and offshore markets during the daytime trading session, we can compare which market is more agile to the arrival of news. As we discussed in Hypothesis Two, the local information advantage hypothesis supports the argument that onshore dealers are more informed about local news because they can gather, observe, and precisely interpret higher quality customer order flows, which convey private local information. However, with institutional quality and telecommunications infrastructure improvements, as discussed before, we expect local information advantage for onshore dealers to have decreased in recent years. Therefore, we expect offshore investors to have become more agile to local macro news in recent years.

2.4 Methodology

In this study, we aim to present comprehensive information distribution across a 24-hour emerging currency market, that is, separating the market into two sequential markets, daytime and overnight, and further separating local business hours into two parallel markets, onshore and offshore. By estimating the Wang and Yang (2011) and Putniņš (2013) IS on a daily basis for daytime/overnight and onshore/offshore dealers, we can examine the distribution shift over the sample period from 1999 to 2017.

[14] As we are investigating currency pairs against the USD, we employ the US and local macro fundamentals as proxies for information flow.

2.4.1 Measuring price discovery in sequential markets

In the spirit of Hasbrouck (1995), Wang and Yang (2011) proposed a variance ratio measure to quantify price discovery share in non-overlapping sequential markets within the 24-hour FX market. In this chapter, different from Wang and Yang (2011), who separated a trading day into four sessions, that is, Asia, Europe, NYLON, and the United States, we only divide a trading day into two sessions, daytime and overnight,[15] because most EMCs are still in their infancy, meaning that trading is largely concentrated in local business hours, especially in their early years. We denote $p_{i,t}$ as the closing log price of market i, where i = 1, 2 indicates the daytime and overnight trading sessions for day t. The $p_{i,t}$ can be decomposed as $p_{i,t}= m_{i,t}+ u_{i,t}$, where $m_{i,t}$ is the efficient price representing the unobservable fundamental value, and $u_{i,t}$ is the noise term reflecting transitory effects. The efficient price change in market 1 and market 2 are $\triangle m_{1,t} = m_{1,t} - m_{2,t-1}$ and $\triangle m_{2,t} = m_{2,t} - m_{1,t}$. Wang and Yang (2011) argued that the information set available at the opening of market i on day t, $\triangle m_{i,t}$ is a martingale difference, so that $\triangle m_{1,t}$ and $\triangle m_{2,t}$ are uncorrelated with each other and over time. The change in the efficient price over day t is $\triangle m_t = \triangle m_{1,t} + \triangle m_{2,t}$. By using the variance of efficient price to measure information flow in market i (Hasbrouck, 1995), the IS of the i^{th} market during day t can be written as,

$$IS_{i,t} = \frac{var(\triangle m_{i,t})}{var(\triangle m_{1,t}) + var(\triangle m_{2,t})}., \; i = 1,2 \tag{2.1}$$

Since the efficient price and the noise term are not observable, many studies have proposed ways to reduce or remove the impact of the noise term on the estimation of the integrated variance. The existing studies prove that the two-scale realized variance (TSRV)

[15] Specifically, daytime period comprises local business hours from local time 9 am to 5 pm and overnight period comprises the non-business hours.

proposed by Zhang et al. (2005) is a consistent estimator of the integrated variance driven by information. Barndorff-Nielsen et al. (2008) show that TSRV can be expressed as a non-parametric estimator, which is based on subsampling as follows:

$$\mathrm{TSRV}_{i,t} = \frac{1}{k}\sum_{j=1}^{k} \mathrm{RV}_{i,t,j} - \frac{[m_i - k + 1]}{m_i k}\mathrm{RV}_{i,t} \tag{2.2}$$

where, $\mathrm{RV}_{i,t} = \sum_{s=1}^{m} r_{i,t,s}^2$ is the realized variance (RV) for session i on day t, that is, the sum of squared 1-minute log-return over the intervals s= 1,2,…., m_i. In our study, we take the daytime period as an example, m_1 equals 480, which is the production of eight local business hours multiplies by sixty 1-minute intervals. $\mathrm{RV}_{i,t,j}$ is the RV based on 5-minute log returns from the beginning of the j^{th} 1-minute interval, and k is the number of sub-grids on the 1-minute grid, which is equal to 5 here. It is a linear combination of the average of the low-frequency RV (five minutes in this study)[16] and the high-frequency RV (one minute here), which can remove the noise component effectively. Therefore, we use the TSRV estimator, as shown in equation (2.3), to obtain the efficient price variance of the market i on day t.

$$\mathrm{IS}_{i,t} = \frac{\mathrm{TSRV}_{i,t}}{\mathrm{TSRV}_{1,t} + \mathrm{TSRV}_{2,t}}.,\ i = 1,2 \tag{2.3}$$

2.4.2 Measuring price discovery in parallel markets

With respect to quantifying price discovery share between parallel markets, this study employs the ILS developed in Yan and Zivot (2010) and Putniņš (2013). The ILS uses Hasbrouck's (1995) IS and Gonzalo and Granger (1995) component share (CS) together to identify the price series that is first to impound new information. Recent studies have proved that IS and CS are both sensitive to the relative noise level between two markets. They actually measure a combination of

[16] Andersen et al. (2005) 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.

leadership in impounding new information which is what price discovery metrics aim to measure, and the relative level of noise in the price series (Yan and Zivot, 2010; Putniņš, 2013). As a result, they tend to overstate the price discovery contribution of the less noisy market.[17] In this chapter, we compare the IS of onshore and offshore markets for EMCs. During the early period, offshore volume share is very low, as shown in Figure 2.2. Taking the BRL as an example, offshore volume share is less than 10% in 2001. The gap in liquidity levels between onshore and offshore markets may cause overestimation of IS in offshore markets, which are the less noisy. Therefore, we employ ILS, which is robust to differences in noise levels and therefore correctly attributes price discovery in a wider range of settings.

Fundamentally, both IS and CS decompose price innovations into permanent and temporary components. They are estimated using a vector error correction model (VECM):

$$\begin{aligned} \triangle p_{3,t} &= \alpha_3(p_{3,t-1} - p_{4,t-1}) + \textstyle\sum_{i=1}^{60} \gamma_i \triangle p_{3,t-i} + \sum_{j=1}^{60} \delta_j \triangle p_{4,t-j} + \varepsilon_{3,t} \\ \triangle p_{4,t} &= \alpha_4(p_{3,t-1} - p_{4,t-1}) + \textstyle\sum_{k=1}^{60} \varphi_k \triangle p_{3,t-k} + \sum_{m=1}^{60} \phi_m \triangle p_{4,t-m} + \varepsilon_{4,t} \end{aligned} \tag{2.4}$$

where $\triangle p_{3,t}$ and $\triangle p_{4,t}$ represent the change in the log price of our EMCs traded in onshore and offshore markets during local business hours on day t on a grid of one-second clock time intervals. Following Baillie et al. (2002), we estimate the IS and CS metrics using the variance-covariance of the error terms and the error correction parameters from the VECM.[18] The CS metrics are obtained from the normalized orthogonal to the vector of error correction coefficients, $\alpha_{\perp} = (\gamma_1 + \gamma_2)'$, thus:

$$CS_3 = \gamma_1 = \frac{\alpha_4}{\alpha_4 - \alpha_3}, CS_4 = \gamma_2 = \frac{\alpha_3}{\alpha_3 - \alpha_4} \tag{2.5}$$

[17] Putniņš (2013) shows that IS places greater weight on the speed at which a price series impounds new information, compared to the CS metric which is largely a measure of the relative levels of noise.

[18] Hasbrouck (1995) defines price discovery in terms of the variance of the innovations to the common factor. Gonzalo and Granger (1995), however, are concerned with only the error correction process which measures the speed of adjustment to the long run equilibrium.

Given the covariance matrix of the reduced form VECM error terms and its Cholesky factorization, $\Omega = MM'$, where

$$\Omega = \begin{pmatrix} \delta_3^2 & \rho\delta_3\delta_4 \\ \rho\delta_3\delta_4 & \delta_4^2 \end{pmatrix} \quad \text{and} \quad M = \begin{pmatrix} m_{11} & 0 \\ m_{21} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_3 & 0 \\ \rho\delta_4 & \sigma_4(1-\rho^2)^{1/2} \end{pmatrix} \tag{2.6}$$

we calculate the IS using:

$$IS_3 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \; IS_4 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} \tag{2.7}$$

Since IS is impacted by the order of the price series in the Cholesky factorization, we calculate IS under each of the potential orderings and take the simple average, as advocated by Baillie et al. (2002).

As mentioned before, the IS and CS are both sensitive to the relative noise level between the two markets. Therefore, we employ ILS, proposed by Yan and Zivot (2010) and Putniņš (2013), which is able to attribute correct contributions to price discovery without being influenced by differences in noise levels of price series. ILS is a combination of IS and CS as follows:

$$ILS_3 = \frac{\left|\frac{IS_3 CS_4}{IS_4 CS_3}\right|}{\left|\frac{IS_3 CS_4}{IS_4 CS_3}\right| + \left|\frac{IS_4 CS_3}{IS_3 CS_4}\right|}, \quad ILS_4 = \frac{\left|\frac{IS_4 CS_3}{IS_3 CS_4}\right|}{\left|\frac{IS_3 CS_4}{IS_4 CS_3}\right| + \left|\frac{IS_4 CS_3}{IS_3 CS_4}\right|} \tag{2.8}$$

2.4.3 Determinants of price discovery: Estimation strategy

As discussed in the hypotheses formation section, our main interest is to test whether macro news is one crucial determinant of the shift in overnight and offshore price discovery shares. We use the number of macro fundamentals as a proxy for information flow. Apart from macro news, we also control the regression with market state variables, following Brandt et al. (2007) and Mizrach and Neely (2008). In order to control for seasonality and extreme market conditions, we added weekday dummies and dummies for two global crises, that is, the Global Financial Crisis (GFC) and the European Debt Crisis (EDC). We utilize a simple ordinary least squares (OLS) approach to estimate the coefficients and use the Newey–West heteroscedasticity and autocorrelation consistent (HAC) standard error to overcome the residual heteroscedasticity and autocorrelation problem. We also report the mean coefficients and the t-statistics associated with them for the Asian and non-Asian currency groups. Following Hameed et al. (2010), the standard error of the kth average coefficient $\overline{\widehat{\beta_k}}$ is given by: Newey-West

$$\mathrm{StDev}\left(\overline{\widehat{\beta_k}}\right) = \mathrm{StDev}\left(\frac{1}{N}\sum_{i=1}^{N}\widehat{\beta_{i,k}}\right) = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\widehat{\omega_{i,j}}\sqrt{\mathrm{Var}\left(\widehat{\beta_{i,k}}\right)\mathrm{Var}\left(\widehat{\beta_{j,k}}\right)}} \tag{2.9}$$

Where $\mathrm{Var}\left(\widehat{\beta_{i,k}}\right)$ is based on the Newey–West standard error of the regression of currency i and $\widehat{\omega_{i,j}}$ is the correlation between the regression residuals for currency i and j.

2.4.3.1 Empirical model for Hypothesis Three

With respect to daytime/overnight IS determinants, we test Hypothesis Three with the following model specification:

$$\ln(\boldsymbol{IS}_{daytime,t}) = \beta_0 + \boldsymbol{\beta_1 ln}\left(\frac{\boldsymbol{1+US\ news}_{day,t}}{\boldsymbol{1+US\ news}_{nite,t}}\right) + \beta_2\ln\left(\frac{\boldsymbol{1+Local\ news}_{day,t}}{\boldsymbol{1+Local\ news}_{nite,t}}\right) + \beta_3\boldsymbol{ln}(\boldsymbol{Qspd}_{day,t}) + \beta_4\boldsymbol{ln}(\boldsymbol{Volatility}_{day,t}) + \beta_5\boldsymbol{ln}(\boldsymbol{Noq}_{day,t}) + \beta_6\,\boldsymbol{ln}(\boldsymbol{IS}_{daytime,t-1}) + \beta_7\boldsymbol{GFC} + \beta_8\boldsymbol{EDC} + \sum_{j=Mon}^{Thu}\beta_j\,\boldsymbol{WD^j} + \boldsymbol{\epsilon}_t \tag{2.10}$$

Except for dummy variables, all the other variables are in natural logarithm form to reduce any effects from extreme values. The dependent variable, $\ln(\mathrm{IS}_{\mathrm{daytime,t}})$, is equal to $\ln\left(\frac{\mathrm{TSRV}_{\mathrm{daytime,t}}}{\mathrm{TSRV}_{\mathrm{daytime,t}}+\mathrm{TSRV}_{\mathrm{overnight,t}}}\right)$, which is the daytime price discovery share measured by TSRV on day t (Wang and Yang, 2011). The first independent variable is our main interest variable, which is the ratio of the number of US announcements released during the daytime to that of the overnight period on day t. The second independent variable is the ratio of daytime and overnight numbers of macro announcements from the issuers. When we constructed the log form of the two variables, we added 1 to both the numerator and denominator of the ratio. This was to avoid calculation problems on non-news during the daytime or overnight periods of the day. This will not disturb the distribution of information flow. Governments tend to publicize macro news during local business hours. As US business hours overlap more or less with those of the issuers, we constructed a US news variable in ratio form. We also constructed an EMCs local news variable in ratio form because South Korea occasionally releases macro news during their overnight period. For Hypothesis Three, we test whether the increasing overnight period IS is due to overnight investors being more responsive to US macro news. Hence, we expect to observe that β_1 is positive and shows a larger size and higher significance in the more recent sub-sample periods.

For market state variables, we follow Mizrach and Neely (2008) by adding $\mathrm{Qspd}_{\mathrm{day,t}}$, $\mathrm{Volatility}_{\mathrm{day,t}}$, and $\mathrm{Noq}_{\mathrm{day,t}}$, which are the time-weighted average quoted spread, standard deviation of 5-minute log returns, and number of quotes (NoQ) for the daytime period. The summary statistics of the market state variables for the daytime and overnight trading sessions are provided in Appendix A. In addition, the Ljung–Box statistics indicate that the two periods' TSRV are significantly auto-correlated for all currency pairs. Hence, we add lagged IS, $\mathrm{IS}_{\mathrm{daytime,t-1}}$, to control the self-dependence. In order to control for extreme market conditions, we add GFC and EDC dummy variables. For the GFC, the key financial crisis months, September 2008–November 2009, equal 1, and the other period equals 0. For the EDC, the key crisis months, April 2010–February 2012, equal 1, and the other period equals 0. Finally, we include the weekday dummy WD^{j} (j= Monday, Tuesday, Wednesday, and Thursday) to capture the day-of-the-week effect.

2.4.3.2 Empirical model for Hypothesis Four

With respect to onshore and offshore IS determinants, we test the hypothesis Four by using the following model specification:

$$\begin{aligned}\ln\left(\boldsymbol{IS}_{on,t}\right) &= \emptyset_0 + \emptyset_1 \boldsymbol{ln}(\mathbf{1} + \boldsymbol{NEWs}_t) + \emptyset_2 \boldsymbol{ln}(\mathbf{1} + \boldsymbol{NEWs}_{\boldsymbol{US}_t}) \\ &+ \emptyset_3 \boldsymbol{ln}(\boldsymbol{Qspd}_{on,t}) + \emptyset_4 \boldsymbol{ln}(\boldsymbol{RV}_{on,t}) + \emptyset_5 \boldsymbol{ln}(\boldsymbol{Noq}_{on,t}) + \emptyset_6\, \boldsymbol{ln}\left(\boldsymbol{IS}_{on,t-1}\right) + \emptyset_7 \boldsymbol{GFC} + \emptyset_8 \boldsymbol{EDC} + \textstyle\sum_{j=Mon}^{Thu} \emptyset_j\, \boldsymbol{WD}^{j} + \boldsymbol{\epsilon}_t \qquad (2.11)\end{aligned}$$

The empirical model is the same as for Hypothesis Three, except for the dummy variables, with all other variables being in natural logarithm form. The dependent variable, $\boldsymbol{IS}_{on,t}$, is an estimation of ILS in Yan and Zivot (2010) and Putniņš (2013), which represents onshore ILS during local business hours on day t. The first and second independent variables are the number of local and US announcements released during the daytime period. To avoid a calculation problem for non-news days, we add 1 to the number of announcements when we construct the log form of the variables; this does not disturb the distribution of information flow. For Asian currencies, we only add the number of local announcements into this model due to zero overlapping hours between their daytime and the US news releasing period. For Latin American and South African currencies, we add the local and US news variables into the regressions. From Hypothesis Four, we test whether the increasing offshore-dealer price discovery share is because offshore investors have gained information advantage from local macro news in the recent years. Hence, we expect that $\emptyset_1$ is positive and shows lower significance in the more recent sub-sample periods.

For market state variables, we follow Mizrach and Neely (2008) to add $\mathrm{Qspd}_{\mathrm{on,t}}$, $\mathrm{RV}_{\mathrm{on,t}}$ and $\mathrm{Noq}_{\mathrm{on,t}}$, which are the time-weighted average quoted spread from onshore quotes, the sum of square onshore-initiated log returns estimated using tick-by-tick indicative quotes data, and the onshore daily number of quotes. The summary statistics of the market state variables for the onshore and offshore markets are provided in Appendix B. The rest of the control variables are the same as in the empirical model used to test Hypothesis Three.

2.5 Data description

In this chapter, we study six currency pairs as representations of EMCs. We include three Asian currencies, the INR, KRW, and PHP; two Latin American currencies, the BRL and MXN; and one African currency, the ZAR; all rates are against the USD. As mentioned in the introduction, EMCs showed an overall upward trend in turnover share and offshore volume share. The six selected currency pairs also displayed the same upward trend presented in Figure 2.3 and Figure 2.4.[19] In terms of trading volume share, INR had the largest growth rate from 2001 to 2016, which was over 500%, while ZAR displayed the mildest upward trend, with a volume share approaching 1% in 2001 and slightly over 1% in 2016. For offshore volume share, the three Asian currencies and BRL saw sharp growth trends. In particular, BRL's share was less than 10% in 2001 and rocketed to about 60% in recent years. In contrast, the offshore volume shares of the other two currencies hovered around 60% over the sample period.

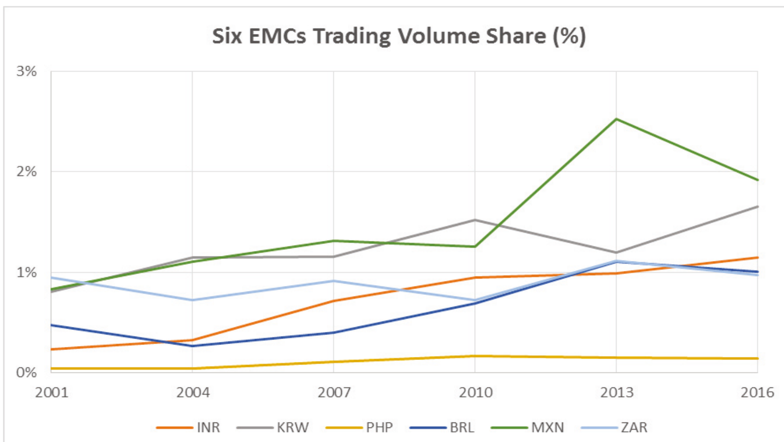


Figure 2.3. Trading Volume Share (%) of BRL, INR, KRW, MXN, PHP and ZAR
Data Source: Author's calculations using BIS FX market triennial survey

[19] In BIS triennial survey, there is no information about offshore trading volume share for PHP after 2010.

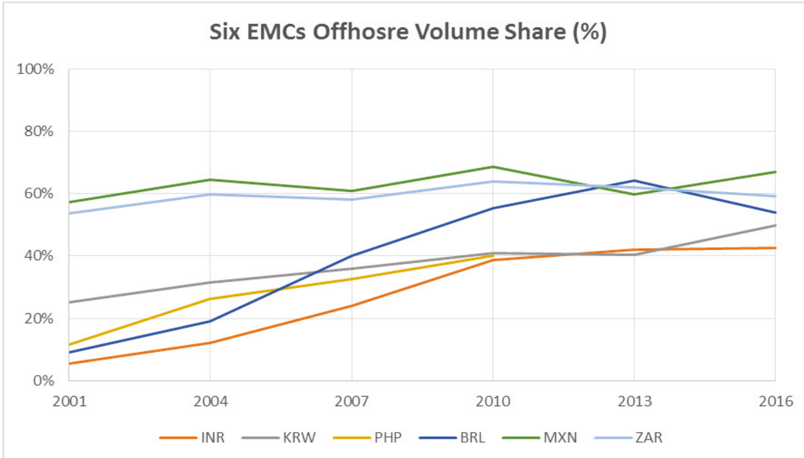


Figure 2.4. Offshore Volume Share (%) of BRL, INR, KRW, MXN, PHP and ZAR
Data Source: Author's calculations using BIS FX market triennial survey

With the aim of presenting comprehensive price discovery distribution of EMCs, we employed intraday indicative quoting data obtained from the Thomson Reuters Tick History (TRTH) database provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). Unlike transaction quotes or firm quotes, indicative quotes do not present a binding commitment to trade at these prices. It is possible that some banks may input excessive and even irrelevant quotes in order to build up a market presence. However, Danıelsson et al. (2002) and Phylaktis and Chen (2009) showed that indicative quotes and firm trades data have very similar properties. Additionally, and especially for big banks, reputational concerns ensure FX transactions occur at prices close to those advertised.

Our data sample period is from January 1, 1999 to December 31, 2017. The TRTH dataset contains information about the time when a new quote is issued rounded to the nearest millisecond, the prices of bid and ask quotes, and the identification of quoting banks' names and locations. In addition, we filter the data to remove outliers following Barndorff-Nielsen et al. (2009), and delete weekends and holidays with thin trading.[20]

[20] For the TRTH data, following procedures of how to filter quote data in Barndorff-Nielsen et al. (2009), we deleted

2.5.1 Sequential markets

One aim of our study is to present the comprehensive information distribution across the 24-hour emerging currency market, that is, separate the market into two sequential markets, daytime and overnight, and further separate the daytime period into two parallel markets, onshore and offshore. With respect to the sequential markets, depending on the daily turnover ebb and flow, the 24-hour market can be separated into four regional trading sessions, that is, Asia (GMT 2300 to 0600), Europe (GMT 0700 to 1200), overlapping London + NYC (GMT 1300 to 1400), and the United States (GMT 1500 to 2200), in Wang and Yang (2011) and Chai et al. (2015). However, EMCs are still in their infancy, so that trading is largely concentrated in local business hours. Taking the year 2014 as an example, Figures 2.5 and 2.6 show graphs of the hourly number of quotes for three Asian currencies and three non-Asian currencies. It can be observed that the majority of quotes update during local business hours for all six emerging market currency pairs, and there is no clear regional time zone pattern for quoting activities. In Table 2.2, we present quote distribution over the daytime and overnight periods for the six EMCs over the whole sample period. INR, KRW, and BRL have as much as 90% of the total number of quotes (NoQ) taking place in the daytime period, whereas the ratio for PHP, MXN, and ZAR is about 60%. The largest daytime to overnight quotes ratio is 19 from BRL, and the lowest ratio is 1.2 from MXN. None of the selected six EMCs have more quotes in the overnight period than in the daytime period. Therefore, we divide a trading day into two sequential sessions, daytime and overnight. The

entries with a bid and ask equal to zero or missing; entries with missing date, time, bank ID, or trading location; entries with a non-positive spread; entries for which the spread is more than 50 times the median spread on that day; and entries for which the mid-quote deviated by more than 10 mean absolute deviations from a rolling centered median (excluding the observation under consideration) of 50 observations (25 observations before and 25 after).

daytime period is local business hours from local time 9 am to 5 pm[21] and the overnight period is outside business hours.

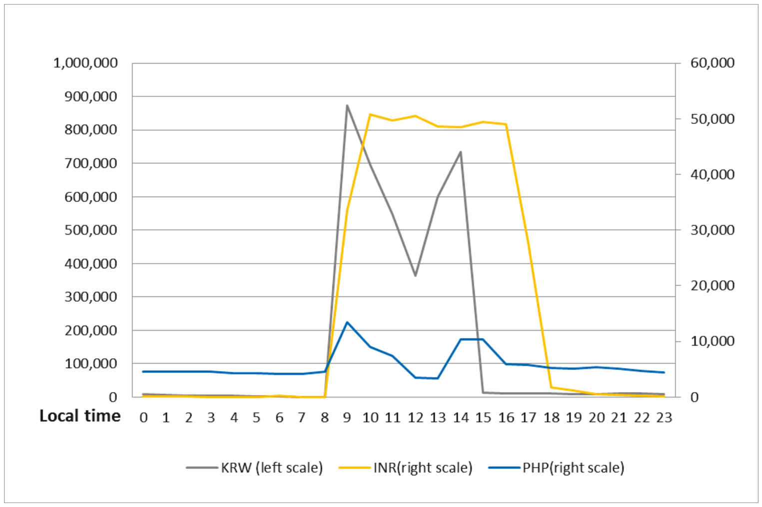


Figure 2.5. Hourly number of quotes for INR, KRW, and PHP (2014)
Data Source: Author's calculations using FX quotes data obtained from the TRTH database

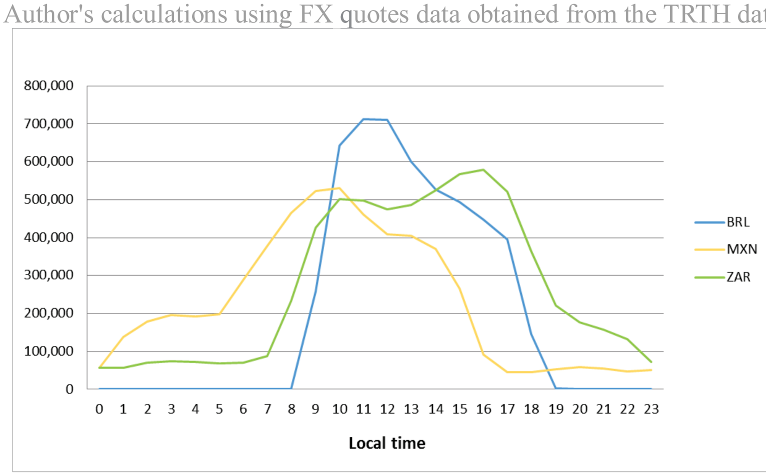


Figure 2.6. 2014 Hourly number of quotes for BRL, MXN, and ZAR (2014)
Data Source: Author's calculations using FX quotes data obtained from the TRTH database

2.5.2 Parallel markets

We separate the daytime period into two parallel markets, onshore and offshore. From the aggregated FX statistics released by BIS, BRL gained a large offshore trading volume share of up to 60% in recent years. However, from the quotes summary in Table 2.1, the BRL daytime to overnight NoQ ratio is 19, which means transaction activities are highly concentrated in daytime

[21] We set PHP/USD local business hours from 9 am to 4 pm because its local trading platform, the Philippine Dealing System, closes at 4 pm.

period, as discussed in the previous section. The seemingly contradictory conclusion is due to the issuer local business hours overlapping with the European and US trading sessions. The local business hours of issuers, especially non-Asian countries, more or less overlap with the European and US trading sessions, which are the two biggest FX trading hubs and intermediated over half of the total FX transactions in 2016 (BIS triennial survey). Therefore, in order to present a comprehensive price discovery distribution of EMCs, we further divide local business hours into onshore and offshore markets, depending on quoting banks' location. In table 2.1, we present GMT as indicating time zone trading sessions and the corresponding local time of the currency issuer countries.

Table 2.2 shows EMCs quoting distribution divided by daytime/overnight trading sessions and quoting locations. There are three main trading venues, according to the trader location provided by TRTH: the onshore market is made up of quotes updating within the issuer border; the offshore market is made up of quotes updating outside the issuer border; global FX trading platform (GFX) is made up of quotes without a specific location identification. For GFX quotes, their quoting distribution implies that they should be categorized as an offshore market.[22] Table 2.2 shows that during the daytime period, around 70% of quotes take place on an onshore venue for INR, KRW, and BRL, and less than 50% of quotes update on an offshore venue for PHP, MXN, and ZAR. Among the latter group, ZAR has the lowest onshore quotes rate, which is 17%.

Table 2.1. Greenwich Mean Time (GMT) with time zone trading sessions and corresponding local times for EMC issuer countries.

In this table, the first column shows GMT as indicating time zone trading sessions in Wang and Yang (2011). The 24-hour market is separated into four regional trading sessions, that is, Asia (GMT 2300 to 0600), Europe (GMT 0700 to 1200), overlapping London + NYC (GMT 1300 to 1400), and the United States (GMT 1500 to 2200). The rest of the table shows the corresponding local times of the EMC issuer countries. Local business hours of those countries are denoted by bold letters. Brazil and Mexico have daylight savings (DLS) practice and the local times during DLS are shown on the bracket, which are shifted forward by 1 hour.

[22] As shown in Table 2.2, GFX quotes tend to take place during the overnight period of Asian currencies and the daytime period of Latin American and African currencies, when the London and New York dealers are actively trading. Therefore, we argue that it is highly possible that most of the GFX dealers are located outside the borders of the EMC issuers due to their trading patterns.

		South Korea GMT+9	Philippines GMT+8	India GMT +5.5	South Africa GMT +2	Brazil GMT-3 (DLS GMT -2)	Mexico GMT -6 (DLS GMT -5)
GMT		**Local hours**					
Asia	0	**9**	8	5.5	2	21(22)	18(19)
	1	**10**	**9**	6.5	3	22(23)	19(20)
	2	**11**	**10**	7.5	4	23(0)	20(21)
	3	**12**	**11**	8.5	5	0(1)	21(22)
	4	**13**	**12**	**9.5**	6	1(2)	22(23)
	5	**14**	**13**	**10.5**	7	2(3)	23(0)
	6	**15**	**14**	**11.5**	8	3(4)	0(1)
Euro	7	**16**	**15**	**12.5**	**9**	4(5)	1(2)
	8	17	16	**13.5**	**10**	5(6)	2(3)
	9	18	17	**14.5**	**11**	6(7)	3(4)
	10	19	18	**15.5**	**12**	7(8)	4(5)
	11	20	19	**16.5**	**13**	8**(9)**	5(6)
	12	21	20	**17.5**	**14**	**9(10)**	6(7)
London +NYC	13	22	21	18.5	**15**	**10(11)**	7(8)
	14	23	22	19.5	**16**	**11(12)**	8**(9)**
US	15	0	23	20.5	17	**12(13)**	**9(10)**
	16	1	0	21.5	18	**13(14)**	**10(11)**
	17	2	1	22.5	19	**14(15)**	**11(12)**
	18	3	2	23.5	20	**15(16)**	**12(13)**
	19	4	3	0.5	21	**16**(17)	**13(14)**
	20	5	4	1.5	22	17(18)	**14(15)**
	21	6	5	2.5	23	18(19)	**15(16)**
	22	7	6	3.5	0	19(20)	**16**(17)
Asia	23	8	7	4.5	1	20(21)	17(18)

Table 2.2. EMCs quoting distribution divided by trading sessions and venues

In this table, we present EMCs quoting distribution divided by daytime/overnight trading sessions and quoting locations using FX quotes data obtained from the TRTH database. We separate the 24-hour market into daytime, from local time 9 am to 5pm[23], and overnight periods, from local time 5pm to next day 9 am. There are three main trading venues, according to the trader location provided by TRTH: the onshore market is made up of quotes updating within the issuer border; the offshore market is made up of quotes updating outside the issuer border; global FX trading platform (GFX) is made up of quotes without a specific location identification. As shown in this tabl e, GFX quotes tend to take place during the overnight period of Asian currencies and the daytime period of Latin American and African currencies, when the London and New York dealers are actively trading. Due to their trading patterns, we argue that it is highly possible that most of the GFX dealers are located outside the borders of the EMC issuers. Therefore, GFX quotes was categorized as an offshore market in this chapter.

Unit: thousands		INR		KRW		PHP		BRL		MXN		ZAR	
	Trading venues	NoQ	Quotes share	NoQ	Quotes share	NoQ	Quotes share	NoQ	Quotes share	NoQ	Quotes share	NoQ	Quotes share
Daytime Period	onshore	3,725	65%	28,550	76%	1,581	49%	44,602	73%	19,437	28%	14,792	17%
	offshore	666	12%	2,784	7%	270	8%	10,783	18%	15,275	22%	32,195	37%
	GFX	243	4%	2,160	6%	116	4%	2,134	3%	2,393	4%	5,924	7%
	Sub-total	4,634	81%	33,494	90%	1,966	61%	57,519	94%	37,105	54%	52,911	61%
Overnight Period	onshore	1	0%	5	0%	88	3%	1,774	3%	12,536	18%	10,085	12%
	offshore	167	3%	641	2%	181	6%	1,553	3%	16,369	24%	17,773	21%
	GFX	918	16%	3,215	9%	978	30%	292	0%	2,287	3%	5,810	7%
	Sub-total	1,086	19%	3,861	10%	1,248	39%	3,619	6%	31,192	46%	33,668	39%
Total Noq		5,720	100%	37,356	100%	100%	100%	61,138	100%	68,297	100%	86,579	100%
Daytime/Overnight Noq ratio		4		9		2		16		1.2		2	
Onshore/Offshore(including GFX) Noq ratio		4		6		4		4		1		0.4	

[23] We set PHP/USD local business hours from 9 am to 4 pm because the local trading platform, the Philippine Dealing System, where commercial banks trade in foreign exchange closes at 4 pm.

2.5.3 Macro announcements

Our study employs macro announcements as a proxy for information flow. We collect both US and issuer scheduled macro announcements[24] from the Bloomberg macro announcement calendar. Table 2.3 shows the Bloomberg daily number of macro news summary. On average, there are 4,672 active trading days for the six EMCs over the sample period. A total of 54% and 87% of trading days have local and US news. On average, there are two pieces of local news and five pieces of US news released on a given news day. Table 2.4 shows hourly average number of releases by the emerging countries and the United States over our sample period. Countries tend to release macro news during local business hours. However, the South Korean government sometimes releases macro news between 6 am and 9 am local time. The United States mainly publicizes their macro news during the morning period from GMT 1200 to 1500, overlapping with the local business hours of South Africa, Brazil, and Mexico.

[24] As we are focusing on currency pairs against the USD, we only collect US macro news as information shock, other than issuers. Cai et al. (2009) investigated how exchange rates in nine emerging markets against the USD react to macro news in the United States and domestic economies. They found that major US macro news has a strong impact on the returns and volatilities of emerging country exchange rates.

Table 2.3. Bloomberg macro news calendar summary

In this table, we present the number of active trading days, the percentage of trading days with local or US macro news, and average pieces of announcements released on a given local or US news day.

	Brazil	India	South Korea	Mexico	Philippines	South Africa	Avg.EMCs
Trading days	4,608	4,734	4,272	4,868	4,670	4,879	4672
Days with local macro news	75%	19%	41%	48%	30%	37%	42%
Days with US macro news	84%	83%	85%	84%	84%	85%	84%
Avg.N of local news	3	2	2	2	2	2	2
Avg.N of US news	5	5	5	5	5	5	5

Table 2.4. Hourly average number of macro announcements

In this table we summarize hourly number of announcements released by emerging countries and US between 1999 and 2017. Data is sourced from Bloomberg macro announcement calendar. Except KRW, all other countries tend to publicize macro news during their local business hours which are denoted by bold letters.

GMT	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Korean	**0.2**	**0.3**	**0.2**	**0.8**	**0.3**	**0**	**0**	**0**	0	0	0	0	0	0	0	0	0	0	0	0	0	0.7	0.1	0.7
Philippines	0.1	**0.6**	**0.1**	**0**	**0.5**	**0.3**	**0.1**	**0.1**	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
India	0	0	0	0	**0.1**	**0.6**	**0.5**	**0.1**	**0.0**	**0.1**	**0.1**	**0.1**	0.2	0	0	0	0	0	0.1	0	0	0	0	0
South Africa	0	0	0	0	0	0	0.4	**0.1**	**0.2**	**0.9**	**0.1**	**0.4**	**0.2**	**0.1**	**0**	0	0	0	0	0	0	0	0	0
Brazil	0	0	0	0	0	0	0	0	0.1	0.0	0.3	**0.6**	**0.7**	**0.7**	**0.3**	**0.1**	**0.1**	**0.2**	**0.2**	**0.1**	0	0	0	0
US	0	0	0	0	0	0	0	0	0	0	0	0.2	**1.9**	**1.5**	**1.1**	**0.5**	**0**	**0**	**0.1**	**0.1**	**0.1**	**0.1**	**0.1**	0
Mexico	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	**0.6**	**0.3**	**0**	**0.1**	**0.1**	**0.3**	**0.3**	**0**	**0**	0

2.6 Empirical results

The empirical results are reported and discussed in this section.

2.6.1 IS distribution for EMCs

2.6.1.1 Estimated IS of the daytime trading period for EMCs

We estimate the daytime and overnight ISs for each trading day during our sample period using the variance ratio proposed by Wang and Yang (2011). The yearly daytime period ISs (simple average of daily IS) are presented in Table 2.5. Figures 2.7 and 2.8 show the graph of the yearly IS evolution of three Asian currencies and three non-Asian currencies. The sum of daily daytime and overnight period IS is equal to one.

Before analyzing the evolution of daytime IS, we first observe the average IS levels of individual currency pairs over the sample period. Daytime investors contribute an average of 78% to the pricing of BRL, which is the highest among the six EMCs. This high contribution from the daytime period is in line with its high liquidity level, shown in Table 2.2,[25] whereas, all other currencies' average daytime IS are around or below 60%. INR has the lowest average daytime IS at 39%. In Wang and Yang (2014), they argue that overnight IS can be an aggregated measure for the level of internationalization of a currency. This is because the overnight price discovery reflects the aggregate impact of overnight news and events, offshore holding and trading of financial assets/instruments denominated in the currency, and the broad economic and financial integration within the global economy. Hence, we can also conclude that among the six EMCs we investigated, INR and BRL have the highest and lowest internationalization levels.

Concerning the IS evolution, the average daytime IS of the EMCs decreased from 60% in 1999 to 50% in 2017. This overall trend confirms our hypothesis that overnight investors are

[25] BRL has the highest daytime to overnight number of quotes ratio which shows the overnight period is extremely illiquid.

playing an increasing role in pricing EMCs. The more active overnight investors do facilitate the incorporation of overnight news and events into the price with higher efficiency, enhancing price discovery contribution. For individual currencies, we can observe a downward trend in daytime IS from BRL, KRW, and MXN. The IS of the other three currencies hover around their average values over the sample period. KRW shows the most dramatic downward trend, from 92% in 1999 to 46% in 2017, which is consistent with the finding in Wang and Yang (2014). Even though EMCs overnight period IS is increasing, the share is still lower than an internationalized currency. Taking the AUD as an example, its overnight IS remained around 70% from 1999 to 2013 (Wang and Yang, 2011; Su and Zhang, 2018).

In Figure 2.9 we present the average yearly IS evolution for Asian and non-Asian currencies. The daytime price discovery contribution of the non-Asian currencies is, on average, higher than that of the Asian currencies. One possible reason is the three non-Asian countries' local business hours overlap with US and Europe trading sessions, which intermediate over half of the total FX transactions (2016 BIS triennial survey). Therefore, it is necessary to further separate the daytime period into two parallel markets, onshore and offshore.

Table 2.5. Annual daytime period IS

This table presents yearly daytime information share gauged by TSRV following equation 2.3. The overnight information share is equal to one minus its daytime information share.

year	BRL	INR	KRW	MXN	PHP	ZAR	Avg.EMCs
1999	92%	39%	92%	52%	33%	52%	**60%**
2000	92%	38%	90%	48%	46%	54%	**61%**
2001	83%	40%	71%	45%	45%	52%	**56%**
Avg. 1999-2001	89%	39%	84%	48%	41%	53%	**59%**
2002	84%	44%	58%	49%	62%	53%	**58%**
2003	80%	33%	79%	55%	57%	56%	**60%**
2004	86%	31%	49%	46%	48%	48%	**51%**
2005	78%	37%	51%	42%	41%	42%	**49%**
Avg. 2002-2005	82%	36%	59%	48%	52%	50%	**55%**
2006	69%	61%	61%	44%	56%	40%	**55%**
2007	71%	24%	56%	44%	47%	34%	**46%**
2008	71%	27%	49%	42%	43%	46%	**46%**
2009	74%	24%	47%	46%	42%	45%	**46%**
Avg. 2006-2009	71%	34%	53%	44%	47%	41%	**48%**
2010	72%	20%	51%	43%	38%	45%	**45%**
2011	71%	26%	48%	39%	65%	51%	**50%**
2012	72%	50%	48%	39%	49%	53%	**52%**
2013	75%	54%	57%	44%	46%	56%	**55%**
Avg. 2010-2013	73%	38%	51%	41%	50%	51%	**51%**
2014	78%	54%	59%	42%	51%	59%	**57%**
2015	79%	39%	50%	41%	25%	60%	**49%**
2016	74%	40%	48%	40%	33%	55%	**48%**
2017	79%	54%	46%	40%	25%	58%	**50%**
Avg. 2014-2017	78%	47%	51%	41%	34%	58%	**52%**
Avg.	78%	39%	58%	44%	45%	50%	**52%**

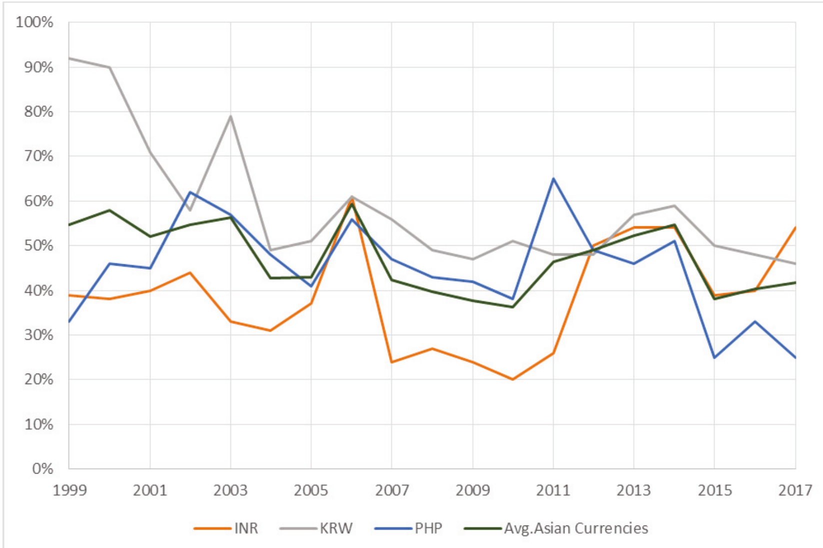


Figure 2.7. Average yearly daytime IS evolution for INR, KRW and PHP

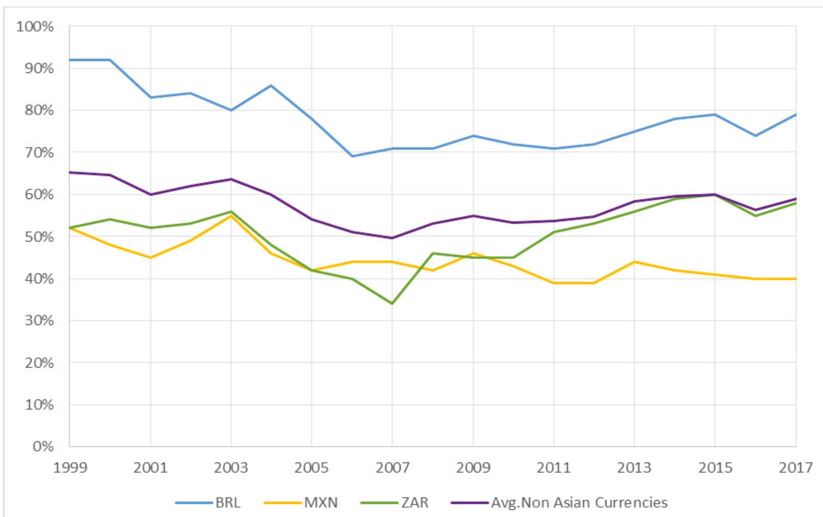


Figure 2.8. Average yearly daytime IS evolution for BRL, MXN and ZAR

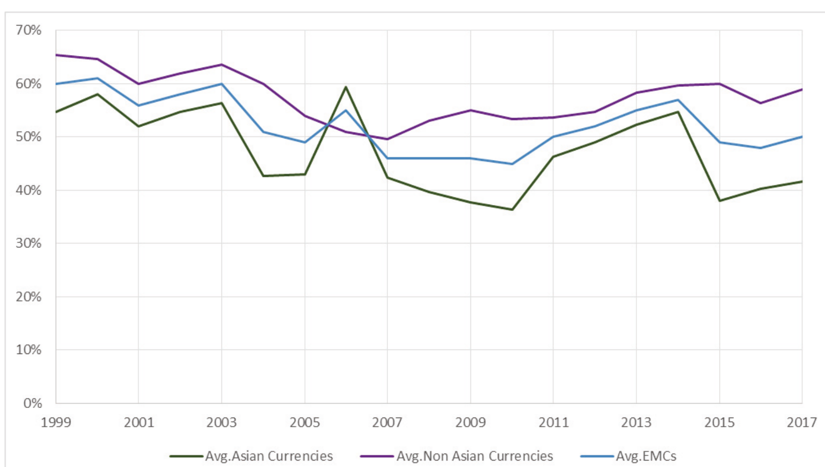


Figure 2.9. Average yearly daytime IS evolution for Asian, non-Asian and all EMCs

2.6.1.2 Estimated IS of the onshore market during the daytime period for EMCs

In order to present comprehensive information distribution of EMCs, as well as sequentially separating the 24-hour market into daytime and overnight periods, we further divide the daytime period into onshore and offshore markets. This is necessary, especially for non-Asian currencies, due to local business hours overlapping with the Europe and US trading sessions.[26] We estimate the onshore/offshore IS proposed by Yan and Zivot (2010) and Putniņš (2013) for each trading day in our sample period using one-second sampling frequency in VECM. The sum of onshore and offshore market IS is equal to one. Table 2.7 shows the overall IS for the onshore markets of each currency, and annual onshore IS are presented in Table 2.8.

One basic requirement for estimating onshore/offshore market IS using VECM is that both of the markets need to be active. In Table 2.7 and 2.8, we report the number of days with inactive onshore and inactive offshore markets. It can be observed that non-Asian currencies have many more onshore inactive days than offshore inactive days, but the converse is true for Asian currencies. This is in line with the fact that offshore markets of non-Asian currencies are more active than those of Asian currencies during the daytime period. Concerning the onshore IS, we report the average IS and inactive-market-weighted IS which takes into consideration the days with an inactive onshore or offshore market.[27] As inactive days are around 10% or less of the total trading days, IS results between the average and the weighted average are quite similar to each other.

In Figures 2.10 to 2.12, we present graphs of annual onshore IS for individual and currencies groups, that is, the Asian and the non-Asian currencies. The two currency groups show

[26] London and New York are the two biggest FX trading hubs intermediating over half of the total FX transactions (2016 BIS triennial survey).

[27] If onshore market/offshore market is inactive, then we assume onshore information share as 0%/100%.

a downward trend for onshore IS. The onshore IS of the Asian currencies decreased from over 80% in the early years to 60% recently. For the non-Asian currencies, their average onshore IS declined from above 70% to below 60%. Unsurprisingly, the onshore IS of the non-Asian currencies are always lower than those of the Asian currencies, which is consistent with higher offshore market liquidity level of the former. In sum, these downward trends support our hypothesis that offshore markets have become more informed in pricing EMCs in recent years because the local information advantage is diminishing with improving country institutional quality (Michaelides et al., 2017) and telecommunications infrastructure (Eichengreen et al., 2017).

During the GFC, most of the crucial information shocks came from the United States during the US trading session. If local information advantage does exist, US local investors should have been better informed during that period. In Figure 2.12, a sharp fall in onshore IS for the two groups of currencies can be observed, and the fall in non-Asian currencies is sharper than that in the Asian currencies during the GFC. A potential reason for this is that non-Asian currencies have overlapping trading hours with the US session. Additionally, the average onshore IS of non-Asian currencies dropped to less than 40%, meaning the offshore dealers were the price leaders[28] during GFC. The price leaders of the Asian currencies were always the onshore dealers, even during the GFC.

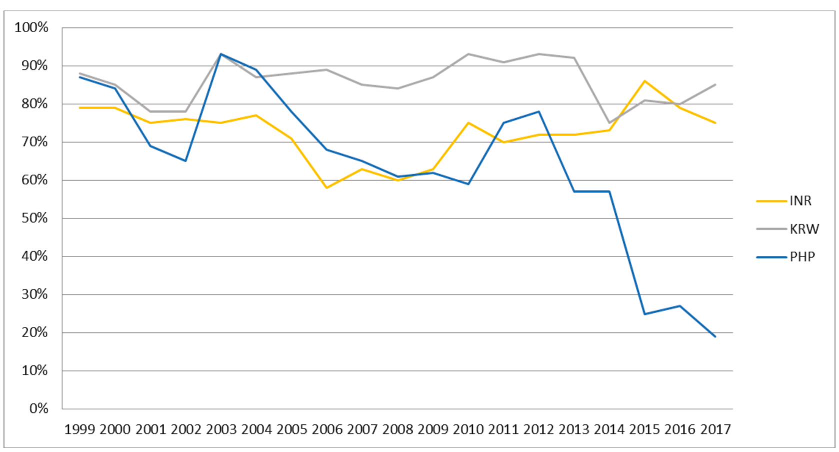
For individual currency pairs of the Asian currencies, the onshore dealers of INR and KRW have absolute information advantage over the offshore dealers over the whole sample period. However, we can observe a dramatic drop in PHP's onshore IS from almost 90% to 20%. In Table 2.8, we can see that the offshore market for PHP becomes more active than the onshore market

[28] The price leader is whoever has over 50% of the ILS.

after 2014.[29] The unambiguous liquidity increase causes the offshore market to become the information leader in pricing PHP after 2014.

For individual currency pairs of non-Asian currencies, we can observe a large smile shaped onshore IS curve for BRL and MXN, which are in line with the onshore market liquidity levels shown in Table 2.8. The IS of the two in the early and recent years are around the same level, 70%–80%, which indicates that the onshore dealers have an information advantage in pricing their local currency pair. In contrast, we can observe that after 2001, the offshore market becomes the price leader in pricing ZAR. This is supported by an active ZAR offshore market showing that its offshore number of quotes share dropped from over 50% to around 30% since 2001.

In sum, consistent with papers focusing on local information advantages in FX markets (Peiers, 1998; Covrig and Melvin, 2007; Menkhoff et al., 2010), we find that dealers located in home countries possess superior information to other dealers in emerging country spot currency markets. However, we can observe that the local advantage is diminishing. Offshore dealers of some EMCs, like ZAR and PHP, have become price leader recently.



[29] The strong offshore volume share change cannot be found in the BIS triennial survey because there is no information released about turnover decomposition by counterparties for PHP after the 2013 triennial survey.

Figure 2.10. Average yearly onshore IS evolution for INR, KRW and PHP

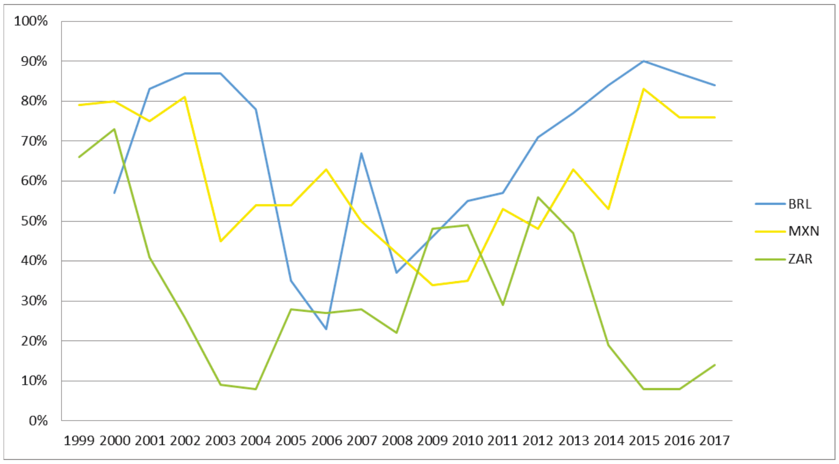


Figure 2.11. Average yearly onshore IS evolution for BRL, MXN and ZAR

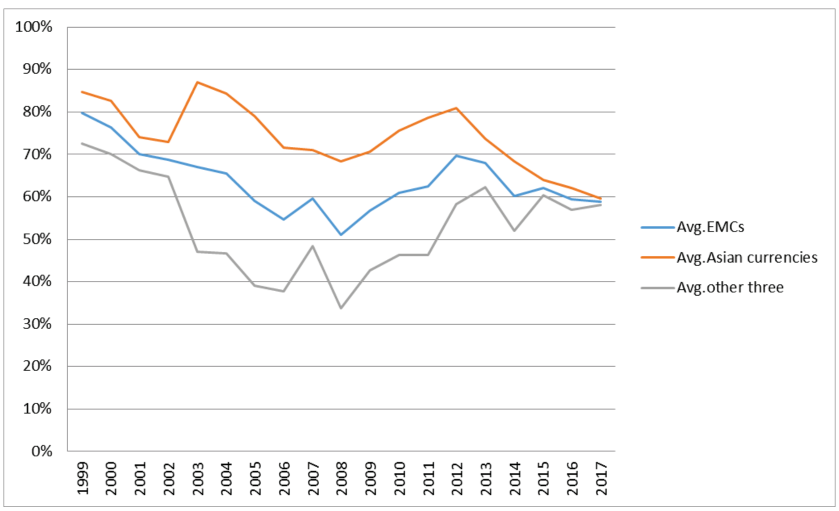


Figure 2.12. Average yearly onshore IS evolution for Asian, non-Asian and all EMCs

Table 2.7. Whole sample average daytime onshore IS

This table shows average daytime onshore dealer ILS proposed by Yan and Zivot (2010) and Putniņš (2013). The sum of onshore and offshore market IS is equal to one. In the second column, we report the total number of trading days over the sample period. For KRW, there are large amount of missing days on 2001 and 2002. Yearly number of trading days please see Table 2.8. In the third/fourth columns, we report number of onshore/offshore inactive days. In the fourth to sixth columns, onshore/offshore NoQ per day and onshore NoQ share are reported. The inactive-market-weighted and simple average onshore IS over whole sample period are presented in the last two columns.

Currency	Trading Days	N.Days onshore inactive	N.Days offshore inactive	NoQ onshore per day	NoQ offshore per day	Onshore NoQ share	IS onshore weighted	IS onshore
BRL	4746	325	75	9609	2774	69%	64%	68%

MXN	4896	327	3	3,914	3,324	51%	60%	64%
ZAR	4903	437	0	3,516	7,848	32%	32%	35%
Avg.Non-Asian currencies	4848	363	26	5680	4649	51%	52%	56%
INR	4759	89	143	800	188	84%	72%	73%
KRW	4498	95	652	6,187	921	88%	86%	86%
PHP	4718	54	637	335	89	76%	64%	59%
Avg.Asian currencies	4658	79	477	2441	399	83%	74%	73%

Table 2.8. Annual daytime onshore IS

This table shows annual average daytime onshore dealer ILS proposed by Yan and Zivot (2010) and Putniņš (2013). The sum of onshore and offshore market IS is equal to one. In the second column, we report the total number of trading days on each year over the sample period. For KRW, there are large amount of missing days on 2001 and 2002. In the third/fourth columns, we report number of onshore/offshore inactive days. In the fourth to sixth columns, onshore/offshore NoQ per day, and onshore NoQ share are reported. The annual inactive-market-weighted and simple average onshore IS period are presented in the last two columns.

BRL	Tradin g Days	N.Days onshore inactive	N.Days offshore inactive	Noq onshore per day	Noq offshore per day	Onshore Noq share	IS onshore weighted	IS onshore
1999	214	214	0	120	21	0%	0%	N.A.
2000	242	46	18	1,314	30	85%	57%	67%
2001	245	2	31	2,100	131	98%	83%	81%
Avg.2000-2001	**244**	**24**	**25**	**1707**	**81**	**92%**	**70%**	**74%**
2002	249	2	4	2,163	385	94%	87%	88%
2003	249	2	2	1,201	595	85%	87%	87%
2004	253	5	0	1,118	2,298	67%	78%	80%
2005	257	6	1	303	1,715	33%	35%	36%
Avg.2002-2005	**252**	**4**	**2**	**1196**	**1248**	**70%**	**72%**	**73%**
2006	252	5	1	2,435	1,562	15%	23%	23%
2007	256	6	1	3,050	3,028	61%	67%	69%
2008	257	5	0	4,158	4,074	50%	37%	37%
2009	253	4	0	5,359	4,023	51%	46%	47%
Avg.2006-2009	**255**	**5**	**1**	**3751**	**3172**	**44%**	**43%**	**44%**
2010	256	6	0	4,948	3,185	57%	55%	56%
2011	253	1	1	7,724	2,940	61%	57%	57%
2012	252	3	1	17,239	4,205	72%	71%	72%
2013	251	2	0	15,271	3,219	80%	77%	77%
Avg.2010-2013	**253**	**3**	**1**	**11296**	**3387**	**68%**	**65%**	**66%**
2014	249	0	0	39,532	6,692	83%	84%	84%
2015	252	6	0	43,442	8,359	86%	90%	92%
2016	259	9	2	21,485	3,467	84%	87%	90%
2017	247	1	13	9,609	2,774	86%	84%	83%
Avg.2014-2017	**252**	**4**	**4**	**28517**	**5323**	**85%**	**86%**	**87%**
Avg.	**4746**	**325**	**75**	**120**	**21**	**69%**	**64%**	**68%**

INR	Tradin g Days	N.Days onshore inactive	N.Days offshore inactive	Noq onshore per day	Noq offshore per day	Onshore Noq share	IS onshore weighted	IS onshore
1999	251	3	22	412	4	99%	79%	78%
2000	257	5	5	250	10	96%	79%	80%
2001	251	6	0	198	9	96%	75%	77%
Avg.1999-2001	**253**	**5**	**9**	**287**	**8**	**97%**	**78%**	**78%**
2002	251	2	1	230	7	97%	76%	77%
2003	250	0	2	170	6	96%	75%	75%
2004	251	1	1	148	19	89%	77%	78%

2005	256	4	1	220	15	94%	71%	72%
Avg.2002-2005	**252**	**2**	**1**	**192**	**12**	**94%**	**75%**	**76%**
2006	256	3	6	233	207	53%	58%	57%
2007	254	3	16	634	158	80%	63%	61%
2008	250	3	2	724	310	70%	60%	60%
2009	246	3	12	1,071	230	82%	63%	62%
Avg.2006-2009	**252**	**3**	**9**	**666**	**226**	**71%**	**61%**	**60%**
2010	249	2	5	1,200	338	78%	75%	75%
2011	241	1	19	1,241	347	78%	70%	68%
2012	245	3	11	1,231	263	82%	72%	72%
2013	249	6	30	1,654	333	83%	72%	70%
Avg.2010-2013	**246**	**3**	**16**	**1332**	**320**	**80%**	**72%**	**71%**
2014	248	13	8	1,336	401	77%	73%	76%
2015	251	11	0	1,443	437	77%	86%	90%
2016	252	11	0	1,467	291	83%	79%	83%
2017	251	9	2	1,343	186	88%	75%	77%
Avg.2014-2017	**251**	**11**	**3**	**1397**	**329**	**81%**	**78%**	**82%**
Avg.	**4759**	**89**	**143**	**800**	**188**	**84%**	**72%**	**73%**

KRW	**Trading Days**	**N.Days onshore inactive**	**N.Days offshore inactive**	**Noq onshore per day**	**Noq offshore per day**	**Onshore Noq share**	**IS onshore weighted**	**IS onshore**
1999	250	0	26	861	20	98%	88%	86%
2000	244	1	53	786	4	100%	85%	80%
2001	86	2	44	331	5	98%	78%	54%
Avg.1999-2001	**193**	**1**	**41**	**659**	**10**	**99%**	**84%**	**73%**
2002	137	23	87	3,431	123	97%	78%	75%
2003	245	0	163	2,856	675	81%	93%	80%
2004	248	0	113	2,216	657	77%	87%	76%
2005	250	0	29	4,031	444	90%	88%	87%
Avg.2002-2005	**220**	**6**	**98**	**3134**	**475**	**86%**	**87%**	**80%**
2006	254	7	0	5,923	2,175	73%	89%	91%
2007	259	13	0	4,155	1,553	73%	85%	90%
2008	252	4	12	7,916	1,246	86%	84%	84%
2009	253	0	37	10,270	1,309	89%	87%	85%
Avg.2006-2009	**255**	**6**	**12**	**7066**	**1571**	**80%**	**86%**	**88%**
2010	251	0	1	10,301	1,216	89%	93%	93%
2011	248	0	24	12,202	939	93%	91%	89%
2012	251	3	15	9,219	492	95%	93%	94%
2013	250	3	8	9,784	525	95%	92%	94%
Avg.2010-2013	**250**	**2**	**12**	**10377**	**793**	**93%**	**92%**	**93%**
2014	246	1	38	13,158	157	99%	75%	71%
2015	257	9	0	7,309	1,046	87%	81%	85%

2016	258	13	2	6,748	2,502	73%	80%	85%
2017	259	16	0	6,054	2,408	72%	85%	92%
Avg.2014-2017	**255**	**10**	**10**	**8317**	**1528**	**83%**	**80%**	**83%**
Avg.	**4498**	**95**	**652**	**6,187**	**921**	**88%**	**86%**	**86%**

MXN	**Trading Days**	**N.Days onshore inactive**	**N.Days offshore inactive**	**Noq onshore per day**	**Noq offshore per day**	**Onshore Noq share**	**IS onshore weighted**	**IS onshore**
1999	256	3	3	147	24	86%	79%	80%
2000	255	3	0	379	149	72%	80%	81%
2001	249	4	0	266	209	56%	75%	76%
Avg.1999-2001	**253**	**3**	**1**	**264**	**127**	**71%**	**78%**	**79%**
2002	254	4	0	259	139	65%	81%	82%
2003	254	1	0	216	351	38%	45%	45%
2004	257	1	0	239	319	43%	54%	55%
2005	260	1	0	1,229	1,865	40%	54%	54%
Avg.2002-2005	**256**	**2**	**0**	**486**	**669**	**47%**	**59%**	**59%**
2006	258	3	0	1,312	1,258	51%	63%	64%
2007	259	5	0	1,789	2,839	39%	50%	51%
2008	260	3	0	2,101	4,644	31%	42%	43%
2009	259	30	0	3,950	7,298	35%	34%	39%
Avg.2006-2009	**259**	**10**	**0**	**2288**	**4010**	**39%**	**47%**	**49%**
2010	260	74	0	3,517	7,129	33%	35%	49%
2011	260	69	0	3,737	5,376	41%	53%	72%
2012	260	71	0	3,733	6,900	35%	48%	67%
2013	259	29	0	2,467	4,719	34%	63%	70%
Avg.2010-2013	**260**	**61**	**0**	**3364**	**6031**	**36%**	**50%**	**65%**
2014	259	16	0	6,017	5,563	52%	53%	57%
2015	258	5	0	9,064	3,929	70%	83%	84%
2016	260	2	0	18,661	5,126	78%	76%	77%
2017	259	3	0	15,285	5,309	74%	76%	77%
Avg.2014-2017	**259**	**7**	**0**	**12257**	**4982**	**69%**	**72%**	**74%**
Avg.	**4896**	**327**	**3**	**3,914**	**3,324**	**51%**	**60%**	**64%**

PHP	**Trading Days**	**N.Days onshore inactive**	**N.Days offshore inactive**	**Noq onshore per day**	**Noq offshore per day**	**Onshore Noq share**	**IS onshore weighted**	**IS onshore**
1999	251	2	15	752	5	99%	87%	87%
2000	252	2	10	542	5	99%	84%	84%
2001	242	1	12	427	9	98%	69%	68%
Avg.1999-2001	**248**	**2**	**12**	**574**	**6**	**99%**	**80%**	**80%**
2002	242	0	33	454	3	99%	65%	60%
2003	245	0	199	306	1	100%	93%	62%
2004	245	0	94	265	84	76%	89%	83%

2005	249	0	55	507	78	87%	78%	71%
Avg.2002-2005	**245**	**0**	**95**	**383**	**42**	**91%**	**81%**	**69%**
2006	248	0	3	456	363	56%	68%	68%
2007	245	0	44	442	71	86%	65%	57%
2008	254	0	6	228	73	76%	61%	60%
2009	249	2	18	237	48	83%	62%	60%
Avg.2006-2009	**249**	**1**	**18**	**341**	**139**	**75%**	**64%**	**61%**
2010	249	3	31	269	63	81%	59%	54%
2011	250	1	75	361	93	80%	75%	65%
2012	249	5	27	578	53	92%	78%	77%
2013	246	4	9	212	5	98%	57%	56%
Avg.2010-2013	**249**	**3**	**36**	**355**	**54**	**88%**	**67%**	**63%**
2014	245	3	3	200	39	84%	57%	57%
2015	243	6	3	49	220	18%	25%	25%
2016	256	10	0	43	180	19%	27%	28%
2017	258	15	0	42	289	13%	19%	20%
Avg.2014-2017	**251**	**9**	**2**	**84**	**182**	**34%**	**32%**	**33%**
Avg.	**4718**	**54**	**637**	**335**	**89**	**76%**	**64%**	**59%**

ZAR	**Trading Days**	**N.Days onshore inactive**	**N.Days offshore inactive**	**Noq onshore per day**	**Noq offshore per day**	**Onshore Noq share**	**IS onshore weighted**	**IS onshore**
1999	255	9	0	113	82	58%	66%	68%
2000	259	9	0	201	122	62%	73%	76%
2001	251	5	0	231	666	26%	41%	42%
Avg.1999-2001	**255**	**8**	**0**	**182**	**290**	**49%**	**60%**	**62%**
2002	253	4	0	162	671	19%	26%	27%
2003	254	2	0	225	1,139	17%	9%	9%
2004	258	1	0	252	1,254	17%	8%	8%
2005	260	1	0	1,296	3,196	29%	28%	28%
Avg.2002-2005	**256**	**2**	**0**	**484**	**1565**	**21%**	**18%**	**18%**
2006	259	0	0	1,702	4,306	28%	27%	27%
2007	259	0	0	3,372	6,948	33%	28%	28%
2008	260	0	0	1,882	7,932	19%	22%	22%
2009	259	0	0	3,403	6,392	35%	48%	48%
Avg.2006-2009	**259**	**0**	**0**	**2590**	**6395**	**29%**	**31%**	**31%**
2010	260	0	0	6,281	8,053	44%	49%	49%
2011	260	0	0	6,048	12,046	33%	29%	29%
2012	260	0	0	8,974	13,662	40%	56%	56%
2013	259	1	0	9,667	14,680	40%	47%	47%
Avg.2010-2013	**260**	**0**	**0**	**7743**	**12110**	**39%**	**45%**	**45%**
2014	259	137	0	11,077	13,321	45%	19%	40%
2015	259	178	0	3,676	11,413	24%	8%	25%

2016	260	80	0	3,757	17,882	17%	8%	12%
2017	259	10	0	4,484	25,349	15%	14%	14%
Avg.2014-2017	**259**	**101**	**0**	**5749**	**16991**	**25%**	**12%**	**23%**
Avg.	**4903**	**437**	**0**	**3,516**	**7,848**	**32%**	**32%**	**35%**

2.6.2 Determinants of IS

In the previous section, we presented and analyzed the ISs for daytime period and for onshore dealers during local business hours. In this section, we are going to test whether macro news is one crucial determinant of the shift in overnight and offshore price discovery shares.

2.6.2.1 Determinants of daytime IS

First, we look at the determinants of daytime IS. Before digging into the empirical results, we can compare the size of daytime IS with US news only versus non-news days[30] (see Table 2.9). We exclude the days with US and local news due to the vague information sources for IS changes. Table 2.9 shows that, except for BRL and INR, the other four currency pairs have a significant increase in price discovery share in the period with US macro news compared to non-news days.

To test the third hypothesis, we employ the model shown in equation 2.10 of the methodology section. We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the problems of heteroscedasticity and autocorrelation. We also present the cross-sectional average of the coefficients and the corresponding t statistics (HKV t stat for short) following Hameed et al. (2010) for the Asian and the none-Asian currencies.

$$\ln\left(\boldsymbol{IS}_{daytime,t}\right) = \beta_0 + \boldsymbol{\beta_1 ln}\left(\frac{\boldsymbol{1+US\ news}_{day,t}}{\boldsymbol{1+US\ news}_{nite,t}}\right) + \beta_2 \ln\left(\frac{\boldsymbol{1+Local\ news}_{day,t}}{\boldsymbol{1+Local\ news}_{nite,t}}\right) + \beta_3 \boldsymbol{ln}(\boldsymbol{Qspd}_{day,t}) + \beta_4 \boldsymbol{ln}(\boldsymbol{Volatility}_{day,t}) + \beta_5 \boldsymbol{ln}(\boldsymbol{Noq}_{day,t}) + \beta_6\, \boldsymbol{ln}\left(\boldsymbol{IS}_{daytime,t-1}\right) + \beta_7 \boldsymbol{GFC} + \beta_8 \boldsymbol{EDC} + \sum_{j=Mon}^{Thu} \beta_j \boldsymbol{WD^j} + \boldsymbol{\epsilon}_t \qquad (2.10)$$

Our third hypothesis tests whether the enhanced price discovery capacity to US macro news is responsible for the trend for increased overnight IS. Therefore, in the model (equation 2.10), we expect β_1 to be positive and show a larger size and higher significance over the sample sub-

[30] As shown in Table 2.3, over 80% and 40% of trading days have US and local news releases, respectively. Therefore, we compare the IS difference between days with only US or local news and non-news days.

periods.[31] As discussed in the hypothesis formation part, the Asian currencies are perfect for testing this hypothesis. Hence, we mainly analyze their sub-period estimation results. We present the estimation results of five sub-periods in Table 2.11. In the first three sub-periods from the start of 1999 to the end of 2009, the coefficients of US news are barely significant. In the last two sub-periods, from the start of 2010 to the end of 2017, the coefficients of Asian currencies present strong significance. The positive sign indicates that release of US macro news will increase overnight price discovery, and the increasing size and significance of β_1 confirms our hypothesis that US macro news contributes to the increasing overnight IS. For US news impact level, we take the last sub-period as an example and β_1 for the Asian currencies is 0.058. Therefore, when all the other variables remain the same, there will be around a 2.5% increase in overnight IS[32] compared with the US news days and the non-news days during last sub-sample period. In Table 2.11, we also present the non-Asian currencies estimation results of the five sub-periods. The main conclusion remains the same as with the Asian currencies. We can also observe that β_1 becomes larger in size and higher in significance over the sample sub-periods.

Table 2.10 reports the whole sample estimation results of the model. HKV t statistics of β_1 is 5.6, which means the coefficient is significant. The cross-sectional β_1 shows positive signs of

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[31] We divide the whole sample from 01 Jan 1999 to 31 Dec 2017 into five sub-periods, that is, period 1: 01 Jan 1999–31 Dec 2001; period 2: 01 Jan 2002–31 Dec 2005; period 3: 01 Jan 2006–31 Dec 2009; period 4: 01 Jan 2010–31 Dec 2013; period 5: 01 Jan 2014–31 Dec 2017. Sub-period 3 covers the GFC and sub-period 4 covers the EDC.

[32] In the empirical model (equation2.10), we use the natural logarithm form for the daytime IS and macro news ratio. The β_1 implies that a 1% increase in the US macro news ratio will affect the percentage point growth of the daily IS, which can be shown as:
$\frac{IS_{News\ days} - IS_{Non-News\ days}}{IS_{Non-News\ days}} = \beta_1 * \frac{US\ news\ ratio_{News\ days} - US\ news\ ratio_{Non-News\ days}}{US\ news\ ratio_{Non-News\ days}}$. Therefore, if we keep all other variables the same, there will be $\beta_1 * \frac{\left(\frac{1}{1+Avg.US_{news\ days}}\right) - \left(\frac{1}{1+0}\right)}{\left(\frac{1}{1+0}\right)} = 0.058 * \frac{\left(\frac{1}{1+6}\right) - \left(\frac{1}{1+0}\right)}{\left(\frac{1}{1+0}\right)} = -0.0497$ percent change of daytime IS compared with days with and without US news overnight (there was an average of six announcements released in US news days during the last subsample period). The average daytime IS of Asian currencies without US news is 50% for the last sub-period. Hence, the overnight IS with average pieces of US news are higher than that for days without US news: $0.0497 \ * IS_{no\ news\ days} = 2.5\%$.

indicating that US macro news will increase the price discovery share of that trading session. This finding is consistent with a large number of papers investigating the impact of macro fundamentals on price discovery, like Gau and Wu (2017).

Table 2.9. Daytime IS comparison between US news and non-news days

This table contains three panels. In panel A, we present the average daytime IS on days with US news only released in daytime or overnight period, and the average daytime IS on days without any news. The respective number of trading days are shown next to the average daytime IS. In panel B, we present the daytime IS gaps between US news days and none-news days. We do the equality test for the differences. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level. If the row (4) or (5) shows positive or negative sign, it means the release of US news in daytime or overnight period increase price discovery share of corresponding period. In the panel C, we show the total trading days included in the test.

							Panel A							
		BRL		INR		KRW		MXN		PHP		ZAR		NO.
	News releasing period	Daytime IS	Trading days	Daytime IS	Trading days	Daytime IS	Trading days	Daytime IS	Trading days	Daytime IS	Trading days	Daytime IS	Trading days	
Days with US news only	Daytime	79.1%	730	N.A.		N.A.		46.0%	377	N.A.		51.1%	1275	(1)
	Overnight	79.4%	41	37.9%	2753	56.4%	2049	45.1%	651	43.4%	2719	46.8%	403	(2)
Days without US and local news		78.2%	176	38.9%	697	65.7%	464	42.8%	400	49.0%	571	47.1%	552	(3)
							Panel B							
(1)-(3)		0.9%		N.A.		N.A.		3.2%***		N.A.		4.0%***		(4)
(2)-(3)		1.1%		-1.10%		-9.3%***		2.3%		-5.6%***		-0.30%		(5)
							Panel C							
total trading days			4746		4759		4498		4896		4718		4903	(6)
trading days included in (1) to (3)			947		3450		2513		1428		3290		2230	(7)
Ratio of (7)/(6)			20%		72%		56%		29%		70%		45%	

Table 2.10. Whole sample estimation results for US macro news impact on daytime IS

This table presents the whole sample regression results of equation 2.10:

$$\ln(\boldsymbol{IS}_{daytime,t}) = \beta_0 + \boldsymbol{\beta_1} \boldsymbol{ln}\left(\frac{\boldsymbol{1+US\ news_{day,t}}}{\boldsymbol{1+US\ news_{nite,t}}}\right) + \beta_2 \ln\left(\frac{\boldsymbol{1+Local\ news_{day,t}}}{\boldsymbol{1+Local\ news_{nite,t}}}\right) + \beta_3 \boldsymbol{ln}(\boldsymbol{Qspd}_{day,t}) + \beta_4 \boldsymbol{ln}(\boldsymbol{Volatility}_{day,t}) + \beta_5 \boldsymbol{ln}(\boldsymbol{Noq}_{day,t}) + \beta_6\, \boldsymbol{ln}(\boldsymbol{IS}_{daytime,t-1}) + \beta_7 \boldsymbol{GFC} + \beta_8 \boldsymbol{EDC} + \sum_{j=Mon}^{Thu} \beta_j \boldsymbol{WD^j} + \boldsymbol{\epsilon}_t \tag{2.10}$$

Except for dummy variables, all the other variables are in natural logarithm form to reduce any effects from extreme values. The dependent variable, $\ln(\mathrm{IS}_{\mathrm{daytime,t}})$, is equal to $\ln\left(\frac{\mathrm{TSRV}_{\mathrm{daytime,t}}}{\mathrm{TSRV}_{\mathrm{daytime,t}}+\mathrm{TSRV}_{\mathrm{overnight,t}}}\right)$, which is the daytime price discovery share measured by TSRV on day t (Wang and Yang, 2011). The first independent variable is our main interest variable, which is the ratio of the number of US announcements released during the daytime to that of the overnight period on day t. The second independent variable is the ratio of daytime and overnight numbers of macro announcements from the issuers. When we constructed the log form of the two variables, we added 1 to both the numerator and denominator of the ratio. This was to avoid calculation problems on non-news during the daytime or overnight periods of the day. This will not disturb the distribution of information flow. Governments tend to publicize macro news during local business hours. As US business hours overlap more or less with those of the issuers, we constructed a US news variable in ratio form. We also constructed an EMCs local news variable in ratio form because South Korea occasionally releases macro news during their overnight period.

For market state variables, we follow Mizrach and Neely (2008) by adding $\mathrm{Qspd}_{\mathrm{day,t}}$, $\mathrm{Volatility}_{\mathrm{day,t}}$, and $\mathrm{Noq}_{\mathrm{day,t}}$, which are the time-weighted average quoted spread, standard deviation of 5-minute log returns, and number of quotes (NoQ) for the daytime period. In addition, the Ljung–Box statistics indicate that the two periods' TSRV are significantly auto-correlated for all currency pairs. Hence, we add lagged IS, $\mathrm{IS}_{\mathrm{daytime,t-1}}$, to control the self-dependence. In order to control for extreme market conditions, we add GFC and EDC dummy variables. For the GFC, the key financial crisis months, September 2008–November 2009, equal 1, and the other period equals 0. For the EDC, the key crisis months, April 2010–February 2012, equal 1, and the other period equals 0. Finally, we include the weekday dummy $\mathrm{WD^j}$ (j= Monday, Tuesday, Wednesday, and Thursday) to capture the day-of-the-week effect.

We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the residual heteroscedasticity and autocorrelation problem. We also present cross-sectional average of the coefficients and the corresponding HKV t statistics in Hameed et al. (2010) for Asian currency and non-Asian currency groups. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Whole sample	$ln\left(\frac{1+US\ news_{day,t}}{1+US\ news_{nite,t}}\right)$	$\ln\left(\frac{1+Local\ news_{day,t}}{1+Local\ news_{nite,t}}\right)$	$ln(Qspd_{day,t})$	$ln(Volatility_{day,t})$	$ln(Noq_{day,t})$	$ln(IS_{day,t-1})$	GFC	EDC	R^2
INR	0.005	0.031	0.027	0.359***	0.002	0.302***	-0.488***	-0.424**	29%
	(0.30)	(1.44)	(0.31)	(5.03)	(0.08)	(7.64)	(-2.70)	(-2.08)	
KRW	0.056***	0.014	0.080	-0.144***	0.208***	0.109***	0.035	0.049	17%
	(3.90)	(1.05)	(1.61)	(-3.02)	(4.78)	(4.45)	(0.35)	(0.82)	
PHP	0.049***	0.020	0.100**	0.328***	0.023	0.170***	-0.033	0.353**	19%
	(3.11)	(1.02)	(2.04)	(7.78)	(0.84)	(7.35)	(-0.26)	(2.20)	
Asian currencies	0.037***	0.022*	0.069*	0.181***	0.078***	0.194***	-0.162*	-0.007	22%
HKV t	(3.73)	(1.89)	(1.72)	(5.28)	(3.80)	(10.42)	(-1.85)	(-0.08)	
BRL	0.009	0.012*	-0.105**	0.126***	0.053***	0.093***	-0.003	0.012	12%
	(1.21)	(1.78)	(-2.19)	(4.17)	(2.89)	(3.72)	(-0.04)	(0.23)	

MXN	0.031***	0.044***	-0.253***	0.475***	-0.047**	-0.022	-0.081	-0.066	20%
	(4.05)	(4.35)	(-5.67)	(13.35)	(-2.21)	(-1.27)	(-1.16)	(-1.37)	
ZAR	0.031***	0.016**	-0.082***	0.358***	0.013	0.067***	-0.264***	-0.015	29%
	(5.17)	(2.01)	(-4.70)	(9.35)	(0.70)	(2.61)	(-5.31)	(-0.44)	
Non-Asian currencies	0.024***	0.024***	-0.147***	0.320***	0.006	0.046***	-0.116***	-0.023	20%
HKV t	(5.55)	(4.77)	(-6.25)	(15.24)	(0.52)	(3.34)	(-3.13)	(-0.86)	

Table 2.11. Sub-sample estimation results for US macro news impact on daytime IS

This table presents the sub-sample regression results of model 2.10:

$$\ln(\boldsymbol{IS}_{daytime,t}) = \beta_0 + \boldsymbol{\beta_1 ln}\left(\frac{1+\boldsymbol{US\ news}_{day,t}}{1+\boldsymbol{US\ news}_{nite,t}}\right) + \beta_2\ln\left(\frac{1+\boldsymbol{Local\ news}_{day,t}}{1+\boldsymbol{Local\ news}_{nite,t}}\right) + \beta_3\boldsymbol{ln}(\boldsymbol{Qspd}_{day,t}) + \beta_4\boldsymbol{ln}(\boldsymbol{Volatility}_{day,t}) + \beta_5\boldsymbol{ln}(\boldsymbol{Noq}_{day,t}) + \beta_6\,\boldsymbol{ln}(\boldsymbol{IS}_{daytime,t-1}) + \beta_7\boldsymbol{GFC} + \beta_8\boldsymbol{EDC} + \sum_{j=Mon}^{Thu}\beta_j\,\boldsymbol{WD}^j + \boldsymbol{\epsilon}_t \qquad (2.10)$$

The construction of variables and all other estimation setting are the same as for the whole sample regressions in table 2.10. We separate whole sample period into 5 sub-samples, that is, period 1: 01 Jan 1999–31 Dec 2001; period 2: 01 Jan 2002–31 Dec 2005; period 3: 01 Jan 2006–31 Dec 2009; period 4: 01 Jan 2010–31 Dec 2013; and period 5: 01 Jan 2014–31 Dec 2017. Period 3 and 4 cover the GFC and EDC. We added the two dummies into respective sub-period regressions.

Sub-Period1	$\boldsymbol{ln}\left(\frac{1+\boldsymbol{US\ news}_{day,t}}{1+\boldsymbol{US\ news}_{nite,t}}\right)$	$\ln\left(\frac{1+\boldsymbol{Local\ news}_{day,t}}{1+\boldsymbol{Local\ news}_{nite,t}}\right)$	$\boldsymbol{ln}(\boldsymbol{Qspd}_{day,t})$	$\boldsymbol{ln}(\boldsymbol{Volatility}_{day,t})$	$\boldsymbol{ln}(\boldsymbol{Noq}_{day,t})$	$\boldsymbol{ln}(\boldsymbol{IS}_{day,t-1})$	$\boldsymbol{GFC}$	$\boldsymbol{EDC}$	R^2
INR	**0.040**	0.062	0.394***	0.231***	0.182***	0.030			14%
	(0.87)	(0.44)	(3.52)	(2.64)	(2.74)	(0.65)			
KRW	**0.012**	0.063	-0.128*	0.157**	0.178**	0.025			30%
	(0.35)	(1.32)	(-1.86)	(2.15)	(2.16)	(0.39)			
PHP	**0.071**	0.004	-0.123	0.392***	-0.094	0.094*			9%
	(1.13)	(0.02)	(-1.20)	(5.40)	(-1.11)	(1.92)			
Asian currencies	**0.041**	0.043	0.048	0.260***	0.089*	0.050			18%
HKV t	**(1.34)**	(0.50)	(0.79)	(5.29)	(1.80)	(1.49)			
BRL	**0.002**	0.014	-0.122***	0.104***	-0.018	0.006			8%
	(0.08)	(0.64)	(-2.77)	(2.86)	(-1.12)	(0.17)			
MXN	**0.065****	0.010	-0.391**	0.493***	-0.146***	-0.046			13%
	(2.04)	(0.16)	(-2.15)	(6.26)	(-3.08)	(-1.31)			
ZAR	**0.014**	0.029	-0.259***	0.445***	-0.100***	0.050			21%
	(0.77)	(0.98)	(-2.96)	(6.03)	(-2.82)	(1.53)			
Non-Asian currencies	**0.027***	0.018	-0.258***	0.348***	-0.088***	0.003			14%
HKV t	**(1.75)**	(0.76)	(-3.71)	(9.02)	(-4.26)	(0.15)			
Sub-Period 2	$\boldsymbol{ln}\left(\frac{1+\boldsymbol{US\ news}_{day,t}}{1+\boldsymbol{US\ news}_{nite,t}}\right)$	$\ln\left(\frac{1+\boldsymbol{Local\ news}_{day,t}}{1+\boldsymbol{Local\ news}_{nite,t}}\right)$	$\boldsymbol{ln}(\boldsymbol{Qspd}_{day,t})$	$\boldsymbol{ln}(\boldsymbol{Volatility}_{day,t})$	$\boldsymbol{ln}(\boldsymbol{Noq}_{day,t})$	$\boldsymbol{ln}(\boldsymbol{IS}_{day,t-1})$	$\boldsymbol{GFC}$	$\boldsymbol{EDC}$	R^2
INR	**-0.048**	-0.098	0.199*	0.741***	0.061	0.210***			39%
	(-1.47)	(-1.42)	(1.82)	(9.22)	(0.94)	(5.66)			

KRW	**0.088***	0.047	0.107	-0.043	0.162**	0.135***			12%
	(1.93)	(1.04)	(0.72)	(-0.41)	(2.00)	(3.50)			
PHP	**0.071***	0.032	0.188***	0.349***	-0.142***	0.130***			16%
	(1.65)	(0.53)	(3.31)	(5.65)	(-3.31)	(3.12)			
Asian currencies	**0.037**	-0.007	0.165**	0.349***	0.027	0.158***			22%
HKV t	**(1.50)**	(-0.18)	(2.45)	(6.87)	(0.68)	(6.71)			
BRL	**0.006**	-0.010	-0.019	0.126***	0.034	0.115***			7%
	(0.31)	(-0.41)	(-0.38)	(2.84)	(1.14)	(2.69)			
MXN	**-0.021**	0.025	-0.079	0.598***	-0.043	-0.043			23%
	(-1.28)	(0.74)	(-0.85)	(11.57)	(-1.59)	(-1.16)			
ZAR	**0.018**	-0.002	-0.186	0.593***	0.011	0.050			28%
	(1.12)	(-0.10)	(-1.33)	(5.37)	(0.27)	(0.85)			
Non-Asian currencies	**0.001**	0.004	-0.095	0.439***	0.001	0.041			19%
HKV t	**(0.06)**	(0.27)	(-1.61)	(10.07)	(0.03)	(1.48)			
Sub-Period 3	$ln\left(\frac{1+US\ news_{day,t}}{1+US\ news_{nite,t}}\right)$	$\ln\left(\frac{1+Local\ news_{day,t}}{1+Local\ news_{nite,t}}\right)$	$ln(Qspd_{day,t})$	$ln(Volatility_{day,t})$	$ln(Noq_{day,t})$	$ln(IS_{day,t-1})$	GFC	EDC	R^2
INR	**0.002**	-0.062	0.226	0.652***	-0.227***	0.408***	-0.225*		38%
	(0.06)	(-0.74)	(1.13)	(5.46)	(-4.03)	(8.89)	(-1.75)		
KRW	**0.027**	0.019	0.116	-0.320***	0.339***	0.132**	0.032		10%
	(0.82)	(0.67)	(0.94)	(-3.80)	(3.88)	(2.07)	(0.26)		
PHP	**0.042**	-0.037	0.145	0.250***	0.094*	0.292***	-0.151		13%
	(1.26)	(-0.87)	(1.31)	(2.91)	(1.87)	(8.80)	(-1.40)		
Asian currencies	**0.023**	-0.027	0.162*	0.194***	0.068	0.277***	-0.115		20%
HKV t	**(1.16)**	(-0.76)	(1.73)	(3.16)	(1.64)	(9.02)	(-1.52)		
BRL	**-0.016**	0.013	-0.231***	0.161***	-0.027	0.159***	-0.071		8%
	(-0.78)	(0.80)	(-2.94)	(3.67)	(-1.08)	(2.68)	(-1.21)		
MXN	**0.024**	0.036	-0.276***	0.448***	-0.057*	-0.013	-0.238***		19%
	(1.50)	(1.57)	(-4.00)	(5.53)	(-1.72)	(-0.51)	(-3.31)		
ZAR	**0.055*****	0.003	-0.205***	0.407***	-0.034	0.101***	0.032		18%

	(3.24)	(0.11)	(-2.74)	(5.57)	(-0.88)	(3.07)	(0.63)		
Non-Asian currencies	**0.021****	0.017	-0.237***	0.339***	-0.039**	0.082***	-0.092**		15%
HKV t	**(1.97)**	(1.33)	(-5.30)	(8.37)	(-2.01)	(3.26)	(-2.51)		
Sub-Period 4	$ln\left(\frac{1+US\ news_{day,t}}{1+US\ news_{nite,t}}\right)$	$\ln\left(\frac{1+Local\ news_{day,t}}{1+Local\ news_{nite,t}}\right)$	$ln(Qspd_{day,t})$	$ln(Volatility_{day,t})$	$ln(Noq_{day,t})$	$ln(IS_{day,t-1})$	GFC	EDC	R^2
INR	**0.054****	0.132***	0.019	0.154***	0.001	0.513***		-0.338***	43%
	(2.23)	(2.91)	(0.08)	(2.82)	(0.01)	(9.21)		(-3.22)	
KRW	**0.053****	0.034	-0.022	-0.196***	0.125**	0.087**		0.010	6%
	(2.18)	(1.26)	(-0.12)	(-2.63)	(2.21)	(2.19)		(0.16)	
PHP	**0.032**	0.004	0.032	0.148**	0.048*	0.236***		0.051	9%
	(1.16)	(0.11)	(0.35)	(2.41)	(1.90)	(5.03)		(0.49)	
Asian currencies	**0.046*****	0.057**	0.010	0.035	0.058**	0.279***		-0.092	19%
HKV t	**(2.89)**	(2.36)	(0.09)	(0.88)	(2.07)	(9.24)		(-1.58)	
BRL	**0.010**	0.023	-0.040	0.072	0.097**	0.066*		0.032	9%
	(0.76)	(1.48)	(-0.53)	(0.72)	(2.29)	(1.79)		(0.80)	
MXN	**0.036*****	0.040**	-0.166**	0.449***	0.021	0.016		-0.072**	28%
	(3.46)	(2.52)	(-2.44)	(9.67)	(0.51)	(0.53)		(-2.18)	
ZAR	**0.024****	0.026**	-0.092***	0.179***	0.045	0.091**		-0.058**	20%
	(2.18)	(2.03)	(-3.44)	(2.82)	(1.05)	(2.11)		(-2.09)	
Non-Asian currencies	**0.023*****	0.030***	-0.100***	0.234***	0.055**	0.058**		-0.033	19%
HKV t	**(3.32)**	(3.33)	(-2.73)	(5.27)	(2.12)	(2.56)		(-1.58)	
Sub-Period 5	$ln\left(\frac{1+US\ news_{day,t}}{1+US\ news_{nite,t}}\right)$	$\ln\left(\frac{1+Local\ news_{day,t}}{1+Local\ news_{nite,t}}\right)$	$ln(Qspd_{day,t})$	$ln(Volatility_{day,t})$	$ln(Noq_{day,t})$	$ln(IS_{day,t-1})$	GFC	EDC	R^2
INR	**0.039****	0.067***	-0.007	0.122	-0.017	0.192***			14%
	(2.05)	(2.63)	(-0.06)	(1.36)	(-0.59)	(3.45)			
KRW	**0.081*****	-0.023	-0.096	0.061	0.151	0.138***			18%
	(4.43)	(-1.28)	(-0.86)	(0.48)	(1.46)	(3.88)			

PHP	**0.054****	0.056**	0.137	0.649***	-0.007	0.093***	39%
	(2.53)	(2.14)	(1.19)	(9.06)	(-0.17)	(2.89)	
Asian currencies	**0.058*****	0.033**	0.012	0.277***	0.042	0.141***	23%
HKV t	**(4.75)**	(2.28)	(0.16)	(4.48)	(1.04)	(5.39)	
BRL	**0.023****	0.010	0.003	-0.096	0.261***	0.008	34%
	(2.15)	(1.12)	(0.03)	(-1.26)	(5.77)	(0.40)	
MXN	**0.039*****	0.037**	-0.291***	0.521***	0.049	0.001	29%
	(3.41)	(2.51)	(-3.45)	(7.98)	(0.86)	(0.03)	
ZAR	**0.030*****	0.015	-0.063**	0.252***	0.044	0.060*	16%
	(3.26)	(1.52)	(-2.33)	(4.68)	(1.40)	(1.94)	
Non-Asian currencies	**0.031*****	0.021***	-0.117***	0.226***	0.118***	0.023	27%
HKV t	**(4.65)**	(2.87)	(-2.70)	(5.47)	(4.10)	(1.38)	

2.6.2.2 Determinants of daytime onshore IS

In this part, we look at the determinants of onshore IS during the daytime period. In Table 2.12, we compare the onshore IS of days with local news only versus days without any news. We can observe mixed results in the whole sample test. Compared with non-news days, the INR onshore market has a significantly higher IS when local news arrives. This means that onshore dealers respond quicker than offshore dealers to local news. Conversely, MXN and PHP have significantly lower IS when local news arrives, which shows offshore dealers know more about local news than onshore dealers. For the other three currencies, the differences are not significant.

To test the fourth hypothesis, we employ the model shown in equation 2.11 of the methodology section. We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the problems of residual heteroscedasticity and autocorrelation. We also present the cross-sectional average of the coefficients and the corresponding t statistics (HKV t stat for short) following Hameed et al. (2010) for the Asian and the non-Asian currencies.

$$\ln(\boldsymbol{IS}_{on,t}) = \emptyset_0 + \emptyset_1 \boldsymbol{ln}(\boldsymbol{1} + \boldsymbol{NEWs}_t) + \emptyset_2 \boldsymbol{ln}(\boldsymbol{1} + \boldsymbol{NEWs}_{\boldsymbol{US}_t})$$

$$+ \emptyset_3 \boldsymbol{ln}(\boldsymbol{Qspd}_{on,t}) + \emptyset_4 \boldsymbol{ln}(\boldsymbol{RV}_{on,t}) + \emptyset_5 \boldsymbol{ln}(\boldsymbol{Noq}_{on,t}) + \emptyset_6 \boldsymbol{ln}(\boldsymbol{IS}_{on,t-1}) + \emptyset_7 \boldsymbol{GFC} + \emptyset_8 \boldsymbol{EDC} + \sum_{j=Mon}^{Thu} \emptyset_j \boldsymbol{WD}^{\boldsymbol{j}} + \boldsymbol{\epsilon}_t \quad (2.11)$$

Our fourth hypothesis tests whether the reduced local information advantage contributes to the increasing offshore price discovery share. Therefore, in the model (equation 2.11), we expect $\emptyset_1$ to be positive and show lower significance over the sample sub-periods[33]. This expected coefficient change means onshore dealers had information advantage with local news in the early years, however, the advantage had diminished in recent years.

[33] We split the whole sample from 01 Jan 1999 to 31 Dec 2017 into five sub-periods:
period 1: 01 Jan 1999-31 Dec 2001; period 2: 01 Jan 2002-31 Dec 2005; period 3: 01 Jan 2006-31 Dec 2009; period 4: 01 Jan 2010-31 Dec 2013; period 5: 01 Jan 2014-31 Dec 2017. Sub-period 3 covers the GFC and sub-period 4 covers the EDC.

We first analyze the whole sample results shown in Table 2.13. HKV t statistics show that coefficients of both the Asian and non-Asian groups are not significant. For individual currencies, only the coefficient of BRL is positively significant, which means onshore dealers tend to incorporate local news before offshore dealers. The size of BRL $\emptyset_1$ is 0.041, which indicates that there will be 7.5%[34] increase in onshore IS when local news arrives. The whole sample results show weak evidence that onshore dealers have superior information about local news than offshore dealers.

Table 2.14 reports the sub-periods' estimation results of the model. In the first sub-sample period, HKV t statistics shows that $\emptyset_1$ of the Asian currency group is positive and significant at 10% level. The size of the coefficients is 0.212 which means there will be a 15.1%[35] increase in onshore IS on local news days compared with non-news days. For non-Asian currencies, only the coefficient of BRL is positively significant. The quantity of the coefficient is even larger than that

[34] In the empirical model (equation2.11), we use the natural logarithm form for the onshore IS and macro news. The $\emptyset_1$ implies that a 1% increase of local macro news will affect the amount of percentage change in the onshore IS, which can be shown as: $\frac{IS_{news\ days} - IS_{non-news\ days}}{IS_{non-news\ days}} = \emptyset_1 * \frac{N.local\ news_{news\ days} - N.local\ news_{non-news\ days}}{N.local\ news_{non-news\ days}}$. Therefore, if all other variables remain the same, there will be $\emptyset_1 * \frac{(1+Avg.local\ news_{news\ days})-(1+0)}{(1+0)} = 0.041 * \frac{(1+3)-(1)}{(1)} = 0.123$ percent change in onshore IS between days with and without local news during the daytime (there are on average three pieces announcements released on local news days). The average onshore IS of the BRL without news is 61%. Hence, the onshore IS with average pieces of local news is higher than that of non-news days: $0.123 \ * IS_{non-news\ days} =$ 7.5%.

[35] In the empirical model (equation 2.11), we use the natural logarithm form for the onshore IS and macro news. The $\emptyset_1$ implies that a 1% increase of local macro news will affect the amount of percentage change in the onshore IS, which can be shown as: $\frac{IS_{news\ days} - IS_{non-news\ days}}{IS_{non-news\ days}} = \emptyset_1 * \frac{N.local\ news_{news\ days} - N.local\ news_{non-news\ days}}{N.local\ news_{non-news\ days}}$. Therefore, if all other variables remain the same, there will be $\emptyset_1 * \frac{(1+Avg.local\ news_{news\ days})-(1+0)}{(1+0)} = 0.212 * \frac{(1+1)-(1)}{(1)} = 0.212$ percent change in onshore IS between days with and without local news during the daytime (there is on average one piece of news released on local news days during the first sub-period). The average onshore IS of the Asian group without news release is 79% for the first sub-period. Hence, the onshore IS with average pieces of local news is higher than that of no news days: $0.212 \ * IS_{non-news\ days} = 16.8\%$.

of the Asian group. Compared with non-news days, BRL onshore IS will increase by 27.3%[36] when local news arrives. In sum, in the first sub-period, we can conclude that onshore dealers do have a large information advantage to local news over offshore dealers.

Then, in the second sub-period, the $\emptyset_1$ of the two currency groups turn out to be not significant. For individual currency pairs, the coefficients of two individual currencies, that is, BRL and KRW, are highly significant. However, the coefficient size of the two currencies is much smaller than that of the first sub-period. On local news days, the IS of BRL and KRW onshore dealers will grow by 17% and 12%[37], which is largely reduced from the first sub-period. Finally, for the third and fourth sub-periods, the local news coefficients do not show any significance. In the last sub-period, even though the coefficient for INR and ZAR are positively significant, the size of the coefficient and IS increase for local news are much smaller compared with the first and second sub-periods.[38]

In sum, we can observe that during the early years, Asian currencies and BRL onshore dealers had about 20% more IS when local news arrived compared to non-news days. This local information advantage has diminished in recent years, allowing offshore dealers to become more agile to local macro news. Therefore, the fourth hypothesis is proved.

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[36] If all other variables remain the same, there will be $\emptyset_1 * \frac{(1+Avg.local\ news_{news\ days})-(1+0)}{(1+0)} = 0.275 * \frac{(1+1.4)-(1)}{(1)} = 0.385$ percent change in onshore IS compared with days with and without local news during the daytime (there is an average of 1.4 news pieces released on local news days during the first sub-period). The average onshore IS of BRL without news release is 71% for the first sub-period. Hence, the onshore IS with average pieces of local news is higher than no news days: $0.385 \ * IS_{non-news\ days} = 27.3\%$

[37] For BRL, the onshore IS increase is calculated by $Agv.IS_{non-news\ days} * \emptyset_1 * \frac{(1+Avg.local\ news_{news\ days})-(1+0)}{(1+0)} = 73\% * 0.121 * \frac{(1+2)-(1)}{(1)} = 17\%$ and for KRW, the onshore IS increase is equal to $80\% * 0.078 * \frac{(1+2)-(1)}{(1)} = 12\%$

[38] For INR, IS will increase $Agv.IS_{non-news\ days} * \emptyset_1 * \frac{(1+Avg.local\ news_{news\ days})-(1+0)}{(1+0)} = 82\% * 0.072 * \frac{(1+2)-(1)}{(1)} = 11\%$

For ZAR, IS will increase $Agv.IS_{non-news\ days} * \emptyset_1 * \frac{(1+Avg.local\ news_{news\ days})-(1+0)}{(1+0)} = 23\% * 0.129 * \frac{(1+2)-(1)}{(1)} = 6\%$

Table 2.12. Daytime onshore IS comparison between days with and without local macro news

This table contains three panels. In panel A, we present the average daytime onshore IS on days with local news only, and the average daytime onshore IS on days without any news. The respective number of trading days are shown next to the IS. In panel B, we present the daytime onshore IS gaps between local news days and none-news days. We do the equality test for the differences. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level. If the row (3) shows positive sign, it means the release of local news increase IS of onshore dealers. In the panel C, we show the total trading days included in the test.

	BRL		INR		KRW		MXN		PHP		ZAR		NO.
	Onshore IS	Trading days	Onshore IS	Trading days	Onshore IS	Trading days	Onshore IS	Trading days	Onshore IS	Trading days	Onshore IS	Trading days	
Panel A													
Days with Local news only	68.5%	539	74.2%	619	86.3%	534	62.4%	665	53.3%	997	35.9%	181	(1)
Days without US and local news	65.1%	253	72.3%	3398	85.8%	2467	66.6%	1178	60.7%	2903	37.8%	973	(2)
Panel B													
(1)-(2)	3.4%		1.9%*		0.6%		-4.2%***		-7.4%***		-1.9%		(3)
Panel C													
Total trading days		4328		4467		3088		4565		3903		4460	(4)
Trading days included in (1) and (2)		792		4017		3001		1843		3900		1154	(5)
Ratio of (5)/(4)		18%		90%		97%		40%		100%		26%	

Table 2.13. Whole sample estimation results for local macro news impact on daytime onshore IS

This table presents the whole sample regression results of equation 2.11:

$$\ln(\boldsymbol{IS}_{on,t}) = \emptyset_0 + \emptyset_1 \boldsymbol{ln}(\boldsymbol{1} + \boldsymbol{NEWs}_t) + \emptyset_2 \boldsymbol{ln}(\boldsymbol{1} + \boldsymbol{NEWs}_{\boldsymbol{US}_t}) + \emptyset_3 \boldsymbol{ln}(\boldsymbol{Qspd}_{on,t}) + \emptyset_4 \boldsymbol{ln}(\boldsymbol{RV}_{on,t}) + \emptyset_5 \boldsymbol{ln}(\boldsymbol{Noq}_{on,t}) + \emptyset_6 \boldsymbol{ln}(\boldsymbol{IS}_{on,t-1}) + \emptyset_7 \boldsymbol{GFC} + \emptyset_8 \boldsymbol{EDC} + \sum_{j=Mon}^{Thu} \emptyset_j \boldsymbol{WD}^{\boldsymbol{j}} + \boldsymbol{\epsilon}_t \qquad (2.11)$$

Except for the dummy variables, with all other variables being in natural logarithm form to reduce effect from extreme values. The dependent variable, $\ln(IS_{on,t})$, is an estimation of ILS in Yan and Zivot (2010) and Putniņš (2013), which represents onshore ILS during local business hours on day t. The first and second independent variables are the number of local and US announcements released during the daytime period. To avoid a calculation problem for non-news days, we add 1 to the number of announcements when we construct the log form of the variables; this does not disturb the distribution of information flow. For Asian currencies, we only add the number of local announcements into this model due to zero overlapping hours between their daytime and the US news releasing period. For Latin American and South African currencies, we add the local and US news variables into the regressions. For market state variables, we follow Mizrach and Neely (2008) to add, $Qspd_{on,t}$, $RV_{on,t}$ and $Noq_{on,t}$, which are the time-weighted average quoted spread from onshore quotes, the sum of square onshore-initiated log returns estimated using tick-by-tick indicative quotes data, and the onshore daily number of quotes. In addition, the Ljung–Box statistics indicate that the onshore ILS are significantly auto-correlated for all currency pairs. Hence, we add lagged IS, $IS_{on,t-1}$, to control the self-dependence. In order to control for extreme market conditions, we add GFC and EDC dummy variables. For the GFC, the key financial crisis months, September 2008–November 2009, equal 1, and the other period equals 0. For the EDC, the key crisis months, April 2010–February 2012, equal 1, and the other period equals 0. Finally, we include the weekday dummy WD^j (j= Monday, Tuesday, Wednesday, and Thursday) to capture the day-of-the-week effect.

We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the residual heteroscedasticity and autocorrelation problem. We present cross-sectional average of the coefficients and the corresponding HKV t statistics in Hameed et al. (2010) for Asian currency and non-Asian currency groups. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Whole sample	$ln(1+NEWs_{day,t})$	$ln((1+NEWs_{US,day,t})$	$\ln(Qspd_{on,t})$	$ln(RV_{on,t})$	$\ln(Noq_{on,t})$	$\ln(IS_{on,t-1})$	GFC	EDC	R^2
				Non-Asian currencies					
BRL	0.041**	0.001	-0.174	0.005	0.294***	0.393***	-0.517	0.109	0.55
	(2.111)	(0.055)	(-1.419)	(0.166)	(4.979)	(7.909)	(-1.482)	(1.427)	
MXN	-0.014	-0.052**	0.082	0.160***	0.050	0.255***	-1.091***	-0.056	0.23
	(-0.616)	(-2.376)	(0.837)	(3.220)	(1.047)	(7.764)	(-6.625)	(-0.522)	
ZAR	0.007	-0.084***	-0.051	0.010	0.089	0.408***	-0.053	-0.289	0.49
	(0.221)	(-4.305)	(-0.268)	(0.204)	(1.345)	(8.079)	(-0.253)	(-1.135)	
non-Asian currencies	0.012	-0.045***	-0.048	0.058**	0.144***	0.352***	-0.554***	-0.079	0.42
HKV t	(0.760)	(-3.807)	(-0.574)	(2.260)	(4.249)	(13.383)	(-3.744)	(-0.816)	
				Asian currencies					
INR	0.034		0.183*	-0.017	0.188***	0.071***	-0.286*	-0.116	0.06
	(0.956)		(1.773)	(-0.710)	(4.315)	(3.814)	(-1.750)	(-1.547)	

KRW	0.014	0.060	-0.023	0.103***	0.002	-0.180*	-0.054	0.07
	(0.582)	(1.094)	(-0.786)	(2.747)	(0.086)	(-1.949)	(-1.002)	
PHP	-0.051	0.000	-0.010	0.238***	0.053***	-0.094	-0.161*	0.14
	(-1.240)	(-0.005)	(-0.333)	(5.711)	(2.766)	(-0.760)	(-1.697)	
Asian currencies	-0.001	0.081*	-0.016	0.176***	0.042***	-0.186**	-0.110**	0.09
HKV t	(-0.038)	(1.745)	(-1.029)	(7.421)	(3.594)	(-2.489)	(-2.492)	

Table 2.14. Sub-sample estimation results for local macro news impact on daytime onshore IS

This table presents the sub-samples results of model 2.11:

$$\ln(\boldsymbol{IS}_{on,t}) = \emptyset_0 + \emptyset_1 \boldsymbol{ln}(\boldsymbol{1} + \boldsymbol{NEWs}_t) + \emptyset_2 \boldsymbol{ln}(\boldsymbol{1} + \boldsymbol{NEWs}_{\boldsymbol{US}_t}) + \emptyset_3 \boldsymbol{ln}(\boldsymbol{Qspd}_{on,t}) + \emptyset_4 \boldsymbol{ln}(\boldsymbol{RV}_{on,t}) + \emptyset_5 \boldsymbol{ln}(\boldsymbol{Noq}_{on,t}) + \emptyset_6 \boldsymbol{ln}(\boldsymbol{IS}_{on,t-1}) + \emptyset_7 \boldsymbol{GFC} + \emptyset_8 \boldsymbol{EDC} + \sum_{j=Mon}^{Thu} \emptyset_j \boldsymbol{WD}^j + \boldsymbol{\epsilon}_t \quad (2.11)$$

The construction of variables and all other estimation setting are the same as for the whole sample regressions in table 2.13. We separate whole sample period into 5 sub-samples, that is, period 1: 01 Jan 1999–31 Dec 2001; period 2: 01 Jan 2002–31 Dec 2005; period 3: 01 Jan 2006–31 Dec 2009; period 4: 01 Jan 2010–31 Dec 2013; and period 5: 01 Jan 2014–31 Dec 2017. Period 3 and 4 cover the GFC and EDC. We added the two dummies into respective sub-period regressions.

Sub-Period 1	$ln(1+NEWs_{day,t})$	$ln((1+NEWs_{US,day,t})$	$\ln(Qspd_{on,t})$	$ln(RV_{on,t})$	$\ln(Noq_{on,t})$	$\ln(IS_{on,t-1})$	GFC	EDC	R^2
BRL	**0.275****	0.099	0.482	0.060	0.114**	-0.028			0.11
	(2.540)	(0.759)	(1.335)	(1.283)	(2.148)	(-0.442)			
MXN	**-0.162**	0.024	0.330**	0.046	0.071	0.265***			0.12
	(-1.331)	(0.389)	(1.988)	(0.554)	(0.912)	(2.872)			
ZAR	**0.041**	-0.099*	-0.193**	0.281***	-0.170*	0.530***			0.57
	(0.542)	(-1.924)	(-2.259)	(4.392)	(-1.908)	(5.299)			
Non-Asian currencies	**0.051**	0.008	0.206	0.129***	0.005	0.255***			0.26
HKV t	**(0.874)**	(0.153)	(1.549)	(3.429)	(0.121)	(5.159)			
INR	**0.035**		-0.152	0.120*	0.171***	-0.031			0.07
	(0.259)		(-1.090)	(1.865)	(2.629)	(-0.995)			
KRW	**0.315**		0.073	0.000	0.331***	-0.048			0.13
	(1.476)		(0.578)	(0.003)	(3.325)	(-1.527)			
PHP	**0.287**		-0.046	-0.021	0.247**	-0.007			0.08
	(1.226)		(-0.332)	(-0.331)	(1.961)	(-0.266)			
Asian currencies	**0.212***		-0.042	0.033	0.250***	-0.029*			0.09
HKV t	**(1.877)**		(-0.538)	(0.858)	(4.384)	(-1.693)			
Sub-Period 2	$ln(1+NEWs_{day,t})$	$ln((1+NEWs_{US,day,t})$	$\ln(Qspd_{on,t})$	$ln(RV_{on,t})$	$\ln(Noq_{on,t})$	$\ln(IS_{on,t-1})$	GFC	EDC	R^2
BRL	**0.121*****	0.014	-0.012	-0.026	0.478***	0.166**			0.50
	(2.687)	(0.366)	(-0.129)	(-0.476)	(4.985)	(2.165)			
MXN	**-0.036**	-0.133**	0.001	0.277***	0.074	0.330***			0.28

	(-0.436)	(-2.422)	(0.005)	(2.897)	(0.625)	(7.881)			
ZAR	**-0.084**	-0.129**	-0.632**	0.068	0.232	0.289***			0.41
	(-0.685)	(-2.430)	(-2.193)	(0.351)	(0.956)	(4.268)			
Non-Asian currencies	**0.000**	-0.082***	-0.214	0.106	0.262***	0.261***			0.39
HKV t	**(0.008)**	(-2.825)	(-1.622)	(1.411)	(2.689)	(7.005)			
INR	**-0.030**		-0.016	0.064**	0.171***	-0.022			0.06
	(-0.358)		(-0.073)	(2.005)	(2.968)	(-0.890)			
KRW	**0.078****		-0.138	0.079*	0.083*	0.062			0.08
	(1.989)		(-1.431)	(1.883)	(1.832)	(0.710)			
PHP	**-0.246***		-0.019	-0.121	-0.060	0.089			0.07
	(-1.877)		(-0.126)	(-1.076)	(-0.320)	(1.277)			
Asian currencies	**-0.066**		-0.058	0.008	0.065	0.043			0.07
HKV t	**(-1.260)**		(-0.631)	(0.187)	(0.974)	(1.163)			
Sub-Period 3	$\boldsymbol{ln(1+NEWs_{day,t})}$	$\boldsymbol{ln((1+NEWs_{US,day,t})}$	$\mathbf{ln}(\boldsymbol{Qspd_{on,t}})$	$\boldsymbol{ln(RV_{on,t})}$	$\mathbf{ln}(\boldsymbol{Noq_{on,t}})$	$\mathbf{ln}(\boldsymbol{IS_{on,t-1}})$	$\boldsymbol{GFC}$	$\boldsymbol{EDC}$	$\boldsymbol{R^2}$
BRL	**-0.008**	-0.009	-0.443*	0.010	0.430***	0.473***	-0.682***		0.53
	(-0.107)	(-0.134)	(-1.726)	(0.161)	(4.756)	(10.635)	(-3.525)		
MXN	**0.038**	-0.040	0.110	-0.017	0.320***	0.180***	-0.737***		0.23
	(0.956)	(-0.698)	(0.751)	(-0.309)	(4.342)	(2.731)	(-5.177)		
ZAR	**0.015**	-0.059*	0.846**	-0.042	0.569***	0.245***	0.088		0.37
	(0.402)	(-1.882)	(2.388)	(-0.530)	(4.138)	(3.661)	(0.551)		
Non-Asian currencies	**0.015**	-0.036	0.171	-0.017	0.440***	0.299***	-0.444***		0.38
HKV t	**(0.493)**	(-1.104)	(1.093)	(-0.426)	(7.170)	(8.427)	(-4.516)		
INR	**0.083**		0.247	0.106**	0.113*	0.072**	-0.243*		0.05
	(1.099)		(1.083)	(2.387)	(1.917)	(2.032)	(-1.703)		
KRW	**0.004**		-0.001	-0.054*	0.045	0.022	-0.048		0.02
	(0.185)		(-0.012)	(-1.734)	(0.890)	(0.869)	(-0.689)		
PHP	**-0.042**		0.006	-0.064	0.197***	0.019	0.079		0.02
	(-0.553)		(0.042)	(-1.198)	(3.191)	(0.683)	(0.594)		

Asian currencies	**0.015**		0.084	-0.004	0.118***	0.038**	-0.070		0.03
HKV t	**(0.409)**		(0.886)	(-0.150)	(3.472)	(2.145)	(-1.003)		
Sub-Period 4	$ln(1+NEWs_{day,t})$	$ln((1+NEWs_{US,day,t})$	$\ln(Qspd_{on,t})$	$ln(RV_{on,t})$	$\ln(Noq_{on,t})$	$\ln(IS_{on,t-1})$	GFC	EDC	R^2
BRL	**0.018**	0.000	-0.013	-0.013	0.092***	0.254***		-0.103**	0.20
	(1.200)	(0.027)	(-0.191)	(-0.688)	(2.695)	(5.216)		(-2.199)	
MXN	**-0.061**	-0.067	-0.091	0.043	0.168**	0.100**		-0.085	0.07
	(-1.248)	(-1.071)	(-0.758)	(0.685)	(2.264)	(2.070)		(-0.755)	
ZAR	**-0.018**	-0.040	0.076	-0.030	0.525***	0.419***		-0.088	0.53
	(-0.389)	(-1.306)	(0.445)	(-0.579)	(6.071)	(5.571)		(-0.910)	
Non-Asian currencies	**-0.020**	-0.036	-0.009	0.000	0.262***	0.258***		-0.092*	0.27
HKV t	**(-0.885)**	(-1.521)	(-0.126)	(-0.009)	(6.623)	(7.558)		(-1.781)	
INR	**0.047**		-0.185	-0.019	-0.083	0.090**		0.012	0.02
	(0.472)		(-0.264)	(-0.325)	(-0.390)	(2.463)		(0.111)	
KRW	**-0.078**		0.247	-0.066	0.197	0.012		-0.051	0.02
	(-1.086)		(1.085)	(-0.816)	(0.941)	(0.912)		(-0.634)	
PHP	**-0.071**		-0.089	0.136**	0.240***	0.028		-0.024	0.05
	(-0.772)		(-0.483)	(2.440)	(3.146)	(0.987)		(-0.257)	
Asian currencies	**-0.034**		-0.009	0.017	0.118	0.043***		-0.021	0.03
HKV t	**(-0.664)**		(-0.035)	(0.438)	(1.119)	(2.722)		(-0.389)	
Sub-Period 5	$ln(1+NEWs_{day,t})$	$ln((1+NEWs_{US,day,t})$	$\ln(Qspd_{on,t})$	$ln(RV_{on,t})$	$\ln(Noq_{on,t})$	$\ln(IS_{on,t-1})$	GFC	EDC	R^2
BRL	**0.011**	0.004	0.049	0.018	0.067	0.002			0.07
	(0.652)	(0.229)	(0.731)	(1.066)	(1.620)	(0.101)			
MXN	**0.016**	-0.007	-0.072	0.395***	-0.060	0.146			0.38
	(0.719)	(-0.305)	(-0.440)	(3.957)	(-0.669)	(1.606)			
ZAR	**0.129*** **	-0.071	0.624***	0.017	-0.025	0.101			0.36
	(2.596)	(-1.579)	(8.107)	(0.186)	(-0.477)	(1.574)			
Non-Asian currencies	**0.052*** **	-0.025	0.200***	0.143***	-0.006	0.083**			0.27

HKV t	**(2.850)**	(-1.473)	(3.262)	(3.299)	(-0.172)	(2.280)	
INR	**0.072****		-0.590	-0.149***	0.382***	0.142*	0.1
	(2.085)		(-0.541)	(-3.519)	(2.760)	(1.773)	
KRW	**0.031**		0.135	-0.073	0.082	-0.015	0.09
	(0.526)		(1.076)	(-0.531)	(0.478)	(-0.326)	
PHP	**0.037**		0.282*	0.046	0.142	0.105***	0.11
	(0.576)		(1.664)	(0.789)	(1.465)	(2.991)	
Asian currencies	**0.047**		-0.058	-0.059	0.202**	0.077**	0.1
HKV t	**(1.486)**		(-0.155)	(-1.130)	(2.486)	(2.311)	

2.7 Conclusion

In EMCs, the offshore market volume share has increased sharply in recent years, from less than 40% to around 60%, approaching the average level of internationalized currencies. This substantial trading location shift motivates us to raise the following question: Does the expansion of offshore transactions have a significant impact on where the EMCs price discovery takes place? We find that the growing transactions of and hedging demands in EMCs lead price discovery shifts from inside to outside issuers' border, and non-local investors' information collection and interpretation abilities of macro news have become largely enhanced in recent years.

To the best of our knowledge, this is the first time that a study has provided a comprehensive evolution of geographic information distribution for EMCs over almost 20 years from 1999 to 2017. The findings should draw the attention of emerging country central banks. On the one hand, the adoption of a floating currency regime and the more active overnight or offshore trading help the EMCs to become more market-determined, and the big trading hubs like New York, London, and Tokyo now have more information and provide more liquidity in the pricing of EMCs than in earlier years. On the other hand, it is getting harder for central banks to successfully control the exchange rates, and EMCs are becoming more fragile if one or two crucial dealers withdraw from supplying liquidity.

Appendix

Appendix A: summary statistics for market state variables in daytime and overnight periods
In this table, we present summary statistics for market state variables, Quoted spread, volatility, and Number of quotes in daytime and overnight periods. The three variables are defined as the time-weighted average quoted spread, standard deviation of 5-minute log returns and number of quotes in daytime/overnight period.

	Daytime Quoted spread*100					Overnight Quoted spread*100				
Currency	Mean	Median	STD	Skew	Ex.Kurt	Mean	Median	STD	Skew	Ex.Kurt
INR	0.027	0.023	0.02	8.63	123.36	0.107	0.070	0.091	1.61	4.72
KRW	0.061	0.051	0.046	5.27	55.34	0.129	0.087	0.119	3.62	23.91
PHP	0.076	0.062	0.057	5.76	55.71	0.201	0.170	0.167	8.67	209.75
BRL	0.088	0.073	0.082	7.07	71.89	0.098	0.080	0.111	10.41	195.47
MXN	0.070	0.059	0.04	4.48	54.94	0.092	0.081	0.057	4.03	33.74
ZAR	0.283	0.272	0.17	0.36	-0.82	0.368	0.370	0.228	0.34	-0.96
EMCs	0.101	0.090	0.07	5.26	60.07	0.166	0.143	0.129	4.78	77.77
	Daytime volatility					Overnight volatility				
Currency	Mean	Median	STD	Skew	Ex.Kurt	Mean	Median	STD	Skew	Ex.Kurt
INR	0.04	0.03	0.03	2.11	8.4	0.02	0.02	0.02	1.62	3.57
KRW	0.05	0.04	0.05	7.08	85.39	0.02	0.01	0.02	7.07	99.63
PHP	0.04	0.03	0.04	6.18	54.83	0.03	0.02	0.03	5.66	83.9
BRL	0.10	0.08	0.07	7.49	128.15	0.03	0.02	0.03	4.82	40.66
MXN	0.04	0.04	0.03	6.94	83.26	0.04	0.03	0.03	7.39	92.63
ZAR	0.08	0.08	0.04	2.81	21.78	0.06	0.05	0.07	45.22	2706.87
EMCs	0.06	0.05	0.04	5.44	63.64	0.03	0.03	0.03	11.96	504.54
	Daytime Number of quotes					Overnight Number of quotes				
Currency	Mean	Median	STD	Skew	Ex.Kurt	Mean	Median	STD	Skew	Ex.Kurt
INR	955.48	796	828.75	4.08	83.63	250.48	27	730.1	4.46	27.26
KRW	7702.52	7807	7238.89	8.59	125.11	904.7	17	1840.89	2.47	5.59
PHP	417.59	343	353.67	9.28	228.39	268	19	1022.14	10.42	216.03
BRL	12109.17	5367.5	15985.6	1.93	3.25	1134.76	470	1743.5	2.58	7.41
MXN	7031.11	5082	7420.45	1.4	1.73	6979.94	3080	10275.68	2.4	6.07
ZAR	10830.18	9136	10033.99	0.9	0.15	6903.46	4572	8015.23	1.74	3.26
EMCs	6507.68	4755.25	6976.89	4.36	73.71	2740.22	1364.17	3937.92	4.01	44.27

Appendix B: summary statistics for market state variables on onshore and offshore markets
In this table, we present summary statistics for market state variables, Quoted spread, Realized variance and Number

of quotes on onshore and offshore markets. The three variables define as the onshore/offshore time-weighted average quoted spread, sum of square onshore/offshore-initiated log returns estimating by tick-by-tick indicative quotes and onshore/offshore number of quotes. We also report the summary statistics of daytime local and US number of announcements here.

	Number of quotes onshore					Number of quotes offshore				
currency	Mean	Median	STD	Skew	EX.kurt	Mean	Median	STD	Skew	EX.kurt
INR	781	708	634	7.43	228.01	183	40	374	4.52	34.45
KRW	6492	6278	5125	4.82	50.35	1133	787	1154	1.27	2.42
PHP	332	254	363	9.73	236.51	98	18	154	3.26	17.39
BRL	9815	3442	14072	1.92	3.11	2854	2267	2774	1.26	1.77
MXN	3955	1529	5845	2.15	4.28	3167	2646	2879	0.54	-0.83
ZAR	3317	1766	3892	1.56	2.48	7411	5885	7426	1.34	2.02
EMCs	4115	2329	4988	4.60	87.46	2474	1940	2460	2.03	9.54
	RV onshore					RV offshore				
currency	Mean	Median	STD	Skew	EX.kurt	Mean	Median	STD	Skew	EX.kurt
INR	0.35	0.14	1.01	32.90	1623.30	0.15	0.02	0.90	45.07	2550.66
KRW	1.14	0.46	4.76	21.54	665.55	0.21	0.06	1.76	37.33	1636.73
PHP	0.99	0.19	8.46	20.82	538.72	0.19	0.03	0.97	17.12	368.85
BRL	8.18	3.45	54.23	40.15	1884.85	4.61	1.66	14.13	12.17	203.97
MXN	1.51	0.37	3.45	8.89	141.73	1.18	0.34	6.00	29.19	1147.50
ZAR	4.26	1.72	40.90	61.84	4011.68	7.25	3.94	47.38	46.52	2432.69
EMCs	2.74	1.06	18.80	31.02	1477.64	2.26	1.01	11.86	31.23	1390.07
	Quoted spread onshore*100					Quoted spread offshore*100				
currency	Mean	Median	STD	Skew	EX.kurt	Mean	Median	STD	Skew	EX.kurt
INR	0.011	0.010	0.005	5.08	45.86	0.034	0.027	0.025	1.51	2.93
KRW	0.023	0.019	0.017	4.18	20.82	0.044	0.033	0.049	6.07	59.88
PHP	0.032	0.026	0.023	7.54	103.92	0.072	0.051	0.066	3.22	23.30
BRL	0.038	0.033	0.021	2.94	18.64	0.045	0.036	0.031	2.11	7.18
MXN	0.043	0.038	0.030	4.36	35.33	0.034	0.028	0.021	7.07	138.33
ZAR	0.271	0.301	0.149	-0.14	-1.01	0.111	0.090	0.072	1.19	0.76
EMCs	0.070	0.071	0.041	3.99	37.26	0.057	0.044	0.044	3.53	38.73
	Daytime local news					Daytime US news				
currency	Mean	Median	STD	Skew	EX.kurt	Mean	Median	STD	Skew	EX.kurt
INR	0.23	0.00	0.61	3.09	10.42		N.A.			
KRW	0.41	0.00	1.03	2.74	6.74		N.A.			
PHP	0.52	0.00	1.02	2.03	3.63		N.A.			
BRL	1.34	1.00	1.52	1.27	1.58	3.77	3.00	3.66	1.41	2.43
MXN	0.56	0.00	0.91	2.12	5.14	1.13	1.00	1.38	1.88	4.95
ZAR	0.59	0.00	1.07	2.29	6.30	3.08	2.00	3.29	1.51	2.74
EMCs	0.61	0.17	1.03	2.26	5.63	2.66	2.00	2.78	1.60	3.38

Chapter 3: Volatility persistence and return asymmetry effect in FX markets

3.1 Introduction

Volatility is a good measure of risk, which is important for asset allocation, asset pricing, and risk management. Researchers have focused on the volatility dynamics of MCs for over 40 years since the inception of floating rate regime in 1973.[39] Following the seminal studies conducted by Engle (1982) and Bollerslev (1986), many variants of the GARCH model have been built to capture FX statistical features. Among the features, two stylized facts draw large attention, volatility persistence and asymmetric volatility. However, limited studies explore these two features of EMCs and further compare them with MCs. As trading volume share increases sharply and exchange rate becomes more market determined, the volatility dynamics of EMCs deserve to be paid more attention.

According to the IMF Annual Report on Exchange Arrangements and Exchange Restrictions, an increasing number of emerging market central banks have announced the adoption of floating instead of pegged currency regimes since the 1990s. In the same period, emerging financial markets have become more liberalized. International investors have begun to have access to and become more active in trading emerging market financial assets, driving up the transaction and hedging demand for EMCs. The BIS 2016 FX market triennial survey shows that total FX trading turnover reached an average of $5.1 trillion per day. EMCs turnover share rose to around 20% in 2016 compared with only 8% in 2001. Therefore, the launch of a floating currency regime and the increasing importance of EMCs motivates us to answer the question: Is there a statistically

[39] The Bretton Woods Conference of 1944 established an international fixed exchange rate system based on the gold exchange standard, in which currencies were pegged to the United States dollar, itself convertible into gold at $35/ounce. The Smithsonian Agreement in 1973 created a new dollar standard whereby the major currencies of the most highly industrialized nations were pegged to the US dollar at central rates, with the currencies being allowed to fluctuate by 2.25%.

significant difference between MCs and EMCs with respect to the two features, that is, volatility persistence and asymmetric effect? If the differences are significant, what determinants cause them?

This chapter contributes to the literature related to volatility dynamics in two ways. First, this chapter provides new evidence that EMCs have lower volatility persistence and higher asymmetric effect than MCs. It is the first time that a paper formally compares the two features for MCs and EMCs using almost 20 years of data. Moreover, it is interesting that the findings in the FX market are completely opposite to those of the equity market. Secondly, it provides explanation and empirical evidence for the differences between MCs and EMCs.

In the equity market, papers find that the volatility persistence of emerging economies with lower market capitalizations is higher than that of developed economies with larger market capitalizations (Cajueriro and Tabk, 2004a, 2004b). The lower pricing efficiency (e.g., Tolvi, 2003; Kim and Shamsuddin, 2008; Hull and McGroarty, 2014), poorer information transparency or the absence of information disclosure regulations (e.g., Chan and Hameed, 2006), and lower market integration levels (Todea, 2016) are potential explanations. However, in the FX market, this paper provides empirical evidence that MCs have higher volatility persistence than EMCs. We explain the difference based on Mixture Distribution Hypothesis. It argues that the source of volatility persistence is the dependency of information flow (Diebold, 1986; Gallant et al., 1991). By using Raven Pack newswire data, we prove that more inconsistent information flow reduces the volatility persistence of EMCs more than MCs.

With respect to the asymmetric effect of return on volatility, the equity market can explain this by the leverage effect (e.g., Black, 1976; Christie, 1982) and the feedback effect (e.g., Bekaert and Wu, 2000). Talpsepp and Rieger (2010) found that emerging equity markets have a weaker asymmetric effect than developed countries because of the lower participation of private investors and coverage by financial analysts. Wang and Yang (2009) used base money theory to explain the phenomenon in the FX market. Park (2011) proved that poorly informed investors trade according to especially negative observed prices, which causes asymmetric trend-following behavior, a source of asymmetric return volatility. In this chapter, we find that EMCs have a much stronger asymmetric effect than MCs, which is opposite to the equity market. In contrast to previous papers, we use market liquidity level to explain the asymmetric effect. By using both high and low frequency liquidity measures, we prove that liquidity asymmetry can help to explain the stronger asymmetric effect of EMCs.

In this chapter, we propose two hypotheses. The first hypothesis is: Less serial dependence of information arrivals causes volatility persistence of EMCs to be lower than that of MCs. Our economic explanation of volatility persistence is closely related to the MDH. Clark (1973) built the original MDH to explain the lack of Gaussianity in daily price changes. He pointed out that the pace of trading activity varies randomly from day to day. The more information that arrives to the market, the more steps prices take within the day. Therefore, he built a mixture model and assumed the daily price change is the sum of a random number of steps. A mixture of random variables is not distributed normally and has a leptokurtic density, thereby showing non-Gaussianity of returns.[40] Later on, Diebold (1986) and Gallant et al. (1991) extended the MDH to explain the relationship between information flow and volatility. By allowing the mixing variable, that is, the underlying information flow, to be serially dependent, the conditional persistence of return variance can be generated. In other words, the suggestion is that the persistence of exogenous information flow is the source of volatility persistence.[41]

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[40] Epps and Epps (1976), Tauchen and Pitts (1983), Harris (1986), and Andersen (1996), among others, extended the original MDH and got empirical success.

[41] The MDH volatility persistence is empirically mixed. By using trading volume as an information flow proxy, Lamoureux and Latrapes (1990) showed that ARCH effects tend to disappear when volume is included in the

This chapter aims to investigate whether there is a significant difference in the volatility persistence of MCs and EMCs, and why this may be. Based on MDH, the source of volatility persistence is the dependency of information flow. Therefore, the ranking of news flow dependency decides volatility persistence. Macroeconomic news is to FX markets as firm-specific news is to the equity market. Hence, we use the daily number of macroeconomic news articles from major newswires as a proxy for information flow. Additionally, due to the two-sided nature of FX rate, both local and US news is taken into consideration (e.g., Melvin and Yin, 2000; Andersen et al. 2003; Bauwens et al. 2005). By comparing the dependency of information flow between issuers of MCs and EMCs, we argue that EMCs should have lower volatility persistence than MCs.

First of all, advanced countries release a larger number of macro fundamentals than EMCs. Aimed at helping countries to disseminate economic and financial data to the public and enhance data quality and transparency, the IMF established the Special Data Dissemination Standard (SDDS) in 1996. Later on, SDDS Plus was introduced, which has stricter releasing standards than SDDS in terms of releasing frequency, quality, and so on. Now, most advanced countries are subscribers to SDDS Plus, however, the main emerging countries are still subscribers to the old standard.[42] In addition, Raven Pack data shows that there is around 60% of trading days covered with macro news reporting from major newswires over our sample period for issuers of EMCs. However, the rate is around 75% for issuers of MCs. In sum, advanced countries should have more

GARCH variance equation in the equity market. By employing the conditional moment method in Lamoureux and Latrapes (1994) to extract the underlying information flow, He and Velu (2014) proved that the GARCH persistence disappears when controlling the information flow for Dow Jones stocks. By using FX market data, Laux and Ng (1993) argued that prior findings that GARCH is the result of the rate of information arrival by using volume as a proxy are overly strong due to specification errors. Fleming and Kirby (2011) found that volume plays only a minor role in explaining the serial dependence in the data with respect to short-run dynamics.

[42] Subscribers of the standard make a commitment to the standard and to provide information in time. And detailed information about SDDS subscribers, please visit: https://dsbb.imf.org/.

persistent information flow than emerging countries, causing the persistence of volatility to be higher than that of EMCs.

Our second hypothesis is: higher illiquidity level causes asymmetric effect of return on volatility in EMCs more than in MCs. With respect to the asymmetric effect in the FX market, Park (2011) proved asymmetric herding behavior, which is where poorly informed investors trade according to especially negative observed prices causing asymmetric trend-following behavior, as a source of asymmetric return volatility. As some economies and currencies are of greater importance than others, Wang and Yang (2009) proposed a base money explanation.[43] Based on their work, we include market liquidity to explain asymmetric effect. We can treat liquidity level as an exogenous variable. The size of the bid-ask spread is an increasing function of asset return and return volatility (e.g., Amihud and Mendelson, 1986; Bollerslev and Melvin, 1994). Considering EMCs have much higher bid-ask spreads than MCs, we expect illiquidity level to explain the stronger return effect of EMCs over MCs.

We apply the following empirical methodology in this study. The first goal is to test the difference between MCs and EMCs in volatility persistence and asymmetric effect. For MCs, we include the AUD, CAD, EUR, and GBP.[44] For EMCs, we investigate three Asian currencies, the INR, KRW, and PHP; two Latin American currencies, BRL and MXN, and one African currency, ZAR. All rates are against the USD and use direct quotation. Our sample period is from January

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[43] Applying the base currency theory to our case: companies and financial institutions may use different currencies to denominate their assets. Obviously, very few of them calculate gain and loss by EMCs compared to MCs. If there is higher expectation of, for example, PHP/USD volatility, it implies greater risk for investors with PHP-denominated assets, but not necessarily for those holding USD-denominated assets. This higher expected volatility may lead to the sale of PHP-denominated assets causing PHP depreciation against the USD. On the contrary, the higher expected USD/EUR volatility may lead Europeans to sell USD-denominated assets, and Americans to sell EUR-denominated assets. Due to similar economy size and development, the base currency effect is weaker for MCs than EMCs, thereby lowering the asymmetric effect of return on volatility.

[44] We do not include Yan/USD in the MCs. The reason is that Yan has opposite asymmetric return effect with other MCs. Wang and Yang (2009) find that the appreciation of Yan/USD have stronger effect on volatility than the depreciation presumably due to the heavy interventions from the Bank of Japan. Therefore, if we include Yan in MCs, the average asymmetric effect of MCs will be distorted.

2000 to December 2017. We employ two models to capture the two features here. One is the HAR-RV-R model proposed by Wang and Yang (2009), which is a variant of the HAR-RV model (Corsi, 2009) to control return asymmetric effect. It is a simple model and can show the relative importance of past daily, weekly, and monthly information to the volatility dynamics. However, it is a restricted model that cannot show us the overall volatility persistence over the past month. Therefore, we also use an unrestricted autoregressive realized volatility model (AR-RV-R model for short) to estimate and compare the long memory of MCs and EMCs. Besides, both the restricted and unrestricted models control return asymmetric effect, so that we can investigate if currency depreciation will lead to higher volatility than currency appreciation and further compare the size of the asymmetric effect between MCs and EMCs.

With respect to the determinants of volatility persistence, we employ the CVP model in Wang and Yang (2017). By allowing the persistence to be time-varying, they proved that volatility persistence is a function of return, which represents a new causal impact from return to future volatility. Constructing an information persistence variable by using Raven Pack newswire data, we investigate whether more inconsistent information flow is the main reason behind lower volatility persistence of EMCs over MCs, as proposed in Hypothesis One. For asymmetric effect, our investigation is based on the conditional asymmetric effect (CAE) model. Inspired by the HAR-CVP model in Wang and Yang (2017), we allow asymmetric effect to also become time-varying. By conditioning based on market liquidity level, we test Hypothesis Two, whether the higher illiquidity level causes asymmetric volatility in EMCs more than MCs.

In this chapter, we provide evidence for the first time that EMCs have significantly lower volatility persistence than MCs. According to the estimation results of the AR-RV-R model, the MCs' volatility persistence over the lagged one month is slightly over 0.9, close to 1, which is consistent with previous literature (e.g., Corsi, 2009; Anderson et al., 2007). With respect to EMCs, the overall volatility persistence is only 0.75, ranging from 0.72 in PHP to 0.89 in INR. Hence, the volatility persistence of EMCs is lower than that of MCs. For volatility on different time horizons, estimation results of the HAR-RV-R model show that significantly lower daily and monthly volatility persistence contribute to the lower dependency of EMCs. The daily RV dependency is around 0.38 for MCs and only 0.23 for EMCs. The weekly RV persistence for MCs and EMCs are both around 0.34. The coefficient of monthly RV is 0.22 for MCs and 0.13 for EMCs.

In terms of the asymmetric effect of return on volatility, we provide new evidence that EMCs have a significantly higher asymmetric effect than MCs. Basically, both MCs and EMCs have an asymmetric effect. In other words, currency depreciation against the USD (positive return) will lead to higher volatility increases than currency appreciation (negative return). Moreover, EMCs have higher asymmetric effect than MCs. Relative to volatility on days following a negative one standard deviation return, volatility on days following a positive one standard deviation return is higher by 0.341 and 0.034 for EMCs and MCs. The asymmetries are equivalent to 11.4% and 6.6% of one-standard-deviation RV of EMCs and MCs.

Furthermore, we investigate the determinants of daily volatility persistence and asymmetric effect. For volatility persistence, we find that a one standard deviation increases in information inconsistency (IIC) will reduce CVP of MCs by 0.09, which is 19% (=0.09/0.471) of average daily CVP. With respect to EMCs, the IIC increase will decrease CVP by 0.18, which is 47% (=0.18/0.384) of average daily CVP. It is clear that the drop in information persistence has a much greater impact on the volatility persistence of EMCs than on that of MCs. In sum, the CVP model helps to prove that there is important channel linking information and volatility persistence. It helps to explain 18% of the asymmetric effect and none of the asymmetric effect for EMCs and

MCs.

3.2 Data and descriptive statistics

In this chapter, we choose to study four MCs and six EMCs. All rates are against USD and use direct quotation. For MCs, we include the AUD/USD, CAD/USD, EUR/USD, and GBP/USD in our study. For EMCs, we investigate three Asian currencies, that is, the INR/USD, KRW/USD, and PHP/USD; two Latin American currencies, that is, BRL/USD and MXN/USD; and one African currency, that is, ZAR/USD. Our sample period is from January 1, 2000 to December 31, 2017.

3.2.1 Construction of daily return and realized volatility

To construct daily return and realized volatility, we employ indicative quote data,[45] which are obtained from the TRTH database provided by the SIRCA.[46] In order to balance accuracy and efficiency, we construct the main interest variables by sampling the rates at a 5-minute frequency.[47] This intra-day 5-minute rates data are constructed using the cleaned tick-size high-frequency data,[48] and the mid-quote price is the average of the bid and ask price.

Due to thin trading, we excluded from the sample all data collected from Friday 17:00 New York time to Sunday 17:00 New York time. We also dropped the two most important holidays: New Year's Day (January 1 each year) and Christmas Day (December 25 each year) for the same

[45] Whether indicative data have the same quality as firm quotes has been questioned for a long time. Researchers have pointed out that indicative quotes do not present a binding commitment to trade at these prices, and some banks may input excessive and even irrelevant quotes to build up a market presence. However, Phylaktis and Chen (2009) showed that indicative data and firm quotes have very similar properties.
[46] Reuters dominates interbank trading for the AUD, CAD, GBP, and EMCs while EBS has long dominated the EUR (e.g. King et al., 2011).
[47] Andersen et al. (2005) argued that the 5-minute sampling interval strikes a good balance between calculation accuracy and efficiency and can help obtain better results for realized variance estimation.
[48] As with the previous chapter, we filtered high-frequency data following the steps suggested in Barndorff-Nielsen et al. (2009). We deleted entries with a bid and ask equal to zero; entries missing date, time, bank ID, or trading location information; entries with negative spread; entries for which the spread is more than 50 times the median spread on that day; and entries where the mid-quote deviated by more than 10 mean absolute deviations from a rolling centered median (excluding the observation under consideration) of 50 observations (25 observations before and 25 after).

reason. Furthermore, we deleted slow trading days, depending on missing hours. Figures 3.1 to 3.3 show the hourly number of quotes for MCs, Asian EMCs, and non-Asian EMCs. With respect to MCs, depending on the daily turnover ebb and flow, the 24-hour market can be separated into four regional trading sessions, that is, Asia (GMT 2300 to 0600), Europe (GMT 0700 to 1200), overlapping London + NYC (GMT 1300 to 1400), and the United States (GMT 1500 to 2200), as in Wang and Yang (2011) and Chai et al. (2015). Therefore, we identify slow trading days if there is no quoting activity over one-third of 24 trading hours, that is, eight hours. With respect to EMCs, their most active trading session is during local business hours.[49] Therefore, we identify slow trading days if there is one-third of local business hours, that is, around three hours, without quoting activity.

Following Andersen et al. (2001), which introduced a natural estimator for integrated variance, daily realized volatility or RV is the sum of squared 5-minute returns over a trading day: $rv_t = \sum_{j=1}^{m} r_{t,j}^2$ where $r_{t,j}$ is the 5-minute return for interval j and m is the number of intraday sampling intervals. We calculate daily RV with m equal to 288 for all currency pairs.

[49] Here, we set local business hours for EMCs from local time 9 am to 5 pm. Two exceptions are PHP/USD and MXN/USD. For PHP, local business hours were set from 9 am to 4 pm because its local trading platform, the Philippine Dealing System, where commercial banks trade in foreign exchange, closes at 4 pm. For MXN, local business hours were set from 8 am to 4 pm. Mexico City local time 4 pm is 5 pm in New York, which is the day break when we calculate daily return and RV.

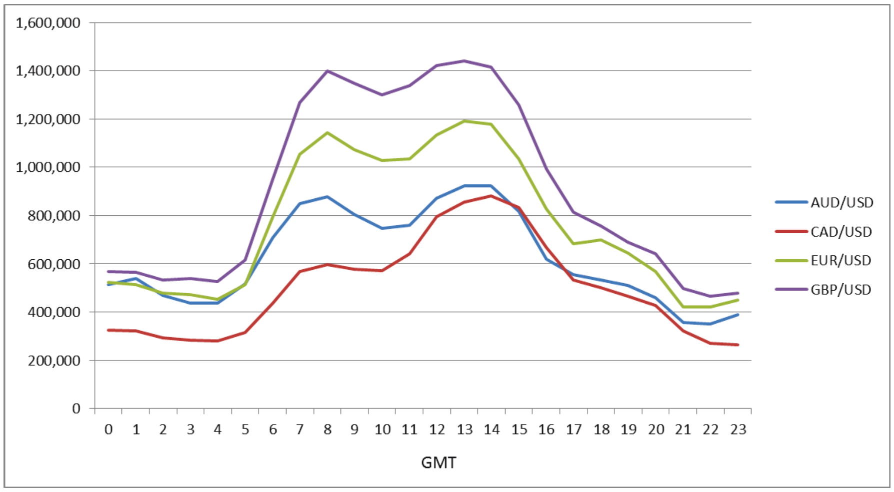


Figure 3.1. 2014 Hourly number of quotes for AUD, CAD, EUR and GBP
Data Source: Author's calculations using FX quotes data obtained from the TRTH database

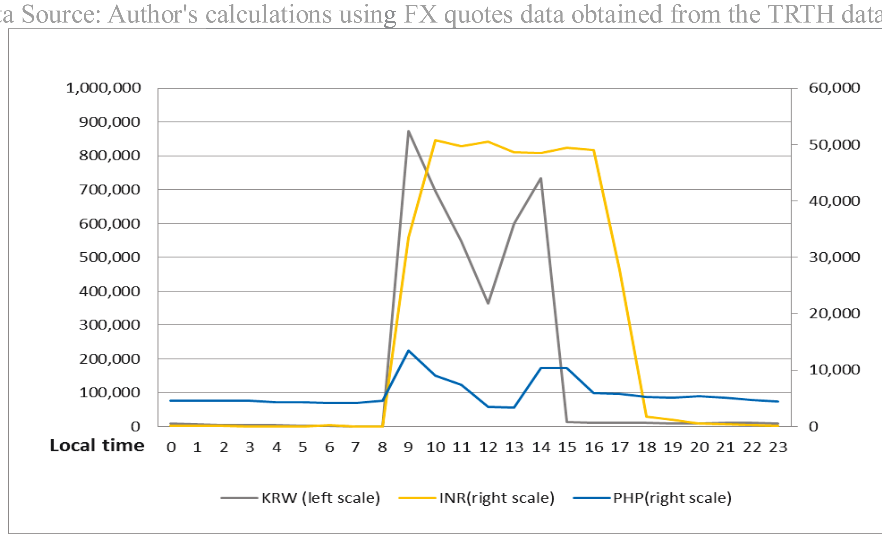


Figure 3.2. 2014 Hourly number of quotes for INR, KRW and PHP
Data Source: Author's calculations using FX quotes data obtained from the TRTH database

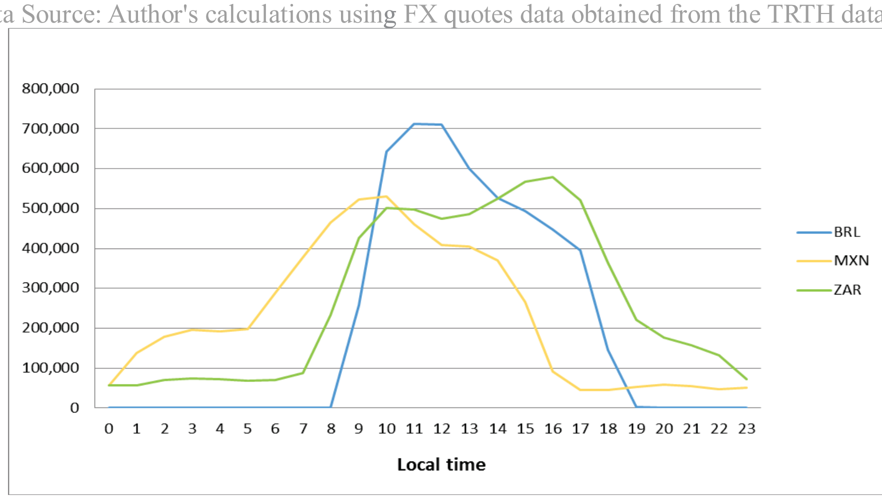


Figure 3.3. 2014 Hourly number of quotes for BRL, MXN and ZAR
Data Source: Author's calculations using FX quotes data obtained from the TRTH database

3.2.2 Data summary

3.2.2.1 Return and RV

Table 3.1 provides a summary of quoting activities. Average total quotes for MCs is around 233 million over the sample period, which is nearly six times that of EMCs. EUR/USD and CAD/USD are the most and least liquid currency pairs among MCs, and quotes for the former are twice that of the latter. With respect to EMCs, non-Asian currency pairs are more liquid than Asian currencies. ZAR/USD is the most liquid currency pair among EMCs with around 87 million quotes. KRW/USD is the most liquid currency pair among Asian currencies with around 40 million quotes. INR and PHP are the least liquid currencies with only six and three million quotes, respectively. On daily frequency, the EUR median number of quotes is four times that of the most liquid EMC, that is, ZAR, and amazingly 136 times of the PHP, the least liquid EMC. Among EMCs, MXN and ZAR have the least number of slow trading days. INR, PHP, and BRL have around 100 slow trading days, which means there are around five thin trading days per year. KRW has the largest number of slow trading days and over half of them are in the year 2001. MCs have around four slow trading days over the sample period.

Figures 3.4 and 3.5 show the exchange rates and RVs of MCs and EMCs over the whole sample period. The most notable feature is that after the start of the GFC, all currencies suffered strong depreciation against the USD, causing volatility, which went up sharply. Additionally, for MCs, we can see that GBP has two extreme RV values on June 24, 2016 and October 7, 2016. On June 24, 2016, the results of the United Kingdom's European Union membership referendum, the so called "Brexit vote", were released. GBP/USD depreciated from 0.68 to 0.76 on that day, which caused the RV to reach 43.61. On October 7, 2016, there was a sterling flash crash, causing a dramatic depreciation in GBP/USD from 0.79 to 0.83.[50] Therefore, these two days are treated as outliers and are excluded from the econometric analysis in the rest of this paper. With respect to EMCs, we found that the RV of BRL on May 7, 2007 and February 11, 2000 were 3,299.75 and 375.75, and 3,266.30 for ZAR on November 3, 2008. These three days are treated as outliers and are excluded from the econometric analysis in the rest of this paper. In Table 3.1 we record the number of extreme RV value days for each currency. Finally, after deleting holidays, slow trading days, and extreme RV value days, MCs have, on average, 4,666 trading days. MXN and ZAR have more than 4,600 trading days, which is similar to MCs. BRL, INR, and PHP have around 4,500 trading days and KRW has only 4,248 trading days, which is due to a large number of slow trading days in 2001.

[50] For details, please check "The sterling 'flash event' of 7 October 2016", BIS: https://www.bis.org/publ/mktc09.pdf.

Table 3.1. Summary statistics for Reuters quotes and trading days

Currency	AUD	CAD	EUR	GBP	**Avg.MCs**	INR	KRW	PHP	BRL	MXN	ZAR	**Avg.EMCs**
Total quotes (unit: million)												
	200	158	302	272	**233**	6	37	3	61	68	87	**44**
Quotes per weekday												
Mean	42,956	33,846	64,723	58,226	**49,938**	1,251	8,744	678	13,475	14,691	18,685	**9,587**
Median	43,369	32,993	59,663	52,930	**47,239**	1,030	8,988	409	6,283	9,611	15,166	**6,914**
Max	217,517	162,197	256,806	313,947	**237,617**	24,940	148,914	37,858	93,308	100,546	135,430	**90,166**
Trading Days												
Total trading days	4,665	4,665	4,667	4,665	**4,666**	4,502	4,248	4,467	4,536	4,650	4,647	**4,508**
Holidays	29	33	34	33	**32**	12	6	3	4	10	14	**8**
Slow trading days	5	5	3	3	**4**	112	217	94	87	12	11	**89**
Extreme value days	0	0	0	2		0	0	0	2	0	1	

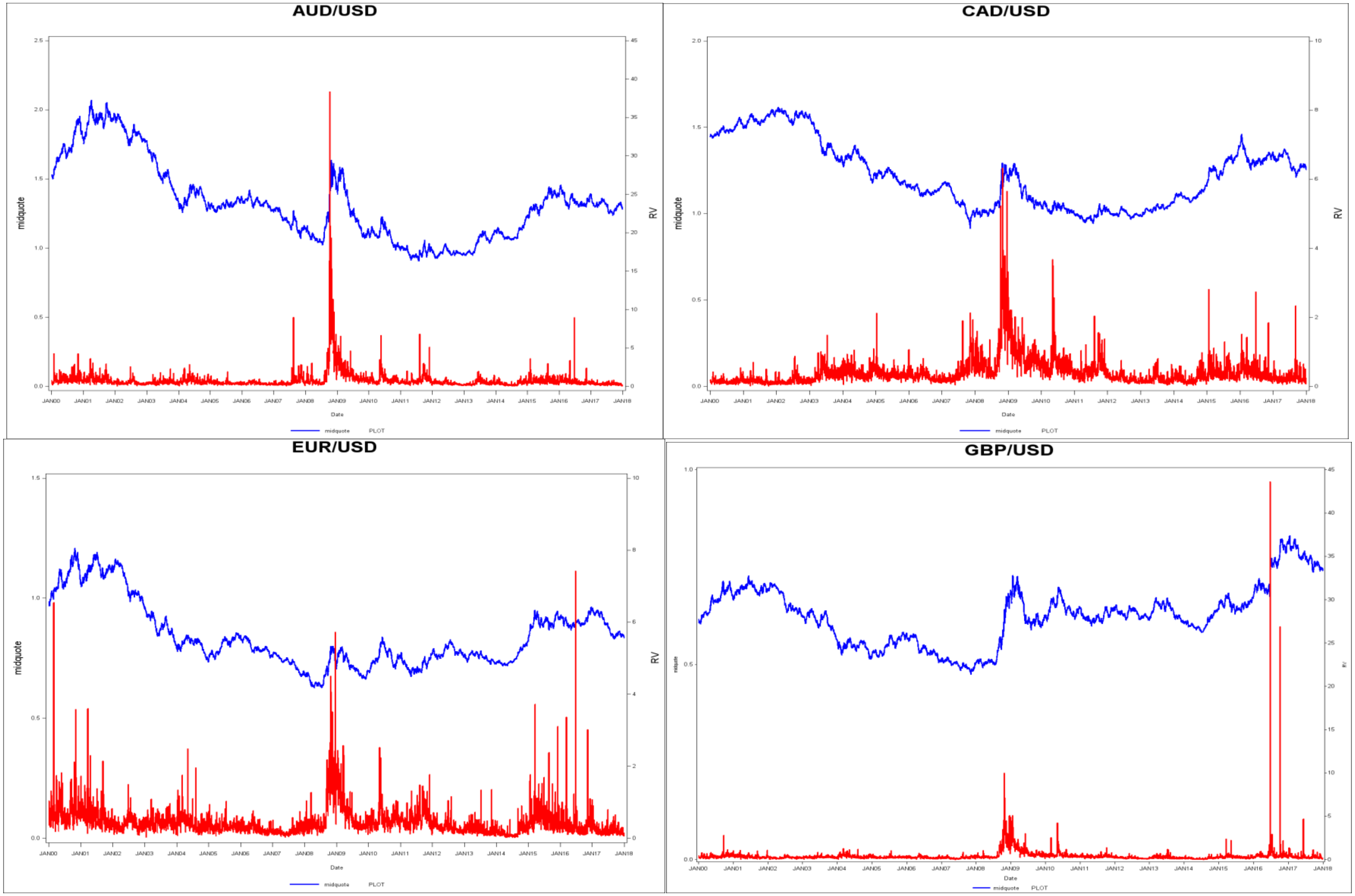
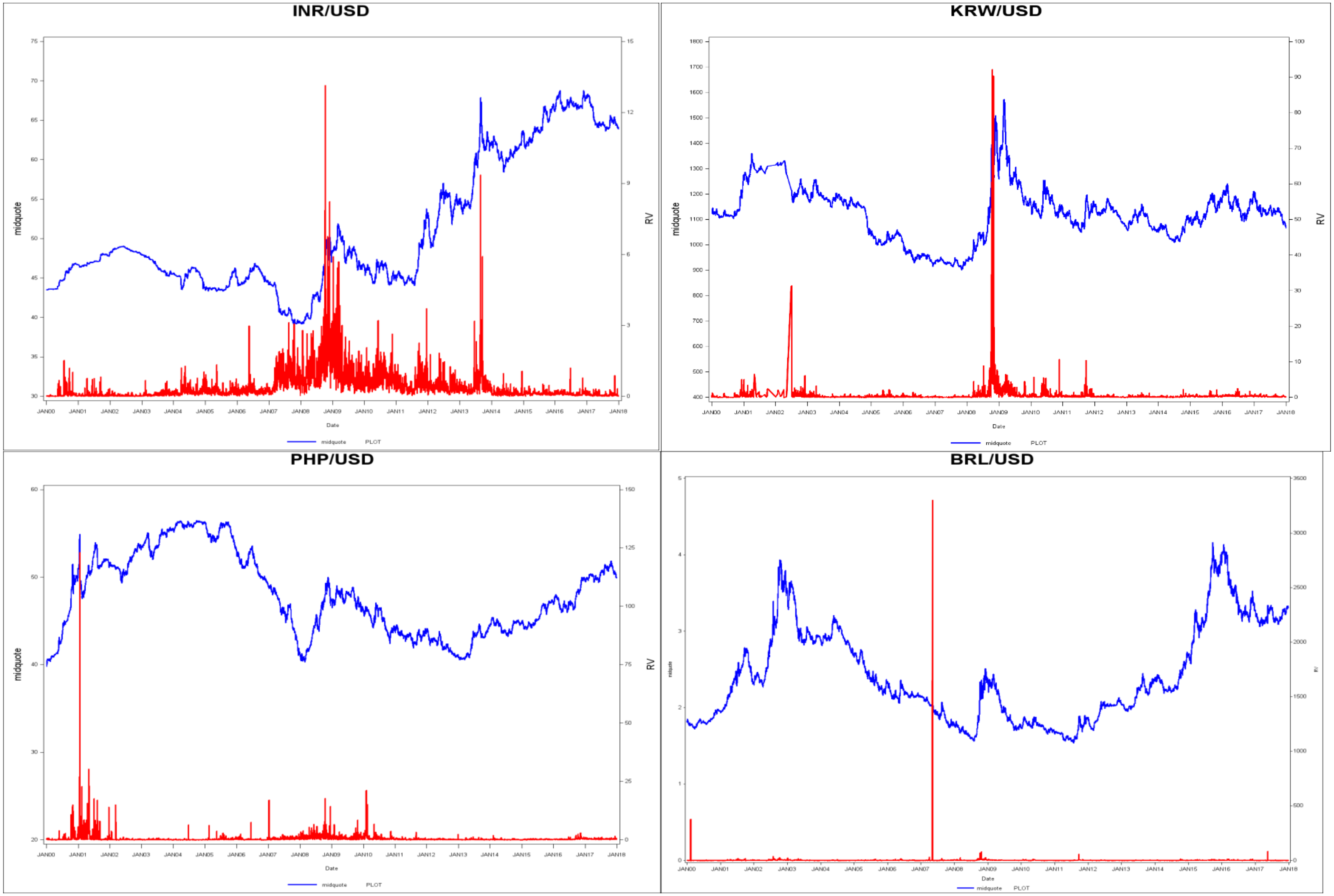


Figure 3.4. Exchange rates and RVs of MCs


INR/USD
KRW/USD
PHP/USD
BRL/USD
midquote
RV
Date
midquote
PLOT

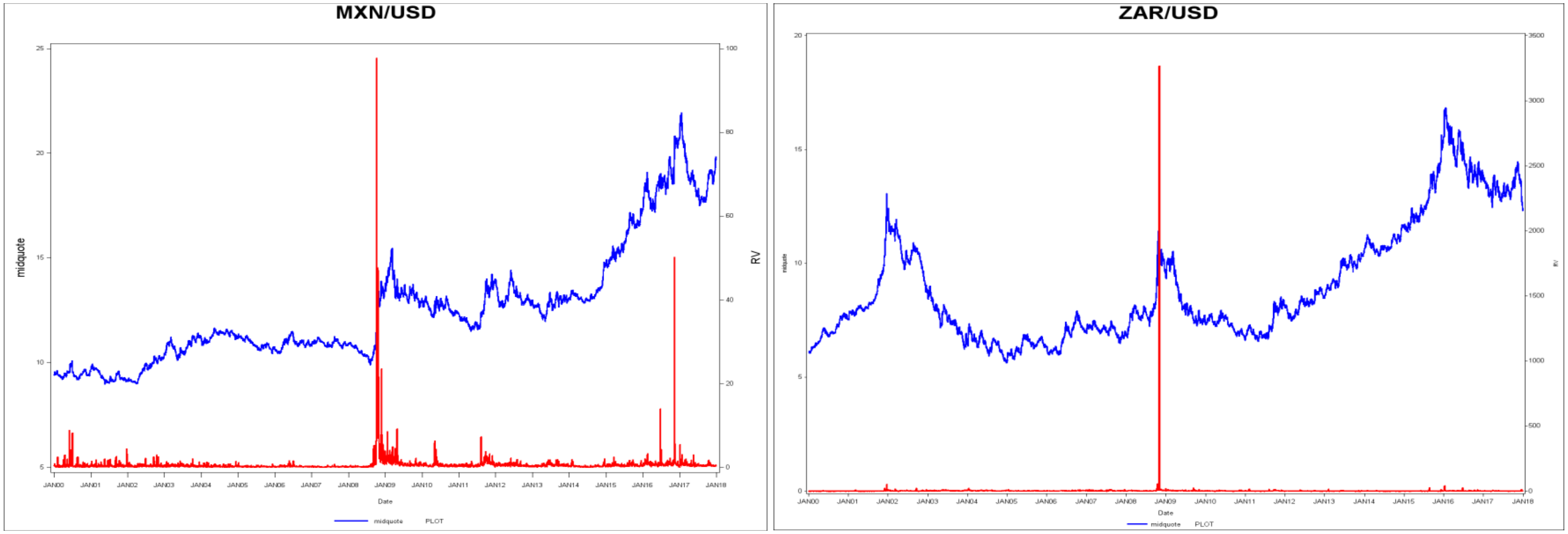


Figure 3.5. Exchange rates and RVs of EMCs

Table 3.2 provides key summary statistics for daily return. All currency returns are based on Reuter quotes at New York local time of 5 pm. Over the sample period, all MCs have negative average daily returns, which means currency appreciation against USD. In contrast, all the EMCs have positive average daily returns, which means currency depreciation against USD. Compared to standard deviation, the average daily return of MCs is close to zero. The size of the average daily return of EMCs is around two times that of MCs, whereas it is still much smaller than the corresponding standard deviation. The return standard deviation (STD) of AUD is 0.803, which is the largest among MCs. CAD and GBP have similar return STD of around 0.567, which are the smallest among MCs. For EMCs, BRL and ZAR have the largest return STD, which are around 1.1, and INR and PHP have the smallest STD, which are around 0.415. The STDs of MCs are distributed around their mean level, 0.642; however, the STDs of EMCs have larger dispersion around their mean level of 0.736. All returns are fat-tailed but EMCs are much more fat-tailed than MCs. PHP returns have prominent left skewness and greatest excess kurtosis. Except for the EUR, PHP, and KRW, all the currencies are right skewed. Again, skewness and kurtosis of MCs are more centered on their mean level than EMCs. Finally, the Ljung–Box statistics for the first 5 lags (Q(5) for short) indicate that daily returns of EUR, GBP, PHP, and ZAR are not auto-correlated at the 1% significance level. Even though the other currencies are auto-correlated, the Q(5) of their daily returns are much smaller than the RV shown in Table 3.3.

Table 3.3 reports summary statistics for daily realized volatility. Not surprisingly, the average RV of EMCs is almost two times that of MCs. We can also observe that EMCs have much larger RV kurtosis than MCs. Among MCs, AUD has the most volatile and fat-tailed RV series, while CAD is the most tranquil with the least STD and kurtosis. Among EMCs, the RV series of BRL and INR have the largest and smallest STD. All the currency pairs have high Ljung–Box Q(5) statistics, which means the RV series are highly persistent. The RV Q(5) statistics for MCs are twice that of EMCs, which means MCs are auto-correlated at a higher significance level.

Table 3.2. Summary statistics for daily returns

Currency pairs	Mean	Median	STD	Skew	Ex.Kurt	Q(5)
AUD/USD	-0.006	-0.035	0.803	0.522	7.3	21.1
CAD/USD	-0.003	-0.005	0.568	0.121	2.8	26.5
EUR/USD	-0.007	-0.011	0.631	-0.058	1.5	7.2
GBP/USD	-0.003	-0.003	0.566	0.192	2.3	4.7
Avg.MCs	-0.005	-0.013	0.642	0.194	3.5	14.9
INR/USD	0.020	0.000	0.419	0.210	8.7	51.9
KRW/USD	0.000	-0.014	0.680	-0.216	35.9	16.9
PHP/USD	0.000	0.000	0.413	-4.093	118.7	15.6
BRL/USD	0.012	0.000	1.083	0.169	7.3	16.5
MXN/USD	0.018	-0.007	0.703	0.853	11.5	22.8
ZAR/USD	0.015	-0.002	1.120	0.778	13.3	4.8
Avg.EMCs	0.011	-0.004	0.736	-0.383	32.6	21.4

Q(5) is the Ljung–Box statistics for the first 5 lags testing autocorrelation in time series. The 1% critical value of $\chi^2(5)$ distribution is 15.9.

Table 3.3. Summary statistics for RVs

Currency	Mean	Median	STD	Skew	Ex.Kurt	Max	Q(5)
AUD/USD	0.7699	0.5089	1.30	13	251	38	12216
CAD/USD	0.4004	0.2913	0.41	5	43	6	13126
EUR/USD	0.4397	0.3393	0.43	7	101	10	5865
GBP/USD	0.3803	0.2754	0.46	7	81	10	12940
Avg.MCs	0.4976	0.3537	0.65	8	119	16	11037
INR/USD	0.3971	0.1805	0.64	6	64	13	8963
KRW/USD	0.5650	0.1953	2.90	22	574	92	4804
PHP/USD	0.5867	0.1971	2.43	31	1467	123	1164
BRL/USD	1.4360	0.7466	3.16	13	255	81	3792
MXN/USD	0.6275	0.3306	2.34	24	794	98	3959
ZAR/USD	1.8427	1.2520	2.42	9	143	55	5782
Avg.EMCs	0.9092	0.4837	2.32	18	549	77	4744

Q(5) is the Ljung–Box statistics for the first 5 lags testing autocorrelation in time series. The 1% critical value of $\chi^2(5)$ distribution is 15.9.

3.2.2.2 Sample Autocorrelation Function of RV

Figures 3.6 to 3.8 show the autocorrelations of RV for lags of up to 100 days for each currency. Figure 3.9 presents the MCs', Asian currencies', and non-Asian currencies' average autocorrelations of RV. The long-memory feature is clear to see for all the series, with the autocorrelations being significantly different from zero, even up to 100 lags. However, the autocorrelations of MCs are much higher and decay slower than those of EMCs throughout 100 lags. The four MCs have similar curve shapes that begin around 0.7 and slowly decline to above 0.2 at a displacement of 100 days. Moreover, non-Asian currencies share one similar decay pattern, starting from 0.5 then sharply dropping to around 0.15 at a displacement of 20 lags, and slowly decaying to 0.05 at 100 lags. However, the decay patterns are varied among Asian currencies. Autocorrelations of INR show a similar pattern to MCs, starting from 0.6 and decaying slowly to above 0.3. For KRW, the pattern is similar to non-Asian currencies. It starts from 0.5 and quickly falls to above 0.1 at 20 lags. Autocorrelations of PHP start from 0.3, which is the lowest among all currencies, and then hovers around 0.1.

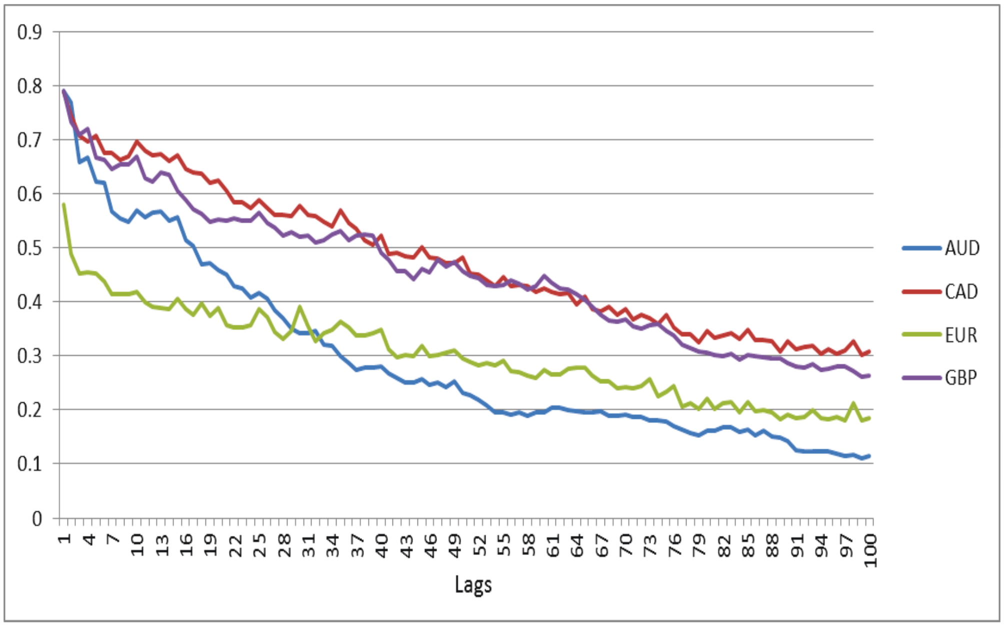


Figure 3.6. Sample autocorrelations of RV for MCs

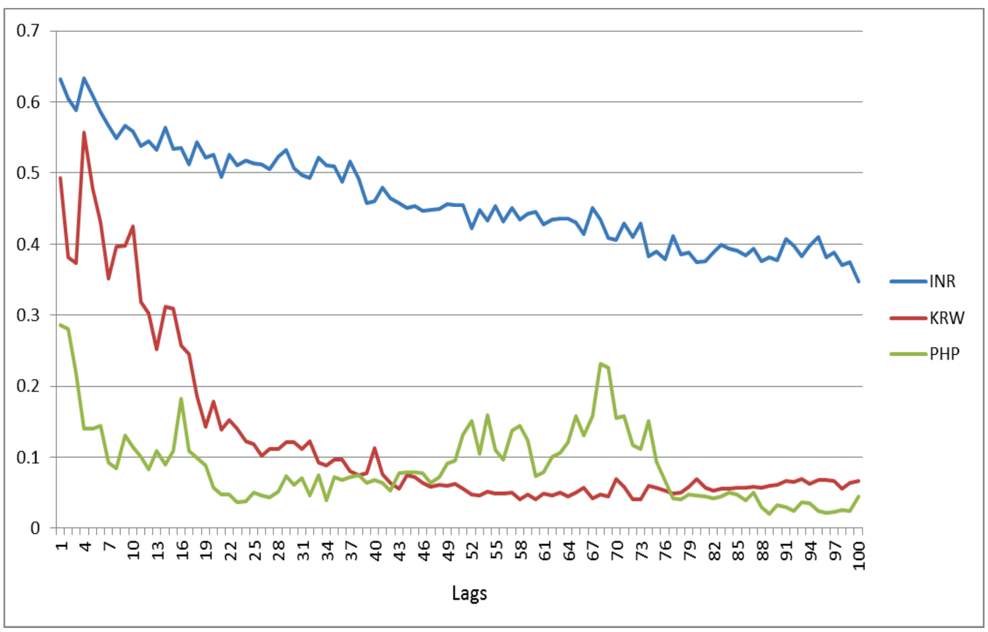


Figure 3.7. Sample Autocorrelations of RV for Asian currencies

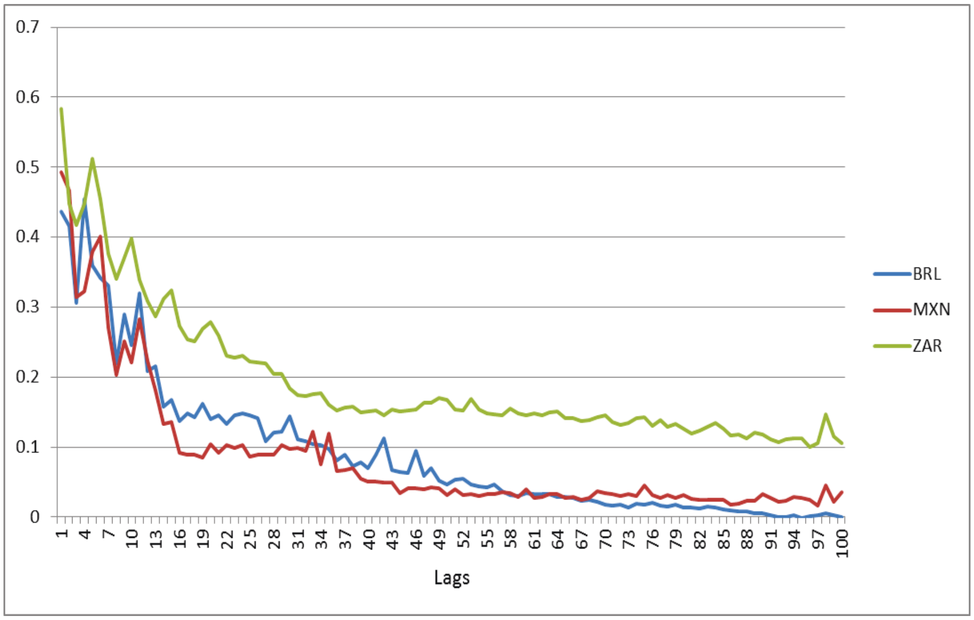


Figure 3.8. Sample Autocorrelations of RV for non-Asian currencies

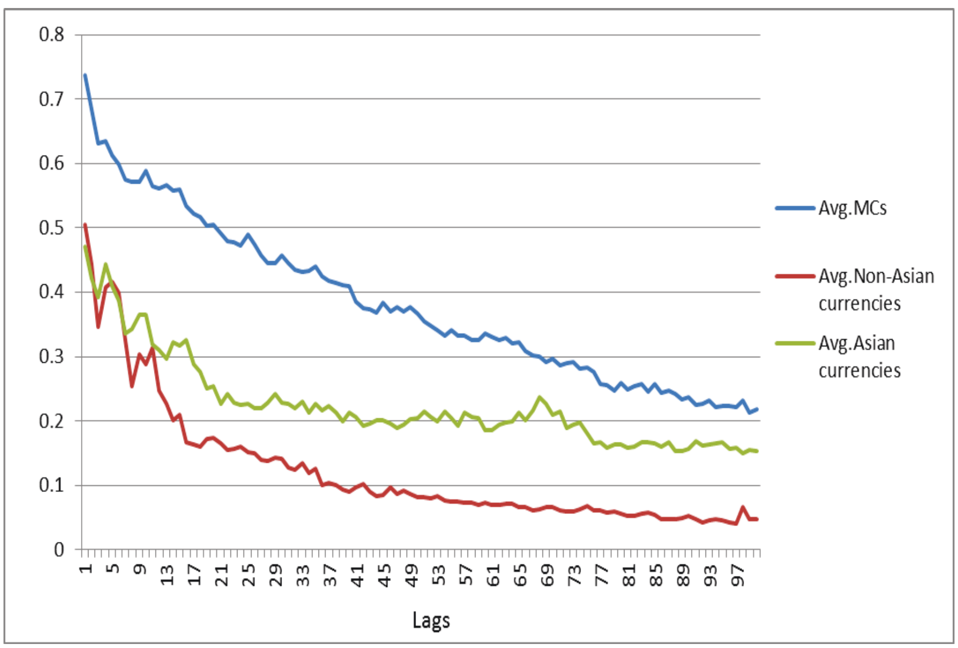


Figure 3.9. Average sample autocorrelations of RV for MCs, Asian currencies and on-Asian currencies

3.2.2 Information flow persistence

In this chapter, we employ the RavenPack News Analytics database to construct the information flow persistence variable. We use the "Global Macro" data, which is sourced from Dow Jones Newswires, Wall Street Journal, Barron's, and MarketWatch. We only keep articles under the "economy" topic and with a score of 100 for both "news relevance" (REL) and "event novelty" (ENS). The REL and ENS scores range from 0 to 100. The macro news REL score shows how strongly the article is related to the economy mentioned in the article. A higher score indicates more relevance. The ENS measures how "new" or "novel" an article in the previous 24 hours is. The first story reporting a categorized event about one or more economies is considered to be the most novel and receives a score of 100.

Table 3.4 presents the summary of the daily number of macro articles. There is an average of 73% of trading days covering local macro articles for the four advanced issuers; however, the percentage is only 59% for the six emerging issuers, with every day essentially covered by US macro articles. In terms of the average number of articles, there are 3.3 and 2.7 local macro articles reporting on news days for the issuers of MCs and EMCs, respectively, and about 10 US macro articles report almost every day. Due to the two-sided nature of FX rates, we should include both local and US macro articles as a proxy of underlying information flow. Q(5) reports the Ljung–Box statistics at five lags of daily number of US and local articles. The statistics indicate that the amount of news for all the currency pairs is highly auto-correlated. However, the significance level of the statistics in MCs is much higher than that of EMCs, which means the information flow of MCs is more persistent than for EMCs.

In this paper, we argue that the lower exogenous information persistence of EMCs is the reason behind the lower volatility persistence of EMCs compared to MCs based on MDH.

Therefore, by using Raven Pack macro news data as described above, we construct the weekly news inconsistency variable: $IIC_w = \frac{SD(I)}{M(I)} = \frac{\sqrt{\frac{\sum_{i=1}^{5}(I_{t-i}-\bar{I})^2}{5-1}}}{\frac{\sum_{i=1}^{5} I_{t-i}}{5}}$. The numerator is the sample standard deviation of the past five-day number of articles. The larger the standard deviation, the more inconsistency in information flow in the past week. To exclude scale influence, we set the denominator as the average of the past five-day number of articles. Therefore, the IIC_w shows the inconsistency of the past week's information flow. Table 3.5 shows the summary statistics for the IIC_w. Because the variable is mean-scaled, the mean and median are quite similar across all currency pairs. However, we can still observe that the mean, median, and max of EMCs are slightly higher than those of MCs, which indicates the information flow of EMCs is more inconsistent than that of MCs, overall.

Table 3.4. Summary for daily number of macro articles sourced from RavenPack database

This table has two panels summarizing daily number of local and US macro articles for the 10 currencies. Panel A presents the number of trading days, and the percentage of trading days covered by local or US macro articles. Panel B shows the average number of local or US macro articles on news days, and the Q(5) statistics of daily number of US and local macro articles.

	AUD	CAD	EUR	GBP	Avg. MCs	INR	KRW	PHP	BRL	MXN	ZAR	Avg. EMCs
Panel A												
trading days	4,665	4,665	4,667	4,665	4,666	4,502	4,248	4,467	4,536	4,650	4,647	4,508
% days coverd by local news	69%	88%	60%	75%	73%	69%	64%	58%	79%	58%	24%	59%
% days coverd by US news	98%	98%	98%	98%	98%	98%	98%	98%	98%	98%	98%	98%
Panel B												
Avg.N of local macro articles	3.3	2.9	3.4	3.7	3.3	3.5	3.2	2.5	2.6	2.4	2.0	2.7
Avg.N of US macro articles	9.7	9.7	9.7	9.7	9.7	9.7	10.0	9.9	9.8	9.8	9.8	9.8
Q(5)	267	268	367	431	333	517	119	126	222	238	220	240

Table 3.5. Summary statistics for IIC_w

	AUD	CAD	EUR	GBP	Avg. MCs	INR	KRW	PHP	BRL	MXN	ZAR	Avg. EMCs
Mean	0.5655	0.5534	0.5840	0.5677	0.5677	0.5571	0.5773	0.5771	0.5384	0.5697	0.6260	0.5743
Median	0.5441	0.5240	0.5606	0.5491	0.5445	0.5320	0.5556	0.5533	0.5108	0.5492	0.6060	0.5512
STD	0.2302	0.2320	0.2376	0.2172	0.2293	0.2295	0.2336	0.2344	0.2226	0.2334	0.2484	0.2337
Skew	0.5228	0.5378	0.5298	0.5485	0.5347	0.6903	0.5168	0.4631	0.5548	0.5851	0.4705	0.5468
Ex.Kurt	0.0398	-0.0206	0.3319	0.4707	0.2055	0.7906	0.1129	-0.0807	0.1247	0.4935	0.1446	0.2643
Max	1.4646	1.5144	2.0000	2.0000	1.7447	2.0000	1.6589	1.6589	1.5280	2.0000	2.0000	1.8076

3.2.3 Liquidity measurement

In this chapter, we use high frequency liquidity measure in the main empirical analysis and low frequency liquidity measure as a robustness check. The daily time-weighted average quoted spread is calculated as follows: $Qspd_t = 100 * \frac{1}{s}\sum_{i=1}^{s}\frac{(ask_i - bid_i)}{(ask_i + bid_i)/2}$. For MCs, the s equals 288, which means there are 288 5-minute time stamps in a day. For EMCs, the s equals 96 because we only take account of quotes during business hours. As discussed previously, the most active trading session for EMCs is the daytime period. The overnight period spreads are huge due to extremely thin trading. Therefore, we only include the daytime period into THE quoted spread calculation for EMCs. Table 3.6 presents the summary statistics for the quoted spread. The mean level of EMCs is more than two times that of MCs, which confirms the former is more illiquid than the latter.

With respect to the low frequency liquidity measure, Karnaukh, Ranaldo and Soderlind (2015) pointed out that FX liquidity can be accurately measured with daily data. The liquidity measure in Corwin and Schultz (2012) performs fairly well compared with the spread constructed by firm quotes. Therefore, we follow Corwin and Schultz (2012) to construct our low frequency liquidity measure (HiLo spread for short). Assuming that the high price is buyer initiated and that the low is seller initiated, the HiLo spread measure combines high and low values over one day with high and low values over two days. It is possible to achieve negative estimations due to large two-day variance. Following Corwin and Schultz (2012), we adjust the value with a two-day average spread. If the daily spread is negative, then the value will be corrected by the following equation:

$$\mathrm{HiLo\_spd}_{\mathrm{two\_day\ corrected}} = \sqrt{\max\{\frac{1}{N}\mathrm{HiLo\_spd}_{\mathrm{t}}, 0\}}$$

Overall, there are less than 25% of trading days with zero HiLo spread. Table 3.7 shows the summary statistics for Hilo spreads. More importantly, Karnaukh, Ranaldo and Soderlind (2015) found that the low frequency measures are not well suited for capturing the levels of transaction costs, however, they do track FX liquidity changes over time. Therefore, following their work, we employ changes of HiLo spread in Corwin and Schultz (2012) as a robustness check for high frequency measure.

Table 3.6. Summary statistics for daily quoted spread

In this table, we present the summary statistics for quoted spread, which is scaled by 10^2.

	AUD	CAD	EUR	GBP	Avg.MCs	INR	KRW	PHP	BRL	MXN	ZAR	Avg.EMCs
Mean	0.06	0.04	0.03	0.03	0.04	0.03	0.06	0.07	0.08	0.06	0.29	0.10
Median	0.05	0.04	0.02	0.02	0.03	0.02	0.05	0.06	0.07	0.05	0.28	0.09
STD	0.02	0.01	0.01	0.01	0.01	0.02	0.04	0.06	0.05	0.03	0.17	0.06
Max	0.14	0.07	0.10	0.06	0.09	0.32	0.76	0.94	0.80	0.27	0.95	0.67
Min	0.03	0.02	0.01	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.04	0.02

Table 3.7. Summary statistics for HiLo spread

In this table, we present the summary statistics for HiLo spread in Corwin and Schultz (2012). The Hilo spread is scaled by 10^2.

	AUD	CAD	EUR	GBP	Avg. MCs	INR	KRW	PHP	BRL	MXN	ZAR	Avg. EMCs
Mean	0.34	0.26	0.27	0.24	0.28	0.23	0.19	0.23	0.4	0.28	0.65	0.33
Median	0.25	0.19	0.2	0.18	0.21	0.18	0.08	0.16	0.24	0.18	0.53	0.23
STD	0.38	0.27	0.3	0.27	0.31	0.23	0.3	0.26	0.5	0.35	0.63	0.38
Max	5.21	2.47	2.51	2.5	3.17	2.22	5.83	3.47	4.49	5.97	8.12	5.02
Min	0	0	0	0	0	0	0	0	0	0	0	0

3.3 Model Specification

3.3.1 AR-RV and HAR-RV models

In the spirit of the heterogeneous market hypothesis presented in Muller et al. (1997), Corsi (2009) built a simple HAR-RV model, which employs daily, weekly, and monthly realized volatilities as lag components representing trading behaviors of short-, medium-, and long-term investors. It is possible to generate long memory in volatility and achieve good performance in RV forecasting.

The original HAR model regresses today's RV on three lagged terms, the past 1-day, 5-day and 22-day average RVs. To ease interpretation, we use a numerically identical reparameterization where the second term consists of only the RVs between lags 2 and 5, and the third term consists of only the RVs between lag 6 and 22 following papers like Patton and Sheppard (2015):

$$\mathrm{RV}_t = \mu + \theta_1 \mathrm{RV}_{t-1} + \theta_5 \left(\frac{1}{4}\sum_{i=2}^{5} \mathrm{RV}_{t-i}\right) + \theta_{22}\left(\frac{1}{17}\sum_{i=6}^{22} \mathrm{RV}_{t-i}\right) + \varepsilon_t \tag{3.1}$$

This reparameterization allows for direct interpretation of the effect of RV_{t-1} on RV_t through θ_1. In the rest of paper, we will use $\overline{\mathrm{RV}}_5$ to indicate the average value over lags 2 to 5, and $\overline{\mathrm{RV}}_{22}$ to denote the average value between lags 6 and 22.

The design of the HAR model is parsimonious and easy to extend. It works so well to capture the dynamic of volatility persistence that Bollerslev, et al. (2017) commented that the HAR model has become "somewhat of a benchmark in the financial econometric literature for judging other RV-based forecasting procedures." However, the HAR-RV model is a restricted AR type model with reparameterization of lagged RV. Therefore, we also built an unrestricted AR (22) model to acquire volatility persistence over a past month, that is, the sum of coefficients of the past 22 days' RV. To achieve that, equations (3.2) to (3.3) show how we get β_{rv} and its standard error in equation (3.4) by using a simple mathematical trick. In equation (3.2), we show the original form of the AR (22) model. Then, in equation (3.3), we add the past day RV, and 61 deduction terms between the RV in days t-2 to t-22 and the past day RV as regressors. Equation (3.3) is equivalent to AR (22) but the coefficient in front of the past day RV turns out to be the sum of the coefficients of the past 22 days' RV. Equation 3.4 shows that we denote the coefficient of the past day RV as β_{rv}, which gauges the volatility persistence over the past one month. After getting the estimation of β_{rv} and its standard error, we can compare the volatility persistence of MCs and EMCs.

$$\mathrm{RV_t} = \alpha + \sum_{i=1}^{22} \beta_{t-i,rv}\, \mathrm{RV_{t-i}} + \varepsilon_t \tag{3.2}$$

$$\mathrm{RV_t} = \alpha + \left(\sum_{i=1}^{22} \beta_{t-i,rv}\right) * \mathrm{RV_{t-1}} + \sum_{i=2}^{22} \beta_{t-i,rv}\, (\mathrm{RV_{t-i}} - \mathrm{RV_{t-1}}) + \varepsilon_t \tag{3.3}$$

$$\mathrm{RV_t} = \alpha + \beta_{rv}\mathrm{RV_{t-1}} + \sum_{i=2}^{22} \beta_{t-i,rv}\, (\mathrm{RV_{t-i}} - \mathrm{RV_{t-1}}) + \varepsilon_t \tag{3.4}$$

3.3.2 AR-RV-R and HAR-RV-R models

Even though the two-sided nature of FX makes asymmetric return impact less likely (Bollerslev et al., 1992), Andersen (2003) mentioned that there is a sign effect in the FX market that bad news has a greater impact than good news. This sign effect shows market response to news in an asymmetric fashion. Corsi and Reno (2009) pointed out that the leverage effect is an indispensable component of RV forecasting. They found negative past returns have high predicting power on future volatility in the equity market. By using FX market data, Wang and Yang (2009) built a HAR-log RV-R model to identify the return asymmetric effect on volatility. They found that, relative to volatility on days following a positive one standard deviation return (in their paper, a positive return means currency appreciation), volatility on days following a negative one standard deviation return is higher by 6.6% for AUD, 6.1% for GBP, and 21.2% for JPY. The realized volatility of EUR appears to be symmetric.

In this study, following Wang and Yang (2009), we add past day return and absolute return into the restricted and unrestricted AR model, that is, HAR-RV and AR models:

$$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22} \overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|} |r_{t-1}| + \varepsilon_t \qquad \text{HAR-RV-R model (3.5)}$$

$$RV_t = \alpha + \beta_{rv} RV_{t-1} + \beta_r r_{t-1} + \beta_{|r|} |r_{t-1}| + \sum_{i=2}^{22} \beta_{t-i,rv} (RV_{t-i} - RV_{t-1}) + \varepsilon_t \quad \text{AR-RV-R model (3.6)}$$

As discussed previously, θ_1, θ_5 and θ_{22} in equation (3.5) capture the importance of short-, mid-, and long-term volatility. To test the difference in volatility persistence in the three horizons between MCs and EMCs, the hypotheses for the HAR-RV-R model are $H_0\colon \theta_i^{MCs} > \theta_i^{EMCs}$ and $H_1\colon \theta_i^{MCs} \leq \theta_i^{EMCs}$, where i=1, 5, and 22. $\theta_{|r|}$ and $\theta_r$represent the size and directional impact of the lagged return. θ_r, the coefficient of return, identifies the asymmetric effect of returns on volatility. As the currency pairs in this study are all against the USD, positive θ_r means currency depreciation causes greater volatility on the next day than appreciation does. Therefore, the hypotheses of this study are $H_0\colon \theta_r^{MCs} < \theta_r^{EMCs}$ and $H_1\colon \theta_r^{MCs} \geq \theta_r^{EMCs}$.

With respect to the AR-RV-R model in equation (3.6), β_{rv} captures the long-memory over the past 22 lags. To test the difference in volatility persistence between MCs and EMCs, the hypotheses for the AR-RV-R model are $H_0\colon \beta_{rv}^{MCs} > \beta_{rv}^{EMCs}$ and $H_1\colon \beta_{rv}^{MCs} \leq \beta_{rv}^{EMCs}$. Moreover, $\beta_{|r|}$ and β_r represent the size and directional impact of the lagged return and the latter identifies the asymmetric effect of returns on volatility. To test the difference in asymmetric effect between MCs and EMCs, the hypotheses for the unrestricted model are $H_0\colon \beta_r^{MCs} < \beta_r^{EMCs}$ and $H_1\colon \beta_r^{MCs} \geq \beta_r^{EMCs}$.

3.3.3 HAR-CVP-IIC and CAE-Qspd models

3.3.3.1 Information inconsistency and volatility persistence

To investigate the determinants of volatility persistence, researchers have allowed daily RV persistence, which is captured by θ_1 in model (3.1), to be time-varying (Forsberg and Ghysels, 2007; Bollerslev, et al., 2016; Wang and Yang, 2017, among others). Wang and Yang (2017) built a HAR-CVP model to explore the determinants of RV persistence. They believe 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. Therefore, the overall "state of the world," as measured by daily return and volatility, is an important determinant of volatility persistence.

Equation 3.7 shows our baseline HAR-CVP model. In financial markets, a large return $|r_t|$ implies a large information shock on day t and is usually associated with high RV on that day. As a proxy for endogenous information flows, a large return draws greater investor attention, triggering more information search and more arrivals of correlated information on day t+1. Such information persistence increases the correlation between today's RV and the future one day's RV. Therefore, it is reasonable to expect that the larger the return, the higher the volatility persistence. In addition, considering that the negative returns are generally associated with greater volatility than positive returns in the equity market (e.g., Bekaert and Wu, 2000) and in the FX market (Wang and Yang, 2009; Park, 2010), we add directional effect variable, that is, return into CVP. Furthermore, following Wang and Yang (2017), we also add RV_t itself as a market state variable. For a given information shock, a high RV_t reflects more information being priced on day t and less spillover of unpriced information to next day. Therefore, we expect that a high RV_t is associated with low dependence of RV_{t+1} on RV_t.

$\mathrm{RV_t} = \lambda + \left(\theta_0 + \theta_{\mathrm{rv},cvp}\mathrm{RV_{t-1}} + \theta_{\mathrm{r},cvp}\mathrm{r_{t-1}} + \theta_{|\mathrm{r}|,cvp}|\mathrm{r_{t-1}}|\right)\mathrm{RV_{t-1}} + \theta_5\overline{RV}_5 + \theta_{22}\overline{RV}_{22} + \theta_\mathrm{r}\mathrm{r_{t-1}} + \theta_{|\mathrm{r}|}|\mathrm{r_{t-1}}| + \varepsilon_\mathrm{t}$ HAR-CVP model (3.7)

In this paper, we argue that lower exogenous information persistence is the reason why EMCs have less volatility persistence than MCs based on MDH. Therefore, by using Raven Pack macro news analytic data, we construct the weekly news inconsistency variable $IIC_w = \frac{SD(I)}{M(I)} = \frac{\sqrt{\frac{\sum_{i=1}^{5}(I_{t-i}-\bar{I})^2}{5-1}}}{\frac{\sum_{i=1}^{5} I_{t-i}}{5}}$. The larger the variable, the more inconsistent the information flow. In equation (3.8), we add the information persistence variable as a conditioning variable for volatility persistence while controlling market state variables:

$$\mathrm{RV_t} = \lambda + \left(\theta_0 + \theta_{\mathrm{rv},cvp}\mathrm{RV_{t-1}} + \theta_{\mathrm{r},cvp}\mathrm{r_{t-1}} + \theta_{|\mathrm{r}|,cvp}|\mathrm{r_{t-1}}| + \theta_{\mathrm{IIC},cvp}\mathrm{IIC_w}\right)\mathrm{RV_{t-1}} + \theta_5\overline{RV}_5 + \theta_{22}\overline{RV}_{22} + \theta_\mathrm{r}\mathrm{r_{t-1}} + \theta_{|\mathrm{r}|}|\mathrm{r_{t-1}}| + \theta_{\mathrm{IIC}}\mathrm{IIC_w} + \varepsilon_\mathrm{t}$$ HAR-CVP-IIC model (3.8)

Based on our hypothesis, we expect the sign of IP_w should be negative, which means the higher the inconsistency of information flow, the lower the volatility persistence. To test the impact of information flow persistence to volatility persistence, our hypotheses are $\mathrm{H_0}$: $|\theta_{\mathrm{IIC},cvp}^{EMCs}| > |\theta_{\mathrm{IIC},cvp}^{MCs}|$ and $\mathrm{H_1}$: $|\theta_{\mathrm{IIC},cvp}^{EMCs}| \leq |\theta_{\mathrm{IIC},cvp}^{MCs}|$.

3.3.3.2 Liquidity level and asymmetric effect

As discussed in the hypothesis formation section, considering EMCs have a much higher bid-ask spread than MCs, we expect liquidity level to be able to explain the stronger return effect of EMCs over MCs. Therefore, we include market liquidity level as a conditioning variable to explain asymmetric volatility. In equation (3.9), we allow asymmetric effect to be time-varying, as well inspired by the HAR-CVP model. We employ past week average quoted spread as a conditioning variable for return and absolute return. It is reasonable to expect the sign of $\theta_{\mathrm{Qspd},r}$ to be positive, which means currency depreciation will lead to a liquidity level drop and thereby increase volatility. To test whether this mechanism is stronger for EMCs than MCs, our hypotheses are $H_0\colon \theta_{Qspd,r}^{EMCs} > \theta_{Qspd,r}^{MCs}$ and $H_1\colon \theta_{Qspd,r}^{EMCs} \leq \theta_{Qspd,r}^{MCs}$. Besides, if the mechanism works, then we also expect that the return direct impact will be deprived, causing a decrease in the coefficient size and significance level in θ_r.

$$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22}\overline{RV}_{22} + \left(\theta_r + \theta_{Qspd,r} Qspd_w\right) r_{t-1} + (\theta_{|r|} + \theta_{Qspd,|r|} Qspd_w)|r_{t-1}|$$
$$+\theta_{Qspd} Qspd_w + \varepsilon_t \qquad \text{CAE-Qspd model (3.9)}$$

3.4 Evidence of volatility persistence and asymmetric effect

In this section, estimation results of each individual currency pairs are reported. We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the problems of heteroscedasticity and autocorrelation. We also report the mean coefficients and the t-statistics associated with them for MCs and EMCs. Following Hameed, Kang and Viswanathan (2010), the standard error of the k^{th} average coefficient $\overline{\widehat{\beta_k}}$ is given by:

$$\text{StDev}\left(\overline{\widehat{\beta_k}}\right) = \text{StDev}\left(\frac{1}{N}\sum_{i=1}^{N}\widehat{\beta_{i,k}}\right) = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\widehat{\omega_{i,j}}\sqrt{\text{Var}\left(\widehat{\beta_{i,k}}\right)\text{Var}\left(\widehat{\beta_{j,k}}\right)}} \qquad (3.11)$$

where $\text{Var}\left(\widehat{\beta_{i,k}}\right)$ is based on the Newey-West standard error of the regression of currency i and $\widehat{\omega_{i,j}}$ is the correlation between the regression residuals for currencies i and j. In addition, we perform the Z-test proposed by Clogg et al. (1995) to test whether the difference of average coefficients between MCs and EMCs is significant or not. The Z-score follows standardized normal distribution. The critical values for the Z-test are 2.33, 1.65, and 1.29 at 1%, 5%, and 10% significance levels, respectively.

Furthermore, we also report the Shapley–Owen R^2 for each regressor of each model in this chapter. It allows us to compare the relative importance of one variable either between the two currency groups or across different models. This technique has its roots in game theory. Shapley (1953) proposed a way to apportion the gains from a cooperative game among cooperating players; Owen (1977) extended this concept to coalitions of players. Later on, Lindeman et al. (1980) applied the same concepts to decompose goodness of fit among regressors and coalitions of regressors in econometrics. It can present the contribution of each independent variable on the explaining dependent variable and the sum of the Shapley–Owen R^2 of each regressor equal to the value of R^2[51].

3.4.1 AR-RV-R model: Volatility persistence and asymmetric effect

Table 3.8 reports the estimation results of equation 3.6, which presents the volatility dependence on the past 22 days in β_{rv} and the past day return asymmetric effect on volatility in β_r. With respect to volatility persistence, our main task is to test H_0: $\beta_{rv}^{MCs} > \beta_{rv}^{EMCs}$. According to the Z-test of average β_{rv} between MCs and EMCs, the null hypothesis is accepted at a 1% significance level. The volatility persistence of MCs is higher than that of EMCs. This is consistent with Figure 3.9, which shows MCs having around 30% higher autocorrelation than EMCs throughout all the 100 lags.

For MCs, average β_{rv} is 0.902, which is close to 1. GBP and CAD have the highest coefficients, which are above 0.9. The coefficient of AUD is slightly below 0.9 and that of EUR is the lowest among MCs at 0.865. The ranking of coefficients' sizes for MCs are consistent with the ranking in Figure 3.6's graphing sample autocorrelations of RV. RV of GBP and CAD are the most auto-correlated and EUR is the least among MCs.

In terms of EMCs, the average β_{rv} of non-Asian currencies is around 0.733 and the β_{rv} of

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

individual currencies are concentrated around the average level. Consistently, sample autocorrelations graphed in Figure 3.8 show that the three non-Asian currencies have similar autocorrelation levels and decaying patterns. As for Asian currencies, the β_{rv} of INR is 0.892, which is the highest among EMCs and the size is approaching that of MCs. The β_{rv} of KRW is 0.72, which is around the average persistence level of non-Asian currencies. PHP has the smallest dependency at 0.66. Again, sample autocorrelations graphed in Figure 3.7 also show that the autocorrelation levels and decaying patterns of the three Asian currencies are quite different from each other.

In terms of asymmetric effect on volatility, we aim to test whether EMCs have higher asymmetric effect than MCs, that is, H_0: $\beta_{\mathrm{r}}^{\mathrm{MCs}} < \beta_{\mathrm{r}}^{\mathrm{EMCs}}$. Table 3.8 shows β_{r} of MCs and EMCs are positive and significant. The positive sign means that past day currency depreciation can cause a higher volatility increase today than currency appreciation can. The average β_r of MCs and EMCs is 0.033 and 0.198. The former is significantly smaller than the latter according to the Z-test. Therefore, the null hypothesis is accepted. Furthermore, we can confirm this asymmetry by calculating the economic or practical significance of the estimated parameters. Allowing σ_r and σ_{rv} to be the standard deviation of the daily return and RV, equation (3.6) can be written as $RV_t = \mathrm{f}(r_{t-1})$ with $\mathrm{f}(+\sigma_r) = \mathrm{f}(0) + (\beta_{|\mathrm{r}|} + \beta_{\mathrm{r}})\sigma_r$ and $\mathrm{f}(-\sigma_r) = \mathrm{f}(0) + (\beta_{|\mathrm{r}|} - \beta_{\mathrm{r}})\sigma_r$. Therefore, the relative asymmetric effect of past day return on RV_t can be measured by

$$\exp[f(+\sigma_r)] - \exp[f(-\sigma_r)] = \exp(2\beta_{\mathrm{r}}\sigma_r) \tag{3.12}$$

This is the impact of $R_{t-1} = +\sigma$ versus $R_{t-1} = -\sigma$ on the following day's RV. Based on the sample standard deviation of the return reported in Table 3.2 and the average coefficient sizes reported in Table 3.8, the values of this measure are 0.042 (2*0.033*0.642) and 0.292 (2*0.198*0.736) for MCs and EMCs. That means, relative to volatility on days following a negative one-standard-deviation return, volatility on days following a positive one-standard-deviation return is higher by 0.042 and 0.292 for MCs and EMCs. Furthermore, the RV size of EMCs is around three times that of MCs shown in Table 3.3. Hence, we can divide the value estimated following equation (3.12) by the standard deviation of daily RV, so that we can get the RV standard deviation change caused by the relative asymmetric effect between one standard deviation positive and negative returns:

$$\exp[f(+\sigma_r)/\sigma_{rv}] - \exp[f(-\sigma_r)/\sigma_{rv}] = \exp(2\gamma_r\sigma_r/\sigma_{rv}) \tag{3.13}$$

Consistently, the asymmetric effect will lead RV to increase 12.6% of one standard deviation for EMCs (=0.292/2.32) and the ratio is only 6.5% for MCs (=0.042/0.65) based on the sample standard deviation of the RV reported in Table 3.3. In sum, no matter if we gauge the asymmetry on RV or RV standard deviation basis, the magnitude of the effect for both MCs and EMCs indicates strong economic significance at a daily frequency and the asymmetry of EMCs is almost eight times and two times that of MCs on RV and RV standard deviation basis, respectively.

For individual currency pairs for MCs, EUR does not have an asymmetric effect. The asymmetry causes 11%, 7.3%, and 4.5% RV standard deviation increases for AUD, CADs and GBP. In Wang and Yang (2009), they used s similar method to identify the asymmetric effect for AUD, EUR, and GBP by using a sample period from 1996 to 2004 (sample period for EUR is from 1999). They also found that volatility of EUR is symmetric and the asymmetries for AUD and GBP are 6.6% and 6.1%. For EMCs, KRW does not show an asymmetric effect. The return coefficient of MXN shows a positive sign but is not significant. The other four EMCs show strong asymmetric effect. The asymmetry causes 8.4%, 14.6%, 15%, and 23.4% RV standard deviation increases for PHP, BRL, INR, and ZAR.

Moreover, to compare the explanatory power of lagged RVs and return for MCs and EMCs, we can utilize the technique of Shapley–Owen R^2 decomposition. It can present the contribution of each independent variable on the explaining dependent variable, and the sum of the Shapley–Owen R^2 of every regressor equal to the value of R^2. In Table 3.9, we report the Shapley R^2 for the past 22 lagged RVs in total, past day return, and absolute return. Overall, 22 lagged RVs explain 55.7% and 34% variations of RV for MCs and EMCs, correspondingly. The former is higher than the latter by 20%. Additionally, lagged RVs are the main contributor to explaining today's RV. There are only 0.3% of variations that can be explained by past day return for MCs. For EMCs, the Shapley R^2 is 1%, which is higher than the MCs. All the findings here are consistent with the results shown in Table 3.6, that lagged RVs of MCs have higher explanatory power to RV due to the higher volatility persistence and lagged return of EMCs helping to explain more due to a stronger asymmetric effect.

Table 3.8. Estimation results of AR-RV-R model

This table presents the estimation results of main variables in model (3.6):

$$RV_t = \alpha + \beta_{rv}RV_{t-1} + \beta_r r_{t-1} + \beta_{|r|}|r_{t-1}| + \sum_{i=2}^{22} \beta_{t-i,rv}(RV_{t-i} - RV_{t-1}) + \varepsilon_t \qquad \text{AR-RV-R model (3.6)}$$

We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the problems of heteroscedasticity and autocorrelation. We also report the mean coefficients and the HKV t-statistics associated with them for MCs and EMCs. In the last row, we present the Z-test proposed by Clogg et al. (1995) to test whether the difference of average coefficients between MCs and EMCs is significant or not. The Z-score follows standardized normal distribution. The critical values for the Z-test are 2.33, 1.65, and 1.29 at 1%, 5%, and 10% significance levels, respectively.

	β_{rv}	β_r	$\beta_{\|r\|}$	R^2
AUD/USD	0.894***	0.090***	0.146***	0.72
	(44.50)	(3.04)	(2.88)	
CAD/USD	0.919***	0.027*	0.072***	0.72
	(64.10)	(1.94)	(2.81)	
EUR/USD	0.865***	-0.002	0.092***	0.45
	(24.79)	(-0.12)	(3.56)	
GBP/USD	0.931***	0.018**	0.047***	0.71
	(46.10)	(2.08)	(3.00)	
MCs	0.902***	0.033***	0.089***	0.65
	(52.93)	(2.59)	(3.97)	
INR/USD	0.892***	0.117**	0.173***	0.58
	(23.25)	(2.31)	(3.17)	
KRW/USD	0.720***	-0.017	0.632*	0.47
	(15.70)	(-0.21)	(1.69)	
PHP/USD	0.660***	0.244*	0.321**	0.17
	(8.15)	(1.67)	(2.00)	
BRL/USD	0.711***	0.301***	0.675***	0.40
	(11.29)	(2.91)	(4.83)	
MXN/USD	0.720***	0.291	0.607*	0.45
	(23.04)	(1.38)	(1.93)	
ZAR/USD	0.768***	0.253***	0.582***	0.49
	(24.85)	(2.71)	(3.14)	
EMCs	0.745***	0.198***	0.498***	0.43
	(31.21)	(3.29)	(4.54)	
Z score	5.35***	-2.68***	-3.65***	

Table 3.9. Shapley R^2 estimation results of AR-RV-R model

This table presents the Shapley R^2 decomposition results of the original form of model (3.6):

$$RV_t = \alpha + \sum_{i=1}^{66} \beta_{rv,i} RV_{t-i} + \beta_r r_{t-1} + \beta_{|r|} |r_{t-1}| + \varepsilon_t \qquad \text{AR-RV-R model (3.6)}$$

The Shapley-Owen R^2 decomposes goodness of fit among regressors and the sum of the Shapley-Owen R^2 of each regressor equal to the value of R^2.

	$\sum_{i=1}^{66} RV_{t-i}$	R_{t-1}	$\lvert R_{t-1}\rvert$	$total\ R^2$
AUD	59.8%	0.7%	11.3%	71.8%
CAD	60.3%	0.2%	11.1%	71.6%
EUR	39.1%	0.0%	6.0%	45.1%
GBP	63.7%	0.2%	7.0%	70.9%
Avg.MCs	55.7%	0.3%	8.9%	64.9%
INR	48.8%	1.2%	8.1%	58.1%
KRW	39.6%	0.0%	7.9%	47.5%
PHP	14.9%	0.1%	2.1%	17.1%
BRL	28.5%	1.3%	10.5%	40.3%
MXN	35.1%	1.5%	8.2%	44.8%
ZAR	35.9%	1.6%	11.6%	49.1%
Avg.EMCs	33.8%	1.0%	8.0%	42.8%

3.4.2 HAR-RV-R model: Volatility persistence on different horizons and asymmetric effect

Table 3.10 reports the estimation results of equation 3.5, the HAR-RV-R model, which presents the volatility dependency on past daily, weekly, and monthly horizons in θ_1, θ_5, and θ_{22}, and past day return asymmetric effect on volatility in θ_1. With respect to volatility persistence, the sum of $\theta_1, \theta_5,$ and θ_{22} are around 0.9 for MCs, which shows substantial persistence. The results are in line with previous literature, for example, Corsi (2009), among others. For EMCs, the sum of $\theta_1, \theta_5,$ and θ_{22} are around 0.7, which is lower than that of MCs. The ranking is in line with the estimation results of the AR-RV-R model. With respect to the lagged RV, the weekly and monthly horizons RV have the most and least importance in explaining RV for EMCs. However, the role of recent RV information diminishes as the horizon increases for MCs. In terms of the asymmetric effect, the results are almost identical with those of the AR-RV-R model shown in Table 3.8.

More importantly, in the HAR-RV-R model, we can test the null hypothesis $H_0: \theta_i^{MCs} > \theta_i^{EMCs}$ (where i=1, 5, and 22) to compare volatility persistence from short to long horizons between MCs and EMCs. According to the Z-test for θ_i, the null hypotheses are accepted at 5% significance level on daily and monthly horizons, and the weekly RV coefficients between MCs and EMCs are not significantly different from each other. From Figure 3.6 to 3.9, we can observe that the autocorrelations of MCs are larger than those of EMCs on first lag and decay much slower than those of EMCs throughout the 100 lags. In sum, the higher daily and monthly RV coefficients of MCs confirm the higher and longer volatility persistence of MCs over EMCs, as shown in Figures 3.6 to 3.9. In terms of asymmetric effect, we can draw the same conclusion that we find in the AR-RV-R model: EMCs have significantly higher asymmetric effect than MCs, that is, $\theta_r^{MCs} < \theta_r^{EMCs}$.

Moreover, we present the Shapley R^2 results for equation (3.5) in Table 3.10. First of all, past RVs have higher explanatory power than returns. Past daily, weekly, and monthly RVs explain

63% and 39% of variations of RV in total for MCs and EMCs. There are only 0.2% and 1.1% of RV variations that can be explained by past day return for MCs and EMCs. Second, the contributions of daily and monthly RVs for MCs are much higher than those of EMCs. This finding is in line with the coefficients' rankings between the two groups shown in Table 3.10. Finally, returns explanatory power to RV for EMCs is higher than that of MCs, which confirms the higher impact of return on volatility of EMCs over MCs.

Table 3.10. Estimation results of HAR-RV-R model

This table presents the estimation results of main variables in model (3.5):

$$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22} \overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|}|r_{t-1}| + \varepsilon_t \qquad \text{HAR-RV-R model (3.5)}$$

We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the problems of heteroscedasticity and autocorrelation. We also report the mean coefficients and the HKV t-statistics associated with them for MCs and EMCs. In the last row, we present the Z-test proposed by Clogg et al. (1995) to test whether the difference of average coefficients between MCs and EMCs is significant or not. The Z-score follows standardized normal distribution. The critical values for the Z-test are 2.33, 1.65, and 1.29 at 1%, 5%, and 10% significance levels, respectively.

	θ_1	θ_5	θ_{22}	θ_r	$\theta_{\|r\|}$	R^2
AUD/USD	0.464***	0.304***	0.126***	0.067**	0.135***	67.3%
	(12.06)	(15.8)	(5.03)	(2.57)	(3.31)	
CAD/USD	0.355***	0.306***	0.260***	0.023	0.074**	69.9%
	(8.22)	(6)	(6.76)	(1.41)	(2.43)	
EUR/USD	0.282***	0.267***	0.318***	-0.001	0.093***	44.9%
	(3.85)	(5.51)	(8.52)	(-0.09)	(3.72)	
GBP/USD	0.411***	0.335***	0.180***	0.020**	0.057**	69.1%
	(6.41)	(7.4)	(5.21)	(2.38)	(2.5)	
MCs	0.378***	0.303***	0.221***	0.027**	0.090***	62.8%
	(9.01)	(9.63)	(8.59)	(2.1)	(3.96)	
INR/USD	0.144***	0.441***	0.307***	0.122**	0.172***	56.6%
	(4)	(8.92)	(6.88)	(2.43)	(4.17)	
KRW/USD	0.152***	0.592***	0.01	-0.045	0.621**	38.7%
	(5.27)	(17.75)	(0.32)	(-0.51)	(1.97)	
PHP/USD	0.209***	0.259***	0.200***	0.356	0.279*	14.1%
	(4.71)	(3.73)	(3.84)	(1.59)	(1.74)	
BRL/USD	0.346***	0.145*	0.221***	0.314***	0.719***	38.7%
	(2.89)	(1.93)	(4.7)	(2.71)	(4.6)	
MXN/USD	0.278***	0.372***	0.029	0.379	0.816*	38.5%
	(5.09)	(9.77)	(0.57)	(1.25)	(1.84)	
ZAR/USD	0.273***	0.377***	0.115	0.259***	0.611***	47.0%
	(5.51)	(9.12)	(1.48)	(2.66)	(2.84)	
EMCs	0.234***	0.364***	0.147***	0.231***	0.537***	38.9%
	(7.6)	(14.23)	(5.62)	(2.83)	(4.24)	
Z score	2.78***	-1.5*	2.01**	-2.47***	-3.48***	

Table 3.11. Shapley R^2 estimation results of HAR-RV-R model

This table presents the Shapley R^2 decomposition results of model (3.5):

$$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22} \overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|} |r_{t-1}| + \varepsilon_t \qquad \text{HAR-RV-R model (3.5)}$$

The Shapley-Owen R^2 decomposes goodness of fit among regressors and the sum of the Shapley-Owen R^2 of each regressor equal to the value of R^2.

	RV_{t-1}	$\overline{RV}_5$	$\overline{RV}_{22}$	R_{t-1}	$\lvert R_{t-1}\rvert$	R^2
AUD	25.9%	20.7%	13.3%	0.6%	6.7%	67.3%
CAD	22.5%	21.4%	19.8%	0.1%	6.2%	69.9%
EUR	14.5%	13.3%	13.0%	0.0%	4.0%	44.8%
GBP	24.8%	22.5%	17.6%	0.2%	4.0%	69.1%
Avg.MCs	21.9%	19.5%	15.9%	0.2%	5.2%	62.8%
INR	13.0%	20.4%	17.5%	1.0%	4.6%	56.5%
KRW	9.3%	18.2%	6.0%	0.0%	5.2%	38.7%
PHP	5.1%	5.0%	2.3%	0.2%	1.6%	14.1%
BRL	15.8%	7.0%	6.4%	1.4%	8.1%	38.7%
MXN	13.3%	13.0%	3.2%	1.9%	7.1%	38.5%
ZAR	14.9%	14.5%	7.0%	1.8%	8.8%	47.0%
Avg.EMCs	11.9%	13.0%	7.1%	1.1%	5.9%	38.9%

3.5 Determinants of volatility persistence

3.5.1 HAR-CVP-IIC model

In this section, we utilize IIC_w as proxy of exogenous information inconsistency. According to our variable construction, a larger value IIC_w means lower information persistence. As discussed before, we expect there to be a negative relationship between IIC_w and volatility persistence. Besides, based on MDH and the macro articles patterns, we also expect that information inconsistency may reduce volatility persistence of EMCs more than MCs. Table 3.12 reports the estimation results of the HAR-RV-R model (equation 3.5) and CVP-IIC model (equation 3.8).

The key empirical findings can be summarized as follows. First of all, we can strongly reject $\theta_{|r|,cvp} = \theta_{r,cvp} = \theta_{rv,cvp} = \theta_{IIC,cvp} = 0$ according to joint test F-statistics. Besides, the coefficient signs of IIC_w are negative for all currency pairs, except for GBP. The IIC_w coefficients are highly significant for both MCs and EMCs, but the size of the latter group is significantly higher than the former. According to Table 3.5, MCs and EMCs have similar standard deviation for IIC_w, which is 0.23. Therefore, one standard deviation increase of IIC_w will reduce the CVP of MCs by 0.09, which is 19% (|-0.397|*0.23/0.471) of average daily CVP. With respect to EMCs, the IIC_w increase will decrease CVP by 0.18, which is 47% (|-0.772|*0.23/0.384) of daily CVP (the daily CVP summary statistics are shown in Table 3.13 and discussed in a later section). Clearly, the drop in information persistence has a much greater influence on the volatility persistence of EMCs than for MCs.

Compared with the impact of IIC_w to CVP, market state variables have much smaller influence overall. One standard deviation of absolute return increases 8.6% (0.064*0.635 /0.471) and 10.9% (0.057*0.738/0.384) of average daily CVP for MCs and EMCs. However, it looks like there is weak return sign effect for volatility persistence. That is different from findings from the equity market in Wang and Yang (2017). They reported that both positive and negative returns increase volatility persistence endogenously and the latter have greater impact. The coefficients of conditioning variable RV_{t-1}^{2} are negatively significant for MCs and EMCs. One standard deviation RV increase will decrease 3.5% (-0.026*0.64 /0.471) and 8.7% (-0.013*2.57/0.384) of average daily CVP for MCs and EMCs.

More importantly, in the HAR-RV-R model, daily volatility persistence for MCs is larger than EMCs. However, the HAR-CVP-IIC model shows that the coefficients' size of past day RV between MCs and EMCs turn out not to be different from each other. That means the volatility persistence gap between MCs and EMCs is mainly because of the stronger negative impact of information flow inconsistency on EMCs.

3.5.2 Characteristics of daily CVP

In this part, we report the daily CVP for MCs and EMCs. The average daily CVP for MCs and EMCs are calculated as: $\widehat{\mathrm{CVP}}_{t,i} = \frac{1}{N}\sum_{i=1}^{N}(\theta_{1,i} + \theta_{|r|,cvp,i} * |r|_{t,i} + \theta_{r,cvp,i} * r_{t,i} + \theta_{rv,cvp,i} * rv_{t,i} + \theta_{IIC,cvp,i} * IIC_{w,i})$, where i is equal to MCs or EMCs, N is equal to 4 if i=MCs and 6 if i=EMCs. Table 3.13 reports the summary statistics of daily CVP and correlations between daily CVP and conditioning variables for MCs and EMCs. The means of daily CVP are 0.47 and 0.38 for MCs and EMCs. The former is higher than the latter by 24% [(0.47-0.38)/0.38]. The medians of MCs and EMCs are nearly identical with their means. This can be further confirmed by the small size of skewness. Besides, the standard deviation of EMCs is two times larger than that of MCs. Figure 3.10 depicts the time series of MCs' and EMCs' daily CVP; the features of daily CVP described here are shown.

Interestingly, the correlations between IIC_w and CVP are nearly negative one with 1%

significance level for both MCs and EMCs. This means the variations of CVP are largely dependent on IIC_w. Daily CVP are also significantly correlated with other conditioning variables, however, the size is far less than the correlation with IIC_w. The correlations between absolute return and CVP are both around 0.15 for MCs and EMCs. The sign is consistent with $\theta_{|r|,cvp}$ in equation 3.8. Even though there is no significant asymmetric volatility persistence shown in the empirical results, the correlations between return and CVP are significantly negative for MCs and significantly positive for EMCs. The correlation between RV and CVP is positive, which is opposite to the sign of $\theta_{rv,cvp}$ in Table 3.12. Wang and Yang (2017) argued that this is because the positive correlation between CVP and the absolute return (around 0.15 for MCs and EMCs) and positive correlation between the absolute return and RV (around 0.58 for MCs and EMCs).

In sum, based on analysis of daily CVP and the empirical results of the CVP-IIC model, we can conclude that the variations of daily CVP are mainly dependent on information flow inconsistency and the negative impact of IIC_w on CVP being stronger for EMCs than MCs, causing the lower volatility persistence.

3.5.3 Evidence from Shapley R^2 decomposition

Furthermore, we can confirm our findings above by computing the Shapley decomposition for each variable in the HAR and HAR-CVP-IIC models. Table 3.14 shows the computation results. The CVP column shows the sum of Shapley R^2 for the four CVP variables, that is, $RV_{t-1} * RV_{t-1}$, $R_{t-1} * RV_{t-1}$, $|R_{t-1}| * RV_{t-1}$ *and* $IIC_w * RV_{t-1}$. There are a few findings:

First, CVP explains a large proportion of the variation of future volatility. The Shapley R^2 of CVP is around 20.8% and 13.6% for MCs and EMCs, correspondingly. In particular, among the conditioning variables, the Shapley R^2 of $IIC_w * RV_{t-1}$ is the highest. The overall importance of the CVP variables can be measured by the ratio of their Shapley R^2 to the regression R^2. CVP of

MCs and EMCs account for a similar percentage, around 32%, of their total R^2.

Second, the Shapley R^2 of $|R_{t-1}| * RV_{t-1}$ is around 6.8% and 4.1% for MCs and EMCs, larger than the Shapley R^2 of direct impact of return at around 3.1% and 3.8%. This linkage between return and future RV through CVP is stronger in MCs than EMCs. However, Wang and Yang (2017) showed that this linkage in the equity market is two to three times more important than the direct return impact on future volatility. Therefore, the return volatility CVP linkage is weak in the FX market, especially for EMCs.

Third, Table 3.12 shows that the coefficient of RV_{t-1} experiences a big size increase in the CVP-IIC model compared to the HAR model. However, the Shapley R^2 of RV_{t-1} in the CVP-IIC model is, on average, lower by 32.4% and 23.5% for MCs and EMCs than in the HAR model. In other words, around 32.4% and 23.5% of the explanatory power of RV_{t-1} in the HAR model comes from the omitted CVP variables.

Fourth, in the HAR-RV-R model, the past day RV's Shapley R^2 of MCs is two times that of EMCs. This is in line with the larger daily volatility persistence for MCs over EMCs. However, the HAR-CVP-IIC models show that the sizes of the past day RV between MCs and EMCs turn out not to be differ from each other. We can observe that the past day RV's Shapley R^2 gap between the two currency groups is greatly reduced compared with that in the HAR-RV-R model.

Overall, the Shapley R^2 analysis of the HAR-RV-R and CVP-IIC models confirm that there is a dominant channel linking information persistence to future volatility and the stronger negative impact of information inconsistency on EMCs is the reason behind the lower volatility persistence.

Table 3.12. Estimation results of HAR-RV-R and HAR-CVP-IIC models

This table presents the estimation results of models (3.5) and (3.8):

$$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22}\overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|}|r_{t-1}| + \varepsilon_t \quad \text{HAR-RV-R model (3.5)}$$

$$RV_t = \lambda + (\theta_1 + \theta_{rv,cvp}RV_{t-1} + \theta_{r,cvp}r_{t-1} + \theta_{|r|,cvp}|r_{t-1}| + \theta_{IIC,cvp}IIC_w)RV_{t-1} + \theta_5\overline{RV}_5 + \theta_{22}\overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|}|r_{t-1}| + \theta_{IIC}IIC_w + \varepsilon_t \quad \text{HAR-CVP-IIC model (3.8)}$$

We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the problems of heteroscedasticity and autocorrelation. We also report the mean coefficients and the HKV t-statistics associated with them for MCs and EMCs. In the last row, we present the Z-test proposed by Clogg et al. (1995) to test whether the difference of average coefficients between MCs and EMCs is significant or not. The Z-score follows standardized normal distribution. The critical values for the Z-test are 2.33, 1.65, and 1.29 at 1%, 5%, and 10% significance levels, respectively.

	θ_1	$\theta_{rv,cvp}$	$\theta_{r,cvp}$	$\theta_{\vert r\vert,cvp}$	$\theta_{IIC,cvp}$	θ_5	θ_{22}	θ_r	$\theta_{\vert r\vert}$	θ_{IIC}	R^2
AUD	0.464***					0.304***	0.126***	0.067**	0.135***		0.67
	(12.06)					(15.8)	(5.03)	(2.57)	(3.31)		
	1.233***	-0.015**	-0.017***	0.016	-0.950**	0.336***	-0.005	0.100***	0.043	0.617**	0.71
	(2.67)	(-2.22)	(-4.32)	(1.24)	(-2.55)	(12.54)	(-0.04)	(4.09)	(1.04)	(2.35)	
CAD	0.355***					0.306***	0.260***	0.023	0.074**		0.70
	(8.22)					(6)	(6.76)	(1.41)	(2.43)		
	0.476***	-0.040**	-0.025	0.123***	-0.270***	0.300***	0.270***	0.045***	-0.026	0.078***	0.71
	(4.38)	(-2.56)	(-1.4)	(6.4)	(-4.11)	(6.5)	(6.19)	(4.05)	(-1.12)	(3.19)	
EUR	0.282***					0.267***	0.318***	-0.001	0.093***		0.45
	(3.85)					(5.51)	(8.52)	(-0.09)	(3.72)		
	0.653***	-0.042**	-0.046*	0.036	-0.376***	0.208***	0.283***	0.035*	0.045	0.150***	0.46
	(5.1)	(-2.43)	(-1.7)	(0.58)	(-2.66)	(3.75)	(8.4)	(1.96)	(1.08)	(2.74)	
GBP	0.411***					0.335***	0.180***	0.020**	0.057**		0.69
	(6.41)					(7.4)	(5.21)	(2.38)	(2.5)		
	0.360***	-0.008	-0.014	0.081***	0.01	0.328***	0.183***	0.026*	0.000	0.005	0.69
	(4.17)	(-1.06)	(-0.75)	(5.36)	(0.1)	(7.42)	(4.08)	(1.8)	(0.00)	(0.15)	
MCs	0.378***					0.303***	0.221***	0.027**	0.090***		0.63
	(9.01)					(9.63)	(8.59)	(2.1)	(3.96)		
	0.680***	-0.026***	-0.026*	0.064***	-0.397***	0.293***	0.183***	0.052***	0.016	0.212***	0.65
	(4.31)	(-2.93)	(-1.95)	(2.93)	(-2.95)	(8.99)	(3.91)	(4.01)	(0.67)	(2.68)	
INR	0.144***					0.441***	0.307***	0.122**	0.172***		0.57

	(4)					(8.92)	(6.88)	(2.43)	(4.17)		
	0.332*	-0.036***	0.044	0.069	-0.054	0.417***	0.258***	0.055	0.06	-0.003	0.58
	(1.7)	(-3.44)	(0.7)	(0.69)	(-0.22)	(5.74)	(3.37)	(1.23)	(0.79)	(-0.05)	
KRW	0.152***					0.592***	0.01	-0.045	0.621**		0.39
	(5.27)					(17.75)	(0.32)	(-0.51)	(1.97)		
	0.759***	-0.010***	0.013***	0.086***	-1.048***	0.598***	-0.069*	0.019	0.368**	0.385***	0.42
	(18.28)	(-7.24)	(11.98)	(10.54)	(-23.58)	(20.54)	(-1.91)	(0.46)	(2.15)	(5.5)	
PHP	0.209***					0.259***	0.200***	0.356	0.279*		0.14
	(4.71)					(3.73)	(3.84)	(1.59)	(1.74)		
	0.795***	-0.01	-0.085***	-0.002	-0.564***	0.210***	0.123**	0.363*	0.460***	0.284***	0.16
	(3.81)	(-1.49)	(-3.47)	(-0.05)	(-3.39)	(3.23)	(2.39)	(1.76)	(3.52)	(2.81)	
BRL	0.346***					0.145*	0.221***	0.314***	0.719***		0.39
	(2.89)					(1.93)	(4.7)	(2.71)	(4.6)		
	0.839***	-0.005***	-0.003	0.03	-0.663*	0.111*	0.200***	0.328***	0.489***	0.845**	0.41
	(3.66)	(-3.57)	(-0.18)	(0.96)	(-1.87)	(1.72)	(3.99)	(2.62)	(3.75)	(2.15)	
MXN	0.278***					0.372***	0.029	0.379	0.816*		0.39
	(5.09)					(9.77)	(0.57)	(1.25)	(1.84)		
	1.688***	-0.009**	0.057***	0.085***	-2.108***	0.303***	-0.016	0.121	0.229*	1.132***	0.51
	(3.2)	(-2.18)	(3.59)	(7.77)	(-5.1)	(3.45)	(-0.27)	(1.19)	(1.89)	(4.57)	
ZAR	0.273***					0.377***	0.115	0.259***	0.611***		0.47
	(5.51)					(9.12)	(1.48)	(2.66)	(2.84)		
	0.401***	-0.006*	0.041***	0.074***	-0.197	0.348***	0.130***	0.003	0.123	0.458*	0.53
	(4.15)	(-1.84)	(2.61)	(4.82)	(-1.37)	(8.68)	(2.73)	(0.07)	(1.23)	(1.82)	
EMCs	0.234***					0.364***	0.147***	0.231***	0.537***		0.39
	(7.6)					(14.23)	(5.62)	(2.83)	(4.24)		
	0.802***	-0.013***	0.011	0.057***	-0.772***	0.331***	0.104***	0.148***	0.288***	0.517***	0.43
	(6.55)	(-5.27)	(0.86)	(2.74)	(-6.19)	(11.28)	(4.14)	(3)	(5.06)	(4.8)	
z-score	2.78***					-1.5*	2.01**	-2.47***	-3.48***		
	-0.61	-1.45*	-1.99**	0.25	2.05**	-0.87	1.48*	-1.9**	-4.43***	-2.28**	

Table 3.13. Daily CVP summary statistics

	Summary statistics							Correlations			
	Mean	Median	STD	Skew	Ex.Kurt	Max	Min	|Return|	Return	RV	IIC_w
MCs	0.47	0.48	0.09	-0.47	0.08	0.71	0.12	0.18***	-0.14***	0.04***	-0.95***
EMCs	0.38	0.40	0.17	-0.57	0.20	0.86	-0.37	0.12***	0.07***	0.04**	-0.98***

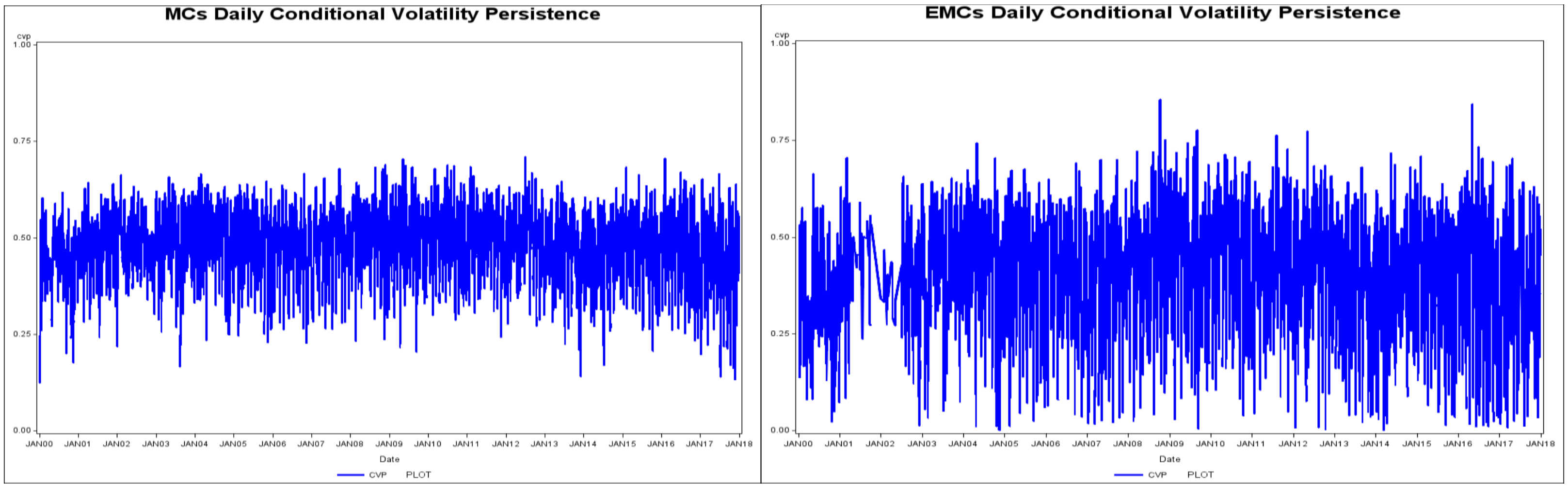


Figure 3.10. Daily CVP for MCs and EMCs

Table 3.14. Shapley R^2 estimation results of HAR-RV-R and HAR-CVP-IIC models

This table presents the Shapley R^2 decomposition results of models (3.5) and (3.8):

$$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22}\overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|}|r_{t-1}| + \varepsilon_t \quad \text{HAR-RV-R model (3.5)}$$

$$RV_t = \lambda + \left(\theta_1 + \theta_{rv,cvp}RV_{t-1} + \theta_{r,cvp}r_{t-1} + \theta_{|r|,cvp}|r_{t-1}| + \theta_{IIC,cvp}IIC_w\right)RV_{t-1} + \theta_5\overline{RV}_5 + \theta_{22}\overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|}|r_{t-1}| + \theta_{IIC}IIC_w + \varepsilon_t \quad \text{HAR-CVP-IIC model (3.8)}$$

The Shapley-Owen R^2 decomposes goodness of fit among regressors and the sum of the Shapley-Owen R^2 of each regressor equal to the value of R^2. The column called CVP shows the sum of Shapley R^2 of four conditioning variables, that is, $RV_{t-1} * RV_{t-1}$, $R_{t-1} * RV_{t-1}$, $|R_{t-1}| * RV_{t-1}$, *and* $IIC_W * RV_{t-1}$. Δ% is the percentage change of Shapley R^2 of regressors in HAR-CVP-IIC model relative to in the HAR-RV-R model.

	RV_{t-1}	$RV_{t-1} * RV_{t-1}$	$R_{t-1} * RV_{t-1}$	$\lvert R_{t-1}\rvert * RV_{t-1}$	$IIC_W * RV_{t-1}$	CVP	$\overline{RV}_5$	$\overline{RV}_{22}$	R_t	$\lvert R_t\rvert$	IIC_W	$R_t + \lvert R_t\rvert$	R^2	CVP/R^2
AUD	25.9%						20.7%	13.3%	0.6%	6.7%		7.4%	67.3%	
	19.3%	5.5%	1.3%	6.5%	10.4%	23.7%	13.9%	9.2%	0.5%	4.1%	0.4%	4.6%	71.1%	33.4%
CAD	22.5%						21.4%	19.8%	0.1%	6.2%		6.3%	69.9%	
	14.3%	7.0%	0.1%	8.6%	7.4%	23.1%	15.3%	14.4%	0.2%	3.7%	0.5%	3.9%	71.4%	32.3%
EUR	14.5%						13.3%	13.0%	0.0%	4.0%		4.0%	44.8%	
	11.1%	2.6%	0.1%	3.9%	5.0%	11.7%	10.4%	10.3%	0.0%	2.5%	0.4%	2.5%	46.4%	25.1%
GBP	24.8%						22.5%	17.6%	0.2%	4.0%		4.2%	69.1%	
	14.5%	6.5%	0.6%	8.2%	9.5%	24.8%	15.3%	12.0%	0.1%	2.3%	0.4%	2.5%	69.4%	35.7%
MCs	21.9%						19.5%	15.9%	0.2%	5.2%		5.5%	62.8%	
	14.8%	5.4%	0.5%	6.8%	8.1%	20.8%	13.7%	11.5%	0.2%	3.1%	0.4%	3.4%	64.6%	32.2%
Δ%	-32.42%						-29.74%	-27.67%	0.00%	-40.38%		-38.18%		
INR	13.0%						20.4%	17.5%	1.0%	4.6%		5.6%	56.5%	
	10.0%	2.8%	0.7%	3.1%	6.6%	13.2%	16.5%	14.0%	0.6%	3.0%	0.5%	3.6%	57.7%	22.8%
KRW	9.3%						18.2%	6.0%	0.0%	5.2%		5.2%	38.7%	
	8.0%	2.8%	0.5%	2.7%	3.7%	9.7%	15.6%	4.8%	0.1%	3.4%	0.1%	3.5%	41.6%	23.2%
PHP	5.1%						5.0%	2.3%	0.2%	1.6%		1.8%	14.1%	
	4.2%	1.0%	0.7%	0.7%	2.4%	4.8%	3.8%	1.8%	0.2%	1.1%	0.0%	1.3%	15.8%	30.1%
BRL	15.8%						7.0%	6.4%	1.4%	8.1%		9.5%	38.7%	
	10.8%	3.3%	0.1%	4.0%	5.6%	13.0%	5.1%	4.9%	1.3%	5.6%	0.1%	6.9%	40.8%	31.9%

MXN	13.3%						13.0%	3.2%	1.9%	7.1%		9.0%	38.5%	
	12.4%	4.6%	2.4%	5.9%	7.7%	20.6%	9.9%	2.6%	1.0%	4.4%	0.3%	5.4%	51.2%	40.2%
ZAR	14.9%						14.5%	7.0%	1.8%	8.8%		10.6%	47.0%	
	9.4%	3.5%	3.2%	8.2%	5.4%	20.3%	11.4%	5.6%	0.9%	5.1%	0.2%	6.0%	52.9%	38.3%
EMCs	11.9%						13.0%	7.1%	1.1%	5.9%		7.0%	38.9%	
	9.1%	3.0%	1.3%	4.1%	5.2%	13.6%	10.4%	5.6%	0.7%	3.8%	0.2%	4.4%	43.4%	31.3%
Δ%	-23.53%						-20.00%	-21.13%	-36.36%	-35.59%		-37.14%		

3.6 Determinants of asymmetric effect

3.6.1 CAE-Qspd model

Table 3.15 reports the estimation results of equations (3.5) and (3.9): HAR-RV-R and CAE-Qspd models. For interpreting convenience, the weekly average quoted spreads here are standardized with zero as mean and one as standard deviation. In CAE-Qspd model, the coefficient sign of $\theta_{\mathrm{Qspd},r}$ is significant and positive for EMCs, which is in line with our expectation. However, the coefficient of MCs is insignificant and negative. Naturally, the size of the coefficient is significantly larger for EMCs over MCs. That means the liquidity mechanism helps to explain the asymmetric effect of EMCs more than MCs. Thus, our hypothesis is proved.

Specifically, relative to volatility on days following a negative one standard deviation return, volatility on days following a positive one standard deviation return is higher by 0.340 (2*0.231*0.736) and 0.035 (2*0.027*0.642) in the HAR-RV-R model, and 0.279 (2*0.190*0.736) and 0.036 (2*0.028*0.642) in the CAE-Qspd model following equation (3.12) for EMCs and MCs. The asymmetric effect in the latter model decreases by 18% [(0.340-0.279)/0.340] and -2.8% [(0.035-0.036)/0.035] compared to former one for EMCs and MCs, correspondingly. In other words, the liquidity mechanism helps to explain 18% of the asymmetric effect for EMCs and none of it for MCs.

3.6.2 Evidence from Shapley R^2 decomposition

Furthermore, we confirm the importance of liquidity mechanism by computing the Shapley decomposition for each variable in the HAR and CAE-Qspd models. Table 3.16 shows the computation results. We can observe that the Shapley R^2 of $\mathrm{R}_{\mathrm{t}-1} * \mathrm{Qspd}_{\mathrm{w}}$ and $|\mathrm{R}_{\mathrm{t}-1}| * \mathrm{Qspd}_{\mathrm{w}}$ for EMCs is around 3% and for MCs, only 0.3%. The former is 10 times the latter. Besides, the Shapley R^2 of direct impact from return and absolute return in the CAE-Qspd model decrease by 5.8% and

8.8% more than in the HAR model for EMCs. For MCs, the Shapley R^2 of return and absolute return remains almost unchanged between the two models. Overall, the CAE-Qspd model shows that there is a liquidity channel linking asymmetric effect to future volatility, and the channel is stronger for EMCs over MCs.

Table 3.15. Estimation results of HAR-RV-R and CAE-Qspd models

This table presents the estimation results of models (3.5) and (3.9):

$$\mathrm{RV_t} = \lambda + \theta_1 \mathrm{RV_{t-1}} + \theta_5 \overline{RV}_5 + \theta_{22} \overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|} |r_{t-1}| + \varepsilon_t \qquad \text{HAR-RV-R model (3.5)}$$

$$\mathrm{RV_t} = \lambda + \theta_1 \mathrm{RV_{t-1}} + \theta_5 \overline{RV}_5 + \theta_{22} \overline{RV}_{22} + \left(\theta_r + \theta_{\mathrm{Qspd},r} \mathrm{Qspd}_w\right) r_{t-1} + (\theta_{|r|} + \theta_{\mathrm{Qspd},|r|} \mathrm{Qspd}_w)|r_{t-1}| + \theta_{\mathrm{Qspd}} \mathrm{Qspd_w} + \varepsilon_t \qquad \text{CAE-Qspd model (3.9)}$$

We utilize a simple OLS approach to estimate the coefficients and use the Newey–West HAC standard errors to correct the problems of heteroscedasticity and autocorrelation. We also report the mean coefficients and the HKV t-statistics associated with them for MCs and EMCs. In the last row, we present the Z-test proposed by Clogg et al. (1995) to test whether the difference of average coefficients between MCs and EMCs is significant or not. The Z-score follows standardized normal distribution. The critical values for the Z-test are 2.33, 1.65, and 1.29 at 1%, 5%, and 10% significance levels, respectively.

	θ_1	θ_5	θ_{22}	$\theta_{\mathrm{Qspd},r}$	θ_r	$\theta_{\mathrm{Qspd},\lvert r\rvert}$	$\theta_{\lvert r\rvert}$	θ_{Qspd}	R^2
AUD	0.464***	0.304***	0.126***		0.067**		0.135***		67.3 %
	(12.06)	(15.8)	(5.03)		(2.57)		(3.31)		
	0.464***	0.304***	0.127***	-0.032*	0.069***	-0.048**	0.137***	0.028***	67.4 %
	(12.74)	(16.94)	(5.37)	(-1.8)	(2.58)	(-2.28)	(3.4)	(3.13)	
CAD	0.355***	0.306***	0.260***		0.023		0.074**		69.9 %
	(8.22)	(6)	(6.76)		(1.41)		(2.43)		
	0.353***	0.307***	0.259***	0.019*	0.025*	-0.003	0.073**	-0.002	70.0 %
	(8.36)	(6.04)	(6.87)	(1.72)	(1.65)	(-0.15)	(2.48)	(-0.25)	
EUR	0.282***	0.267***	0.318***		-0.001		0.093***		44.9 %
	(3.85)	(5.51)	(8.52)		(-0.09)		(3.72)		
	0.282***	0.264***	0.311***	0.004	-0.002	-0.012	0.095***	0.013**	44.9 %
	(3.66)	(6.29)	(9.24)	(0.3)	(-0.11)	(-0.53)	(3.8)	(2.04)	
GBP	0.411***	0.335***	0.180***		0.020**		0.057**		69.1 %
	(6.41)	(7.4)	(5.21)		(2.38)		(2.5)		
	0.410***	0.336***	0.180***	-0.014*	0.022***	0.005	0.057**	-0.003	69.1 %
	(6.24)	(7.7)	(6.06)	(-1.72)	(3.04)	(0.3)	(2.14)	(-0.7)	
MCs	0.378***	0.303***	0.221***		0.027**		0.090***		62.8 %
	(9.01)	(9.63)	(8.59)		(2.1)		(3.96)		
	0.377***	0.303***	0.219***	-0.006	0.028**	-0.014	0.090***	0.009*	62.8 %
	(8.86)	(10.21)	(9.26)	(-0.62)	(2.21)	(-0.95)	(3.93)	(1.79)	
INR	0.144***	0.441***	0.307***		0.122**		0.172***		56.6 %
	(4)	(8.92)	(6.88)		(2.43)		(4.17)		
	0.144***	0.440***	0.305***	-0.047	0.121**	0.013	0.174***	0.005	56.6 %
	(3.99)	(7.56)	(6.9)	(-1.57)	(2.45)	(0.53)	(4.15)	(0.71)	

KRW	0.152***	0.592***	0.01		-0.045		0.621**		38.7%
	(5.27)	(17.75)	(0.32)		(-0.51)		(1.97)		
	0.093*	0.585***	0.004	-0.069	-0.002	0.401**	0.449**	-0.146***	39.3%
	(1.75)	(15.5)	(0.11)	(-0.91)	(-0.03)	(2.35)	(2.31)	(-4.28)	
PHP	0.209***	0.259***	0.200***		0.356		0.279*		14.1%
	(4.71)	(3.73)	(3.84)		(1.59)		(1.74)		
	0.313***	0.163***	0.097	0.105***	0.146	-0.208**	0.462**	0.384*	16.2%
	(6.76)	(2.71)	(1.5)	(4.61)	(0.96)	(-2.47)	(2.24)	(1.92)	
BRL	0.346***	0.145*	0.221***		0.314***		0.719***		38.7%
	(2.89)	(1.93)	(4.7)		(2.71)		(4.6)		
	0.345***	0.143**	0.219***	-0.037	0.331***	-0.005	0.715***	0.038	38.8%
	(2.86)	(1.97)	(4.27)	(-1.31)	(2.87)	(-0.11)	(4.51)	(0.67)	
MXN	0.278***	0.372***	0.029		0.379		0.816*		38.5%
	(5.09)	(9.77)	(0.57)		(1.25)		(1.84)		
	0.278***	0.312***	-0.037	0.310**	0.296	0.515**	0.726**	-0.224**	41.8%
	(5.16)	(5.2)	(-0.51)	(2.29)	(1.29)	(2.22)	(2.06)	(-2.29)	
ZAR	0.273***	0.377***	0.115		0.259***		0.611***		47.0%
	(5.51)	(9.12)	(1.48)		(2.66)		(2.84)		
	0.272***	0.371***	0.101	0.048	0.251***	-0.004	0.620***	0.085*	47.2%
	(5.68)	(8.44)	(1.43)	(0.87)	(2.65)	(-0.06)	(2.85)	(1.77)	
EMCs	0.234***	0.364***	0.147***		0.231***		0.537***		38.9%
	(7.6)	(14.23)	(5.62)		(2.83)		(4.24)		
	0.241***	0.336***	0.115***	0.052	0.190***	0.119**	0.524***	0.024	40.0%
	(7.6)	(12.22)	(3.99)	(1.55)	(3.02)	(2.03)	(4.96)	(0.55)	
z-score	2.78***	-1.5*	2.01**		-2.47***		-3.48***		
	2.57***	-0.81	2.81***	-1.66**	-2.52***	-2.2**	-4.01***	-0.34	

Table 3.16. Shapley R^2 estimation results of HAR-RV-R and CAE-Qspd models

This table presents the Shapley R^2 decomposition results of models (3.5) and (3.8):

$$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22} \overline{RV}_{22} + \theta_r r_{t-1} + \theta_{|r|} |r_{t-1}| + \varepsilon_t \qquad \text{HAR-RV-R model (3.5)}$$

$$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22} \overline{RV}_{22} + (\theta_r + \theta_{Qspd,r} Qspd_w) r_{t-1} + (\theta_{|r|} + \theta_{Qspd,|r|} Qspd_w)|r_{t-1}| + \theta_{Qspd} Qspd_w + \varepsilon_t \qquad \text{CAE-Qspd model (3.9)}$$

The Shapley-Owen R^2 decomposes goodness of fit among regressors and the sum of the Shapley-Owen R^2 of each regressor equal to the value of R^2. Δ% is the percentage change of Shapley R^2 of regressors in CAE-Qspd model relative to in the HAR-RV-R model.

	RV_{t-1}	RV_w	RV_m	$R_{t-1} * Qspd_w$	R_{t-1}	$\lvert R_{t-1}\rvert * Qspd_w$	$\lvert R_{t-1}\rvert$	$Qspd_w$	R^2
AUD	25.9%	20.7%	13.3%		0.6%		6.7%		67.3%
	25.9%	20.7%	13.3%	0.0%	0.7%	0.1%	6.7%	0.1%	67.4%
CAD	22.5%	21.4%	19.8%		0.1%		6.2%		69.9%
	22.3%	21.3%	19.6%	0.1%	0.1%	0.3%	6.1%	0.2%	70.0%
EUR	14.5%	13.3%	13.0%		0.0%		4.0%		44.8%
	14.1%	12.8%	12.4%	0.0%	0.0%	0.5%	3.9%	1.1%	44.9%
GBP	24.8%	22.5%	17.6%		0.2%		4.0%		69.1%
	24.6%	22.4%	17.5%	0.0%	0.2%	0.4%	3.9%	0.2%	69.1%
MCs	21.9%	19.5%	15.9%		0.2%		5.2%		62.8%
	21.7%	19.3%	15.7%	0.0%	0.2%	0.3%	5.2%	0.4%	62.8%
Δ%	-0.9%	-1.1%	-1.5%		2.7%		-1.5%		
INR	13.0%	20.4%	17.5%		1.0%		4.6%		56.5%
	12.7%	20.0%	17.2%	0.1%	1.0%	0.8%	4.6%	0.2%	56.6%
KRW	9.3%	18.2%	6.0%		0.0%		5.2%		38.7%
	7.3%	16.4%	5.1%	0.1%	0.0%	5.7%	3.9%	0.9%	39.3%
PHP	5.1%	5.0%	2.3%		0.2%		1.6%		14.1%
	4.5%	3.3%	1.6%	0.5%	0.1%	1.3%	1.1%	3.7%	16.1%
BRL	15.8%	7.0%	6.4%		1.4%		8.1%		38.7%
	15.3%	6.5%	6.0%	0.1%	1.5%	0.9%	7.8%	0.6%	38.8%
MXN	13.3%	13.0%	3.2%		1.9%		7.1%		38.5%
	12.3%	11.0%	2.5%	1.6%	1.5%	5.7%	6.3%	0.8%	41.7%
ZAR	14.9%	14.5%	7.0%		1.8%		8.8%		47.0%
	14.3%	13.7%	6.4%	0.1%	1.8%	1.2%	8.6%	1.1%	47.2%
EMCs	11.9%	13.0%	7.1%		1.1%		5.9%		38.9%
	11.1%	11.8%	6.5%	0.4%	1.0%	2.6%	5.4%	1.2%	40.0%
Δ%	-6.8%	-9.2%	-8.7%		-5.8%		-8.8%		

3.7 Robustness

3.7.1 Sub-sample estimation results for AR-RV-R and HAR-RV-R models

In this section, we report the sub-sample estimation results for AR-RV-R and HAR-RV-R models in table 3.17 and table 3.18. We split the whole sample from 01 Jan 1999 to 31 Dec 2017 into five sub-periods: period 1: 01 Jan 2000-31 Dec 2005; period 2: 01 Jan 2006-31 Dec 2009; period 3: 01 Jan 2010-31 Dec 2013; and period 4: 01 Jan 2014-31 Dec 2017. Sub-period 3 covers the GFC and sub-period 4 covers the EDC.

Table 3.17. Sub-periods estimation results for AR-RV-R model

Sub-period 1	β_{rv}	γ_r	δ_{abs_r}	R^2	***Sub-period*** 2	β_{rv}	γ_r	δ_{abs_r}	R^2	***Sub-period*** 3	β_{rv}	γ_r	δ_{abs_r}	R^2
AUD/USD	0.744***	0.032	0.144***	0.31	AUD/USD	0.806***	0.081***	0.066***	0.40	AUD/USD	0.852***	0.151*	0.338***	0.76
	(11.86)	(1.52)	(3.70)			(19.29)	(5.21)	(2.81)			(23.71)	(1.72)	(2.90)	
CAD/USD	0.718***	0.012	0.058***	0.23	CAD/USD	0.913***	0.022**	0.005	0.46	CAD/USD	0.889***	0.011	0.150***	0.76
	(9.76)	(1.44)	(3.66)			(27.35)	(2.13)	(0.25)			(38.04)	(0.68)	(2.67)	
EUR/USD	0.549***	0.031	0.160**	0.12	EUR/USD	0.782***	0.009	0.035**	0.25	EUR/USD	0.923***	-0.057	0.098**	0.79
	(5.39)	(0.71)	(2.02)			(16.01)	(0.88)	(2.32)			(27.46)	(-1.61)	(1.99)	
GBP/USD	0.746***	0.012	0.085***	0.30	GBP/USD	0.830***	0.017*	0.028**	0.39	GBP/USD	0.933***	0.004	0.084***	0.80
	(20.71)	(0.85)	(2.62)			(18.67)	(1.76)	(2.19)			(52.51)	(0.17)	(2.98)	
MCs	0.689***	0.022	0.112***	0.24	MCs	0.833***	0.032***	0.033**	0.37	MCs	0.899***	0.027	0.167***	0.78
	(13.71)	(1.27)	(3.42)			(23.92)	(3.44)	(2.34)			(42.20)	(0.85)	(3.43)	
INR/USD	0.524***	0.009	0.361**	0.31	INR/USD	0.837***	0.018	0.107**	0.44	INR/USD	0.882***	0.085***	0.161***	0.47
	(6.24)	(0.10)	(2.34)			(14.44)	(0.65)	(2.25)			(46.21)	(2.82)	(6.13)	
KRW/USD	0.726***	0.224**	0.324***	0.36	KRW/USD	0.543***	-0.043	0.104	0.05	KRW/USD	0.615***	-0.152	1.464*	0.51
	(7.73)	(2.16)	(2.86)			(3.52)	(-1.16)	(1.20)			(5.46)	(-0.48)	(1.92)	
PHP/USD	0.591***	0.872**	0.377	0.15	PHP/USD	0.430***	-0.047	0.193	0.13	PHP/USD	0.745***	0.054	0.220	0.16
	(4.84)	(2.44)	(0.59)			(4.22)	(-0.45)	(1.37)			(9.29)	(0.53)	(1.14)	

BRL/USD	0.606***	0.149	0.657***	0.37	BRL/USD	0.725***	0.135	0.650***	0.59	BRL/USD	0.760***	0.627***	0.671***	0.61
	(7.40)	(1.50)	(3.43)			(17.14)	(0.93)	(5.21)			(10.41)	(2.95)	(3.98)	
MXN/USD	0.393**	0.004	0.302***	0.07	MXN/USD	0.651***	0.060***	0.122***	0.23	MXN/USD	0.614***	0.931**	1.661*	0.58
	(2.02)	(0.08)	(4.22)			(11.32)	(4.11)	(5.11)			(5.37)	(2.23)	(1.84)	
ZAR/USD	0.833***	0.166	0.672**	0.77	ZAR/USD	0.680***	0.139***	0.341***	0.35	ZAR/USD	0.744***	0.337**	0.862**	0.65
	(8.38)	(1.04)	(2.42)			(13.30)	(2.59)	(4.14)			(18.89)	(2.03)	(2.52)	
EMCs	0.612***	0.237***	0.449***	0.34	EMCs	0.644***	0.044	0.253***	0.30	EMCs	0.727***	0.314***	0.840***	0.50
	(12.03)	(3.20)	(3.48)			(17.26)	(1.31)	(6.29)			(18.60)	(2.64)	(3.56)	
Z score	1.08	-2.83***	-2.53***		Z score	3.69***	-0.33	-5.15***		Z score	3.88***	-2.33**	-2.79***	

Sub-period 4	β_{rv}	γ_r	δ_{abs_r}	R^2	***Sub-period*** 5	β_{rv}	γ_r	δ_{abs_r}	R^2
AUD/USD	0.833***	0.173***	0.122***	0.61	AUD/USD	0.784***	-0.018	0.093	0.22
	(25.25)	(5.09)	(2.79)			(10.23)	(-0.49)	(1.43)	
CAD/USD	0.910***	0.086***	0.012	0.65	CAD/USD	0.762***	0.000	0.091***	0.29
	(30.13)	(4.60)	(0.48)			(15.30)	(0.02)	(2.66)	
EUR/USD	0.840***	0.054***	0.071***	0.60	EUR/USD	0.737***	-0.048*	0.102**	0.22
	(25.66)	(4.62)	(4.09)			(11.59)	(-1.68)	(2.58)	
GBP/USD	0.869***	0.050**	0.050	0.51	GBP/USD	0.826***	-0.003	0.033	0.35
	(27.00)	(2.14)	(1.12)			(11.68)	(-0.15)	(1.17)	
MCs	0.863***	0.091***	0.064**	0.59	MCs	0.777***	-0.017	0.080**	0.27
	(33.91)	(5.16)	(2.45)			(15.34)	(-0.85)	(2.38)	
INR/USD	0.731***	0.180**	0.223*	0.39	INR/USD	0.546***	0.024	0.071**	0.17
	(10.84)	(2.08)	(1.96)			(6.66)	(1.44)	(2.58)	
KRW/USD	0.679***	0.167***	0.180***	0.25	KRW/USD	0.759***	0.004	0.086***	0.26
	(10.63)	(3.09)	(3.56)			(14.74)	(0.36)	(3.59)	
PHP/USD	0.794***	-0.055	0.171	0.46	PHP/USD	0.897***	0.021	-0.010	0.43
	(9.85)	(-0.50)	(1.46)			(13.04)	(1.02)	(-0.27)	
BRL/USD	0.447**	0.519*	0.910	0.23	BRL/USD	0.259	0.112	0.658***	0.04
	(2.33)	(1.93)	(1.50)			(1.19)	(1.07)	(3.30)	
MXN/USD	0.751***	0.158***	0.190**	0.60	MXN/USD	0.372***	-0.174	0.540**	0.09

	(19.13)	(3.40)	(2.58)			(5.69)	(-1.02)	(2.08)	
ZAR/USD	0.713***	0.148***	0.317***	0.41	ZAR/USD	0.595***	0.094	0.368***	0.12
	(13.67)	(2.77)	(2.62)			(6.37)	(1.27)	(3.61)	
EMCs	0.686***	0.186***	0.332***	0.39	EMCs	0.571***	0.014	0.285***	0.19
	(14.85)	(3.11)	(2.80)			(10.00)	(0.31)	(4.09)	
Z score	3.36***	-1.53*	-2.21**		Z score	2.70***	-0.64	-2.66***	

Table 3.18. Sub-periods estimation results for HAR-RV-R model

Sub-period1	θ_1	θ_5	θ_{22}	φ_1	μ_1	R^2	***Sub-period 2***	θ_1	θ_5	θ_{22}	φ_1	μ_1	R^2
AUD/USD	0.174**	0.417***	0.137**	0.034*	0.153***	0.27	AUD/USD	0.250***	0.281***	0.276***	0.082***	0.068***	0.37
	(2.32)	(5.17)	(2.23)	(1.81)	(4.19)			(7.06)	(5.22)	(4.72)	(4.83)	(2.88)	
CAD/USD	0.162***	0.325***	0.210**	0.011	0.053***	0.19	CAD/USD	0.150**	0.412***	0.349***	0.021**	0.007	0.44
	(3.73)	(5.50)	(2.44)	(1.35)	(3.40)			(2.49)	(8.56)	(4.69)	(2.09)	(0.37)	
EUR/USD	0.186*	0.165**	0.190**	0.017	0.148**	0.10	EUR/USD	0.132**	0.387***	0.271***	0.009	0.024	0.22
	(1.85)	(2.16)	(2.34)	(0.38)	(2.09)			(2.39)	(6.44)	(4.42)	(0.90)	(1.57)	
GBP/USD	0.211**	0.359***	0.175**	0.012	0.082	0.27	GBP/USD	0.228***	0.388***	0.222***	0.016*	0.024*	0.35
	(2.49)	(5.91)	(2.06)	(0.49)	(1.51)			(4.55)	(4.51)	(3.14)	(1.82)	(1.88)	
MCs	0.183***	0.317***	0.178***	0.018	0.109***	0.21	MCs	0.190***	0.367***	0.279***	0.032***	0.031**	0.35
	(3.18)	(6.21)	(3.09)	(0.97)	(3.12)			(4.58)	(7.08)	(5.13)	(3.38)	(2.11)	
INR/USD	0.258***	0.122**	0.150**	0.024	0.322**	0.26	INR/USD	0.261***	0.242***	0.320***	0.021	0.119***	0.40
	(4.09)	(2.09)	(1.99)	(0.27)	(2.29)			(3.79)	(3.25)	(6.05)	(0.81)	(2.66)	
KRW/USD	0.213***	0.248***	0.266***	0.207**	0.298***	0.31	KRW/USD	-0.006	0.087	0.460**	-0.054	0.093	0.03
	(2.85)	(3.27)	(2.77)	(2.10)	(5.28)			(-0.31)	(1.62)	(2.51)	(-1.38)	(0.86)	
PHP/USD	0.233***	0.224**	0.138*	0.965*	0.296	0.11	PHP/USD	0.083***	0.203***	0.119	-0.045	0.170	0.04
	(2.92)	(2.47)	(1.85)	(1.93)	(0.52)			(3.70)	(4.27)	(0.99)	(-0.45)	(1.14)	
BRL/USD	0.235***	0.175**	0.117***	0.240*	0.677***	0.44	BRL/USD	0.517***	0.133	0.100**	0.157	0.558***	0.57
	(2.90)	(2.49)	(4.28)	(1.95)	(4.44)			(4.92)	(1.24)	(1.98)	(1.08)	(3.77)	
MXN/USD	0.046	0.111*	-0.009	-0.009	0.321***	0.04	MXN/USD	0.168***	0.236***	0.235***	0.055***	0.128***	0.20

	(1.48)	(1.71)	(-0.78)	(-0.16)	(4.38)			(3.17)	(3.89)	(3.69)	(4.00)	(5.50)	
ZAR/USD	-0.046	0.208	0.838*	0.581*	1.250*	0.41	ZAR/USD	0.269***	0.336***	0.079*	0.132**	0.351***	0.34
	(-0.28)	(1.40)	(1.66)	(1.85)	(1.82)			(4.85)	(6.88)	(1.70)	(2.50)	(4.09)	
EMCs	0.157***	0.181***	0.250***	0.335***	0.527***	0.26	EMCs	0.215***	0.206***	0.219***	0.044	0.236***	0.26
	(3.97)	(4.68)	(2.79)	(3.17)	(3.36)			(8.12)	(6.95)	(5.17)	(1.35)	(5.28)	
Z score	0.38	2.11**	-0.68	-2.95***	-2.60***		Z score	-0.52	2.69***	0.88	-0.35	-4.37***	

Sub-period *3*	θ_1	θ_5	θ_{22}	φ_1	μ_1	R^2	***Sub-period*** *4*	θ_1	θ_5	θ_{22}	φ_1	μ_1	R^2
AUD/USD	0.486***	0.280***	0.102***	0.044	0.259***	0.69	AUD/USD	0.465***	0.214***	0.153***	0.175***	0.119**	0.58
	(19.81)	(17.02)	(5.46)	(1.20)	(4.84)			(6.95)	(4.12)	(4.28)	(4.04)	(2.42)	
CAD/USD	0.385***	0.282***	0.224***	-0.002	0.153***	0.74	CAD/USD	0.515***	0.171*	0.231***	0.086***	0.008	0.62
	(8.04)	(3.73)	(3.18)	(-0.05)	(3.75)			(6.98)	(1.79)	(3.42)	(3.63)	(0.28)	
EUR/USD	0.561***	0.146	0.220**	-0.054	0.092*	0.77	EUR/USD	0.482***	0.217***	0.147***	0.052***	0.074***	0.58
	(7.34)	(1.02)	(2.25)	(-1.43)	(1.94)			(5.29)	(2.96)	(3.56)	(4.25)	(3.72)	
GBP/USD	0.507***	0.259***	0.144**	0.004	0.137**	0.77	GBP/USD	0.373***	0.290***	0.211***	0.054**	0.039	0.49
	(8.34)	(3.54)	(2.44)	(0.10)	(1.97)			(6.24)	(6.22)	(2.99)	(2.30)	(0.98)	
MCs	0.485***	0.242***	0.173***	-0.002	0.160***	0.74	MCs	0.459***	0.223***	0.186***	0.092***	0.060**	0.57
	(11.55)	(3.83)	(3.48)	(-0.07)	(3.87)			(7.72)	(4.06)	(4.25)	(4.36)	(2.17)	
INR/USD	0.110***	0.460***	0.309***	0.090**	0.164**	0.46	INR/USD	0.184***	0.391***	0.167*	0.187**	0.213*	0.33
	(2.99)	(4.76)	(5.33)	(2.12)	(2.21)			(3.97)	(7.56)	(1.67)	(2.03)	(1.95)	
KRW/USD	0.090	0.619***	-0.036	-0.204	1.302***	0.40	KRW/USD	0.173**	0.257***	0.237***	0.164***	0.202***	0.23
	(0.81)	(2.90)	(-0.42)	(-0.47)	(2.59)			(1.99)	(4.23)	(3.46)	(2.83)	(3.40)	
PHP/USD	0.132*	0.165***	0.448***	0.032	0.224	0.14	PHP/USD	0.392***	0.309***	0.082	-0.134	0.266**	0.34
	(1.69)	(2.73)	(3.92)	(0.29)	(1.20)			(3.87)	(5.09)	(1.26)	(-0.85)	(2.24)	
BRL/USD	0.524***	0.030	0.173***	0.667***	0.915***	0.55	BRL/USD	0.115**	0.159**	0.178**	0.497*	0.901	0.21
	(9.50)	(0.47)	(3.61)	(2.78)	(2.62)			(2.31)	(2.10)	(2.57)	(1.74)	(1.48)	
MXN/USD	0.318***	0.294***	-0.064	1.185**	2.103**	0.52	MXN/USD	0.517***	0.114*	0.106***	0.159***	0.217***	0.57

	(24.03)	(5.25)	(-1.64)	(2.52)	(2.42)			(8.90)	(1.82)	(2.59)	(3.32)	(3.05)	
ZAR/USD	0.362***	0.365***	-0.009	0.323*	0.996**	0.61	ZAR/USD	0.451***	0.165***	0.098***	0.147***	0.321**	0.40
	(10.15)	(9.98)	(-0.17)	(1.96)	(2.14)			(8.43)	(3.09)	(2.78)	(3.02)	(2.54)	
EMCs	0.256***	0.322***	0.137***	0.349**	0.951***	0.45	EMCs	0.305***	0.232***	0.145***	0.170**	0.353***	0.35
	(8.48)	(6.66)	(3.94)	(2.46)	(3.88)			(9.05)	(7.46)	(4.46)	(2.58)	(2.96)	
Z score	4.42***	-1.01	0.59	-2.43***	-3.18***		Z score	2.25**	-0.15	0.75	-1.13	-2.39***	

***Sub-period** 5*	θ_1	θ_5	θ_{22}	φ_1	μ_1	R^2
AUD/USD	0.156***	0.268***	0.359***	-0.025	0.093	0.21
	(3.01)	(3.19)	(3.82)	(-0.71)	(1.51)	
CAD/USD	0.088**	0.322***	0.357***	-0.004	0.092***	0.24
	(2.51)	(5.02)	(5.55)	(-0.21)	(2.67)	
EUR/USD	0.139***	0.270***	0.320***	-0.048*	0.109**	0.21
	(4.27)	(4.02)	(4.56)	(-1.71)	(2.51)	
GBP/USD	0.192***	0.415***	0.225**	-0.005	0.030	0.32
	(3.04)	(4.87)	(2.20)	(-0.26)	(1.15)	
MCs	0.144***	0.319***	0.315***	-0.020	0.081**	0.25
	(4.06)	(5.44)	(4.89)	(-1.02)	(2.41)	
INR/USD	0.149**	0.305***	0.088	0.024	0.068**	0.16
	(2.31)	(3.80)	(1.38)	(1.48)	(2.48)	
KRW/USD	0.147**	0.253***	0.361***	0.004	0.082***	0.24
	(2.24)	(3.19)	(5.48)	(0.32)	(3.75)	
PHP/USD	0.341***	0.279***	0.273***	0.024	-0.012	0.41
	(6.28)	(7.24)	(3.31)	(1.11)	(-0.27)	
BRL/USD	0.009	0.089	0.162	0.113	0.648***	0.04
	(0.19)	(1.14)	(1.56)	(1.05)	(3.49)	
MXN/USD	0.044	0.246***	0.061	-0.126	0.569**	0.08
	(1.44)	(6.49)	(1.42)	(-1.07)	(2.01)	
ZAR/USD	0.086**	0.174***	0.334***	0.108	0.369***	0.10
	(2.18)	(4.32)	(3.58)	(1.28)	(3.43)	

EMCs	0.129***	0.224***	0.213***	0.024	0.287***	0.17
	(4.29)	(6.39)	(4.87)	(0.65)	(3.95)	
Z score	0.31	1.38*	1.31*	-1.05	-2.57***	

3.7.2 Robustness checks for CVP-IIC and CAE-Qspd models

For robustness check for CVP-IIC model, we use log form of IIC_w to confirm the impact of information inconsistency to volatility persistence. Consist with IIC_w, $\ln(IIC_w)$ also has negative impact to daily volatility persistence and the impact is stronger for EMCs than MCs as shown in table 3.19. For robustness check for CAE-Qspd model, instead of using high frequency liquidity measurement, we use low frequency liquidity measure in Corwin and Schultz (2012) this time. The estimation results show that the liquidity mechanism still works as shown in table 3.20.

Table 3.19. Estimation results for CVP-ln(IIC) model

$RV_t = \lambda + (\theta_1 + \theta_{|r|,cvp}|r_{t-1}| + \theta_{r,cvp}r_{t-1} + \theta_{rv,cvp}RV_{t-1} + \theta_{\ln(IIC),cvp}\ln(IIC_w))RV_{t-1} + \theta_5\left(\frac{1}{4}\sum_{i=2}^{5} RV_{t-i}\right) + \theta_{22}\left(\frac{1}{17}\sum_{i=6}^{22} RV_{t-i}\right) + \theta_{|r|}|r_{t-1}| + \theta_r r_{t-1} + \theta_{\ln(IIC)}\ln(IIC_w) + \varepsilon_t$ HAR-CVP-ln(IIC) model

	θ_1	$\theta_{rv,cvp}$	$\theta_{r,cvp}$	$\theta_{\lvert r\rvert,cvp}$	$\theta_{\ln(IIC),cvp}$	θ_5	θ_{22}	θ_r	$\theta_{\lvert r\rvert}$	$\theta_{\ln(IIC)}$	R^2
AUD	0.365***	-0.016**	-0.016***	0.020*	-0.485**	0.362***	-0.013	0.100***	0.036	0.354**	71.2%
	(2.58)	(-2.1)	(-4.29)	(1.67)	(-2.37)	(11.28)	(-0.1)	(4.17)	(0.77)	(2.28)	
CAD	0.209***	-0.042***	-0.028	0.116***	-0.191***	0.296***	0.268***	0.048***	-0.023	0.063***	72.5%
	(3.7)	(-2.83)	(-1.52)	(5.59)	(-3.59)	(5.19)	(4.74)	(4.17)	(-1.05)	(3.24)	
EUR	0.325***	-0.042**	-0.046*	0.036	-0.178***	0.207***	0.278***	0.037**	0.047	0.083***	45.8%
	(4.36)	(-2.53)	(-1.88)	(0.61)	(-2.7)	(3.59)	(7.61)	(2.14)	(1.13)	(3.09)	
GBP	0.438***	-0.011	-0.012	0.087***	0.042	0.317***	0.159***	0.027*	0	-0.018	71.9%
	(3.28)	(-1.37)	(-0.66)	(6.38)	(0.85)	(8.83)	(3.55)	(1.88)	(-0.01)	(-0.99)	
MCs	0.334***	-0.028***	-0.026**	0.065***	-0.203***	0.295***	0.173***	0.053***	0.015	0.121**	65.4%
	(4.29)	(-3.08)	(-2.02)	(3.04)	(-2.73)	(8.5)	(3.39)	(4.15)	(0.62)	(2.56)	
INR	0.275***	-0.036***	0.044	0.067	-0.039	0.418***	0.256***	0.056	0.064	0.006	57.1%
	(4.14)	(-3.53)	(0.68)	(0.66)	(-0.34)	(5.81)	(3.48)	(1.2)	(0.8)	(0.19)	
KRW	-0.139***	-0.009***	0.011***	0.080***	-0.487***	0.586***	-0.076*	0.025	0.421**	0.214***	42.1%
	(-2.74)	(-6.69)	(11.37)	(10.24)	(-26.44)	(18.39)	(-1.87)	(0.56)	(2.05)	(4.9)	
PHP	0.309**	-0.009	-0.082***	-0.011	-0.243**	0.215***	0.124**	0.365*	0.481***	0.133**	15.7%
	(2.56)	(-1.32)	(-3.41)	(-0.21)	(-2.43)	(3.29)	(2.31)	(1.77)	(3.69)	(2.19)	

BRL	0.007	0	0.078***	0.118***	-0.251***	0.145**	0.183***	-0.046	0.227**	0.368***	55.2%
	(0.05)	(-0.26)	(3.9)	(3.34)	(-2.62)	(1.96)	(3.74)	(-0.43)	(2.05)	(2.96)	
MXN	-0.156	-0.011	0.036*	0.090***	-1.062***	0.344***	-0.031	0.17	0.174	0.573***	51.0%
	(-0.61)	(-1.56)	(1.92)	(6.14)	(-3.06)	(3.03)	(-0.45)	(1.57)	(0.96)	(3.12)	
ZAR	0.199**	-0.006*	0.041***	0.074***	-0.138	0.350***	0.127***	0.003	0.122	0.343**	53.0%
	(2.02)	(-1.72)	(2.64)	(4.83)	(-1.52)	(8.56)	(2.61)	(0.08)	(1.17)	(2.08)	
EMCs	0.082	-0.012***	0.021	0.070***	-0.370***	0.343***	0.097***	0.096**	0.248***	0.273***	45.7%
	(1.29)	(-4.57)	(1.6)	(3.27)	(-4.98)	(10.46)	(3.72)	(2)	(3.91)	(4.85)	71.2%
z-score	2.5***	-1.68**	-2.55***	-0.16	1.59*	-0.99	1.32*	-0.87	-3.43***	-2.08**	

Table 3.20. Estimation results for CAE-HiLo spread models

$RV_t = \lambda + \theta_1 RV_{t-1} + \theta_5 \overline{RV}_5 + \theta_{22} \overline{RV}_{22} + (\theta_r + \theta_{\Delta Spd,r} \Delta Spd_{t-1}) r_{t-1} + (\theta_{|r|} + \theta_{\Delta Spd,|r|} \Delta Spd_{t-1}) |r_{t-1}| + \theta_{\Delta Spd} \Delta Spd_{t-1} + \varepsilon_t$ CAE-HiLo spd model

	Model	θ_1	θ_5	θ_{22}	$\theta_{\Delta Spd,r}$	θ_r	$\theta_{\Delta Spd,\|r\|}$	$\theta_{\|r\|}$	$\theta_{\Delta Spd}$	R^2
AUD	HAR	0.464***	0.304***	0.126***		0.067**		0.135***		67.3%
		(12.06)	(15.8)	(5.03)		(2.57)		(3.31)		
	CAE	0.464***	0.296***	0.130***	0.007	0.073***	-0.002	0.139***	-0.038	67.2%
		(7.72)	(11.1)	(4.59)	(0.44)	(2.76)	(-0.1)	(3.27)	(-1.57)	
CAD	HAR	0.355***	0.306***	0.260***		0.023		0.074**		69.9%
		(8.22)	(6)	(6.76)		(1.41)		(2.43)		
	CAE	0.360***	0.301***	0.261***	0.015	0.021	0.025*	0.074***	-0.011	70.8%
		(9.44)	(4.84)	(5.13)	(1.57)	(1.25)	(1.71)	(2.67)	(-1.19)	
EUR	HAR	0.282***	0.267***	0.318***		-0.001		0.093***		44.9%
		(3.85)	(5.51)	(8.52)		(-0.09)		(3.72)		
	CAE	0.285***	0.255***	0.322***	0.022***	-0.002	-0.004	0.095***	-0.005	44.5%
		(4.34)	(4.39)	(7.02)	(2.94)	(-0.14)	(-0.22)	(3.57)	(-0.5)	
GBP	HAR	0.411***	0.335***	0.180***		0.020**		0.057**		69.1%
		(6.41)	(7.4)	(5.21)		(2.38)		(2.5)		
	CAE	0.439***	0.325***	0.163***	-0.012	0.022	0.011	0.064***	-0.005	71.6%
		(11.43)	(6.04)	(2.95)	(-1.11)	(1.52)	(0.7)	(2.9)	(-0.57)	
MCs	HAR	0.378***	0.303***	0.221***		0.027**		0.090***		62.8%
		(9.01)	(9.63)	(8.59)		(2.1)		(3.96)		
	CAE	0.387***	0.294***	0.219***	0.008	0.028**	0.007	0.093***	-0.015	63.5%
		(9.98)	(7.6)	(6.31)	(0.96)	(2.02)	(0.56)	(4.08)	(-1.43)	
INR	HAR	0.144***	0.441***	0.307***		0.122**		0.172***		56.6%
		(4)	(8.92)	(6.88)		(2.43)		(4.17)		
	CAE-Spd	0.137***	0.448***	0.302***	-0.035**	0.131**	-0.021	0.173***	0.053	56.4%
		(3.78)	(7.07)	(6.03)	(-2.36)	(2.49)	(-0.61)	(2.86)	(1.35)	
KRW	HAR	0.152***	0.592***	0.01		-0.045		0.621**		38.7%
		(5.27)	(17.75)	(0.32)		(-0.51)		(1.97)		
	CAE-Spd	0.169***	0.583***	0.001	-0.031***	-0.003	-0.022	0.663**	-0.043	38.8%
		(7.23)	(20.39)	(0.02)	(-5.98)	(-0.05)	(-0.89)	(2.14)	(-1.11)	
PHP	HAR	0.209***	0.259***	0.200***		0.356		0.279*		14.1%

		(4.71)	(3.73)	(3.84)		(1.59)		(1.74)		
	CAE	0.306***	0.238***	0.159***	0.145**	0.167	-0.059	0.528***	-0.01	15.0%
		(5.05)	(6.03)	(3.42)	(2.34)	(0.94)	(-1.54)	(2.97)	(-0.14)	
BRL	HAR	0.346***	0.145*	0.221***		0.314***		0.719***		38.7%
		(2.89)	(1.93)	(4.7)		(2.71)		(4.6)		
	CAE	0.436***	0.123*	0.180***	0.059	0.302***	0.214*	0.660***	-0.246	49.1%
		(5.06)	(1.84)	(5.31)	(0.86)	(2.72)	(1.92)	(4.15)	(-1.59)	
MXN	HAR	0.278***	0.372***	0.029		0.379		0.816*		38.5%
		(5.09)	(9.77)	(0.57)		(1.25)		(1.84)		
	CAE	0.251***	0.386***	0.025	0.073	0.353	0.133	0.786**	-0.083	39.4%
		(4.95)	(10.25)	(0.43)	(0.67)	(1.24)	(0.85)	(2.02)	(-0.53)	
ZAR	HAR	0.273***	0.377***	0.115		0.259***		0.611***		47.0%
		(5.51)	(9.12)	(1.48)		(2.66)		(2.84)		
	CAE	0.278***	0.337***	0.144**	0.079***	0.059	0.286***	0.340***	-0.304***	56.5%
		(6.82)	(10.1)	(2.29)	(2.74)	(1.3)	(9.59)	(4.86)	(-6.38)	
EMCs	HAR	0.234***	0.364***	0.147***		0.231***		0.537***		38.9%
		(7.6)	(14.23)	(5.62)		(2.83)		(4.24)		
	CAE	0.263***	0.352***	0.135***	0.048*	0.168**	0.089**	0.525***	-0.105**	42.5%
		(10.3)	(15.79)	(5.79)	(1.69)	(2.42)	(2.21)	(4.96)	(-2.19)	
z-score	HAR	2.78***	-1.5*	2.01**		-2.47***		-3.48***		
	CAE	2.68***	-1.31*	2**	-1.36*	-1.97**	-1.92**	-3.99***	1.83**	

3.8 Conclusion

Volatility is a good measure of risk, which is important for asset allocation, asset pricing, and risk management. After seminal studies conducted by Engle (1982) and Bollerslev (1986), many variants of the GARCH model have been built to capture FX statistical features. Among the features, two stylized facts draw large attention: Volatility persistence and asymmetric volatility. These features are well-documented and examined for MCs, however, limited studies investigate them for EMCs. Hence, in this chapter we aimed to compare the two features between MCs and EMCs and further investigate the determinants of the differences.

For MCs, we included AUD, CAD, EUR, and GBP and for EMCs, we used INR, KRW, PHP, BRL, MXN, and ZAR. All rates are against the USD and the sample period is from January 2000 to December 2017. We used restricted (AR model) and unrestricted (HAR model) autoregressive models to provide robust empirical evidence that EMCs have lower volatility persistence and larger asymmetric return effect than MCs. Then, we examined the determinants of the differences. With respect to volatility persistence, the MDH theory suggests that the persistence of exogenous information flow is the source for it. To test this hypothesis, we build HAR-CVP-IIC model allowing daily volatility to be time-varying inspired by HAR-CVP model in Wang and Yang (2017). We found that daily volatility persistence decreases with inconsistency of information flow, and the stronger negative impact causes EMCs to have lower volatility persistence than MCs. For the return asymmetric effect, we expected the higher market illiquidity associated with higher asymmetric effect, considering the positive relationship between illiquidity level and return. To test this hypothesis, we built a CAE-Qspd model allowing return direct impact to be time-varying. We found that return asymmetry increases with the illiquidity level and it can partly explain why EMCs have higher asymmetric volatility than MCs.

This essay compared two stylized features of volatility between MCs and EMCs for the first time and suggested that information arrival patterns and market state are crucial determinants. Besides, in the equity market, papers found that volatility persistence of emerging economies is higher than that of developed ones due to lower pricing efficiency (e.g., Cajueriro and Tabk 2004a, 2004b; Tolvi, 2003), and emerging equity markets have weaker asymmetric effect than developed countries because of the lower participation of private investors and coverage by financial analysts (e.g., Talpsepp and Rieger, 2010). It is interesting that our findings are completed opposite to those of the equity market, which shows the uniqueness of the FX market and its volatility dynamics.

Chapter 4: The source of long memory in FX volatility

4.1 Introduction

It is a stylized fact that the volatility of asset prices changes over time in a fairly persistent manner. However, there is no consensus on the source of its long memory. The most common hypothesis is from MDH, which proposes that the price changes and trading volume of financial assets are equilibrium outcomes of the impact of information and are jointly related to an unobservable dynamic information flow variable (e.g., Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983). However, because the underlying information flow is unobservable, the empirical results of the potential theories are mixed and depend on how well the latent variable is estimated.[52]

One study among these takes a different approach. Besides the latent information flow process, Liesenfeld (2001) argues that the impact of information on prices is also a crucial determinant of the persistence of volatility. His extended MDH model captures much more of the persistence of volatility. More importantly, he finds that the long-run dynamics of volatility are associated with market sensitivity, whereas information flow directs the short-run dynamics. Motivated by Liesenfeld (2001), Berger et al. (2009) construct an empirical specification to explain the persistence of volatility using time-varying trader sensitivity to new information. They estimate the daily market sensitivity parameters by regressing return on order flow using high-frequency data.[53] They find that time-varying market sensitivity explains a large share of the long-run

[52] The MDH volatility persistence is empirically mixed. By using trading volume as an information flow proxy, Lamoureux and Latrapes (1990) showed that ARCH effects tend to disappear when volume is included in the GARCH variance equation in the equity market. By employing the conditional moment method in Lamoureux and Latrapes (1994) to extract the underlying information flow, He and Velu (2014) proved that the GARCH persistence disappears when controlling the information flow for Dow Jones stocks. By using FX market data, Laux and Ng (1993) argued that prior findings that GARCH is the result of the rate of information arrival by using volume as a proxy are overly strong due to specification errors. Fleming and Kirby (2011) found that volume plays only a minor role in explaining the serial dependence in the data with respect to short-run dynamics.
[53] The relationship between returns and order flow has been studied extensively in the FX market. Evans et al. (2002) show that order flow explains daily FX changes with R-square ranging from 40 to 60%.

variation in volatility. Their idea is interesting and intuitive, but no following study extends or modifies their models.

Asymmetric volatility, or the leverage effect, was discussed broadly in previous studies (e.g., Black, 1976; Christie, 1982; Bekaert and Wu, 2000, among others). It originates from a stylized fact that the market reacts to news asymmetrically: bad news has a greater impact than does good news. Recently, Patton and Sheppard (2015) investigate the dynamic of volatility using realized semi-variance.[54] They find that "bad" volatility associated with negative returns (negative realized semi-variance) drives the persistence of volatility.

Motivated by both Berger et al. (2009) and Patton and Sheppard (2015), we propose a new empirical specification that links volatility to good and bad news, measured as the order imbalance (OI) in the market, and to traders' sensitivity to that news. Because the long-run dynamics of volatility are associated with market sensitivity more than order flow, as Liesenfeld (2001) and Berger et al. (2009) show, we mainly test whether market sensitivity to bad news can explain the long memory of volatility more than sensitivity to good news does. We estimate the time-varying daily market sensitivity related to good or bad news from high-frequency data. Surprisingly, we find that the two have similar explanatory power for volatility at a daily frequency. This finding is different from that of Patton and Sheppard (2015), where bad volatility drives the persistence of volatility.

Furthermore, it is important to understand the dynamics of tail risk and the tail risk premium, which is shown to predict returns (e.g., Kelly and Jiang, 2014). Therefore, we also connect volatility with market sensitivity to tail risks. We use Koenker and Bassett's (1978)

[54] The"realized semivariance" is a new estimator proposed by Barndorff-Nielsen, Kinnebrock, and Shephard (2010) which decomposes the usual realized variance into a component that relates only to positive high frequency returns and a component that relates only to negative high frequency returns.

quantile regression model to estimate time-varying trader sensitivity to information across the quantiles of the conditional distribution. Again, we test whether market sensitivity to extreme bad news can explain the long memory of volatility more than sensitivity to extreme good news does. The empirical results show that market sensitivity to extreme good and bad news does not contribute differently to the long memory of volatility. However, we find that sensitivity to tail risk has stronger explanatory power than that to average news, which emphasizes the importance of the tail persistence of volatility.

In sum, this study expands on Berger et al. (2009) and Patton and Sheppard (2015). It finds interesting results that price sensitivity to (extreme) good and bad news has similar importance to explain the long memory of volatility. This finding is different from Patton and Sheppard (2015), who find that bad volatility drives volatility persistence. However, we find that sensitivity to tail risk has stronger explanatory power than that to average news, which emphasizes the importance of the tail persistence of volatility.

4.2 Data

In this chapter, we employ high-frequency spot AUD/USD exchange rate data from January 1, 2000 to December 31, 2013 sourced from TRTH database maintained by SIRCA. The data 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. To clean the data, we first drop all entries from Friday 17:00 New York time to Sunday 17:00 New York time due to slow trading. Then, we remove outliers following Barndorff–Nielsen et al. (2009) and delete thin trading weekdays and holidays.[55]

[55] As with the previous chapter, we filtered high-frequency data following the steps suggested in Barndorff-Nielsen et al. (2009). We deleted entries with a bid, ask and trade price equal to zero; entries missing bid, ask, price, date or time; entries with negative spread; entries for which the spread is more than 50 times the median spread on that day; and entries where the mid-quote deviated by more than 10 mean absolute deviations from a rolling centered median (excluding the observation under consideration) of 50 observations (25 observations before and 25 after). We also dropped the two most important holidays: New Year's Day (January 1 each year) and Christmas Day (December 25 each year) due to thin trading. Furthermore, we deleted 32 slow trading days over the sample period, which have over

Based on the cleaned high-frequency data, we construct quotes and price–time series sampled at a 5-minute frequency and then build 5-minute log-return ($100 * \ln(P_t/P_{t-1})$). Because we use direct quotations, the positive and negative returns indicate currency and appreciation, respectively. We also construct 5-minute OI. Following Lee and Ready (1991), we identify the trade initiator by the "mid-quote test": if a trade occurs at a price above (below) the prevailing mid-quote, we classify it as buyer (seller) initiated. OI is the net of AUD buyer- and seller-initiated trades per 5 minutes. For easier coefficient documentation, we divide OI by 1,000. Using 5-minute variables, we build or estimate the daily variables, which we describe in the following sections.

4.3 Empirical specification

4.3.1 Motivation

4.3.1.1 Good and bad market sensitivity

Our starting point is the behavior of intra-daily FX returns. Evans and Lyons (2002) show that order flow explains daily FX changes with R^2 ranging from 40% to 60%.[56] Additionally, order flow could reflect institutional research on macro fundamentals long before an announcement (e.g., Peiers, 1997). Hence, order flow is a crucial determinant of returns and conveys information that is either private or public known among economic agents. Empirically, the parameter λ_t in relationship (4.1) can reflect how traders adjust the price in reaction to order flow. In addition, the positive relationship between order flow and returns (e.g., Evans and Lyons, 2002 and Berger el at., 2008) implies that the sign of λ_t should be positive and when λ_t increases, prices absorb information via order flow in a more timely manner.

$$r_{t,i} = \lambda_t * OI_{t,i} \tag{4.1}$$

5 hours quoting gap during a day.

[56] In this chapter, we employ TRTH firm quotes data which do not provide volume information of each transaction. Therefore, we use order imbalance which is the net of buyer- and seller- initiated number of trades as a proxy for order flows.

By squaring and summing each side of Equation (4.1) over all daily intervals, we obtain the following equation for daily RV:

$$RV_t = \sum_{i=1}^{m} r_{t,i}^2 = \lambda_t^2 \sum_{i=1}^{m} OI_{t,i}^2 \tag{4.2}$$

Define $OI_t^{(2)} = \sum_{i=1}^{m} OI_{t,i}^2$ and write

$$\mathrm{RV_t} = \lambda_t^2 OI_t^{(2)}. \tag{4.3}$$

That is, daily variance is a function of the aggregate daily squared OI and the squared sensitivity of the price to order flow.

Patton and Sheppard (2015) argue that future volatility is much more related to the volatility containing bad news than that containing good news. Inspired by their study, we propose a new empirical specification of volatility that links volatility to positive and negative return-related price sensitivity and order flow. Specifically, we consider the relationships in Equation (4.4). We decompose intra-day returns into positive and negative parts, and thus separate OI into two groups. For positive/negative returns, it is not necessary for the respective OI to be positive/negative. However, over 70% of the intra-day returns and OI have the same sign direction over our sample period, which shows the positive relationship between order flow and price changes. Therefore, we note the corresponding OI as $\mathrm{r}_{t,i}^{+}/\mathrm{r}_{t,i}^{-}$ as $OI_{t,i}^{+}/OI_{t,i}^{-}$. Then, λ_t^{+} and λ_t^{-} show how traders react to bad and good news:

$$\mathrm{r}_{t,i}^{+} = \lambda_t^{+} * OI_{t,i}^{+} \quad \& \quad \mathrm{r}_{t,i}^{-} = \lambda_t^{-} * OI_{t,i}^{-} \tag{4.4}$$

Again, by squaring and summing each side in Equation (4.4) over all daily intervals, we obtain the following equation for the daily positive and negative realized semi-variance in Barndorff-Nielsen et al. (2010):

$$PSV_t = \sum_{i=1}^{m} r_{t,i}^{+2} = \lambda_t^{+2} \sum_{i=1}^{m} OI_{t,i}^{+2} \;\; \& \;\; NSV_t = \sum_{i=1}^{m} r_{t,i}^{-2} = \lambda_t^{-2} \sum_{i=1}^{m} OI_{t,i}^{-2} \tag{4.5}$$

Define $OI_t^{+(2)} = \sum_{i=1}^{m} OI_{t,i}^{+2}$ and $OI_t^{-(2)} = \sum_{i=1}^{m} OI_{t,i}^{-2}$, then write:

$$\mathrm{PSV_t} = \lambda_t^{+2} OI_t^{+(2)} \quad \& \quad \mathrm{NSV_t} = \lambda_t^{-2} OI_t^{-(2)} \tag{4.6}$$

That is, daily positive/negative semi-variance is a function of the aggregate daily squared positive/negative OI and the squared positive/negative market sensitivity. The sum of $\mathrm{PSV_t}$ and $\mathrm{NSV_t}$ is daily RV. Therefore, daily variance is a function of the aggregate daily squared good and bad OI, and the squared traders' sensitivity to good and bad news.

Based on the derivation above, we can write the empirical specification for the overall and good/bad market sensitivity in Equations (4.7) and (4.8):

$$\mathrm{r_{t,i}} = \lambda_\mathrm{t} * \mathrm{OI_{t,i}} + \varepsilon_\mathrm{t,i} \tag{4.7}$$

$$\mathrm{r}_{t,i}^{+} = \lambda_t^{+} * OI_{t,i}^{+} + \varepsilon_\mathrm{t,i} \quad \& \quad \mathrm{r}_{t,i}^{-} = \lambda_t^{-} * OI_{t,i}^{-} + \varepsilon_\mathrm{t,i} \tag{4.8}$$

We present the estimation results of models (4.7) and (4.8) in Table 4.1 with fixed slope coefficients of $\lambda_\mathrm{t}, \lambda_t^{+}$, and λ_t^{-} for the entire sample, allowing for a non-zero intercept. Additionally, we summarize the daily results for λ_t, λ_t^{+} and λ_t^{-} in Table 4.2. In Table 4.1, the R^2 of model (4.7) is 30%, which is slightly below the R^2 reporting in Evans and Lyons (2002), who investigate the impact of daily order flow on daily exchange rate returns. However, after allowing λ_t to be estimated at a daily frequency, the mean and median of the R^2 increase to around 40%, as in Table 4.2. The results are similar to those of Evans and Lyons (2002). The R^2 improvement may suggest that it is better to study the features of market sensitivity by allowing for time variation. For the size of market sensitivity, the median and mean of the daily λ_t estimates are 2.4 and 3, respectively, which are higher than the fixed λ_t. We also report the percentiles of the daily λ_t and R^2 in Table 4.2. They show the strong positive relationship between returns and OI.

Inspired by Patton and Sheppard (2015), we also estimate good and bad market sensitivity by regressing the positive and negative returns onto contemporaneous OI. In Table 4.1, we observe that the R^2 of the two regressions in Equation (4.8) are almost identical, which are around 17%.

Again, after allowing λ_t^+ and λ_t^- to be estimated at a daily frequency, the mean and median of their R^2 increase to around 25%. For both fixed and daily market sensitivity, λ_t^+ is always slightly larger than or equal to λ_t^-. The results provide weak evidence that prices react more with AUD selling than to buying pressures. However, the gap between λ_t^+ and λ_t^- is much smaller than our expectation. It might be due to the "two-sided" nature of the FX market (Bollerslev, Chou, and Kroner, 1992). This implies that the order selling/buying pressure on AUD is equivalent to the buying/selling pressures to USD. Bad news from the United States will cause AUD/USD appreciation and bad news from Australia will cause AUD/USD deprecation. If the economies' sizes and development are similar, the market is not necessarily more sensitive to either downward or upward order pressures. Finally, we report the percentiles of the daily λ_t^+ and λ_t^- and R^2 in Table 4.2. Again, they show the strong positive relationship between positive/negative returns and the respective OI.

Table 4.1. Estimation results from regressing returns onto contemporaneous OI

This table reports OLS estimates of Equations (4.7) and (4.8) with the Newey–West HAC t statistics. The regression is estimated using the entire 2000–2013 sample of intra-day observations, allowing for a non-zero intercept and treating the slope coefficients, λ_t, λ_t^+, and λ_t^-, as identical for all trading days. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

$$r_{t,i} = \lambda_t * OI_{t,i} + \varepsilon_{t,i} \tag{4.7}$$

$$r_{t,i}^+ = \lambda_t^+ * OI_{t,i}^+ + \varepsilon_{t,i} \quad \& \quad r_{t,i}^- = \lambda_t^- * OI_{t,i}^- + \varepsilon_{t,i} \tag{4.8}$$

Dependent variables	N	Intercept	Market sensitivity	R^2
$r_{t,i}$	1,013,917	0.000***	2.191***	0.296
		(3.84)	(49.42)	
$r_{t,i}^+$	446,005	0.029***	1.391***	0.172
		(61.52)	(35.2)	
$r_{t,i}^-$	453,291	-0.029***	1.385***	0.169
		(-67.56)	(33.38)	

Table 4.2. Summary of daily results from regressing returns onto contemporaneous order flow (I).

This table summarizes the daily OLS estimates of λ_t, λ_t^+, and λ_t^- from Equations (4.7) and (4.8) with the Newey–West HAC t statistics. The estimates are obtained daily using intra-daily data for each day in the 2000–2013 sample, which contains T=3604 days. The table also presents the R^2s for the daily regressions. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

$$r_{t,i} = \lambda_t * OI_{t,i} + \varepsilon_{t,i} \tag{4.7}$$

$$r_{t,i}^+ = \lambda_t^+ * OI_{t,i}^+ + \varepsilon_{t,i} \quad \& \quad r_{t,i}^- = \lambda_t^- * OI_{t,i}^- + \varepsilon_{t,i} \tag{4.8}$$

	Mean	STD	P1	P5	P10	P25	P50	P75	P90	P95	P99
λ_t	3	1.7	0.8	1.1	1.3	1.7	2.4	4	5.5	6.4	8.2
R^2	0.39	0.09	0.16	0.24	0.28	0.33	0.40	0.45	0.50	0.53	0.59
λ_t^-	1.79	1.19	0.32	0.52	0.66	0.95	1.45	2.31	3.37	4.01	5.85
R^2	0.25	0.13	0.02	0.07	0.09	0.16	0.23	0.33	0.42	0.49	0.62
λ_t^+	1.82	1.42	0.30	0.52	0.66	0.97	1.49	2.37	3.50	4.27	6.09
R^2	0.26	0.13	0.02	0.06	0.10	0.16	0.24	0.34	0.43	0.49	0.62

4.3.1.2 Market sensitivity to tail risk

In the previous section, we employed an OLS regression to estimate the average relation between positive or negative returns and OI. Though we decompose returns into positive and negative parts, the OLS regression cannot detect significant differences between good and bad market sensitivity. Hence, we use Koenker and Bassett's (1978) quantile regression model to estimate traders' sensitivity to new information across the quantiles of the conditional distribution and test whether the market is more sensitive to extreme bad news than to extreme good news, which people would normally expect.

We first do the derivation. Equation (4.9) shows the relationship between OI and returns across the quantiles of the return distribution. Then, λ_t^Q show how the price will absorb timely buying/selling pressures depending on the quantile of returns:

$$\mathrm{r}_{t,i}^{Q} = \lambda_t^Q * OI_{t,i}^{Q} \tag{4.9}$$

By squaring and summing each side in Equation (4.9) over all daily intervals, we obtain the following equation for daily variance:

$$\mathrm{RV_t} = \sum_Q {\mathrm{r}_{t,i}^{Q}}^2 = \sum_Q {\lambda_t^Q}^2 {OI_{t,i}^{Q}}^2, \text{ define } OI_t^{Q(2)} = \sum_Q {OI_{t,i}^{Q}}^2 \tag{4.10}$$

For the empirical specification, we estimate Equation (4.11) using Koenker and Bassett's (1978) quantile regression model to estimate market sensitivity with upper (95%), median (50%), and lower (5%) quantiles at a daily frequency, and then use the results to study the tail persistence of volatility.

$$\mathrm{r}_{t,i}^{Q} = \lambda_t^Q * OI_{t,i}^{Q} + \varepsilon_{\mathrm{t,i}} \tag{4.11}$$

Figure 4.3 plots the market sensitivity in Equation (4.11) for quantiles from 5% to 95%

using the quantile regression model. We see that market sensitivity increases with return quantiles, but increases more with AUD depreciation. Thus, prices react more to AUD selling than to buying pressure according to the entire sample. However, the daily estimates for the 95%, 50%, and 5% quantiles show different results. In Table 4.4, we summarize the daily estimates of $\lambda_t^{95\%}$, $\lambda_t^{50\%}$, and $\lambda_t^{5\%}$ in Equation (4.11). The mean and median of extreme quantile market sensitivity are larger than that of the 50% quantile, which is in line with the results for the fixed estimates. However, the size of the $\lambda_t^{5\%}$ is consistently larger than those for $\lambda_t^{95\%}$ for all percentiles, and the equality test shows that $\lambda_t^{5\%}$ is larger than $\lambda_t^{95\%}$ at the 10% significance level. The results for the daily frequency are contrary to those for the whole sample. Here, we provide one potential explanation. The importance of good or bad news varies at different data frequencies. Given that extreme bad events do not occur every day, using the whole sample to estimate market sensitivity shows that traders are more sensitive to AUD selling than to buying pressures, which is consistent with prior studies and our expectation. However, when we estimate the parameters at the daily frequency, AUD buying pressure or USD selling pressure turn out to be more important to traders.

Figure 4.1. Fixed quantile market sensitivity

In this figure, the red line presents the fixed slope coefficient λ_t^Q in Equation (4.11) for quantiles from 5% to 95% using Koenker and Bassett's (1978) quantile regression model. The quantiles of the return distribution are on the x-line. The lower (upper) quantiles indicate AUD appreciation (depreciation). The λ_t^Q are on y-line. The green/blue line show the 95% confidence upper/lower limits.

$$r_{t,i}^Q = \lambda_t^Q * OI_{t,i}^Q + \varepsilon_{t,i} \quad (4.11)$$

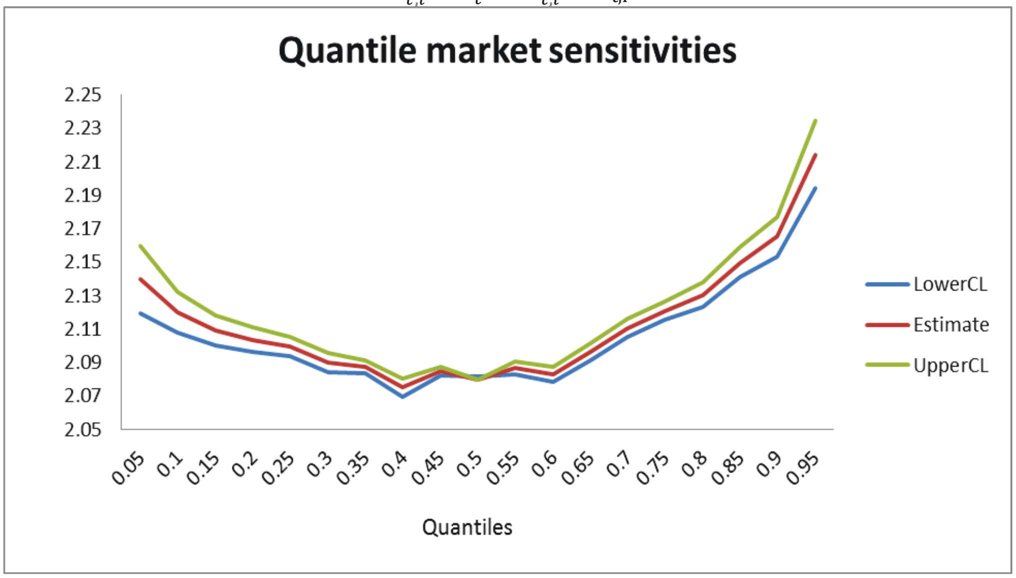


Table 4.3. Summary of daily results from regressing returns onto contemporaneous order flow (II)

This table summarizes the daily OLS estimates of λ_t^{Q5}, λ_t^{Q50} and λ_t^{Q95} from Equation (4.11) with the Newey–West HAC t statistics. The estimates are obtained daily using intra-daily data for each day in the 2000–2013 sample, which contains T=3604 days. The table also presents the R^2s for the daily regressions. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

$$r_{t,i}^Q = \lambda_t^Q * OI_{t,i}^Q + \varepsilon_{t,i} \quad (4.11)$$

	Mean	STD	P1	P5	P10	P25	P50	P75	P90	P95	P99
λ_t^{Q5}	3.13	2.06	0.70	0.97	1.17	1.67	2.54	4.17	5.87	6.93	9.28
λ_t^{Q50}	2.90	1.56	0.87	1.09	1.28	1.72	2.43	3.84	5.11	5.95	7.49
λ_t^{Q95}	3.05	1.94	0.65	0.94	1.16	1.65	2.48	4.00	5.80	6.92	8.89

4.3.2 Empirical Specification

We test the following empirical log version of Equations (4.3), (4.6), and (4.10):

$$ln(\mathrm{RV_t}) = \alpha + 2\beta_\lambda \ln(\lambda_t) + \beta_{OI}\ln(OI_t^{(2)}) + \varepsilon_t \quad (4.12)$$

$$ln(\mathrm{RV_t}) = \alpha + 2\beta_\lambda^+ \ln(\lambda_t^+) + \beta_{\mathrm{OI}}^+ \ln\left(OI_t^{(2)+}\right) + 2\beta_\lambda^- \ln(\lambda_t^-) + \beta_{\mathrm{OI}}^- \ln(OI_t^{(2)-}) + \varepsilon_t \quad (4.13)$$

$$ln(\mathrm{RV_t}) = \alpha + \sum_Q 2\beta_\lambda^Q \ln(\lambda_t^Q) + \sum_Q \beta_{\mathrm{oi}}^Q \ln(OI_t^{(2),Q}) + \varepsilon_t,$$

where Q equals quantile 5%, 50%, and 95%. (4.14)

Now, the log RV is not only a function of the market sensitivity parameters and the integrated squared order flow in Equation (4.12), but also a function of the two determinants associated with positive and negative returns in Equation (4.13) or extreme tail risk in Equation (4.14). The model extensions provide the opportunity to test whether bad or extreme bad news can help explain realized volatility more than good news, as in Patton and Sheppard (2015). With respect to the size of the coefficients, we can also test whether $\beta_\lambda = \beta_{OI} = 1$, as Equation (4.12) implies; whether $\beta_\lambda^+ + \beta_\lambda^- = \beta_{\mathrm{OI}}^+ + \beta_{\mathrm{OI}}^- = 1$, as Equation (4.13) implies; and whether $\beta_\lambda^{5\%} + \beta_\lambda^{50\%} + \beta_\lambda^{95\%} = \beta_{\mathrm{OI}}^{5\%} + \beta_{\mathrm{OI}}^{50\%} + \beta_{\mathrm{OI}}^{95\%} = 1$ as Equation (4.14) implies. As previous studies show, we expect that information from currency depreciation can explain more than appreciation does about the long memory of volatility. Therefore, we can test whether $\beta_\lambda^- > \beta_\lambda^+$ and $\beta_{\mathrm{OI}}^- > \beta_{\mathrm{OI}}^+$ in Equation (4.13) and $\beta_\lambda^{95\%} > \beta_\lambda^{5\%}$ and $\beta_{\mathrm{OI}}^{95\%} > \beta_{\mathrm{OI}}^{5\%}$ in Equation (4.14). We introduce the daily variable in next section.

4.3.3 Construction of the daily data

We construct the daily variables for our empirical models following the description in the motivation section. Daily return is the continuously compounded returns: $r_t = \sum_{\mathrm{i}=1}^{\mathrm{m}} 100 * \ln\left(\frac{\mathrm{P_{t,i}}}{\mathrm{P_{t-1,i}}}\right) = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{r_{t,i}}$, where $\mathrm{P_{t,i}}$ is the AUD/USD opening mid-quote for interval i, $\mathrm{r_{t,i}}$ is the log return in interval i, and m is the number of intraday sampling intervals. We calculate the daily variables with m equal to 288. The first interval of a trading day is the period from 17:00 to 17:05 (New York time). Thus, AUD is appreciating or depreciating when return shows negative or positive signs, respectively. Additionally, the returns in the 5%/95% quantiles mean extreme AUD appreciation/depreciation. Following Andersen et al. (2001), who introduce a natural estimator for integrated variance, the daily realized volatility or RV is the sum of the squared 5-min log returns over a trading day: $rv_t = \sum_{i=1}^{m} r_{t,i}^2$.

We construct market sensitivity and its variants using 5-minute return and order flow. $\lambda_t^+ / \lambda_t^-$ is the coefficient from regressing $r_{t,i}^+ / r_{t,i}^-$ on its respective OI in Equation (4.8). The $OI_t^{(2)+} / OI_t^{(2)-}$ in Equation (4.13) is the sum of the squared 5-minute OI associated with positive/negative returns over a trading day. To test tail persistence, we estimate market sensitivity for 5%, 50%, and 95% quantiles of the conditional distribution using Koenker and Bassett's (1978) quantile regression model in Equation (4.11). The $OI_t^{(2),5\%} /\ OI_t^{(2),50\%} /\ OI_t^{(2),95\%}$ in Equation (4.14) are the sum of the squared 5-minute OI associated with returns less than or equal to the 5% quantile/between the 5% and 95% quantiles/higher than or equal to the 95% quantile over a trading day.

Table 4.5 reports the summary statistics of all daily log-transformed variables we discuss above. The last two columns present the variables' correlation with log RV and Lo's (1991) modified R/S (MRS) statistic. The correlations show that market sensitivity and squared OI, and their decompositions, are significantly correlated with log RV. The modified Lo test shows that log RV and all other potential determinants have a long memory at the 1% significance level.

Table 4.4. Summary statistics for the daily log-transformed variables

Daily Variables	Mean	Median	STD	Skew	Ex.kurt	Max	Min	Correlations with $ln(\mathrm{RV_t})$	R/S statistic
$ln(\mathrm{RV_t})$	-0.653	-0.729	0.796	0.768	1.612	3.637	-3.964	1.00	2.38***
$\ln(\lambda_t)$	0.948	0.894	0.553	0.099	-0.677	2.701	-0.507	0.45***	2.61***
$\ln(\lambda_t^-)$	0.388	0.376	0.632	-0.073	-0.133	2.403	-2.376	0.41***	3.86***
$\ln(\lambda_t^+)$	0.405	0.398	0.653	-0.232	0.682	2.438	-3.38	0.43***	3.88***
$\ln(\lambda_t^{5\%})$	0.957	0.933	0.612	0.004	-0.444	3.74	-1.043	0.38***	3.24***
$\ln(\lambda_t^{50\%})$	0.928	0.886	0.522	0.07	-0.702	2.289	-0.469	0.47***	2.49***
$\ln(\lambda_t^{95\%})$	0.932	0.91	0.611	-0.034	-0.371	2.732	-1.611	0.43***	3.24***
$\ln(OI_t^{(2)})$	-5.816	-5.7	1.094	-0.488	0	-3.353	-11.687	0.31***	3.95***
$\ln(OI_t^{(2),-})$	-4.281	-4.162	1.117	-0.468	0.157	-1.348	-10.289	0.28***	4.35***
$\ln(OI_t^{(2),+})$	-4.329	-4.25	1.192	-0.289	-0.143	-1.539	-10.725	0.32***	4.31***
$\ln(OI_t^{(2),5\%})$	-6.092	-6.05	1.304	-0.148	-0.154	-1.778	-11.331	0.27***	5.34***
$\ln(OI_t^{(2),50\%})$	-3.84	-3.74	1.099	-0.458	0.016	-1.323	-9.808	0.31***	3.89***
$\ln(OI_t^{(2),95\%})$	-5.57	-5.508	1.322	-0.249	0.03	-1.716	-11.513	0.24***	5.58***

4.4 Empirical results

In this section, we report the estimation results of models (4.12) to (4.14). We utilize a simple OLS approach to estimate the coefficients and use the Newey–West heteroscedasticity-autocorrelation-consistent standard errors to correct the problems of heteroscedasticity and autocorrelation. In this chapter, we investigate the source of the long memory of RV. Therefore, the models should explain the persistence of the RV. Otherwise, the error term will have the same persistence as do the original data. Therefore, we employ Lo's (1991) MRS statistic to test the presence of long memory in residuals. It is a modification of Mandelbrot's (1972) classical R/S test, which often fails to reject long memory when there is no. Consider a time series $\mathrm{X}_1, \mathrm{X}_2, \ldots, \mathrm{X}_\mathrm{T}$. The sample mean, variance, and auto-covariance of j^{th} order are $X, \hat{\sigma}_0^2,$ and $\hat{\gamma}_j$, respectively. The modified sample variance, after accounting for auto-covariance, is $\hat{\sigma}^2(q) \equiv \hat{\sigma}_0^2 + \sum_{j=1}^{q}(1-\frac{j}{q+1})\hat{\gamma}_j$, where q is the number of lags with 0<q<T. The MRS statistic is then

$$Q_{(T)}(q) = \frac{1}{\sigma(q)}[\max_{1\le k\le T}\sum_{j=1}^{k}(X_j-\bar{X}) - \min_{1\le k\le T}\sum_{j=1}^{k}(X_j-\bar{X})].$$

The numerator is the range of the running sum of the deviations from the sample mean, while the denominator is the modified standard deviation (hence the name, R/S test). Instead of $\hat{\sigma}(q)$, the classical R/S statistics use the sample standard deviation $\hat{\sigma}_0^2$ in the denominator. Lo (1991) suggests choosing the lag value q as the integer part of $\left(\frac{3T}{2}\right)^{1/3}\left(\frac{2\hat{\rho}}{1-\hat{\rho}^2}\right)^{2/3}$, with $\hat{\rho}$ being the first-order autocorrelation coefficient of X. Lo (1991) derives the asymptotic distribution of $MRS(q) = Q_{(T)}(q)/\sqrt{T}$. For a one-sided test of the null hypothesis of no long memory, the null is rejected at the 1% significance level when $MRS(q) > 2.098$.

Additionally, prior studies show that volatility persistence varies on its regimes (e.g., Lastrapes, 1990 and Hamilton and Susmel, 1994). Hence, we also conduct an endogenous structural break test for each model. In addition, depending on the structural break dates, we separate the whole sample into a few sub-samples. We use the $supW$ (maximum Wald) statistic to identify the structural break here. Let τ be a potential change date, from which the parameters in the models may change. The null of the test is that the parameters of the restricted model are the same in the two sub-samples, and the alternative is that the parameters of the unrestricted model in the sub sample [1, τ-1] are different from those in the sub-sample [τ, T], where T is the full sample size. The Wald statistic is $W_{(\tau)} = T(SSR_R - SSR_U)/SSR_U$, where SSR_R and SSR_U are the sums of the squared residuals for the restricted and unrestricted models, respectively. The $supW$ statistic is then $supW = \max_{\tau}\{W(\tau)\}$, where τ is between $\pi_0 T$ and $(1 - \pi_0)T$ and $\pi_0 \epsilon (0,1)$ is the fraction of trimming. A popular choice is $\pi_0 = 0.15$, which we use in this chapter. If the null of no change is rejected (see Hansen, 1997 for more details), then the $\hat{\tau}$ with maximized $W(\tau)$ is the estimated date of change.

Finally, we also report the Shapley-Owen R^2 for each regressor of our models. This allows us to compare the relative importance of the variables in explaining the long memory of volatility. This technique has its roots in game theory. Shapley (1953) proposes a method to apportion the gains from a cooperative game among cooperating players; Owen (1977) extends this concept to coalitions of players. Later, Lindeman et al. (1980) apply the same concepts to decompose goodness-of-fit among regressors and coalitions of regressors in econometrics. The results can indicate the contribution of each independent variable in explaining the dependent variable and the sum of the Shapley-Owen R^2 of each regressor equal to the value of R^2.[57]

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

4.4.1 Empirical Evidence

Table 4.5 shows the results from the estimation of Equation (4.12). The model provides a reasonably good fit to the data, with a large R^2 in whole sample period and the sub-periods (around 90%), and highly significant t statistics for all parameters. The coefficients β_λ and β_{OI} have similar sizes, which are around 0.8, but they are less than one, which are their theoretical values. The Shapley R^2s of market sensitivity are larger than the integrated square of order flow, meaning that the former explains the variation of volatility more than do the later. The estimation results are in line with those of Berger et al. (2009). Furthermore, we employ the MRS statistic to test long memory in the model residuals, which should disappear because the regressors explain the persistence of the RV. However, we find that the residuals of whole sample estimation have long memory. Though the statistics are largely reduced for the residuals of the sub-sample estimations when we account for structural breaks, most still have long memory.

To test whether volatility is related more to the variables containing bad news or good news, we estimate Equation (4.13) and show the results in Table 4.6. The R^2 of the whole sample and sub-periods is around 70%, and all parameters show high significance. The sum of β_λ^- and β_λ^+, and β_{OI}^- and β_{OI}^+, are both around 0.65, but significantly different from one, the theoretical value of the sum. The size of β_λ^- and β_λ^+ do not differ; however, β_{OI}^+ is significantly higher than β_{OI}^-, meaning that a 1% change in a negative OI will cause a higher percentage change in volatility than a positive change will. The Shapley R^2 results also support this conclusion. We can observe that good and bad market sensitivity have similar Shapley R^2s. However, bad OI has consistently higher Shapley R^2s than the good one does among the whole and sub sample period results. That implies that whether market sensitivity is related to good or bad news, they have the same importance in explaining volatility, but OI containing bad news plays a greater role than that containing good news. In addition, the overall explanatory power of market sensitivity is higher than that of the OI, which is in line with the results of Equation (4.12).

Further, to investigate the persistence of volatility from the two tails of intra-day returns, we use Koenker and Bassett's (1978) quantile regression model to estimate daily trader sensitivity to new information across the quantiles of the conditional distribution as in the previous sections. Then, we construct daily integrated square order flow depending on the return distribution with intra-day data. Table 4.7 presents the estimation results of Equation (4.14), which connects volatility with extreme events. The R^2 of the whole sample and sub-periods is around 90%, and all parameters show high significance. The sum of β_{λ}^{Q5}, β_{λ}^{Q50}, and β_{λ}^{Q95}, and β_{OI}^{Q5}, β_{OI}^{Q50}, and β_{OI}^{Q95} are both around 0.8, but significantly different that one, the theoretical value of the sum. Market sensitivity containing extreme bad news, which is the coefficient of $\ln(\lambda_t^{Q95})$, is significantly lower than that containing extreme good news, which is the coefficient of $\ln(\lambda_t^{Q5})$. That is, a 1% change in the market sensitivity to extreme good news will cause a higher percentage change in volatility than that to extreme bad news. However, the Shapley R^2 of $\ln(\lambda_t^{Q95})$ is similar with that of $\ln(\lambda_t^{Q5})$, consistent with the conclusion in Equation (4.13) that market sensitivity related to good or bad news has similar explanatory power for volatility. For the integrated square order flow, the coefficients of $\ln(OI_t^{(2),Q95})$ are significantly larger than those of $\ln(OI_t^{(2),Q5})$, but with a small gap between their Shapley R^2. Therefore, both market sensitivity and order flow cannot provide evidence supporting the finding in Patton and Sheppard (2015) that bad news drives volatility. However, we find that sensitivity related to extreme events has stronger explanatory power than does that to average news, which emphasizes the importance of the tail persistence of volatility. Furthermore, the sum of the Shapley R^2s of $\ln(\lambda_t^{Q5})$ and $\ln(\lambda_t^{Q95})$ is around 6% higher than that of $\ln(OI_t^{(2),Q5})$ and $\ln(OI_t^{(2),Q95})$. This result suggests that extreme events explain volatility more through traders' sensitivity than through the OI itself.

Overall, we find empirical evidence that price sensitivity to (extreme) good and bad news has similar importance to explain the long memory of volatility. However, the sensitivity related to extreme events has stronger explanatory power than does that to average news, which emphasizes the importance of the tail persistence of volatility.

Table 4.5. Estimation results for model connecting volatility with market sensitivity and OI

This table have two parts. Panel A presents the estimation results of equation (4.12). The last two columns show the R^2 of the model and the modified R/S statistic of Lo (1991) of the model residuals. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Panel B shows the estimation results of Shapely R2 of each regressor in model (4.12). The last column shows the gap of the Shalpey R^2 between coefficients $\ln(\lambda_t)$ and $\ln(OI_t^{(2)})$. We separate whole sample period into five sub-samples according to structural breaks detected by the supW test, that is, sub-period: 01 Jan 2000–10 Sep 2003; sub-period 2: 11 Sep 2003–06 Jul 2006; sub-period 3: 07 Jul 2006–09 Jun 2008; sub-period 4: 10 Jun 2008–2 Sep 2010; and sub-period 5: 3 Sep 2010–31 Dec 2013.

$$ln(\mathrm{RV_t}) = \alpha + 2\beta_\lambda \ln(\lambda_t) + \beta_{OI}\ln(OI_t^{(2)}) + \varepsilon_t \quad (4.12)$$

Panel A: Model Estimation Results

Sample periods	$\ln(\lambda_t)$	$\ln(OI_t^{(2)})$	**R^2**	**Residual R/S stat**
whole sample	0.891***	0.838***	91.4%	5.83***
	(39.39)	(38.74)		
Sub-period 1	0.937***	0.685***	83.1%	3.07***
	(38.15)	(21.95)		
Sub-period 2	0.834***	0.713***	90.6%	1.50
	(47.21)	(18.79)		
Sub-period 3	0.878***	0.860***	96.0%	2.83***
	(45.29)	(66.28)		
Sub-period 4	0.961***	0.816***	96.1%	1.66
	(39.21)	(33.4)		
Sub-period 5	0.882***	0.799***	90.7%	3.10***
	(36.30)	(42.19)		

Panel B: Estimation Results for Shapley R^2

	$\ln(\lambda_t)$	$\ln(OI_t^{(2)})$	Δ
whole sample	51.2%	40.1%	11.10%
Sub-period 1	54.0%	29.1%	24.90%
Sub-period 2	51.9%	38.8%	13.10%
Sub-period 3	39.3%	56.7%	-17.40%
Sub-period 4	79.0%	17.2%	61.80%
Sub-period 5	48.1%	42.6%	5.50%

Table 4.6. Estimation results for model connecting volatility with good and bad news

This table have two parts. Panel A presents the estimation results of equation (4.13). The last two columns show the R^2 of the model and the modified R/S statistic of Lo (1991) of the model residuals. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Panel B shows the estimation results of Shapely R^2 of each regressor in model (4.13). The last two columns show the gaps of Shalpey R^2 between $\ln(\lambda_t^+)$ and $\ln(\lambda_t^-)$, and $\ln\left(OI_t^{(2)+}\right)$ and $\ln\left(OI_t^{(2)-}\right)$ respectively. We separate whole sample period into five sub-samples according to structural breaks detected by the supW test, that is, sub-period: 01 Jan 2000–06 Jul 2004; sub-period 2: 07 Jul 2004–12 Jul 2007; sub-period 3: 13 Jul 2007–03 Feb 2010; and sub-period 4: 04 Feb 2010–31 Dec 2013.

$$ln(\mathrm{RV_t}) = \alpha + 2\beta_\lambda^+ \ln(\lambda_t^+) + \beta_{OI}^+ \ln\left(OI_t^{(2)+}\right) + 2\beta_\lambda^- \ln(\lambda_t^-) + \beta_{OI}^- \ln(OI_t^{(2)-}) + \varepsilon_t \tag{4.13}$$

Panel A: Model Estimation Results

Sample periods	$\ln(\lambda_t^-)$	$\ln(OI_t^{(2)-})$	$\ln(\lambda_t^+)$	$\ln\left(OI_t^{(2)+}\right)$	$\mathbf{R^2}$	**Residual R/S stat**
whole sample	0.346***	0.310***	0.316***	0.346***	74.2%	4.19***
	(13.87)	(11.08)	(14.46)	(18.43)		
Sub-period 1	0.259***	0.226***	0.258***	0.266***	60.4%	3.45***
	(10.51)	(8.94)	(13.50)	(8.64)		
Sub-period 2	0.302***	0.267***	0.246***	0.244***	73.5%	3.31***
	(14.40)	(16.38)	(11.27)	(21.48)		
Sub-period 3	0.424***	0.314***	0.458***	0.372***	83.8%	3.17***
	(11.28)	(10.59)	(13.10)	(13.53)		
Sub-period 4	0.333***	0.299***	0.283***	0.374***	72.9%	3.24***
	(11.54)	(10.61)	(9.17)	(16.29)		

Panel B: Estimation Results for Shapley R^2

	$\ln(\lambda_t^-)$	$\ln(OI_t^{(2)-})$	$\ln(\lambda_t^+)$	$\ln\left(OI_t^{(2)+}\right)$	$\Delta \ln(\lambda_t)$	$\Delta\ln\left(OI_t^{(2)}\right)$
whole sample	21.8%	13.9%	21.8%	16.7%	0.00%	2.80%
Sub-period 1	15.4%	11.2%	18.5%	15.3%	3.10%	4.10%
Sub-period 2	25.2%	11.2%	22.5%	14.6%	-2.70%	3.40%
Sub-period 3	32.8%	6.8%	32.5%	11.6%	-0.30%	4.80%
Sub-period 4	20.7%	14.2%	19.3%	18.7%	-1.40%	4.50%

Table 4.7. Estimation results for model connecting volatility with tail risk

This table have two parts. Panel A presents the estimation results of equation (4.14). The last two columns show the R^2 of the model and the modified R/S statistic of Lo (1991) of the model residuals. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Panel B shows the estimation results of Shapely R^2 of each regressor in model (4.14). The last two columns, $\Delta\ln(\lambda_t)$ and $\Delta\ln\left(OI_t^{(2)}\right)$, show the Shapley R^2 gaps between coefficients of $\ln(\lambda_t^{Q95})$ and $\ln(\lambda_t^{Q5})$, and $\ln(OI_t^{(2),Q95})$ and $\ln(OI_t^{(2),Q5})$. We separate whole sample period into five sub-samples according to structural breaks detected by the supW test, that is, sub-period: 01 Jan 2000–01 Sep 2003; sub-period 2: 02 Sep 2003–04 Jul 2006; sub-period 3: 05 Jul 2006–06 Jun 2008; sub-period 4: 07 Jun 2008–31 Aug 2010; and sub-period 5: 01 Sep 2010–31 Dec 2013.

$$ln(\mathrm{RV_t}) = \alpha + \sum_Q 2\beta_\lambda^Q \ln(\lambda_t^Q) + \sum_Q \beta_{oi}^Q \ln(OI_t^{(2),Q}) + \varepsilon_t, \text{ where Q equal to quantile 5\%, 50\% and 95\%.} \quad (4.14)$$

Panel A: Model Estimation Results

Sample periods	$\ln(\lambda_t^{Q5})$	$\ln(\lambda_t^{Q50})$	$\ln(\lambda_t^{Q95})$	$\ln(OI_t^{(2),Q5})$	$\ln(OI_t^{(2),Q50})$	$\ln(OI_t^{(2),Q95})$	$\mathbf{R^2}$	**Residual R/S stat**
whole sample	0.198***	0.564***	0.131***	0.098***	0.620***	0.110***	89.7%	5.87***
	(12.05)	(22.58)	(10.55)	(13.68)	(30.11)	(13.37)		
Sub-Period 1	0.262***	0.497***	0.174***	0.078***	0.555***	0.075***	80.8%	3.41***
	(12.93)	(16.66)	(11.29)	(5.62)	(22.2)	(6.08)		
Sub-Period 2	0.225***	0.457***	0.161***	0.088***	0.499***	0.132***	87.4%	1.82*
	(11.24)	(13.87)	(7.11)	(8.44)	(21.48)	(13.07)		
Sub-Period 3	0.267***	0.410***	0.185***	0.100***	0.604***	0.145***	94.5%	2.71***
	(11.04)	(12.30)	(11.59)	(9.12)	(37.36)	(16.34)		
Sub-Period 4	0.177***	0.638***	0.145***	0.090***	0.594***	0.120***	94.7%	1.80*
	(9.85)	(14.93)	(4.25)	(8.18)	(20.63)	(8.58)		
Sub-Period 5	0.141***	0.630***	0.127***	0.130***	0.516***	0.140***	88.4%	2.91***
	(5.82)	(14.95)	(5.46)	(13.66)	(17.93)	(10.27)		

Panel B: Estimation Results for Shapley R^2

	$\ln(\lambda_t^{Q5})$	$\ln(\lambda_t^{Q50})$	$\ln(\lambda_t^{Q95})$	$\ln(OI_t^{(2),Q5})$	$\ln(OI_t^{(2),Q50})$	$\ln(OI_t^{(2),Q95})$	$\Delta\ln(\lambda_t)$	$\Delta\ln\left(OI_t^{(2)}\right)$
whole sample	13.1%	20.0%	13.7%	9.7%	24.5%	8.7%	0.60%	-1.00%
Sub-Period 1	14.0%	22.3%	13.2%	5.7%	19.4%	6.2%	-0.80%	0.50%
Sub-Period 2	13.2%	20.9%	13.1%	8.5%	21.7%	10.1%	-0.10%	1.60%
Sub-Period 3	8.7%	18.5%	11.6%	12.7%	32.7%	10.2%	2.90%	-2.50%
Sub-Period 4	22.5%	29.8%	24.1%	3.4%	11.6%	3.3%	1.60%	-0.10%
Sub-Period 5	11.2%	22.6%	11.6%	11.1%	22.4%	9.5%	0.40%	-1.60%

4.5 Conclusion

This chapter investigates the source of long memory in foreign exchange volatility. Inspired by Berger et al. (2009) and Patton and Sheppard (2015), we propose a new empirical specification that links volatility to good and bad news, measured as the order imbalance in the market, and to traders' sensitivity to that news. We estimate the time-varying daily market sensitivity to good or bad news from high-frequency data. We find the explanatory power of bad market sensitivity to volatility is similar to that of good market sensitivity. This finding is different from Patton and Sheppard (2015), who find that bad volatility drives volatility persistence. Furthermore, we use Koenker and Bassett's (1978) quantile regression model to estimate traders' time-varying sensitivity to information across the quantiles of the conditional distribution. The empirical results also do not show a different influence on the long memory of volatility between the market sensitivity to extreme good or bad news. However, we find that sensitivity to extreme events has stronger explanatory power than that to other news, which emphasizes the importance of volatility tail persistence. Overall, this chapter expands on Berger et al. (2009) and Patton and Sheppard (2015) and finds the interesting result that price sensitivity to (extreme) good and bad news has similar importance in explaining the long memory of volatility.

There are two thoughts about future research directions. The first is when we estimate daily market sensitivity across different return quantiles, we are aiming to determine the market reaction to extreme news. However, it is nonsense that extreme events occur every day. Therefore, we should conduct a quality test to identify days with extreme events. The second is that AUD/USD, the currency pair we use in this chapter, is an internationalized currency; however, the trading volume is much lower than that for GBP, EUR, and other major currencies. We can investigate more currencies to test our hypothesis if data is available.

Chapter 5: Conclusion

In this thesis, using high frequency exchange rate data, we investigated the price discovery and volatility dynamics in the emerging foreign exchange market. It consists of three independent essays, which examine information distribution and volatility dynamics in the FX market from different perspectives.

In the first essay, we found that, with more liberalizing of emerging financial markets, the growing transaction and hedging demands in EMCs leads to information distribution shift from inside to outside issuers' borders. Non-local investors' information collection and interpretation ability to macro news have been largely enhanced in recent years. To the best of our knowledge, it is the first time that a study has provided a comprehensive location-related information distribution shift of EMCs over almost 20 years from 1999 to 2017. Our findings should draw the attention of emerging country central banks. On the one hand, the adoption of a floating currency regime and more active non-local trading helps the EMCs to become more market-determined. The big trading hubs like New York, London, and Tokyo now have more information and provide more liquidity in pricing EMCs than in the early years. It is getting harder for central banks to successfully control the exchange rate, and EMCs are becoming more fragile if one or two crucial dealers withdraw from supplying liquidity.

In the second essay, we focused on the volatility dynamics of EMCs. Volatility persistence and return asymmetric effect are two crucial statistical features. Despite these features being well documented and examined for MCs, they have rarely been investigated for EMCs. Therefore, we aimed to compare the two features between MCs and EMCs and further investigate the determinants of the differences. By using HAR model and its variants, we provided new empirical evidence that EMCs have lower volatility persistence and larger asymmetric return effect than MCs. Furthermore, we found that the daily volatility persistence and asymmetric effect change over time. The former decreases with information flow inconsistency and the latter increases with market illiquidity. The stronger negative impact of news inconsistency and the lower market liquidity cause EMCs to have lower daily volatility persistence and higher asymmetric volatility than MCs. This essay compared two stylized features of volatility between MCs and EMCs for the first time and suggests information arrival pattern and market state are crucial determinants. The findings are totally opposite to the equity market: emerging equity markets have higher volatility persistence and lower asymmetric effect. Our findings confirm the uniqueness of the FX market and its volatility dynamics and calls for more work to be conducted upon it in the future.

The last essay investigates the source of long memory in foreign exchange volatility. Inspired by Berger et al. (2009) and Patton and Sheppard (2015), we propose a new empirical specification that links volatility to good and bad news, measured as the order imbalance in the market, and to traders' sensitivity to that news. We estimate the time-varying daily market sensitivity to good or bad news from high-frequency data. We find the explanatory power of bad market sensitivity to volatility is similar to that of good market sensitivity. This finding is different from Patton and Sheppard (2015), who find that bad volatility drives volatility persistence. Furthermore, we use Koenker and Bassett's (1978) quantile regression model to estimate traders' time-varying sensitivity to information across the quantiles of the conditional distribution. The empirical results also do not show a different influence on the long memory of volatility between the market sensitivity to extreme good or bad news. However, we find that sensitivity to extreme events has stronger explanatory power than that to other news, which emphasizes the importance of volatility tail persistence. Overall, this chapter expands on Berger et al. (2009) and Patton and Sheppard (2015) and finds the interesting result that price sensitivity to (extreme) good and bad news has similar importance in explaining the long memory of volatility.

For the third essay, there are two thoughts about future research directions. The first is when we estimate daily market sensitivity across different return quantiles, we are aiming to determine the market reaction to extreme news. However, it is nonsense that extreme events occur every day. Therefore, we should conduct a quality test to identify days with extreme events. The second is that AUD/USD, the currency pair we use in this chapter, is an internationalized currency; however, the trading volume is much lower than that for GBP, EUR, and other major currencies. We can investigate more currencies to test our hypothesis if firm quotes data is available.

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