# Essays in Empirical Finance

by

Valère Fourel

B.S., Ecole Supérieure d'Electricité (2009)
MSc, Imperial College London (2009)
MS, Massachusetts Institute of Technology (2018)

Submitted to the Department of Management
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Management

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

February 2020



Signature redacted

Author ................................................
Department of Management
January 10, 2020

Signature redacted

Certified by ................................................
Adrien Verdelhan
Stephens Naphtal Professor of Finance
Associate Professor, Finance
Thesis Supervisor

Signature redacted

Accepted by ................................................
Catherine Tucker
Sloan Distinguished Professor of Management
Professor of Marketing
Chair, MIT Sloan PhD Program

**Essays in Empirical Finance**

by

Valère Fourel

Submitted to the Department of Management
on January 10, 2020, in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy in Management


## Abstract

This dissertation consists of three chapters.

Considering that monetary policy is multi-dimensional and cannot be solely reduced to changes in the short-term interest rate, Chapter 1 revisits the bank lending channel literature. Our approach consists in finding whether there are some significant cross-sectional disparities in the way French banks that exhibit different bank characteristics respond to *various types* of monetary policy shocks. We first extract from changes in interest rates around ECB's monetary policy announcements four different types of monetary policy shocks. The *Target* factor affects mostly the very-short end of the yield curve, the *Timing* factor, the 6-month interest rate and the *Forward Guidance*, interest rates at the 5-year horizon. The *Quantitative Easing* factor essentially moves interest rates at longer maturities. We then combine these monetary policy shocks that we first aggregate at the monthly frequency with our sample of monthly data on French banks for the period 2007 to 2018. We uncover three new facts: 1) bank's size matters for monetary policy transmission when we consider a *Forward Guidance* shock; 2) Liquid assets held by a bank can be a vector of the smooth transmission of monetary policy; 3) Banks with a high share of deposits on their liability side tend to reduce their lending to non-financial corporations after an expansionary *Timing* or a *Forward Guidance* shock. Using a loan-level dataset, our results are robust when controlling for any firm-specific demand shock.

In the second chapter which is a joint work with D. Rime, L. Sarno, M. Schmeling and A. Verdelhan, we build the largest dataset of high-frequency exchange rates so far: our sample covers the spot prices and order flows of 19 currency pairs over the last 15 years measured on the two main trading platforms at the 30-second frequency. We uncover four new facts on intraday exchange rates: 1) The carry and dollar risk factors explain a large share of the intraday exchange rate variations; their explanatory power increase from 30-second to daily frequencies, while the explanatory power of order flows is more limited and decreases from 30-second to daily frequencies; 2) Dollar and carry betas are very persistent: their autocorrelation coefficients are around 0.5 at the daily horizon and 0.7 at the weekly horizon, thus offering a new key characteristic of exchange rates; 3) Dollar betas are correlated to bond yields; and 4) they are caused by additional trading.

In the third chapter, exploiting a high frequency dealer-specific quote database of the FX market, we show that shocks to the CDS of a financial intermediary, proxy for its financial wealth, makes her quote larger bid-ask spreads when uncertainty about the underlying traded asset is high or when market competition is low. We first establish that markets are dominated by a handful of dealers who are responsible for more than 90% of the quotes in the different FX spot markets. We then document that, when exchange rate volatility is high, a 1% increase in intermediary's default probability does translate into a 4 bps increase in the bid-ask spread that she quotes. When competition is low, a similar deterioration in financial wealth leads to a 6.4 bps increase in bid-ask spread size. We finally show that in the case of emerging country currencies, the average CDS spread of the financial intermediaries quoting in the FX market is a statistically significant predictor for the volatility of the idiosyncratic component of the currency risk premium.


Thesis Supervisor: Adrien Verdelhan
Title: Stephens Naphtal Professor of Finance
Associate Professor, Finance

# Acknowledgments

I am incredibly grateful for all the help I received in completing this thesis.
I am deeply indebted to my thesis advisor, Adrien Verdelhan, for his considerable patience, continuous guidance and precious suggestions and comments throughout the entire process. Words cannot express my gratitude towards David Thesmar. He has always provided me with great advice and encouragements. He has also helped me to better define my research interests, especially for my future career. I am immensely honored that Jonathan Parker has accepted to be part of my thesis committee. I had the extreme privilege to be his student for two of his classes (Advanced Macroeconomics and Empirical Finance), to be his Teaching Assistant and I have always been impressed by his brilliance and his encyclopedic knowledge.

I also benefited a lot from discussions with Hui Chen, John Cox, Leonid Kogan, Erik Loualiche, Andrey Malenko, Paul Mende, Haoxiang Zhu. I am extremely thankful to my fellow students and friends including Bill Goulding, Daniel Green, Vikram Jambulapati and Anton Petukhov who provided encouragement and useful discussions in the completion of this work. I would like to thank Hillary Ross, Davin Schnappauf and Sarah Massey for their administrative help. Finally, this work would not have been possible without the financial support of the Banque de France, which has also allowed me to have access to the Thomson Reuters Tick History Database.[1] During my time at the Banque de France, I also had the chance to interact with extremely talented economists who helped me in my research, especially for the first chapter of this thesis.

I am extremely grateful to have been surrounded by wonderful friends who have supported me all along. Let me therefore thank, in particular, Lisa, André, Andrea, Gabriel, Lishen, Julie, Gabriel, Gustave, Clotilde, Marion, Pegah, Babak, Silvia, Roberto, Pierre, Olivier, Alexandra, Ludwig, Loreen, Egle, Jonas, Marie, Christophe, Sandrine, Jean-Louis, Gaïa, Daniel, Ankur, Sarah, Olivier, Aurélie, Béatrice, Sarah, Klodiana, Hugues, Florens, Stéphane, Jenn and Araceli.

This journey would have been much harder without the company of Virginia W., Patti S., Ernest H., Bruce S., Charlotte G., Ludovico E., Bret E. E., Christine and the Q., Florence and the M., Lana D. R., Boris V., Nina S., Jack K., Alfred H., Greta G., Marguerite D., Arthur R., John S., René C., Adele, Simone de B., Hannah A., Marcel P., Jane A., Lena D., Honoré de B., Guy de M.. Among many others.

I would like to deeply thank my parents, Christiane and Jean-Louis and my sisters, Stéphanie and Florie.
I would like to dedicate this thesis to my dear missed friend, Cyril, and to the wonderful and caring woman that Maria was. But most importantly, to my wife, Anne-Emmanuelle Thomas who has always stood by my side like a rock and to our two wonderful kids, the "apples of my eyes", Lubin and Adèle. Their unconditional love and support, the great moments of joy and happiness shared with them have helped carry me through the entire endeavor.

To Anne-Emmanuelle,

*Mon amour ce qui fut sera,*
*Le ciel est sur nous comme un drap*
*J'ai refermé sur toi mes bras*
*Et tant je t'aime que j'en tremble*
*Aussi longtemps que tu voudras*
*Nous dormirons ensemble*

Louis ARAGON

[1] As a disclaimer, this work reflects the author's independent research and does not necessarily reflect the views of the Banque de France or France. All errors are my own.

# Chapter 1

# The Bank Lending Channel of Conventional and Unconventional Monetary Policy

## 1.1. Introduction

The main concern of central bankers across the globe is to ensure that their monetary policy is smoothly transmitted to the real economy. To do so, they rely on financial intermediaries and, in particular, on banks. For decades, at least in advanced economies, central banks have used their unique and *conventional* monetary policy instrument, the one under their direct control, their official interest rate. To boost or curb inflation and aggregate demand, they have adjusted the short-term interest rates at which banks can borrow from and lend to the central bank. Changes in these rates should be ultimately passed on to rates at which households and firms can borrow and save. Naturally, a voluminous empirical literature on the bank lending channel has tried to analyze and measure how, after a monetary policy shock on the short-term interest rate, banks expand or contract their lending to the real economy depending on whether 1) they are small (Kashyap & Stein (1995)), 2) they are leveraged (Kishan & Opiela (2000)), 3) they hold a high share of liquid assets in their portfolio (Kashyap & Stein (2000)), 4) they operate in an area where deposits are concentrated (Drechsler *et al.* (2017)), 5) they operate in an area where the share of adjustable-rate mortgages is high (Di Maggio *et al.* (2017)), 6) their balance sheet exhibits a large maturity mismatch (English *et al.* (2018)), 7) their income gap, corresponding to the difference between the interest rate sensitivities of a bank's assets and liabilities, is positive and large (Gomez *et al.* (2016)). The Great Recession has forced central bankers to reconsider and expand their toolkit of monetary policy instruments. As short-term interest rates quickly reached the so-called *effective zero lower bound*, they have started implementing a large variety of *unconventional* monetary policy measures. This new set of monetary policy measures has taken the form of large-scale asset purchase programmes also known as *quantitative easing* and intensified communication by central banks, the *forward guidance*[1]. By design, these measures have had different implications on the money market yield curve. *Forward guidance* whose main goal is to manage economic agents' expectations on future interest rates should have a strong impact on interest rates for maturities between 2 and 5 years. On the other hand, even if *quantitative easing* measures target the whole yield curve, the main objective is to lower interest rates for long maturities.

With the implementation of these *unconventional* measures that initially ought to be temporary but which ended up being prolonged in the euro area or Japan, it becomes difficult to argue that monetary policy can be reduced to and should be studied as a one-dimensional object. The multi-dimensional feature of monetary policy leads us to revisit the bank lending channel. In particular, are there some significant cross-sectional disparities in the way French banks that exhibit different bank characteristics respond to *various types* of monetary policy shocks? To my knowledge, this chapter is the first empirical work which attempts to offer a systematic approach to answer this question. In a nutshell, the shocks what we consider in this chapter correspond to surprises on different segments of the money market yield curve occurring on euro area monetary policy announcement days. We discover that monetary policy shocks affecting mostly the medium-run (between 2 and 5 years) or the long-run (10 years) of the yield curve can generate statistically and economically significant differences in terms of bank lending whether 1) a bank is small, 2) whether it holds a higher share of liquid assets (cash, excess reserves and securities) or 3) whether it relies more on deposits to finance its business. Bank leverage, on the other hand, is found not to play a major role for monetary policy transmission.

To shed new light on the bank lending channel of *conventional* and *unconventional* monetary policy, we proceed step-by-step. To properly identify the causal effects of a monetary policy loosening, for instance, on bank loan supply depending on whether a bank is small or large, we have to construct

[1]The interested reader can find a timeline of the different monetary policy measures implemented by the Eurosystem since 2013 (see Figure ??).

a times series of exogenous monetary policy shocks. Our first major challenge comes from the fact that monetary policy is endogenous. There is always an economically legitimate reason why a central bank decides to change its key interest rates or to intensify its large-scale asset purchase programme. A standard way to get a clear identification is to implement a vector autoregression approach (see Christiano *et al.* (2005), Bernanke *et al.* (2005) for seminal papers). However, this econometric procedure is not immune from any endogeneity bias (Rudebusch (1998)). We rely on another technique, the high-frequency identification. This strategy introduced by Cook & Hahn (1989), and further developed by Kuttner (2001), Cochrane & Piazzesi (2002) and Gürkaynak *et al.* (2005) allows us to address this endogeneity problem. We focus on changes in interest rates of the entire euro area money market yield curve around ECB's monetary policy announcements at a very high frequency. In general, these models assume that the yield curve reacts to monetary policy news according to a simple factor structure where the number of unobservable factors has to be determined.

We closely follow the methodology implemented by Altavilla *et al.* (2019), which decomposes each ECB's monetary policy event into two distinct communication windows: the Press Release window where key measures such as interest rate decisions are announced and the Press Conference window where the President of the ECB reads an introductory statement and answers questions from the audience. Looking at how financial markets react over these two windows allows us to extract different types of monetary policy shocks or surprises. During the Press Release window, only one statistically significant factor drives changes in interest rates of the entire yield curve and with a strong effect on short-term interest rates. This factor is named the *Target* factor. In the Press Conference window, there are three statistically significant factors. The factors are identified up to an orthonormal transformation. The statistical decomposition carried out by Altavilla *et al.* (2019) on euro area data over the Press Conference window was originally introduced by Swanson (2017) on U.S. data. The *Forward Guidance* (FG) and *Quantitative Easing* (QE) monetary policy shocks are assumed to be uncorrelated with the one-month OIS rate as they target longer maturities. Once these two factors are identified, the third factor, the *Timing* factor, is unequivocally determined. The *QE* factor is uniquely pinned down assuming that it explains very little of the variance of the the yield curve changes before the beginning of the financial crisis in October 2008. Contrary to what is claimed by Altavilla *et al.* (2019), we do find that the *QE* factor is present before 2014. Such a finding is not remarkable *per se*: even before the launch of the Asset Purchase Programme (APP) in December 2014, some other large-scale asset purchase programmes, in particular the Securities

Market Programme (SMP) in May 2010, had been implemented by the Eurosystem.

Equipped with our four monetary policy shocks that we aggregate at the monthly frequency, we then test the bank lending channel on French banks following the state-of-the-art methodology developed by Kashyap & Stein (2000). Using detailed monthly data on French banks' balance sheets for the period running from August 2007 to September 2018, we first show that monetary policy shocks at the very short-end of the yield curve (*Target* shocks) do not generate any cross-sectional differences in the way French banks expand or contract their lending to the real economy.

We document, however, that bank's size matters for monetary policy transmission when we consider a *Forward Guidance* shock. Indeed, after an expansionary *Forward Guidance* shock of one standard deviation (i.e. a 4.23 bps drop in the 2-year OIS rate), a bank which is at the $25^{th}$-percentile in terms of size distribution expands its lending to households and non-financial corporations over the next quarter by 0.55% more than a bank at the $75^{th}$-percentile. This effect must be compared to the average 0.46% monthly growth rate for the lending to the real economy observed over the whole sample.

Moreover, we discover a unique empirical finding regarding the role played by liquid assets (cash, securities and deposits at the central banks) held by a bank for the transmission of monetary policy shock affecting the long-run of the yield curve. Kashyap & Stein (2000) had previously documented that the more liquid assets a bank holds in its portfolio, the less it is responsive to any monetary policy expansion (shock to the short-term interest rate). Liquidity-constrained banks expand their lending more since they are the ones which are the most likely to experience a drop in their external cost of funding when interest rates decrease. Over the period running from 2007 to 2018, we observe a different pattern. Indeed, if a *QE* shock decreases the 10-year interest rate by 1.955 bps (one standard deviation of our shock), a bank expands its lending to non-financial corporations over the next quarter by 0.24 percentage points more than any other bank which holds ten percentage points less of liquid assets in its portfolio. We argue that this conclusion which might seem counterintuitive at first can be rationalized by the wealth effect associated with any increase in the value of the sovereign bonds that banks might possess on their balance sheet when a *QE* shock occurs.

This chapter also highlights the adverse role of deposits on banks' liability side. Banks with a high share of deposits on their liability side tend to reduce their lending to non-financial corporations after a *Timing* or a *Forward Guidance* shock. For instance, if the 6-month interest rate decreases by 3.25 bps due to a *Timing* shock, bank A with 10% more deposits on its liability side than another bank, bank $B$, will decrease its lending by 0.10% over the next quarter compared to bank $B$. This relatively novel empirical result is consistent with the idea of a *reversal interest rate* (Brunnermeier & Koby (2019)), i.e. an interest rate threshold below which any accommodative monetary policy decision could depress the economy instead of stimulating it. Our finding is also related to the work of Heider *et al.* (2019) who show, using European data, that banks are reluctant to pass on negative rates to depositors, which increases the funding cost of high-deposit banks, and reduces their net worth, relative to low-deposit banks. As a result, they are most likely to reduce their loan supply to the real economy.

To address any concern regarding the potential endogenous matching between banks and firms, we exploit a detailed bank-firm loan-level database. Indeed, if banks with a low share of deposits on their liability side tend to lend to firms which react more to expansionary monetary policy shocks, the estimates obtained with the bank-level dataset would be spurious. By focussing on firms which borrow from multiple banks and by including firm-time fixed effects as in , we are able to control for any demand shock allowing us to fully characterize the bank loan supply channel. This multi-bank analysis display, in terms of signs and magnitude, similar results in comparison with the ones obtained with the bank-level dataset. This reassuring outcome suggests that firms and banks are indeed randomly matched and that our initial concern should .

Our results highlights the role played by the different types of shocks for monetary policy transmission. More specifically, the size of bank is a key determinant for *Forward Guidance* shock to be transmitted to the real economy. A bank holding a high share of liquid assets in its portfolio reacts positively to any accommodative *Quantitative Easing* shock. The more deposits a bank holds on its liability side, the more it will contract its lending to the real economy after an expansionary *Timing* or *Forward Guidance* shock. In our empirical setting, bank's leverage seems not to matter for the transmission of monetary policy.

## 1.2. Related Literature

This chapter combines elements and methodologies from two seemingly unrelated strands of the finance literature, one in asset pricing and one in corporate finance. From the asset pricing literature, this chapter borrows an identification strategy relying on high-frequency data and which has allowed a long series of researchers to properly identify the causal effects of major news announcements (monetary policy decisions, press releases of major macroeconomic outcomes, etc.) on asset prices. This approach which consists in looking at intraday changes in interest rates and/or asset prices just around news announcements has been introduced by Cook & Hahn (1989), and further developed by Kuttner (2001), Cochrane & Piazzesi (2002). Gürkaynak *et al.* (2005) is one of the seminal empirical paper measuring the effects of the FOMC's pre-2005 forward guidance announcements on asset prices. Looking at changes in the Federal Funds rate around FOMC's announcements, Nakamura & Steinsson (2018) show that monetary shocks on the short-end of the yield curve can have significant effects on long-term yields by affecting market expectations about the future path of interest rates and, in particular, by modifying their perception about the real state of the economy. This public revelation of fundamental information about the state of the economy is labelled the *Fed Information Effect.* In another spirit but focussing on real outcomes, Wong (2016) studies how high-frequency monetary policy shocks affect household consumption and highlights the key role played by the mortgage market and the refinancing channel. On the supply side, Winberry & Ottonello (2017) looks at how high-frequency monetary policy shocks can generate differences in terms of firm's investment depending on how leveraged the firm is. However, this chapter borrows the technique developed by Swanson (2017) on U.S. data and Altavilla *et al.* (2019) on euro area data which decomposes changes in the entire yield curve around monetary policy announcement into several types of monetary policy shocks. More specifically, they are able to extract *Forward Guidance* and Quantitative Easing (or Large-Scale Asset Purchases programme) surprises to analyze the heterogenous effects of these shocks on stock prices and foreign exchange rates. This chapter therefore relies on their robust statistical decomposition to quantify the effects of monetary policy shocks or surprises on bank loan supply.

This chapter is naturally related to the extensive literature on one of the main monetary policy transmission channels, the bank lending channel. In particular, Kashyap & Stein (1995) show that a monetary expansion stimulates lending especially for small banks. According to Kashyap & Stein (2000), banks which hold less liquid assets in their portfolio tend to expand their lending after an accommodative monetary policy shock. Banks which do not belong to a banking group (Campello (2002)) or banks which are highly leveraged (Kishan & Opiela (2000)) are the most responsive ones to monetary policy shocks. Monetary policy plays a significant role for banks which operate in areas where the share of adjustable-rate mortgages is high (Di Maggio *et al.* (2017)) or where deposits are concentrated (Drechsler *et al.* (2017)). The income gap, corresponding to the difference between the interest rate sensitivities of a bank's assets and liabilities, is also a key determinant for monetary policy transmission (Gomez *et al.* (2016)). This chapter also builds upon two other key papers on the idea of a *reversal interest rate*. Brunnermeier & Koby (2019) introduced this theoretical concept. It corresponds to the level of interest rate below which any accommodative monetary decision could depress the economy instead of stimulating it. Exploiting data on European banks, Heider *et al.* (2019) show that banks are reluctant to pass on negative rates to depositors, which increases the funding cost of high-deposit banks, and reduces their net worth, relative to low-deposit banks. Our empirical results suggest that indeed, in a low rate environment, expansionary monetary policy shocks seem to adversely affect banks relying on a high share of deposits on their liability side as they tend to reduce their lending to non-financial corporations.

The remainder of this chapter proceeds as follows. Section 1.3. discusses the identification challenges that arise when dealing with monetary policy shocks and therefore the use of high-frequency data to remedy this problem. Section 1.4. describes the datasets we use in our analysis. Section 1.5. examines the link between different types of monetary policy shocks, key bank characteristics and lending at the bank level. Section 1.6. estimates credit supply regressions using loan-level data. Section 1.7. concludes.

## 1.3. Identification Challenges and Strategy

This chapter aims at estimating the causal effects of bank exposure to monetary policy shocks on firms loan supply. There are two well-known identification challenges. The first one is related to the true exogenous feature of the monetary policy shocks that we want to consider. Indeed, if a change in the monetary policy stance is expected by some types of banks but not by others, any effect on lending to the real economy, empirically measured and directly attributed to changes in interest rates, might simply reflect the diffusion of now public information about the real state of the economy to the entire set of French banks. For instance, it is reasonable to think that, at any point in time, large banks, in comparison with smaller ones, might have a relatively better understanding of the economic situation of the euro area thanks to their extended business activities. Moreover, prior to any public monetary policy announcement, they might also benefit from some private information that they were able to extract, purposefully or not, from policy-makers with whom they might have closer relationships because of the major role they play in terms of lending to the real economy. As a result, any causal effect would reflect, in part or simply, a reduction in any information asymmetry prevailing before monetary policy decisions between these two groups of banks. Besides, banks having access to some private information about future monetary policy might take preemptive actions to boost their future profitability. An emblematic example is the case of quantitative easing measures: a bank which is aware that the central bank is about to start or intensify its large-scale asset purchases should acquire *ex-ante* sovereign bonds and could, at the same time, increase its lending to the real economy in anticipation of the future expected wealth effect. The effect of quantitative easing measures on bank lending would therefore be underestimated. The second identification challenge is that loan supply and demand emanating from firms may simultaneously react to monetary policy. A cut in interest rates would reduce the cost of funding for financially constrained firms which tend to rely more on bank loans to finance their investment or day-to-day activities. If those types of firms tend to borrow from small banks, for instance, an expansionary monetary policy would make them ask for more loans. As a result, small banks would increase their loan supply after this positive demand shock. A naive approach would infer that small banks tend to react more to interest rate cuts than big banks. However, the main driver would come from the demand side. These two identification challenges could generate misleading and biased correlations between monetary policy changes and bank lending, preventing us from making any rigorous causal inference.

We overcome the first identification challenge by using high frequency data in terms of changes in money market interest rates around key euro area monetary policy announcements as proxy for monetary policy surprises. For the second econometric problem, we rely on a detailed loan-level dataset which allows us to look at differences in terms of loan supply when a firm borrows from at least two different banks. As a result, we are able to control for any demand shock and the concern of an endogenous matching between banks and firms should not be considered as a threat any more.

### 1.3.1. Measuring Monetary Policy Surprises: The Use of High Frequency Financial Data

In order to properly measure the effects of different types of monetary policy shocks associated with key monetary policy announcements, we resort to a nowadays standard, clear, and robust identification strategy. Following the methodology implemented by Gürkaynak *et al.* (2005), and more recently Swanson (2017) and Altavilla *et al.* (2019), we build *Target, Timing, Forward Guidance* and *Quantitative Easing* surprise factors[2] from the high-frequency Thomson Reuters Tick History database which offers tick-by-tick data for a large spectrum of financial assets. The main identifying assumption behind such a strategy is that, at high frequencies (i.e. intraday frequency), changes in asset prices and interest rates around key monetary policy announcements are only the results of monetary policy actions and words. Consequently, asset prices reactions around these events can be reasonably and entirely attributed to monetary policy decisions or surprises. These asset price changes can be interpreted as causal effects of the ECB monetary policy decisions to financial markets. An extensive literature studying the effects of monetary policy decisions on asset prices has been done for the U.S. by Gürkaynak *et al.* (2005), and Swanson (2017), Nakamura & Steinsson (2018) but also for the euro area (Brand *et al.* (2010) and Jardet & Monks (2014)). However, none of these papers really analyze the causal effects of monetary policy decisions on loan supply depending on banks' financial wealth and business characteristics through a micro lens.

#### 1.3.1.1. The ECB Policy Communication Window

The ECB policy communication window is essentially made of two separate windows. During the first communication window, referred to as the Press Release window (PR hereafter), the Eurosystem issues its main policy actions without providing any explanation about them. Policy actions take different forms, from changes in the main refinancing operations rate, deposit facility rate, lending facility rate to more recently, net purchase of assets, changes in the forward guidance with respect to interest rates or reinvestment of asset purchase programme. During the second communication window, the Press Conference (PC hereafter), the ECB's President reads a statement and then replies to interrogations raised during a question-and-answer session. In terms of timing, on a Governing Council's monetary policy decision day, the Press Release is published at 1:45 PM. The Press Conference usually runs from 2:30 PM to approximatively 3:30 PM.

Consequently, market participants will react not only to unexpected news coming from the Press Release but also to any kind of information revealed by the ECB's President during the Press Conference window. As a result, we consider two different windows, one surrounding the Press Release and one surrounding the Press Conference.

[2]The construction and the interpretation of these factors will be explained in Section 1.3.1.3.

#### 1.3.1.2. The High-Frequency Identification Strategy of Monetary Policy Surprises

**Description of the High-Frequency Database.** The electronic platform, Thomson Reuters Tick History, offers tick-by-tick data (transaction and quotes) for a large spectrum of financial securities.To be able to separately identify the different components and, in particular, the *Forward Guidance* and *Quantitative Easing* dimensions of money market rates reactions around ECB's Governing Council decisions, we analyze the systematic reactions of 8 representative money market instruments around the two windows. The sample period includes all the Eurosystem's monetary policy decisions days from January 2002 to September 2018. We exclude dates before January 2002 since the data available exhibit some extreme observations probably due to the fact that, at the inception of the common currency, euro area money markets were not as liquid as they are nowadays. The dataset therefore is made of changes around each monetary policy window in the money market interest rates for eight maturities, which can reasonably be argued to represent the whole money market term structure. More specifically, we focus on the 1-month, the 3-month, the 6-month, the 1-year, the 2-year, the 5-year, the 7-year and the 10-year Overnight Interest Rate Swaps (OIS). Since high-frequency OIS data are not available for maturities above 2-year before August 2011, we rely on the German sovereign interest rates for those maturities prior to that date in the same vein as Altavilla *et al.* (2019). However, contrary to their sample composition, we decide to also include the 7-year OIS interest rate as it is often the case in the term-structure literature. Such a choice can conceivably be justified by the fact that we try to look at the effects of quantitative easing measures on interest rates for long maturities.

**Factor Structure.** All the yield changes are then collected into a $T \times n$ matrix $X^l$ where $l = \{\text{PR,PC}\}$: the element $x^l_{i,j}$ of the matrix $X^l$ corresponds to the change in the $j^{th}$ money market interest rate around the $l$ window on the $i^{th}$ policy date. This dataset can be reformulated according to a factor structure:

$$X^l = \mu^l + F^l \times \Lambda^l + \varepsilon^l \tag{1.1}$$

where $\mu^l$ is the mean vector of the interest changes, $F^l$ is the $T \times k$ matrix of the $k$ common factors, $\Lambda^l$ is the $k \times n$ matrix of weights associated with each factor and $\varepsilon^l$ the idiosyncratic variations of the yield curve changes. If $k = 0$, money market yield curve changes are described by a white noise. However, if $k > 0$, $X$ would be responding to $k$ dimensions of the monetary policy decisions occurring over a certain policy window event, plus some white noise. Apart from the works of Swanson (2017) and Altavilla *et al.* (2019), most of the empirical literature analyzing the high-frequency reaction of financial markets around monetary policy announcements has focused on one or two factors at most. This literature argues that monetary policy decisions could be entirely summarized by changes in the short-term interest rate. With the implementation of unconventional monetary policy measures whose main objective has been to impact the entire yield curve, it is natural to consider more than one single factor. Two natural other factors could therefore be 1) a *forward guidance* factor reflecting the surprise component of any communication regarding future monetary policy decisions in the medium run and 2) a *quantitative easing* factor corresponding to the surprise component of any large-scale asset purchase announcements.

**Number of latent factors.** Since the whole motivation of this chapter is to claim that monetary policy is multi-dimensional, we first need to make sure that there is indeed more than one statistically significant factor explaining changes in the yield curve around policy announcements. To do so, we follow the standard procedure implemented by Gürkaynak *et al.* (2005) and perform a Cragg-Donald rank test on the matrix $X$ (see Cragg & Donald (1997) for further details). In a nutshell, given the null hypothesis that there are $k_0$ factors describing the evolution of the yield curve versus the alternative that there are $k > k_0$ latent factors, this test searches over all potential factor models with $k_0$ factors the one which generates the lowest "distance" between the residuals and a simple white noise process. This distance measure follows a Wald statistic with $\frac{(n-k_0)\times(n-k_0+1)}{2} - n$ degrees of freedom. There are 187 Eurosystem's press releases between January 2002 and September 2018 and 181 Eurosystem's press conferences over the same period. As a result, the matrix $X^{PR}$ is of dimensions $187 \times 8$ and $X^{PC}$ is a $181 \times 8$ matrix.

[INSERT TABLE 1.1]

Table 1.1 reports the results of this test. We find there is, at least, one statistically significant factor at the 1% level for both monetary event windows. The hypothesis that, for the Press Conference window, there is one latent factor is also overwhelmingly rejected at the 1% level. However, the different Wald statistics for the Press Conference event suggest that there is also more than two factors: the null hypothesis that $X^{PC}$ can be described by $k_0 = 2$ factors is also rejected at the 5% level. More surprisingly, our results seem to contradict the finding that there is only one statistically significant latent factor for the Press Release window as argued by Altavilla *et al.* (2019). To be consistent with the previous literature exploiting similar data and techniques, we decide to consider only one latent factor for this monetary event. Nevertheless, this empirical exercise clearly suggests that there is more than one dimension associated with monetary policy announcements. Looking at the effects of the different components of monetary policy decisions on financial and real economy variables seems to be a natural venue for research in monetary economics.

#### 1.3.1.3. The Target, the Timing, the Forward Guidance and the QE Factors of Monetary Policy

We extract the different latent factors from the $X$ data by implementing a principal component analysis. As a result, for the Press Release window, we consider only the first principal component, i.e. the systematic component of $X^{PR}$ which explains most of the variation in the data (64%). For the Press Conference window, we keep the three first principal components, explaining 86%, 10% and 2% of the variation in $X^{PC}$.

**Structural Identification of Latent Factors.** The main drawback with these raw principal components is that there are only another statistical representation of the underlying data without any economic interpretation. Since we only consider one factor for the Press Release window, there is no need for us to apply any transformation on the first principal component extracted from yield changes over this window. We call this unique latent factor considered the *Target* factor. However, for the Press Conference window, without any transformation, it would be a pure coincidence if the first factor corresponded to a shock in the short-end of the yield curve only and therefore could be interpreted as a surprise on the short-term interest rates. The same criticism could be applied to the other types of announcements, the *Forward Guidance* and the *Quantitative Easing* surprises. We therefore have to make some transformation to these raw principal components to make them economically interpretable.

More specifically, if $F^{PC}$ is the normalized principal component matrix (i.e. $\mathbb{E}[F.F'] = I$) and $\Lambda$ the weight matrix of $X^{PC}$, for any $3 \times 3$ orthonormal matrix $U$, i.e. such that $U.U' = I$, then the matrix $\tilde{F}^{PC} \equiv F^{PC} \times U$ and loadings $\tilde{\Lambda}^{PC} \equiv U'.\Lambda^{PC}$ represent an alternative factor model that fits the data $X^{PC}$ exactly as well as $F^{PC}$ and $\Lambda^{PC}$. There are nine parameters to estimate to fully characterize this orthonormal matrix $U$. Out of those 9 elements, 6 of those are fully determined by the orthonormality assumption, which can be summarized by the following standard conditions:

$$\sum_{j=1}^{3} u_{i,j}^2 = 1, \forall i \in [1,3]$$

$$\sum_{l=1}^{3} u_{i,l}u_{j,l}, \ \forall (i,j) \in [1,3]^2 \text{ and } i \neq j$$

The three other parameters need to be extracted by imposing three other restrictions. We adopt the strategy implemented by Swanson (2017) and Altavilla *et al.* (2019): 1) the second factor is assumed not to be correlated with the one-month OIS rate, 2) the third factor factor is also assumed not to be correlated with the one-month OIS, and 3) the third factor is assumed to have the smallest variance over the pre-crisis period (January 2002-August 2008)[3]. Mathematical details of these restrictions are provided in greater details in the section 1.10.1.2. of the Appendix.

**Analysis of the Different Factors.** For the Press Conference window, we call the second factor, the *Forward Guidance* factor and the third factor, the *Quantitative Easing* factor. The main rationale behind such a factor decomposition[4] and denomination choice is the following one: the *Forward Guidance* and the *Quantitative Easing* factors are assumed not to affect the short-term end of the yield curve, which is traditionally the role of *conventional* monetary policy. The *Forward Guidance* factor is present even before the implementation of *unconventional*monetary policy measures: indeed, the ECB has always had the ability to shape economic agents' expectations about future interest rates during its press conference. On the other hand, the *QE* factor is assumed to be have the minimum impact possible on the whole yield curve before the beginning of the financial crisis which corresponds to August 2008 in our chapter[5]. These three latent factors extracted are then normalized such that the *Timing* factor has a beta of $-1$ with the 6-month interest rate, the *Forward Guidance* factor a beta of $-1$ with the 2-year OIS and the *Quantitative Easing* factor a beta

[3]We run the same analysis when considering that the third factor has the smallest variance over the period form January 2002 to May 2010, date at which the Eurosystem announced the implementation of the *Securities Market Programme.* The main goal of this large-asset purchase programme was to reduce the pressure on euro area sovereign bond yields and in particular, for Greece.

[4]The monetary shock identification literature offers other decompositions of monetary policy surprises. Jarociński and Karadi (2018) use stock-bond correlations to identify central bank information signaling contrary to monetary policy surprises. Cieslak & Schrimpf (2019) look at stock market reactions and changes in short-term and long-term interest rates to disentangle surprises in risk premia from information surprises and standard monetary policy surprises. Andrade *et al.* (2018) use changes in interest rates and in inflation-linked swaps to extract the Delphic (economic state-revealing information) and Odyssean (central bank's future commitment) components of monetary policy surprises.

[5]An alternative specification could have been to consider the beginning of the real implementation of the Asset Purchase Programme in September 2014. The correlation between these two alternative *QE* factors is 0.96 suggesting that our *QE* factor is consistent with a more conservative view on what we mean by the start date of *quantitative easing* measures.

of $-1$ with the 10-year interest rate. Consequently, an increase in any of these factors corresponds to an expansionary monetary policy surprise.

[INSERT TABLE 1.2]

Table 1.2 reports the relative contributions (variance shares) of each factor in the change of every interest rate considered in our sample over the two different windows. One first interesting result is related to the volatility of interest rates over the two different windows. As expected, the Press Release seems to convey much more information on short-term maturities of the yield curve: the standard deviation for the 1-month OIS is significantly higher (2.8%) than for the 10-year OIS (1.26%). On the other hand, the Press Conference, as it deliberately reveals more information about the current and, most importantly, the expected future state of the euro area economy seems to have bigger effects on the medium-run and long-end parts of the yield curve. For this reason, the two monetary policy windows are interesting to analyze separately since they have different impacts on the yield curve across maturities. Another interesting but unsurprising finding is that the higher the maturity, the lower the share of the variance of interest rates changes is explained by the *Target* factor. Interest rates at longer maturities are driven by other factors beyond the monetary policy decisions taken during the press release window. For the Press Conference window, the main striking facts can be summarized as follows: 1) the *Timing* factor explains most of the interest rate variance for short-term maturities (between 51% and 86%), 2) the *Forward Guidance (FG)* factor the medium-run part of the term structure with a peak at 81% for the 5-year OIS, and 3) the variance explained by the *Quantitative Easing (QE)* factor is an increasing function of maturity going from 0% for the one-month interest rate to 25% for the 10-year interest rate. It is worth pointing out that the transformation operated on the first three principal components does not guarantee that the *Forward Guidance* factor mainly explains medium-run yield changes and that the *Quantitative Easing* factor has higher variance contribution as the maturity increases. As a result, labeling these two latent factors the *FG* and the *QE* factors seems to be a reasonable denomination choice based on how much of the variance in interest rate changes for different maturities each of them explains.

[INSERT TABLE 1.3]

Table 1.3 shows how the various OIS-rates are correlated with the different factors. Without any surprise, the longer the maturity, the less correlated the interest rate is with the *Target* factor. The single factor extracted from the Press Release window mainly explains changes at the short-end of the term structure.

For the Press Conference window, the *Timing* factor mostly affects the medium-run of the yield curve between 6 months and 2 years. The effects of the *Forward Guidance* factor are slightly different. By construction, a shock to the *Forward Guidance* factor has no effect on the one-month OIS rate. At longer maturities, however, the *Forward Guidance*'s effects increase, peaking at the 5-year horizon and diminishing at longer horizons. The effects of the *Quantitative Easing* factor are also significantly different from the first two factors of the Press Conference window. As the *Forward Guidance* factor, a change in the *QE* factor has, by construction, no effect on the one-month OIS rate. However, the effect of the *QE* factor is relatively small at short maturities and much larger at the long end of the yield curve. Such a feature is in line with the main goal of large scale asset purchase programme which has been to lower long-term interest rates. Moreover, consistent with the findings of Swanson (2017) on U.S. data and unlike the loadings found by Altavilla *et al.* (2019) on euro area data, our *QE* factor has a positive impact on short-term maturities and negative impact on long-term maturities. This result also suggests that the *QE* factor that we identify for the euro area shares some characteristics with the "Operation Twist" pursued by the Federal Reserve in September 2011[6].

Figures 1.2, 1.3, 1.4 and 1.5 show the times series of the four different monetary policy shocks considered. The reader should keep in mind that any positive shock is synonym of an expansionary monetary policy surprise. In particular, for the *QE* factor, the large positive shock observed in mid-2012 corresponds to the day of the announcement of the Outright Monetary Transactions programme by the president of the ECB at the time, Mario Draghi. Even if this programme has never been ultimately implemented, it was supposed to reassure financial markets by asserting that the Eurosystem would do "whatever it takes" to save the euro area. The large positive shocks which can be seen at the beginning of 2015 correspond to the Governing Council days where details and conditions about the Asset Purchase Programme, i.e. the European *quantitative easing* programme, were finally revealed.

[INSERT FIGURES 1.2, 1.3, 1.4 AND 1.5]

[6]On September 21, 2011, the FOMC announced an "Operation Twist" program, where it would sell $400 billion of short-term Treasuries from its portfolio and buy a like quantity of long-term Treasuries.

#### 1.3.1.4. From Very High-Frequency to the Monthly Frequency

We time aggregate these different high-frequency shocks to the monthly frequency in order to be able to merge these monetary policy shocks with our bank and loan-level datasets. We follow two different procedures standard in the literature. In the first specification, as in Wong (2016), for each type of monetary policy shock, we build a simple sum of the different shocks occurring within the month. Alternatively, in a more elaborate way following Winberry & Ottonello (2017), we construct a moving average of the high-frequency shocks weighted by the number of business days in the month after the monetary policy decision has been taken according to the following formula:

$$\varepsilon_m^{mp} = \sum_{t \in \mathcal{S}(m)} \omega(t) \times \varepsilon_t^{mp} \tag{1.2}$$

where $\varepsilon_m^{mp}$ are the monthly monetary policy shocks, $\varepsilon_t^{mp}$ is the monetary policy shock observed on the monetary policy announcement day $t$, $\mathcal{S}(m)$ is the set of monetary policy announcement days occurring during the month $m$ and $\omega(t') \equiv \frac{\tau_m^n - \tau_m^d(t)}{\tau_m^n}$ where $\tau_m^n$ is the number of business days during the month $m$ and $\tau_m^d(t)$ the number of business days after day $t$ within the month $m$. The latter strategy allows us to take into account the reaction period that banks had during the month to adjust their quantity of loans. Table 1.4 shows the various moments of these different shocks. The time series of monthly monetary shocks under the two time aggregation techniques do not significantly differ from each other. For each type of monetary policy shock, their correlation is close to 1. For the rest of the chapter, we will use monthly monetary policy shocks which have been time aggregated using the weighted average technique[7]. Moreover, table 1.5 which reports the correlation coefficients between two monthly monetary policy shocks should convince the reader that the four different monetary policy shocks considered for the rest of the analysis are indeed uncorrelated.

[INSERT TABLES 1.4 AND 1.5]

[7] As a robustness check, results using the other technique are also available from the author upon request.

## 1.4. Data Description

We conduct our analysis at the monthly frequency at the bank level for the most part but also at the firm-bank level. Our sample period runs from June 2007 to September 2018. Our whole empirical strategy relies on six different sources of data. As we have previously seen, the first major dataset used in this chapter is made of high frequency data about euro area monetary rates (Overnight Interest Rate Swap, hereafter OIS) and European sovereign bond rates. This dataset and its use has been intensively discussed in Section 1.3.1.. In terms of real economic outcomes, we turn to proprietary data provided by the French Central Bank (Banque de France) and the European Central Bank. The major dataset of interest in our study corresponds to the monthly bank balance sheet database. However, to properly measure bank lending to firms, we also use firm-bank datasets at the loan-level level, more specifically one about banks' credit exposure to firms (monthly data on outstanding amount of bank credit) and another one about new loans issued by banks to the real economy (collection of new loans issued by a random and representative sample of banks every quarter) and which includes more detailed characteristics about the new loans granted. The fifth database (the FIBEN individual company database) used in our study is made of yearly financial statements, with detailed information about firm size, investment, employment, profits and credit ratings among others. Finally, we combine this dataset with the FIBEN internal credit rating of Banque de France.

### 1.4.1. Bank Balance Sheet Data

The key dataset exploited in this chapter is the IBSI (Individual Balance Sheet Indicators) database, which provides balance sheet items for a large panel of euro area banks. The sample period runs from June 2007 to December 2019. We restrict our sample to only French financial institutions which own the license of a credit institution and regulated by the French supervisory entity, the *Autorité de Contrôle Prudentiel et de Résolution* (ACPR). We also include foreign credit institutions whose subsidiaries operate in France. Each credit institution is a principal or a subsidiary institution and therefore corresponds to an independent entity[8]. This dataset gathers information about the whole balance sheet of these credit institutions at the monthly frequency. Table 1.6 displays the different

[8]Branches are not included as internal capital markets might play an important role in terms of within bank distribution and therefore lending and risk-taking behavior

balance sheet elements that can be found in this dataset.

[INSERT TABLE 1.6]

In particular, on the asset side, there is information about the amount of cash, outstanding loans (to households, non-financial corporations and government), securities (bonds and shares both issued by monetary and financial institutions and governments), shares in money market funds, the exposure to sovereign debt and other relevant bank balance sheet information. Our main dependent variables are: 1) monthly growth rate of total lending, ($\Delta$Log(Loans) in %, and 2) monthly growth rate of lending to non-financial corporations, ($\Delta$Log(NFC Loans) in %. The explanatory variables which also serve as controls are: 1) the size, Log(Assets), 2) the equity-to-asset ratio, (E/A), 3) the share of liquid assets corresponding to the ratio of available-for-sale securities (debt securities+equity shares+money market fund shares) over total assets, (Share Liquid Assets), and 4) the share of deposit liabilities defined as the ratio of deposits over total assets, (Share Deposits Liabilities). To remove any outlier which could strongly bias our estimates, we delete observations for which at least one of these variables deviates more than five times the interquartile range from the median. Appendix 1.10.2. explains in detail how we construct these variables.

We report the summary statistics for our variables of interest, both dependent and explanatory variables, in Table 1.7. This table shows that, over our sample period, there is a lot of heterogeneity across banks according to several dimensions. The average monthly growth rate for total lending and lending to non-financial corporations is 0.46% and 0.29% respectively, which is in line with previous studies on U.S. data but for different time periods (see Gomez *et al.* (2016)). For instance, the average equity-to-assets ratio of 8.46% is also consistent with the one found by Altavilla *et al.* (2019) of 6.84% for all euro area banks.

### 1.4.2. The Firm-Level Datasets

#### 1.4.2.1. The Firm Accounting Dataset: the FIBEN individual company database

The Banque de France gathers economic, financial and mostly accounting information about each French firm required to submit accounting documents to the tax authority. Created in 1982 primarily for monetary policy implementation purposes, this database, FIBEN (*Fichier Bancaire des Entreprises*), is also used for credit risk management by financial intermediaries (see Section 1.4.2.2.). In order to obtain an informed, clear and detailed vision of the business and financial health of French companies, the Banque de France relies on its ubiquity over the whole French territory. Indeed, its 95 local branches and 19 economic units allows the Banque de France to offer a granular coverage of the French economic and business fabric. As a result, FIBEN includes all French firms with annual sales at least equal to €75,000.

Accounting and financial information about firms (financial statements about firm balance sheet and income statement) is available at the annual frequency and goes back up to 1989. In our study, we only focus on our period of interest, from 2006 to 2018. Every firm $f$ registered and listed as a legal unit in the National Business Directory (*Répertoire National des Entreprises*) is fully identified by its 9-digit SIREN number issued by INSEE (the French National Institute of Statistics). The location of its headquarters as well as its industry are also We drop firms with negative debt, negative or zero total assets, missing number of employees. We also exclude from our sample financial companies and public sector firms.

#### 1.4.2.2. The Firm Credit Rating Dataset: the FIBEN internal credit rating

In FIBEN, Banque de France assigns an internal credit rating (ICR) to every non-financial firm with a minimum annual revenue of €75,00 and which provides the Banque de France with accounting information. These credit ratings are not only derived from *hard* firm-specific, sectoral and regional data but also from *soft* individual information. Firm-specific *hard* data include firm's financial statements, information on supplier/customer trade bill payment incidents, default payment incidents, legal information. Regular meetings with firm's CEOs and local reputation are also a valuable piece of information to assess the prospect of a company. Every year, when new financial statements of a firm are received, Banque de France's local branch checks, and revises if necessary, the credit rating of this company. If a major event (payment default event, etc.) occurs to a specific firm, the Banque de France can also choose to change its rating. In 2018, Banque de France has analyzed the financial statements of and assigned credit ratings to approximatively 266,000 French companies. Banque de France's financial analysts have met with 50,000 CEOs. Whenever a significant new development is brought to the attention of the Banque de France, the French centra bank can decide to revise their credit rating.

The ICR intends to reflect the firm's ability to honor its financial commitments in the medium run, i.e. over a three-year horizon. It constitutes a fundamental piece of information for any financial intermediary deciding whether or not it should start lending or roll-over its credit lines to a specific company. In addition to the role played by this rating as an objective firm's credit risk measure, the ICR is also used to determine whether a loan is eligible as collateral for Eurosystem refinancing operations.

#### 1.4.2.3. Credit Exposure and New Loans Datasets

##### 1.4.2.3.1. The Firm-Bank Credit Exposure Dataset: the *Centrale des Risques*

Since the enactement of the Banque de France Nationalization Act in January 1946, every financial intermediary[9] in France has been required by law to periodically report to the Banque de France its credit exposure with respect to any French non-financial firm, individual entrepreneur or public administration as long as this credit exposure is above a certain threshold. This threshold amount is €25,000[10]. The Banque de France's *Service Central des Risques* (Central Credit Division) is in charge of collecting such data which are then stored in the *Centrale des Risques* (Central Credit Registry) database[11].

This dataset is then made available at the monthly frequency since January 2006. Every bank is identified by its CIB (*Code Interbancaire* or Interbank Code), a 5-digit number issued by Banque de France for any credit institution operating in France or in Monaco. Moreover, this dataset allows

[9]Financial intermediaries correspond to credit institutions, investment firms but also public institutions, such as, for instance, the Caisse des Dépôts et Consignations (Deposits and Consignments Fund) which is a French public sector financial institution created in 1816, and which is part of the government institutions under the control of the Parliament.

[10]However, regarding this threshold, some remarks need to be made.? assert that "in practice, a significant methodological change regarding the scope of this reporting threshold happened in April 2012. Before this date, a bank had to report its bilateral exposures larger than €25,000 as measured at the level of its local branches. After this date, a bank has to report any bilateral exposure that is greater than €25,000 as measured at the level of the whole bank". Following their methodology and the one implemented by Cahn *et al.*, we dropped all bilateral branch-firm links with a total exposure smaller than €25,000.

[11]Historically, the main financial and economic reasons behind this legal obligation goes back to the 30's. Prior to this period, it was considered inappropriate for a credit institution to ask a company about its other credit commitments with respect to other banks. During the Great Depression, bankers started realizing that they were competing with potentially many other credit institutions when they were trying to recover the amount due by a defaulting company. Consequently, it became obvious that a database gathering information about firms' total credit lines was necessary. See Rattier (1951) for further explanations.

us to get an even more granular description of the dynamics of bank loan supply within the French territory. Indeed, a firm $f$ can borrow from a bank $b$ through different local branches, especially when this company tends to operate in different locations within France. With this dataset, we can potentially observe bank $b$'s credit exposure to firm $f$ through branches $br$ and $br'$, allowing us to potentially control for regional characteristics. This dataset reports not only the global credit exposure of every French bank's branch towards any French firm as long as its credit exposure is above a certain threshold but also some basic loan characteristics. For instance, banks have to declare if the credit granted is rather short-term (less than a year) or medium/long-term (more than a year). In addition, banks disclose their credit exposures to firms not only through standard credit loans *per se* but also via undrawn credit lines, guarantees and different types of specific operations such as factoring, medium and long-term leases with purchase option and securitized loans.

#### 1.4.2.3.2. The New Loans Dataset

In addition to the Central Credit Registry, the Banque de France collects information about new loans issued by credit institutions at the quarterly frequency since 2006. This New Loans dataset presents one major drawback: it does not cover all the new loans granted by all French financial institutions to all French firms over a quarter. It only corresponds to new loans issued by a random sub-sample of local branches of banks over the whole universe of French banks. The random selection of banks' branches allows us to reasonably argue that this sample does not suffer from any selection bias. Thus, there should be no concern that our results might be biased by the sample composition.

This database contains, among others, information about the borrowing firm, the branch identifier of the lending bank, the amount borrowed, the interest rate charged, the annual percentage rate of charge (APRC), which corresponds to both the underlying interest rate and the fees, the type of loans (e.g. mortgage loans, leasing), the loan maturity in months. This dataset which, to my knowledge, has never been exploited so far is essential to check whether our simple algorithm (see 1.6.2.) allowing us to detect the initiation of new loans from the Credit Exposure dataset is efficient or not. We cannot directly use this dataset to estimate our credit supply equation in 1.6.1. as there is not a sufficient number of firms borrowing from at least two different banks in this dataset. Nevertheless, measuring the heterogeneous causal effects of different types of monetary policy shocks on loan prices and maturities is also essential and is left for future research.

# 1.5. Banks' Heterogeneous Responses to Monetary Policy Shocks: Bank-Level Evidence

This section lays out the empirical framework allowing us to test how the response of loan supply to different types of monetary policy shocks varies across banks. We provide some evidence on how size, capital level, share of liquid assets and share of deposit liabilities can explain different intensities of reactions in terms of lending to the real economy after different types of monetary policy shocks. However, one of the main drawbacks of this first empirical exercise is that we do not control for different investment opportunities that banks face and which could be correlated with their own characteristics. To remedy this problem, we look in section 1.6. at the heterogeneous loan supply of banks when the same firm borrows from multiple banks within a month. This specification therefore allows us to control for any demand shock coming from firms.

## 1.5.1. Methodology and Baseline Specification

**Baseline Specification.** In the same vein as Kashyap & Stein (1995), Kashyap & Stein (2000), Campello (2002) or Gomez *et al.* (2016), our baseline specification consists in running the following panel regression:

$$\begin{aligned}\Delta \mathrm{Y}_{b,t} = \alpha_t + \sum_{k=0}^{3} \beta_k \times \left(\mathrm{x}_{b,t-k} \times \varepsilon^{\mathrm{mp}}_{t-k}\right) + \sum_{k=0}^{3} \sum_{z \in \mathrm{Control}} \gamma_{z,k} \times \left(\mathrm{z}_{b,t-1} \times \varepsilon^{\mathrm{mp}}_{t-k}\right) + \\ \phi \times \mathrm{x}_{b,t-1} + \sum_{z \in \mathrm{Control}} \mu_z \times z_{b,t-1} + \sum_{k=1}^{3} \delta_k \times \Delta \mathrm{Y}_{b,t-k} + \varepsilon_{b,t}\end{aligned} \tag{1.3}$$

where the dependent variable $Y_{b,t}$ is either, $\Delta\text{Log(Total Loans)}_{b,t}$, the percentage change in the quantity of loan granted by bank $b$ to the real economy (households and non-financial corporations) between month $t-1$ and month $t$, or $\Delta\text{Log(Total Loans to NFC)}_{b,t}$, the monthly growth in the quantity of loan granted by bank $b$ to to non-financial corporations, $\alpha_t$ is a month $t$-fixed effect, $x_{b,t-1}$ is our independent variable of interest (e.g. liquid assets of bank $b$ at the beginning of the month, or its leverage ratio of bank $b$ at the beginning of month $t$ ), $\varepsilon_t^{mp}$ is our monthly monetary policy factor where $mp$ = *Target*, *Timing*, *FG* or *QE*[12], $Z_{b,t-1} = \{z_{b,t-1}\}$ is a vector of usual bank-level controls such as leverage, size, the share of liquid assets held on banks balance sheet, the exposure to sovereign debt and $\varepsilon_{b,t}$ is a residual. We lag both the independent variable $x_{b,t-1}$ and the control variables $z_{b,t-1}$ to ensure that they are predetermined at the time of the monetary policy shocks. Our specification is such that we try to control for any aggregate demand shock which could explain any increase or decrease in the quantity of loan granted overall in the French economy for a specific month via the time-fixed effect. Standard errors are two-way clustered at the bank and month level.

**Theoretical Predictions.** The coefficient of interest is $\sum_{k=0}^{3} \beta_k$ which corresponds to how the semi-elasticity of loan supply with respect to current ($\varepsilon_t^{mp}$) and past monetary shocks ($\varepsilon_{t-1}^{mp}$,$\varepsilon_{t-2}^{mp}$,$\varepsilon_{t-3}^{mp}$) depends on the bank's size, its capital level, its share of liquid assets, or its share of deposits in its liabilities. In the case of the independent variable being the share of liquid assets (as in Kashyap & Stein (2000)), we expect that $\sum\limits_{k=0}^{3} \beta_k < 0$. The more liquid assets a bank holds on its balance sheet, the less it should respond to expansionary monetary policy which, in theory, tends to release the pressure on the most liquidity constrained banks. However, since sovereign debt is considered as a liquid asset, *wealth* effects could potentially dominate. When long-term sovereign interest rates fall after large scale asset purchases, banks detaining more sovereign securities should see their wealth increase and therefore could expand their lending to the real economy. If we consider the equity-over-asset ratio of banks, the higher it is, the less responsive the bank should be to any change in the monetary policy stance. In general, more financially constrained (either in terms of solvency or liquidity) banks should react more to accommodative monetary policy shocks. When looking at the share of deposit liabilities, the predicted sign is also ambiguous. Indeed, banks that issue a large share of interest-bearing deposits will experience an increase in their profitability when interest rates drop. However, when interest rates decrease, deposits become less attractive for households and firms. A deposit run is more likely and could therefore push banks to preemptively reduce their lending business.

**Empirical Challenges and How to Address Them.** Equation 1.3 will provide unbiased estimates of the $\beta$' under the identifying assumption that the correlation between banks lending

[12]Remember that we consider four different monetary policy factors in our study: the *Target* (*Target*), the *Timing*, the *Forward Guidance* (*FG*) and the *Quantitative Easing* (*QE*) factors.

opportunity ($\varepsilon_{b,t}$) and monetary policy shocks ($\varepsilon_{t-k}^{mp}$) is not systematically related to banks' independent variable under consideration (share of liquid assets, equity-over-asset ratio, size, and share of deposit liabilities). As usual in this type of empirical exercise, there are essentially two identification challenges for the $\beta$'s. The first and most natural empirical challenge is the question of endogeneity and, in particular, any potential endogenous matching between banks and their borrowers. More specifically, if the estimation residuals $\varepsilon_{b,t}$ are correlated with the $x_b$'s, the estimates for the $\beta$'s will be biased. For instance, if banks with higher liquid assets tend to attract borrowers which respond more to monetary policy shocks, our estimate will be biased upwards. For this reason, in a second empirical exercise, we control for any demand shock that could bias our estimates of the sum of the $\beta$'s. Another typical threat with such empirical exercise is the issue of omitted variables. Bank's independent variable under consideration might be correlated with other bank characteristics that could also explain how monetary policy shocks affect banks' lending. To remedy this problem, we include as many control variables as possible. They correspond to the set of other bank's characteristics that we want to consider when analyzing the effects of different types of monetary policy shocks.

**Bank Fixed Effects.** Our baseline specification does not include bank fixed effects. Including some bank fixed effects can be key if different lending behavior is fundamentally observed across the banks in our sample. However, adding them would drastically reduce the cross-sectional variation of our explanatory variable. Moreover, it could tend to emphasize too much on the time-variation of our independent variable that could be driven by outlier observations. Nevertheless, given the number of controls included in our baseline panel regression, we think that this issue is rather limited. Econometrically, running an Hausman test on whether we should include bank fixed effects concludes in the vast majority of our regressions that we should not.

### 1.5.2. Results and Discussion

#### 1.5.2.1. Does Size Still Matter?

In this section, we first test whether the size of a bank's balance sheet plays a role in transmitting monetary policy shocks to the real economy. Kashyap & Stein (1995) argue that small and large banks should react differently to monetary policy changes. Table 1.7 reports the results of Equation 1.3 with the log of total assets (i.e. size) as the main dependent variable. We also include in this regression the different control variables (equity-over-asset ratio, share of liquid assets, share of deposit liabilities) discussed previously to try to avoid any omitted variable issue. In Panel A, we look at how the effects of monetary policy shocks on lending to the real economy (households and non-financial corporations) depend on bank's size. In Panel B, the dependent variable is the percentage monthly change in the loan supply to non-financial corporations. Overall, the estimate of $\sum_{k=0}^{3} \beta_k$ is statistically insignificant. This result holds for monetary shocks which tend to rely heavily on the short end of the yield curve (the *Target* and the *Timing* factors) and contradicts previous empirical works (see Kashyap & Stein (1995)). At first glance, such a finding argues in favor of the absence of any bank lending channel related to bank's size over the last decade. Nevertheless, transmission to the real economy of monetary policy shock of type *Forward Guidance* seems to be sensitive to bank's balance sheet size. The corresponding estimate of $\sum_{k=0}^{3} \beta_k$ is equal to -6.6 and statistically significant at the 10%-level, and almost at the 5%-level (p-value of 0.057). The bigger a bank, the less it responds to *Forward Guidance* monetary policy shock. This estimate is also economically significant. Indeed, after a *Forward Guidance* shock of one standard deviation (i.e. 4.23 bps), a bank which is at the $25^{th}$-percentile in terms of total assets (a log of total assets of 10.35) expands its lending to households and non-financial corporations over the next quarter by 0.55% more than a bank at the $75^{th}$-percentile. This effect is really strong compared to the average 0.46% monthly growth rate for the lending to the real economy observed over the whole sample. In terms of lending to non-financial corporations only, the results are qualitatively similar. In particular, the estimate of $\sum_{k=0}^{3} \beta_k$ for the *FG* monetary policy shock (-7.3) is close the one obtained for total lending to the real economy. This result suggests that such monetary policy shocks are essentially transmitted to firms.

[INSERT TABLE 1.7]

#### 1.5.2.2. Capital and Monetary Policy Transmission

When the Eurosystem decides to implement an expansionary monetary policy, banks which are more financially constrained and, in particular, the ones with low levels of equity with respect to their total assets should benefit from a decrease in their external cost of funding resulting from any interest rate cut. In theory, these financially constrained banks should eventually increase their lending to the real economy. Table 1.8 analyzes how bank's capital ratio can be a catalyst or not for monetary policy transmission. In terms of both total lending to the real economy (Panel A) and lending to non-financial corporations (Panel B), our estimates for $\sum_{k=0}^{3} \beta_k$ are statistically insignificant. If anything, most of them are positive and the estimated effects rather have the "opposite" sign of what the theory would predict: banks with higher capital should lend even more to the real economy when interest rates decrease. This outcome contrasts not only with the theory but also with previous empirical works on the role played by banks' leverage for monetary policy transmission (Kishan & Opiela (2000)). This major discrepancy mainly comes from the fact that Kishan & Opiela (2000) look at U.S. commercial banks and at a different time period. Our sample covers a period of significant changes in terms of financial regulation taking, in particular, the form of additional capital requirement for banks (e.g. implementation of Basel III's regulatory framework). These concomitant changes in the regulatory landscape renders any statistical inference with respect to this important dimension less straightforward. The interaction between monetary policy transmission and financial regulation albeit essential is left for future research.

[INSERT TABLE 1.8]

#### 1.5.2.3. Are Illiquid Banks More Responsive to Expansionary Monetary Policy Shocks?

As previously discussed, the effects of an expansionary monetary policy shock for a bank which holds a lot of liquid assets (cash and securities) is not univocal. Banks with a high fraction of liquid assets in its portfolio should react less to such a shock as they are less financially constrained. On the other hand, banks which are relatively short of liquid assets should benefit from lower interest rates which tend to decrease their external cost of funding. This is the main empirical finding observed by Kashyap & Stein (1995). However, another theoretical prediction can also be considered. If a bank holds in its portfolio of liquid assets a significant amount of securities which are directly targeted by a large-scale asset purchase programme, the value of its securities portfolio would increase[13]. The wealth effect associated could benefit these banks according to two dimensions. First, they are able to sell these assets at a higher price. Moreover, they can use these assets as collateral and therefore be able to borrow at lower interest rates. The second alternative seems to explain the behavior of French banks over the 2007-2018 period after a $QE$-type monetary policy shock. Indeed, table 1.9 shows that the estimate of $\sum_{k=0}^{3} \beta_k$ is positive and statistically significant only for this type of monetary policy shock, at the 1%-level for total lending to the real economy and at the 10%-level for

[13] At the same, the value of its cash should also surge as the opportunity cost of holding cash gets lower when interest rates decrease.

lending to non-financial corporations. If a *QE* shock decreases the 10-year interest rate by 1.955 bps (one standard deviation of our shock), a bank expands its lending to non-financial corporations over the next quarter by 0.24 percentage points more than any other bank which holds ten percentage points less of liquid assets in its portfolio. This effect is economically relatively strong as well.

[INSERT TABLE 1.9]

#### 1.5.2.4. The Role of Deposits in Monetary Policy Transmission: A Reversal Interest Rate?

Deposits are one of the most important sources of funding for banks. There are two views on the role played by deposits. On the one hand, they provide liquidity to households (Diamond & Dybvig (1983) and Gorton & Pennacchi (1990)). Moreover, they are a stable and dependable source of funding for banks (Stein (1998), Kashyap *et al.* (2002), Hanson *et al.* (2015)). Drechsler *et al.* (2017) introduced a new monetary policy transmission channel, the deposits channel. Looking at U.S. data, they argue that when the Fed funds rate rises, banks widen the spreads they charge on deposits and as a result, deposits flow out of the banking system. The economic rationale behind this phenomenon comes from the market power of banks. Their entire identification strategy relies on geographical variations in terms of deposit concentration. We cannot run the same type of empirical exercise in this chapter due to data limitation. However, we can look at how two banks with different levels of deposits on their liability side are affected by different types of monetary policy shocks and how they react in terms of lending. Our empirical findings suggest that banks with a higher share of deposit liabilities are more likely to reduce their lending to non-financial corporations after a *Timing* or a *Forward Guidance* shock. Table 1.10 shows that, regarding total lending to the real economy, the share of deposits of a bank is not a factor affecting monetary policy transmission. However, banks with a high share of deposits on their liability side tend to reduce their lending to non-financial corporations after a *Timing* or a *Forward Guidance* shock. Indeed, for these shocks and for lending to non-financial corporations, the estimate of $\sum_{k=0}^{3} \beta_k$ is negative and statistically significant. If the 6-month interest rate decreases by 3.25 bps due to a *Timing* shock, bank A with 10% more deposits on its liability side than another bank, bank $B$, will decrease its lending by 0.10% over the next quarter compared to bank $B$. This finding is relatively novel: most of the bank lending literature argues that lower interest rates, as they reduce the cost of liabilities and increase the profitability of commercial banks, should boost lending to the real economy. Our empirical result is consistent with the idea of a *reversal interest rate*, i.e. an interest rate threshold below which any accommodative monetary decision could depress the economy instead of stimulating it. This concept has been introduced by Brunnermeier & Koby (2019). Using European data, Heider *et al.* (2019) show that banks are reluctant to pass on negative rates to depositors, which increases the funding cost of high-deposit banks, and reduces their net worth, relative to low-deposit banks. As a result, they are most likely to reduce their loan supply to the real economy.

[INSERT TABLE 1.10]

# 1.6. Loan-Level Evidence

## 1.6.1. Empirical Strategy

One main issue and limitation with our previous empirical strategy is any omitted variable bias which might arise from the potential endogenous matching between banks and firms. For the sake of exposition, let us consider a concrete example: assume that small banks supply loans on average to firms which tend to respond more to *Forward Guidance* monetary policy shocks. The significant and negative estimate of $\sum_{k=0}^{3} \beta_k$ found in Section 1.5.2.1. would be wrongfully attributed to bank's size when it simply reflects the differential demand response coming from the typical firms which borrow from small banks after such a monetary policy shock. To remedy this issue, we estimate a loan supply equation in the spirit of Khwaja & Mian (2008). This equation includes firm-month fixed effects, which allows us to control for loan demand. To do so, we use the Credit Exposure dataset for a subsample of firms which are randomly selected according to the last figure in their SIREN number. The introduction of firm-month fixed effects is only possible as long as we focus on firms borrowing from at least two different banks within a month. As a result, we estimate the following linear model linking the exposure of bank $b$ to firm $f$ for month $t$:

$$\begin{aligned}\text{New Loans}_{f,b,t} = \alpha_{f,t} + \sum_{k=0}^{3} \beta_k \times \left(\mathrm{x}_{b,t-k} \times \varepsilon^{\mathrm{mp}}_{t-k}\right) + \sum_{k=0}^{3} \gamma_{z,k} \times \left(\mathrm{z}_{b,t-1} \times \varepsilon^{\mathrm{mp}}_{t-k}\right) + \\ \phi \times \mathrm{x}_{b,t-1} + \sum_{z \in \text{Control}} \mu_z \times z_{b,t-1} + \varepsilon_{f,b,t}\end{aligned} \tag{1.4}$$

where the dependent variable New $\text{Loans}_{f,b,t}$ corresponds to the new loans granted by bank $b$ for firm $f$ between month $t-1$ and month $t$ normalized by the credit exposure at month $t-1$, $x_{b,t-1}$ is our independent variable of interest ($(\text{Size})_{b,t-1}$, $(\text{E/A})_{b,t-1}$, $(\text{Share of Liquid Assets})_{b,t-1}$ or $(\text{Share of Deposit Liabilities})_{b,t-1}$), $\varepsilon_t^{mp}$ is our monthly monetary policy factor. Thanks to our firm-month fixed effect, $\alpha_{f,t}$, we are able to control for any aggregate demand shock coming from firm $f$. Standard errors are two-way clustered at the bank and firm-month level.

### 1.6.2. How to Properly Account for New Loans

One of our main datasets provides us with a rather detailed picture of the credit exposures of each French bank with respect to each French firm at the end of each month in our sample period. However, a key limitation with this dataset is the fact that we do not know whether a new loan has been initiated over a month. Credit exposures are extremely persistent: they do not vary much from one month to the other as the average firm does not contract a new loan every month. Consequently, looking at changes in the credit exposures without any transformation could be extremely misleading. These changes can potentially and mainly reveal past decisions in terms of loans. Indeed, a negative growth in terms of credit exposure between bank $b$ and firm $f$ could essentially reflect the termination of a loan contracted years ago. Our empirical specification given by 1.5 where the dependent variable would be changes in credit exposure would not be very informative. Instead, we decide to focus on new loans and see whether, when a new loan is initiated, a firm would rather obtain it from a bank with a high share of liquid assets or not for instance. Ideally, we would like to have access to a dataset made of new loans applications similar to the one exploited by Jimenez *et al.* (2012).

Even if we do not know whether or not a new loan has been initiated over a specific month, we can infer it from the Credit Exposures dataset to a certain extent. As this dataset provides us with a detailed decomposition of the different types of credit exposures, we adopt a simple rule to decide whether or not a new loan has been contracted over a specific month. If the change in the credit exposure with respect to a certain type of exposure is positive, we arguably assume that a new loan whose size corresponds to this positive change has been agreed upon over a month. Such an assumption is not controversial *per se.* What our algorithm cannot detect is when we observe a negative growth in the credit exposure and when a new loan has in fact been granted. We are not able to detect this type of error. As a robustness check, we use the New Loans dataset. This database allows us to verify whether a new loan recorded in this dataset is indeed detected by the simple algorithm we implemented. We find that 91% of the new loans present in the New Loans dataset are indeed correctly identified by this simple rule. For every month $t$ and for each pair of bank $b$ and firm $f$, we then collapse the new loans coming from different types of contracts into one variable called New $\text{Loans}_{f,b,t}$ which is also normalized by the credit exposure of bank $b$ with respect to firm $f$ at the end of month $t-1$ to account for firm's size. We only keep observations for which a new loan from at least one bank has been contracted over the month.

### 1.6.3. Results

Table 1.11 reports estimates of $\sum_{k=0}^{3} \beta_k$ in equation 1.5 associated with the different bank characteristics that we have already considered in Section 1.5. and the four different monetary policy shocks extracted in Section 1.3.. Corroborating the results found in Section 1.5., the estimates are significant at the 5%-level for size and *Forward Guidance* shock, for share of liquid assets and *Quantitative Easing* shock and for share of deposit liabilities and both *Timing* and *Forward Guidance* shocks. Quantitatively, the signs and magnitude for $\sum_{k=0}^{3} \beta_k$ are also consistent with the ones found when not controlling for any demand shock. This finding suggests that there is no endogenous matching between firms and banks which would have biased our first set of results when looking at the bank-level evidence. Surprisingly, the sum of the estimated coefficients for size and the *Forward Guidance* shock is half the one estimated previously whereas the sum of the coefficients for the share or liquid assets and *QE* shock is a little bit higher. Another notable difference between these new estimates and the previous ones is that the sum of the estimates for the equity-over-assets ratio when interacted with the *Forward Guidance* shock is now significant at the 10%-level.

[INSERT TABLE 1.11]

## 1.7. Conclusion

Starting from the premise that monetary policy is multi-dimensional, this chapter revisits the bank lending channel literature. Our approach consists in finding whether there are some significant cross-sectional disparities in the way French banks that exhibit different bank characteristics respond to *various types* of monetary policy shocks. Building upon the asset pricing literature on high-frequency identification, we first extract from changes in interest rates around ECB's monetary policy announcements four different types of monetary policy shocks. The *Target* factor affects mostly the very-short end of the yield curve. The *Timing* factor has the biggest impact on the 6-month interest rate whereas the *Forward Guidance* affects interest rates at the 5-year horizon. The *Quantitative Easing* factor essentially moves interest rates at longer maturities. We then combine this monetary policy shocks that we first aggregate at the monthly frequency with our sample of monthly data on French banks for the period 2007 to 2018. We find that bank's size matters for monetary policy transmission when we consider a *Forward Guidance* shock. After an expansionary *Forward Guidance* shock of one standard deviation (i.e. a 4.23 bps drop in the 2-year OIS rate), a bank which is at the $25^{th}$-percentile in terms of size distribution expands its lending to households and non-financial corporations over the next quarter by 0.55% more than a bank at the $75^{th}$-percentile. This effect must be compared to the average 0.46% monthly growth rate for the lending to the real economy observed over the whole sample. We also document that liquid assets (cash, securities and deposits at the central banks) held by a bank can be a vector of the smooth transmission of monetary policy. In particular, if a *QE* shock decreases the 10-year interest rate by 1.955 bps, a bank expands its lending to non-financial corporations over the next quarter by 0.24 percentage points more than any other bank which holds ten percentage points less of liquid assets in its portfolio. This finding can be rationalized by the wealth effect associated with any increase in the value of the sovereign bonds that banks might possess on their balance sheet when a *QE* shock occurs. This chapter also highlights the adverse role of deposits. Banks with a high share of deposits on their liability side tend to reduce their lending to non-financial corporations after a *Timing* or a *Forward Guidance* shock. This relatively novel empirical result is consistent with the idea of a *reversal interest rate* (Brunnermeier & Koby (2019)), i.e. an interest rate threshold below which any accommodative monetary policy decision could depress the economy instead of stimulating it. We finally rely on a detailed firm-bank loan-level dataset to confirm the results coming from our bank-level analysis: the endogenous matching of banks and firms does not explain our initial results.

## 1.8. Figures

### 1.8.1. Eurosystem's Monetary Policy Decisions since 2013

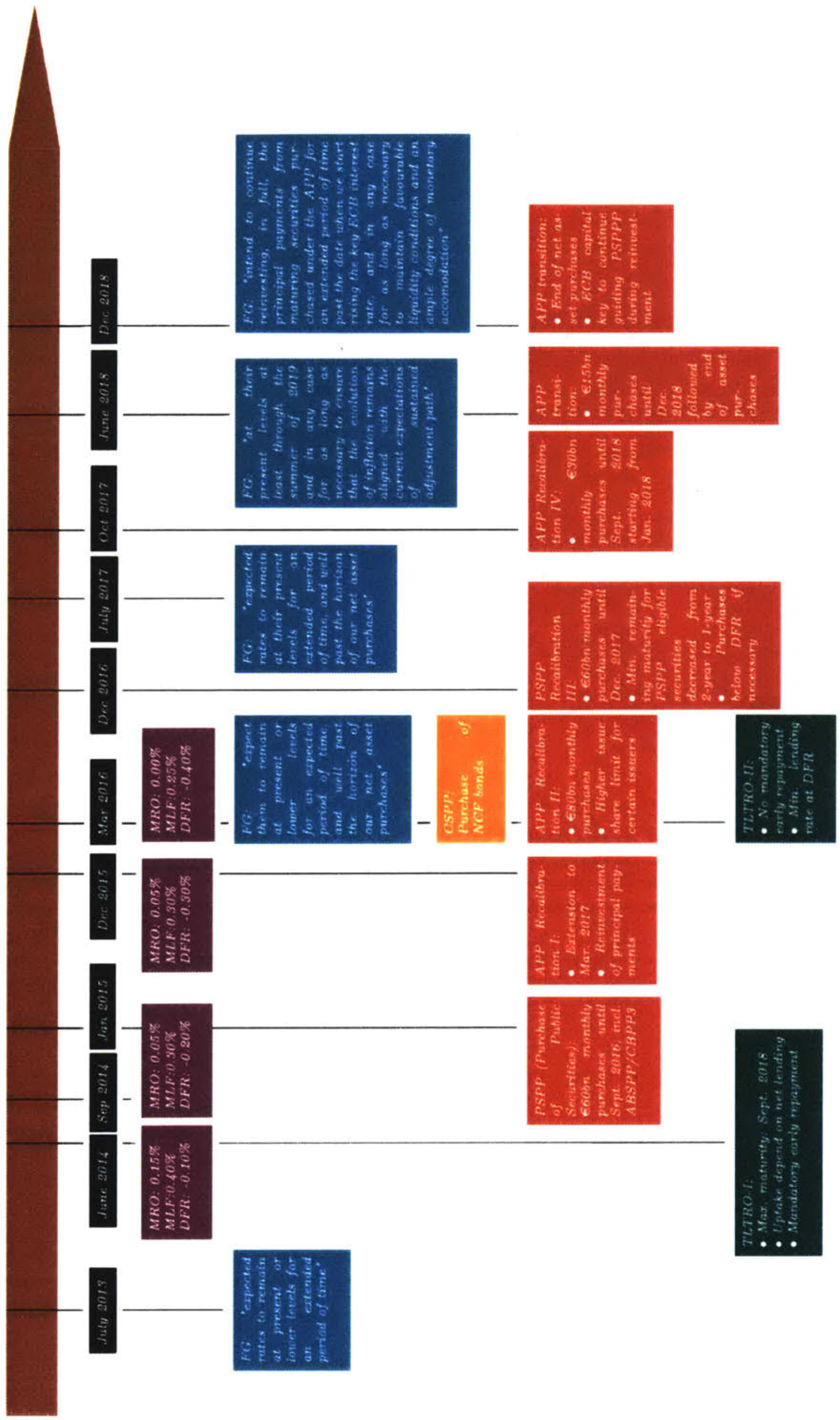


Figure 1.1: Eurosystem's Key Monetary Policy Decisions between January 2013 and December 2018. Interest rate decisions for the Main Refinancing Operations (MRO), for Marginal Lending Facility (MLF) and for Deposit Facility Rate (DFR) are in purple. Forward guidance (FG) decisions are in turquoise. Asset Purchase Program (APP) are either in orange for the private asset purchases (Corporate Sector Purchase Program, CSPP) or in red for public asset purchases (Public Sector Purchase Program, PSPP). Targeted Long-Term Refinancing Operations (TLTRO) are in green.

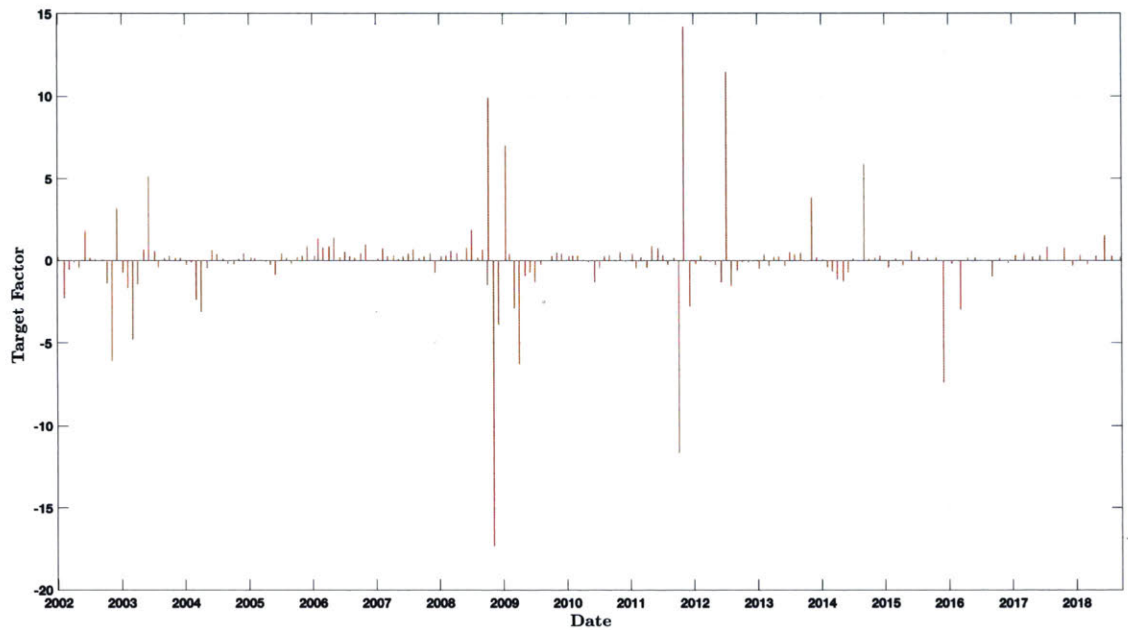



Figure 1.2: The figure shows the *Target* estimated factor over the period January 2002 to September 2018 in basis points. As the factor is identified up to scale, we scale it such that the *Target* factor has a negative unit effect on the one-month OIS.

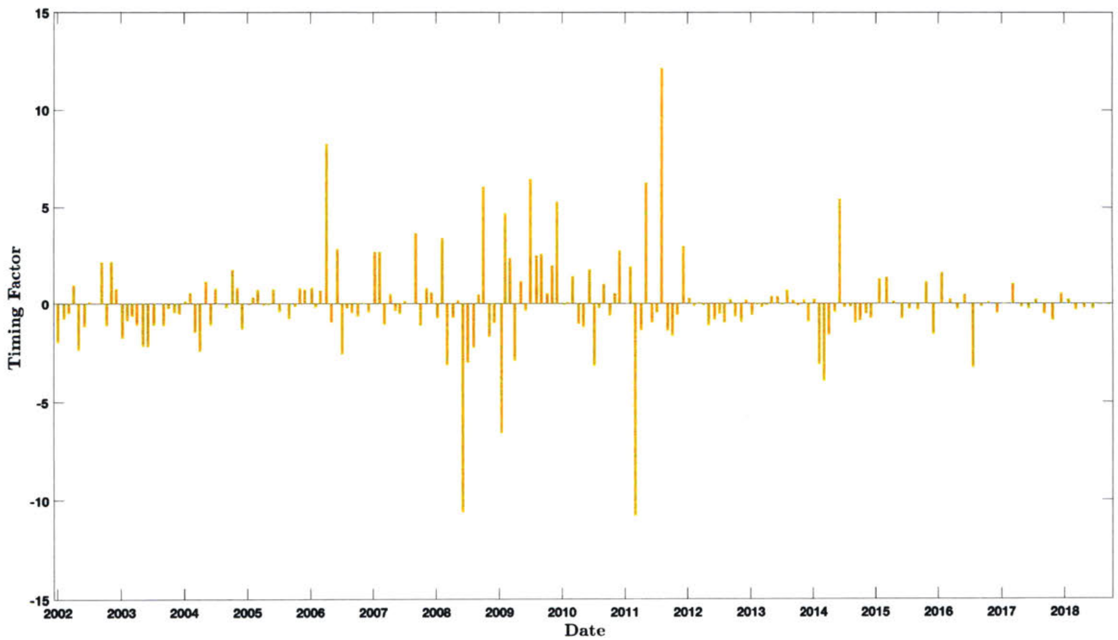



Figure 1.3: The figure shows the *Timing* estimated factor over the period January 2002 to September 2018 in basis points. As the factor is identified up to scale, we scale it such that the *Timing* factor has a negative unit effect on the six-month OIS.

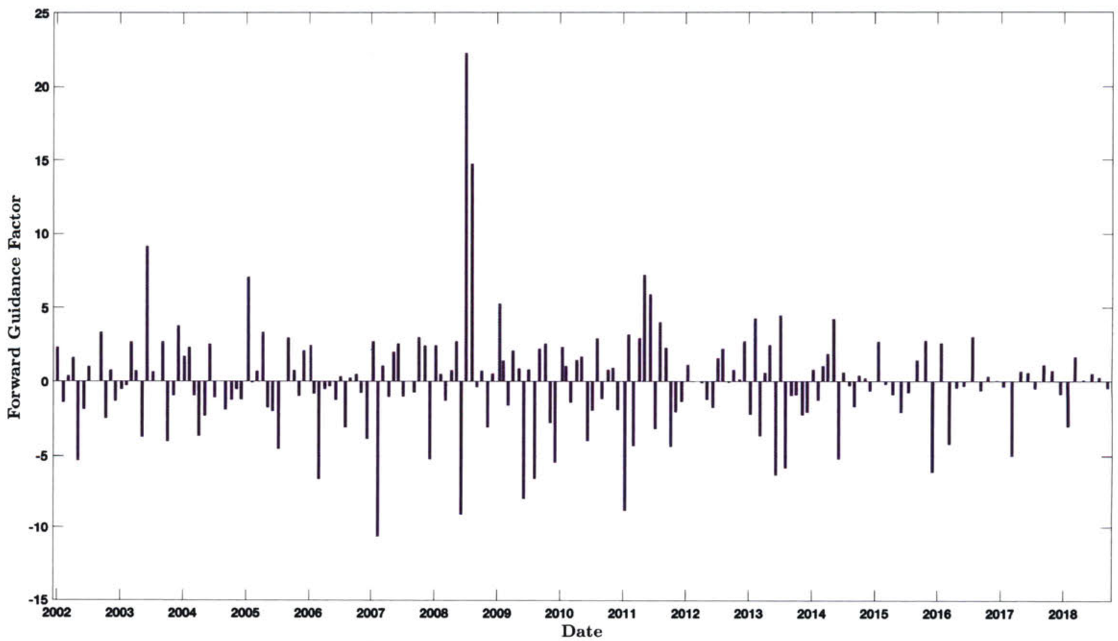



Figure 1.4: The figure shows the *Forward Guidance* estimated factor over the period January 2002 to September 2018 in basis points. As the factor is identified up to scale, we scale it such that the *Forward Guidance* factor has a negative unit effect on the two-year OIS.

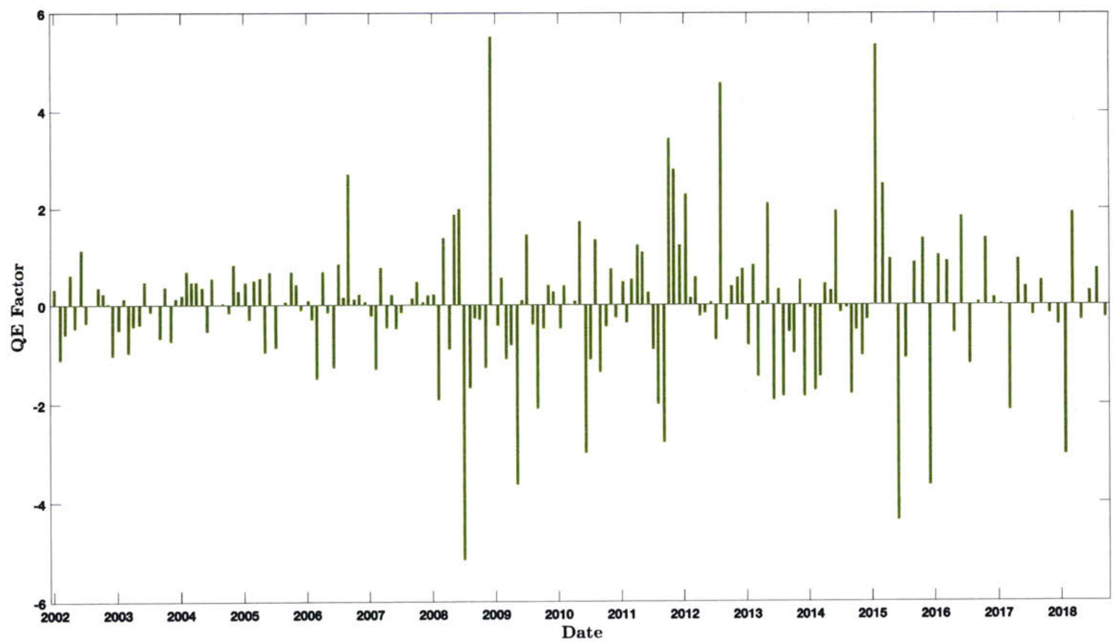



Figure 1.5: The figure shows the *Quantitative Easing* estimated factor over the period January 2002 to September 2018 in basis points. As the factor is identified up to scale, we scale it such that the *Quantitative Easing* factor has a negative unit effect on the ten-year OIS.

## 1.9. Tables

Table 1.1: Test of the number of factors explaining changes in the money market term structure around euro area monetary policy announcements.

| | **Press Release** | **Press Conference** |
|---|---|---|
| $H_0 : k = 0$ | 50.490***<br>(0.000) | 109.160***<br>(0.000) |
| $H_0 : k = 1$ | 23.819**<br>(0.048) | 39.824***<br>(0.000) |
| $H_0 : k = 2$ | 11.183<br>(0.192) | 17.528**<br>(0.025) |
| $H_0 : k = 3$ | 2.325<br>(0.508) | 3.560<br>(0.313) |

Note: The table reports the Wald statistics and the associated p-values of the Cragg-Donald rank test (1997) (see the Online Appendix for further explanation) for testing the null hypothesis that there are $k = k_0$ factors versus the alternative hypothesis that $k > k_0$. The same test is performed for both monetary policy windows, the Press Release and the Press Conference windows. The sample period is from January 2002 to September 2018.

Table 1.2: Relative contribution of the different factors explaining monetary policy surprises.

| | 1M-OIS | 3M-OIS | 6M-OIS | 1Y-OIS | 2Y-OIS | 5Y-OIS | 7Y-OIS | 10Y-OIS | SD Factor |
|---|---|---|---|---|---|---|---|---|---|
| **Press Release** | | | | | | | | | |
| Target Factor | 81.025 | 92.167 | 92.352 | 85.539 | 65.445 | 31.970 | 16.648 | 6.406 | 2.574 |
| Residual | 18.975 | 7.833 | 7.648 | 14.461 | 34.555 | 68.030 | 83.352 | 93.594 | |
| SD OIS | 2.860 | 2.064 | 1.827 | 1.659 | 1.545 | 1.572 | 1.389 | 1.276 | |
| **Press Conference** | | | | | | | | | |
| Timing Factor | 53.702 | 86.595 | 71.341 | 51.324 | 30.582 | 14.415 | 14.034 | 9.151 | 2.356 |
| FG Factor | 0.000 | 8.646 | 24.734 | 44.034 | 66.329 | 81.300 | 75.541 | 63.399 | 3.547 |
| QE Factor | 0.000 | 0.250 | 2.354 | 3.659 | 2.227 | 1.341 | 9.543 | 25.560 | 1.378 |
| Residual | 46.298 | 4.509 | 1.571 | 0.983 | 0.862 | 2.943 | 0.882 | 1.889 | |
| SD OIS | 1.049 | 2.101 | 2.790 | 3.861 | 4.356 | 4.145 | 3.239 | 2.725 | |

Note: The table reports, for each maturity of the OIS rate considered, the share of the variance (in percentage points) explained by each factor in the Press Release window and the Press Conference window. The only latent factor considered for the Press Release window is the Target factor. The three factors of the Press Conference window are the Timing, the FG (Forward Guidance) and the QE (Quantitative Easing) factors. For each window, the last column reports the standard deviation of each latent factor. The "Residual" row reports the variance not explained by the factors. The "SD OIS" reports the standard deviation of the change in the OIS rate. Before August 2011, interest rates for maturities above 2 years correspond to German sovereign yields. The sample period is from January 2002 to September 2018.

Table 1.3: Estimated effects of conventional and unconventional monetary policy shocks on money market interest rates.

| | 1M-OIS | 3M-OIS | 6M-OIS | 1Y-OIS | 2Y-OIS | 5Y-OIS | 7Y-OIS | 10Y-OIS |
|---|---|---|---|---|---|---|---|---|
| **Press Release** | | | | | | | | |
| Intercept | 0.171* | 0.118*** | 0.167*** | 0.204*** | 0.100 | 0.016 | -0.014 | -0.021 |
| | (0.091) | (0.042) | (0.037) | (0.046) | (0.067) | (0.095) | (0.093) | (0.091) |
| Target Factor | -1.000*** | -0.770*** | -0.682*** | -0.596*** | -0.486*** | -0.345*** | -0.220*** | -0.126*** |
| | (0.036) | (0.016) | (0.014) | (0.018) | (0.026) | (0.037) | (0.036) | (0.035) |
| **Press Conference** | | | | | | | | |
| Intercept | -0.132** | -0.120*** | -0.122*** | -0.200*** | -0.314*** | -0.194*** | -0.153*** | -0.079*** |
| | (0.053) | (0.033) | (0.026) | (0.029) | (0.030) | (0.053) | (0.023) | (0.028) |
| Timing Factor | -0.326*** | -0.830*** | -1.000*** | -1.174*** | -1.022*** | -0.668*** | -0.515*** | -0.350*** |
| | (0.023) | (0.014) | (0.011) | (0.012) | (0.013) | (0.023) | (0.010) | (0.012) |
| FG Factor | -0.000 | -0.174*** | -0.391*** | -0.722*** | -1.000*** | -1.054*** | -0.794*** | -0.612*** |
| | (0.015) | (0.009) | (0.007) | (0.008) | (0.009) | (0.015) | (0.006) | (0.008) |
| QE Factor | 0.000 | 0.076*** | 0.311*** | 0.536*** | 0.472*** | -0.348*** | -0.726*** | -1.000*** |
| | (0.039) | (0.024) | (0.019) | (0.021) | (0.022) | (0.039) | (0.017) | (0.020) |

Note: The table reports the estimated coefficients and the associated robust standard deviations of regressing yield curve changes occuring over the Press Release on the Target Factor and occuring over the Press Conference window on the Timing, the FG (Forward Guidance) and the QE (Quantitative Easing) factors. Before August 2011, interest rates for maturities above 2 years correspond to German sovereign yields. The sample period is from January 2002 to September 2018.

| | Target | Timing | FG | QE |
|---|---|---|---|---|
| **Sum** | | | | |
| Mean | 0 | 0 | 0 | 0 |
| Median | 0.152 | -0.162 | 0.029 | 0.049 |
| Standard Deviation | 2.562 | 2.331 | 3.506 | 1.364 |
| Min | 13.98 | 12.31 | 21.76 | 5.62 |
| Max | -16.82 | -10.96 | -10.58 | -5.39 |
| **Smoothed** | | | | |
| Mean | -0.073 | 0.044 | -0.142 | -0.018 |
| Median | 0.148 | -0.191 | 0.045 | 0.053 |
| Standard Deviation | 3.943 | 3.257 | 4.235 | 1.955 |
| Min | 23.59 | 20.335 | 20.73 | 8.767 |
| Max | -27.329 | -18.59 | -13.054 | -7.308 |
| **Correlation** | 0.98 | 0.96 | 0.96 | 0.96 |

Table 1.4: Summary statistics of the monthly monetary policy shocks in basis points. The "Sum" panel refers to monetary policy shocks which are time aggregated to the monthly frequency by simply summing all the shocks within the month. The "Smoothed" panel refers to monetary policy shocks which are time aggregated by computing the weighted average. The "Correlation" row reports the correlation between the two time series obtained under the two different time aggregation techniques for each type of monetary policy shock.

| | **Target** | **Timing** | **FG** | **QE** |
|---|---|---|---|---|
| **Target** | 1 | 0.03 | 0.15 | 0 |
| **Timing** | 0.03 | 1 | 0.04 | 0 |
| **FG** | 0.15 | 0.04 | 1 | 0.14 |
| **QE** | 0 | 0 | 0.14 | 1 |

Table 1.5: Correlations between the different monthly monetary policy shocks obtained using the weighted average time aggregation technique.

| Bank | Foreign | Bank | Foreign |
|---|---|---|---|
| Fonds d'Épargne - CDC | | HSBC France | |
| BRED-Banque Populaire | | Crédit Industriel et Commercial-CIC | |
| Banque Populaire Rives de Paris | | Crédit du Nord | |
| Renault Crédit International Banque | | ING Bank NV | |
| C.R.H. - Caisse de Refinancement de l'Habitat | | Barclays Bank plc | |
| Banque Fédérative du Crédit Mutuel | | Crédit Agricole Corporate and Investment Bank | |
| Axa Banque | | Caisse Nationale de Crédit Agricole Mutuel | |
| Sogefinancement | | Caisse des Dépôts et Consignations-Section Générale | |
| Caisse d'Épargne et de Prévoyance de Rhône Alpes | | The Bank of Tokyo-Mitsubishi UFJ Ltd | |
| Caisse Francaise de Financement Local | | BNP Paribas Securities Services | |
| Caisse d'Épargne et de Prévoyance Bretagne-Pays de Loire | | CA Consumer Finance | |
| ING Direct N.V. - merged with ING Bank NV (FR30438) | | Crédit Coopératif | |
| Sumitomo Mitsui Banking Corporation Europe Limited | | Crédit Foncier de France | |
| BPCE | | KBC Bank | ✓ |
| Dexia Crédit Local | | Deutsche Bank AG | ✓ |
| Caisse d'Épargne et de Prévoyance d'Ile-de-France | | Commerzbank AG | ✓ |
| Banque Centrale de Compensation | | Deutsche Pfandbriefbank AG | ✓ |
| BNP Paribas Personal Finance | | Volkswagen Bank GmbH | ✓ |
| HSBC Bank Plc | | Banco Santander SA | ✓ |
| BPIFrance Financement | | Banco de Sabadell | ✓ |
| Sofax Banque | | Bank of Ireland | ✓ |
| La Banque Postale | | Cooperative Rabobank U.A. | ✓ |
| Confédération Nationale du Crédit Mutuel | | Caixa Geral de Depositos S.A. | ✓ |
| Crédit Lyonnais | | | |
| Société Générale | | | |
| BNP Paribas | | | |
| NATIXIS | | | |
| Compagnie de Financement Foncier | | | |

Table 1.6: List of financial institutions considered in the sample. Foreign banks are mentioned with a ✓.

Table 1.7: Monetary Policy Shocks, Size and Lending to the Real Economy

| **Type of Shocks** | **Target** | **Timing** | **Forward Guidance** | **Quantitative Easing** |
|---|---|---|---|---|
| | | **Panel A: Lending to Real Economy** | | |
| $(Size)_{b,t-1} \times \varepsilon_t^{\text{MP}}$ | 1.477 | -1.393 | -0.515 | 3.123* |
| | ( 1.012) | ( -1.441) | ( -0.531) | ( 1.769) |
| $(Size)_{b,t-1} \times \varepsilon_{t-1}^{\text{MP}}$ | -0.803 | 0.165 | -2.866* | 0.398 |
| | ( -1.341) | ( 0.363) | ( -1.676) | ( 0.221) |
| $(Size)_{b,t-1} \times \varepsilon_{t-2}^{\text{MP}}$ | 1.542 | 0.857 | -1.140 | -2.154 |
| | ( 1.546) | ( 0.500) | ( -1.246) | ( -0.856) |
| $(Size)_{b,t-1} \times \varepsilon_{t-3}^{\text{MP}}$ | -0.407 | 2.157 | -2.056 | 0.110 |
| | ( -0.756) | ( 1.424) | ( -1.212) | ( 0.060) |
| Sum of coeff. | 1.809 | 1.787 | -6.575* | 1.477 |
| P-value of sum of coeff. | 0.499 | 0.342 | 0.057 | 0.607 |
| Adjusted $\bar{R}^2$ | 0.060 | 0.058 | 0.068 | 0.065 |
| Nobs | 6970 | 6970 | 6970 | 6970 |
| | | **Panel B: Lending to Non-Financial Corporations** | | |
| $(Size)_{b,t-1} \times \varepsilon_t^{\text{MP}}$ | 2.320 | -1.727 | -0.189 | 3.158 |
| | ( 1.456) | ( -1.543) | ( -0.120) | ( 1.145) |
| $(Size)_{b,t-1} \times \varepsilon_{t-1}^{\text{MP}}$ | -1.639 | -0.022 | -2.672 | 0.186 |
| | ( -1.179) | ( -0.029) | ( -1.480) | ( 0.067) |
| $(Size)_{b,t-1} \times \varepsilon_{t-2}^{\text{MP}}$ | 1.371 | 0.702 | -1.689 | -2.113 |
| | ( 0.830) | ( 0.667) | ( -1.572) | ( -0.763) |
| $(Size)_{b,t-1} \times \varepsilon_{t-3}^{\text{MP}}$ | -1.026** | 2.915 | -2.780 | -0.859 |
| | ( -2.098) | ( 1.553) | ( -1.430) | ( -0.421) |
| Sum of coeff. | 1.025 | 1.868 | -7.331** | 0.372 |
| P-value of sum of coeff. | 0.774 | 0.163 | 0.043 | 0.912 |
| Adjusted $\bar{R}^2$ | 0.028 | 0.028 | 0.034 | 0.030 |
| Nobs | 6970 | 6970 | 6970 | 6970 |

This table reports results from the regression of the form:

$$\Delta Y_{b,t} = \alpha_b + \alpha_t + \sum_{k=0}^{3} \beta_k \times \left(\text{Size}_{b,t-1} \times \varepsilon_{t-k}^{\text{MP}}\right) + \sum_{z \in \text{Control}} \sum_{k=0}^{3} \gamma_{z,k} \times \left(z_{b,t-1} \times \varepsilon_{t-k}^{\text{MP}}\right) +$$
$$\phi \times \text{Size}_{b,t-1} + \sum_{z \in \text{Control}} \mu_z \times z_{b,t-1} + \delta \times \Delta\text{Log(Total Loans)}_{b,t-1} + \varepsilon_{b,t}$$

where $\Delta Y_{b,t}$ is either $\Delta\text{Log(Total Loans)}_{b,t}$ which denotes the monthly growth (in %) in loan supply to the real economy (households and non-financial corporations) between $t-1$ and $t$ (Panel A) or $\Delta\text{Log(Total Loans to NFC)}_{b,t}$, the monthly growth (in %) in loan supply to non-financial corporations (Panel B). The controls $z$ are $(\text{E/A})_{b,t-1}$, $(\text{Share of Liquid Assets})_{b,t-1}$ and $(\text{Share of Dep. Liab.})_{b,t-1}$. Column (1), (2), (3) and (4) report the estimates of the coefficients of interest for the different types of monetary policy shocks (*Target*, *Timing*, *Forward Guidance*, *Quantitative Easing* respectively). All the regressions include month fixed effects. $\overline{R}^2$ denotes the adjusted regression $R^2$. Standard errors are two-way clustered at the bank and month level. "Sum of coefficients" reports the coefficient estimate for $\sum_{k=0}^{3} \beta_k$.The row "P-value of sum of coeff." reports the p-value of a test of significance for $\sum_{k=0}^{3} \beta_k$.

Table 1.8: Monetary Policy Shocks, Leverage and Lending to the Real Economy

| **Type of Shocks** | **Target** | **Timing** | **Forward Guidance** | **Quantitative Easing** |
|---|---|---|---|---|
| | | **Panel A: Lending to Real Economy** | | |
| $(E/A)_{b,t-1} \times \varepsilon_{t}^{MP}$ | -0.877 | -0.617 | 0.211 | 0.335 |
| | ( -0.822) | ( -0.763) | ( 0.409) | ( 0.345) |
| $(E/A)_{b,t-1} \times \varepsilon_{t-1}^{MP}$ | -0.024 | 0.342 | 0.190 | -0.134 |
| | ( -0.070) | ( 1.064) | ( 0.308) | ( -0.120) |
| $(E/A)_{b,t-1} \times \varepsilon_{t-2}^{MP}$ | 1.219* | 0.795 | -1.092 | -4.360 |
| | ( 1.712) | ( 0.914) | ( -1.255) | ( -1.710) |
| $(E/A)_{b,t-1} \times \varepsilon_{t-3}^{MP}$ | 1.324* | 0.216 | 2.701 | 2.477 |
| | ( 1.774) | ( 0.536) | ( 1.226) | ( 1.169) |
| Sum of coeff. | 1.641 | 0.738 | 2.009 | -1.683 |
| P-value of sum of coeff. | 0.154 | 0.601 | 0.399 | 0.532 |
| Adjusted $\bar{R}^2$ | 0.060 | 0.058 | 0.068 | 0.065 |
| Nobs | 6970 | 6970 | 6970 | 6970 |
| | | **Panel B: Lending to Non-Financial Corporations** | | |
| $(E/A)_{b,t-1} \times \varepsilon_{t}^{MP}$ | -1.178 | -0.283 | 0.505 | 0.918 |
| | ( -1.288) | ( -0.280) | ( 0.597) | ( 1.117) |
| $(E/A)_{b,t-1} \times \varepsilon_{t-1}^{MP}$ | -0.296 | 1.197 | 1.148 | 0.667 |
| | ( -0.528) | ( 1.520) | ( 1.042) | ( 0.519) |
| $(E/A)_{b,t-1} \times \varepsilon_{t-2}^{MP}$ | 0.536 | 1.429* | -0.547 | -4.240** |
| | ( 0.569) | ( 1.739) | ( -1.101) | ( -2.132) |
| $(E/A)_{b,t-1} \times \varepsilon_{t-3}^{MP}$ | 1.353* | -0.941 | 2.549 | 2.124 |
| | ( 1.880) | ( -0.826) | ( 1.138) | ( 0.891) |
| Sum of coeff. | 0.413 | 1.403 | 3.655 | -0.532 |
| P-value of sum of coeff. | 0.806 | 0.446 | 0.172 | 0.851 |
| Adjusted $\bar{R}^2$ | 0.028 | 0.028 | 0.034 | 0.030 |
| Nobs | 6970 | 6970 | 6970 | 6970 |

This table reports results from the regression of the form:

$$\Delta\text{Log(Total Loans)}_{b,t} = \alpha_b + \alpha_t + \sum_{k=0}^{3} \beta_k \times \left(\text{E/A}_{b,t-1} \times \varepsilon_{t-k}^{\text{MP}}\right) + \sum_{z \in \text{Control}} \sum_{k=0}^{3} \gamma_{z,k} \times \left(z_{b,t-1} \times \varepsilon_{t-k}^{\text{MP}}\right) + \phi \times \text{E/A}_{b,t-1} + \sum_{z \in \text{Control}} \mu_z \times z_{b,t-1} + \delta \times \Delta\text{Log(Total Loans)}_{b,t-1} + \varepsilon_{b,t}$$

where $\Delta Y_{b,t}$ is either $\Delta\text{Log(Total Loans)}_{b,t}$ which denotes the monthly growth (in %) in loan supply to the real economy (households and non-financial corporations) between $t-1$ and $t$ (Panel A) or $\Delta\text{Log(Total Loans to NFC)}_{b,t}$, the monthly growth (in %) in loan supply to non-financial corporations (Panel B). The controls $z$ are $(\text{Size})_{b,t-1}$, $(\text{Share of Liquid Assets})_{b,t-1}$ and $(\text{Share of Dep. Liab.})_{b,t-1}$. Column (1), (2), (3) and (4) report the estimates of the coefficients of interest for the different types of monetary policy shocks (*Target*, *Timing*, *Forward Guidance*, *Quantitative Easing* respectively). All the regressions include month fixed effects. $\overline{R}^2$ denotes the adjusted regression $R^2$. Standard errors are two-way clustered at the bank and month level. "Sum of coefficients" reports the coefficient estimate for $\sum_{k=0}^{3} \beta_k$.The row "P-value of sum of coeff." reports the p-value of a test of significance for $\sum_{k=0}^{3} \beta_k$.

Table 1.9: Monetary Policy Shocks, Share of Liquid Assets and Lending to the Real Economy

| Type of Shocks | Target | Timing | Forward Guidance | Quantitative Easing |
|---|---|---|---|---|
| | **Panel A: Lending to Real Economy** | | | |
| (Share of Liquid Assets)$_{b,t-1}$ × $\varepsilon_t^{\mathrm{MP}}$ | 0.176 | -0.194 | -0.035 | 0.432** |
| | ( 0.797) | ( -0.689) | ( -0.194) | ( 2.209) |
| (Share of Liquid Assets)$_{b,t-1}$ × $\varepsilon_{t-1}^{\mathrm{MP}}$ | 0.064 | -0.041 | 0.042 | 0.468 |
| | ( 0.691) | ( -0.480) | ( 0.218) | ( 1.268) |
| (Share of Liquid Assets)$_{b,t-1}$ × $\varepsilon_{t-2}^{\mathrm{MP}}$ | -0.033 | -0.217 | 0.141 | 0.911* |
| | ( -0.223) | ( -1.405) | ( 0.494) | ( 1.860) |
| (Share of Liquid Assets)$_{b,t-1}$ × $\varepsilon_{t-3}^{\mathrm{MP}}$ | -0.288 | 0.092 | -0.559 | -0.577 |
| | ( -1.257) | ( 0.963) | ( -1.209) | ( -0.999) |
| Sum of coeff. | -0.081 | -0.360 | -0.411 | 1.234 |
| P-value of sum of coeff. | 0.839 | 0.300 | 0.520 | 0.008*** |
| Adjusted $\bar{R}^2$ | 0.060 | 0.058 | 0.068 | 0.065 |
| Nobs | 6970 | 6970 | 6970 | 6970 |
| | **Panel B: Lending to Non-Financial Corporations** | | | |
| (Share of Liquid Assets)$_{b,t-1}$ × $\varepsilon_t^{\mathrm{MP}}$ | 0.320* | -0.176 | -0.100 | 0.370 |
| | ( 1.832) | ( -0.490) | ( -0.353) | ( 1.661) |
| (Share of Liquid Assets)$_{b,t-1}$ × $\varepsilon_{t-1}^{\mathrm{MP}}$ | 0.159 | -0.145 | -0.083 | 0.524 |
| | ( 1.409) | ( -0.724) | ( -0.249) | ( 1.181) |
| (Share of Liquid Assets)$_{b,t-1}$ × $\varepsilon_{t-2}^{\mathrm{MP}}$ | 0.088 | -0.309 | 0.063 | 1.111** |
| | ( 0.638) | ( -1.204) | ( 0.204) | ( 2.301) |
| (Share of Liquid Assets)$_{b,t-1}$ × $\varepsilon_{t-3}^{\mathrm{MP}}$ | -0.350 | 0.394 | -0.690 | -0.730 |
| | ( -1.317) | ( 1.473) | ( -1.400) | ( -1.228) |
| Sum of coeff. | 0.217 | -0.236 | -0.810 | 1.275 |
| P-value of sum of coeff. | 0.587 | 0.645 | 0.337 | 0.073* |
| Adjusted $\bar{R}^2$ | 0.028 | 0.028 | 0.034 | 0.030 |
| Nobs | 6970 | 6970 | 6970 | 6970 |

This table reports results from the regression of the form:

$$\Delta\text{Log(Total Loans)}_{b,t} = \alpha_b + \alpha_t + \sum_{k=0}^{3} \beta_k \times \left((\text{Share of Liquid Assets})_{b,t-1} \times \varepsilon_{t-k}^{\mathrm{MP}}\right) + \sum_{z\in\text{Control}} \sum_{k=0}^{3} \gamma_{z,k} \times \left(z_{b,t-1} \times \varepsilon_{t-k}^{\mathrm{MP}}\right) +$$
$$\phi \times (\text{Share of Liquid Assets})_{b,t-1} + \sum_{z\in\text{Control}} \mu_z \times z_{b,t-1} + \delta \times \Delta\text{Log(Total Loans)}_{b,t-1} + \varepsilon_{b,t}$$

where $\Delta Y_{b,t}$ is either $\Delta$Log(Total Loans)$_{b,t}$ which denotes the monthly growth (in %) in loan supply to the real economy (households and non-financial corporations) between $t-1$ and $t$ (Panel A) or $\Delta$Log(Total Loans to NFC)$_{b,t}$, the monthly growth (in %) in loan supply to non-financial corporations (Panel B). The controls $z$ are (Size)$_{b,t-1}$, (E/A)$_{b,t-1}$ and (Share of Dep. Liab.)$_{b,t-1}$. Column (1), (2), (3) and (4) report the estimates of the coefficients of interest for the different types of monetary policy shocks (*Target*, *Timing*, *Forward Guidance*, *Quantitative Easing* respectively). All the regressions include month fixed effects. $\overline{R}^2$ denotes the adjusted regression $R^2$. Standard errors are two-way clustered at the bank and month level. "Sum of coefficients" reports the coefficient estimate for $\sum_{k=0}^{3} \beta_k$.The row "P-value of sum of coeff." reports the p-value of a test of significance for $\sum_{k=0}^{3} \beta_k$.

Table 1.10: Monetary Policy Shocks, Share of Deposit Liabilities and Lending to the Real Economy

| **Type of Shocks** | **Target** | **Timing** | **Forward Guidance** | **Quantitative Easing** |
|---|---|---|---|---|
| | | **Panel A: Lending to Real Economy** | | |
| (Share of Dep. Liab.)$_{b,t-1} \times \varepsilon_t^{\text{MP}}$ | 0.082 | -0.059 | -0.013 | 0.239 |
| | ( 1.280) | ( -1.224) | ( -0.131) | ( 1.262) |
| (Share of Dep. Liab.)$_{b,t-1} \times \varepsilon_{t-1}^{\text{MP}}$ | 0.067 | -0.010 | -0.177 | -0.095 |
| | ( 1.295) | ( -0.186) | ( -1.813) | ( -0.659) |
| (Share of Dep. Liab.)$_{b,t-1} \times \varepsilon_{t-2}^{\text{MP}}$ | 0.054 | 0.022 | -0.048 | 0.050 |
| | ( 0.811) | ( 0.217) | ( -0.389) | ( 0.264) |
| (Share of Dep. Liab.)$_{b,t-1} \times \varepsilon_{t-3}^{\text{MP}}$ | -0.030 | 0.104 | -0.012 | 0.284** |
| | ( -0.463) | ( 1.074) | ( -0.110) | ( 2.222) |
| Sum of coeff. | 0.172 | 0.057 | -0.250 | 0.477 |
| P-value of sum of coeff. | 0.278 | 0.750 | 0.201 | 0.172 |
| Adjusted $\bar{R}^2$ | 0.060 | 0.058 | 0.068 | 0.065 |
| Nobs | 6970 | 6970 | 6970 | 6970 |
| | | **Panel B: Lending to Non-Financial Corporations** | | |
| (Share of Dep. Liab.)$_{b,t-1} \times \varepsilon_t^{\text{MP}}$ | 0.246* | -0.177 | 0.009 | 0.271 |
| | ( 1.898) | ( -1.586) | ( 0.072) | ( 1.556) |
| (Share of Dep. Liab.)$_{b,t-1} \times \varepsilon_{t-1}^{\text{MP}}$ | 0.077 | -0.191 | -0.328 | -0.154 |
| | ( 0.713) | ( -1.512) | ( -1.798) | ( -0.858) |
| (Share of Dep. Liab.)$_{b,t-1} \times \varepsilon_{t-2}^{\text{MP}}$ | 0.163 | -0.248** | -0.226* | 0.085 |
| | ( 1.022) | ( -2.197) | ( -1.886) | ( 0.407) |
| (Share of Dep. Liab.)$_{b,t-1} \times \varepsilon_{t-3}^{\text{MP}}$ | 0.015 | 0.298 | -0.082 | 0.090 |
| | ( 0.103) | ( 1.545) | ( -0.721) | ( 0.577) |
| Sum of coeff. | 0.501 | -0.318 | -0.627 | 0.292 |
| P-value of sum of coeff. | 0.204 | 0.073* | 0.038** | 0.375 |
| Adjusted $\bar{R}^2$ | 0.028 | 0.028 | 0.034 | 0.030 |
| Nobs | 6970 | 6970 | 6970 | 6970 |

This table reports results from the regression of the form:

$$\Delta\text{Log(Total Loans)}_{b,t} = \alpha_b + \alpha_t + \sum_{k=0}^{3} \beta_k \times \left((\text{Share of Dep. Liab})_{b,t-1} \times \varepsilon_{t-k}^{\text{MP}}\right) + \sum_{z \in \text{Control}} \sum_{k=0}^{3} \gamma_{z,k} \times \left(z_{b,t-1} \times \varepsilon_{t-k}^{\text{MP}}\right) +$$
$$\phi \times (\text{Share of Dep. Liab.})_{b,t-1} + \sum_{z \in \text{Control}} \mu_z \times z_{b,t-1} + \delta \times \Delta\text{Log(Total Loans)}_{b,t-1} + \varepsilon_{b,t}$$

where $\Delta Y_{b,t}$ is either $\Delta$Log(Total Loans)$_{b,t}$ which denotes the monthly growth (in %) in loan supply to the real economy (households and non-financial corporations) between $t-1$ and $t$ (Panel A) or $\Delta$Log(Total Loans to NFC)$_{b,t}$, the monthly growth (in %) in loan supply to non-financial corporations (Panel B). The controls $z$ are (Size)$_{b,t-1}$, (E/A)$_{b,t-1}$ and (Share of Liquid Assets)$_{b,t-1}$. Column (1), (2), (3) and (4) report the estimates of the coefficients of interest for the different types of monetary policy shocks (*Target*, *Timing*, *Forward Guidance*, *Quantitative Easing* respectively). All the regressions include month fixed effects. $\overline{R}^2$ denotes the adjusted regression $R^2$. Standard errors are two-way clustered at the bank and month level. "Sum of coefficients" reports the coefficient estimate for $\sum_{k=0}^{3} \beta_k$.The row "P-value of sum of coeff." reports the p-value of a test of significance for $\sum_{k=0}^{3} \beta_k$.

Table 1.11: Monetary Policy Shocks, Key Bank Characteristics and Lending Within Borrowers

| **Type of Shocks** | **Target** | **Timing** | **Forward Guidance** | **Quantitative Easing** |
|---|---|---|---|---|
| | | | **Size** | |
| Sum of coeff. | -0.985 | 1.184 | -3.450** | 0.682 |
| P-value of sum of coeff. | 0.577 | 0.234 | 0.036 | 0.857 |
| | | | **Equity-Over-Assets Ratio** | |
| Sum of coeff. | 0.522 | 2.398 | 4.771* | 0.104 |
| P-value of sum of coeff. | 0.667 | 0.375 | 0.086 | 0.980 |
| | | | **Share of Liquid Assets** | |
| Sum of coeff. | 0.632 | 0.455 | 0.321 | 1.899** |
| P-value of sum of coeff. | 0.329 | 0.781 | 0.407 | 0.024 |
| | | | **Share of Deposit Liabilities** | |
| Sum of coeff. | 0.367 | -0.567** | -0.988*** | -0.198 |
| P-value of sum of coeff. | 0.435 | 0.034 | 0.012 | 0.375 |
| Nobs | 563,012 | 563,012 | 563,012 | 563,012 |
| Firms | 8,054 | 8,054 | 8,054 | 8,054 |
| Lender | 45 | 45 | 45 | 45 |
| FE | Firm × Month | Firm × Month | Firm × Month | Firm × Month |
| Adjusted $\bar{R}^2$ | 0.62 | 0.65 | 0.66 | 0.63 |

This table reports results from the regression of the form:

$$\text{New Loans}_{f,b,t} = \alpha_{f,t} + \sum_{k=0}^{3} \beta_k \times \left(\mathrm{x}_{b,t-k} \times \varepsilon_{t-k}^{\mathrm{mp}}\right) + \sum_{k=0}^{3} \gamma_{z,k} \times \left(\mathrm{z}_{b,t-1} \times \varepsilon_{t-k}^{\mathrm{mp}}\right) + \phi \times \mathrm{x}_{b,t-1} + \sum_{z \in \text{Control}} \mu_z \times z_{b,t-1} + \varepsilon_{b,f,t} \tag{1.5}$$

where the dependent variable New Loans$_{f,b,t}$ corresponds to the new loans granted by bank $b$ for firm $f$ between month $t-1$ and month $t$ normalized by the credit exposure at month $t-1$, $x_{b,t-1}$ is our independent variable of interest (e.g. $(\text{Size})_{b,t-1}$, $(\text{E/A})_{b,t-1}$, $(\text{Share of Liquid Assets})_{b,t-1}$ or $(\text{Share of Deposit Liabilities})_{b,t-1}$), $\varepsilon_t^{mp}$ is our monthly monetary policy factor. Column (1), (2), (3) and (4) report the estimates of the coefficients of interest for the different types of monetary policy shocks (*Target*, *Timing*, *Forward Guidance*, *Quantitative Easing* respectively). All the regressions include firm-month fixed effects. $\overline{R}^2$ denotes the adjusted regression $R^2$. Standard errors are two-way clustered at the bank and firm-month level. "Sum of coefficients" reports the coefficient estimate for $\sum_{k=0}^{3} \beta_k$.The row "P-value of sum of coeff." reports the p-value of a test of significance for $\sum_{k=0}^{3} \beta_k$.

# 1.10. Appendix

## 1.10.1. The High Frequency Database

The underlying dataset from which we use interest rates changes for our high-frequency identification strategy is the Thomson Reuters Tick History. Table 1.12 reports the different financial instruments used in this chapter, along with their Thomson Reuters code (RIC) and when the data starts becoming available.

| Financial Instrument | RIC | Start Date |
|---|---|---|
| **Overnight Index Swaps** | | |
| 1M-OIS | EUREON1M= | 01/02/1999 |
| 3M-OIS | EUREON3M= | 01/02/1999 |
| 6M-OIS | EUREON6M= | 01/02/1999 |
| 1Y-OIS | EUREON1Y= | 01/02/1999 |
| 2Y-OIS | EUREON2Y= | 11/19/1999 |
| 5Y-OIS | EUREON5Y= | 06/24/2011 |
| 7Y-OIS | EUREON7Y= | 06/24/2011 |
| 10Y-OIS | EUREON10Y= | 06/24/2011 |
| **Sovereign Bonds** | | |
| 2Y-GER | DE2YT=RR | 01/01/1998 |
| 5Y-GER | DE5YT=RR | 01/01/1998 |
| 7Y-GER | DE7YT=RR | 01/01/1998 |
| 10Y-GER | DE10YT=RR | 01/01/1998 |

Table 1.12: List of financial instruments considered in the sample. The first column reports the asset name, the second column the RIC (Reuters Identification Code) and the final column the first date the data for this particular RIC is available.

The OIS financial contracts correspond to over-the-counter interest rate swaps whose underlying financial variable is the overnight unsecured euro area inter-bank rate, the EONIA. Under this contract, one party (the fixed leg) accepts to pay, at maturity, a fixed interest rate which is agreed upon at the initiation of the contract whereas the other party (floating leg) agrees to pay a floating interest rate, corresponding to the average realized overnight interest rate over the period of the whole contract. Unlike Federal Funds futures contracts whose settlement dates correspond to specific calendar days of the year, OIS contract are offered for a given maturity. At initiation, the fixed interest rate for the fixed leg is determined such that any investor should be indifferent between paying the fixed leg or the floating leg. As a result, the fixed interest rate, i.e. the OIS rate, corresponds to the expected average of the overnight unsecured euro area interest rate for the period under the risk-neutral measure. To a certain extent, the OIS rate reveals the same information as a zero-coupon bond in the money market for the same maturity. Yet, the main difference between these two contracts is the fact that in the case of a zero-coupon bond, there is some default risk involved. The debtor to whom you lent money through a simple bond might potentially not be able to reimburse you in the future. Under the limited liability assumption, a default risk component is *de facto* embedded in the pricing of any bond. Moreover, OIS contracts are extremely liquid and do not suffer from any liquidity risk. To be able to look at the whole yield curve (up to the 10-years maturity), we also include the German sovereign bond rates in our sample for dates where OIS data for a specific maturity is not available. For each maturity, the German sovereign bond for which the interest rate is reported is the on-the-run bond whose maturity is closest to the one under consideration. Since these bonds correspond to really traded bonds, they potentially bear some coupons. Our whole high-frequency strategy ignores the side effects that changes in the zero-coupon bonds with the same maturity and lower can have on the pricing of the coupons *per se.* We can reasonably argue that the coupons represent only a small fraction of the present value of any sovereign bond and therefore changes in rates observed for these coupon-bearing sovereign bonds is assumed to be entirely due to changes in the interest rate at the maturity for which the face value is due.

#### 1.10.1.1. The Filtering Algorithm

In this section, we explain how we clean the Thomson Reuters Tick History database, This platform offers tick-by-tick bid and ask quotes for a large variety of financial instruments. For each quote observation, there is either a bid or an ask interest rate or both. These bid and ask rates correspond to the best buy and sale rates from the order book at which any investor can buy or sell the financial instrument in question. We build high frequency series of the bid-ask spread and naturally of the changes in the bid interest rate, the ask interest rate and the midquote interest rate, which is simply computed as the average of the bid and the ask rates. The information on quotes is handled in the following way: each new quote on either the bid, the ask or both bid and ask rates is taken into account. For instance, if we assume that at time $t_1$, there is a new quote with information on both the bid and the ask sides, the bid and the ask interest rates become the ones observed at time $t_1$. However, if, just after at time $t_2$, there is a new quote with only information on the bid interest rate (i.e. all the fields except the bid interest rate are empty), then the bid rate will change and take the value observed at this $t_2$ observation. On the other side of the order book, the ask rate is set as a missing observation if the duration since the previous quote available on this side of the book is larger than a certain value. Hereinafter, we take a value of one minute. Such a choice relies on the assumption that indicative quotes have a very short-term life and therefore it is unrealistic and even misleading to consider that a quote which was available more than one minute ago is still active. Moreover, if the bid-ask spread is negative, we delete this entry as well.

The idea behind our simple filter is to get rid of clear outliers in the quote time series, often referred as "fat fingers" by financial practitioners. To do so, we remove bid and ask rates which are below and above a certain time-varying threshold which allow us to detect "aberrant" interest rates. We first compute daily summary statistics on the tick-by-tick data, focusing only on business days and the time period between 7:00:00 AM and 6:00:00 PM GMT to avoid taking into account extreme observations and erratic jumps occurring overnight. In particular, for each financial instrument, we build daily time series of the number of ask and bid quotes and of various summary statistics (daily minimum, maximum, mean, median and quantiles at different levels) on bid and ask rates and bid-ask spread. The time-varying threshold mentioned above is then a direct function of the dynamics of some of these summary statistics. More specifically, after obtaining daily time series of the minimum and maximum of observed bid and ask interest rates, we compute backward- and forward looking moving median of these summary statistics over a window of $D$ days. In particular, for instance, for each currency, ask interest rates which are higher than $k$ times the backward-looking moving median of daily maximum ask interest rate and $k$ times the forward-looking moving median of daily maximum ask rates.

We can sum up our filtering procedure applied to any tick-by-tick quoted or interest rate $r_{i,d^*,t^*}$ (either bid or ask interest rate observed on day $d^*$ at time $t^*$, for currency $i$) in the following mathematical terms:

$$\text{if } r_{i,d^*,t^*} \geq k \times \max \left\{ \underset{d\in[d^*-D,d^*-1]}{\text{median}} \{\max_t r_{i,d,t}\}, \underset{d\in[d^*+1,d^*+T]}{\text{median}} \{\max_t r_{i,d,t}\} \right\},$$

or

$$\text{if } r_{i,d^*,t^*} \leq k \times \min \left\{ \underset{d\in[d^*-D,d^*-1]}{\text{median}} \{\min_t r_{i,d,t}\}, \underset{d\in[d^*+1,d^*+T]}{\text{median}} \{\min_t r_{i,d,t}\} \right\},$$

then $r_{i,d^*,t^*}$ is set as missing. In particular, we consider $D = 10$, corresponding to a window of approximatively half a month, and $k = 1.1$. Such a value for $k$ is relatively conservative in the sense that it leads us to remove only observations which are clearly not in line with the dynamics of interest rates in the medium run.

#### 1.10.1.2. The Factor Rotation

In this section, we explain more formally the identification strategy proposed initially by Gürkaynak *et al.* (2005), then further enriched by Swanson (2017) on U.S. data and Altavilla *et al.* (2019) on European data to allow for a *Quantitative Easing* factor. The factor extracted from the Press Release window, the *Target* factor, corresponds to the principal component of the changes in the entire yield curve.
However, for the Press Conference windows, since there are three factors to consider, we have to make some transformation to make them economically interpretable.
As explained in the main text, let us denote by $X^{PC}$ the $181 \times 8$ matrix made of the interest changes for the different maturities considered as columns. This matrix follows a factor structure:

$$X^{PC} = \mu^{PC} + F^{PC} \times \Lambda^{PC} + \varepsilon^{PC}$$

where $\mu^{PC}$ is the vector column of the unconditional mean of the interest rate changes over the Press Conference window, $F^{PC}$ is the matrix whose columns corresponds to the time series of each unobserved factor and $\Lambda^{PC}$ is the matrix of loadings. As the unobserved factors are simply another way to statistically describe the data $X^{PC}$, we need to apply some transformations to make them interpretable. In particular, any orthonormal transformation, i.e. any $3 \times 3$ matrix, $U$, such that $U \times U' = \mathbb{I}_3$, applied to $F^{PC}$ yields another set of factors, $\tilde{F}^{PC} = F^{PC} \times U$. The matrix $X^{PC}$ can therefore be expressed as:

$$X^{PC} = \mu^{PC} + \underbrace{F^{PC} \times U}_{\equiv \tilde{F}^{PC}} \times \underbrace{U' \times \Lambda^{PC}}_{\equiv \tilde{\Lambda}^{PC}} + \varepsilon^{PC}$$

To uniquely identify the orthonormal matrix $U$ and therefore the latent factors, $\tilde{F}^{PC}$, we need to impose some restrictions on the $U$ matrix. A $3 \times 3$ matrix is made of nine elements which need to be pinned down. There are 6 orthonormality restrictions, namely $U \times U' = \mathbb{I}_3$:

$$\begin{aligned} &\textbf{unit length for the rows:} && \sum_{j=1}^{3} u_{i,j}^2 = 1, && \forall i \in [1,3] \\ &\textbf{orthogonality restrictions:} && \sum_{l=1}^{3} u_{i,l} u_{j,l} = 0, && \forall (i,j) \in [1,3]^2 \text{ and } i \neq j \end{aligned}$$

As a result, six elements are *de facto* determined by these six restrictions. Consequently, we need three additional restrictions on the elements of $U$. For them to be labeled *Forward Guidance* and *Quantitative Easing* factors, the second and third factors should not have any impact on the very short-end of the yield curve and, in particular, on the 1-month OIS rate. Mathematically, these two restrictions take the following form:

$$U' \times \tilde{\Lambda}^{PC} = \begin{pmatrix} \cdot & \cdot & \cdot \\ 0 & \cdot & \cdot \\ 0 & \cdot & \cdot \end{pmatrix}$$

These restrictions can be reformulated as

$$\begin{aligned} \sum_{j=1}^{3} u_{j,2} \lambda_{j,1}^{PC} &= 0, \\ \sum_{j=1}^{3} u_{j,3} \lambda_{j,1}^{PC} &= 0 \end{aligned}$$

Following Swanson (2017) and Altavilla *et al.* (2019), the final restriction concerns the relative weight of *Quantitative Easing* factor in the cross-sectional dynamics of the yield curve before the beginning of the crisis. Formally, $U$ must be such that the *Quantitative Easing* factor has the smallest variance possible before August 2008. An alternative restriction has also been tested. In this alternative specification, the *Quantitative Easing* factor is assumed to have the smallest variance before the implementation of the first wave of euro area sovereign debt purchases on the secondary market by the Eurosystem, the *Securities Market Programme* which started in May 2010. However, we decide to keep August 2008 as the starting point of any potential large scale asset purchase programme for a very simple reason. When the Fed decided in November 2008 to massively buy *government-sponsored enterprises* (GSE) debt, they created a precedent and financial markets started considering that QE measures could also be quickly implemented in other economic areas. As a result, even if in theory, the Eurosystem has not officially launched a vast asset purchase programme until December 2014, there were instances when through its communication, the ECB suggested that it could be ready to start such a programme (e.g. the Outright Monetary Transactions in September 2012). In other words, the mere absence of any LSAP is also some information that should be taken into account when looking at monetary policy surprises.

To summarize the entire identification strategy, if we denote by $t'$ the number of the last observation whose date is before August 2008, we want to solve over the different elements of $U$ the following variance minimization problem:

$$\min_{(u_{i,j})} \quad \frac{1}{t'}\sum_{t=0}^{t'} \tilde{f}_{t,3}^2 = \min_{(u_{i,j})} \quad \frac{1}{t'}\sum_{t=0}^{t'}(f_{t,1}u_{1,3} + f_{t,2}u_{2,3} + f_{t,3}u_{3,3})^2$$

subject to

$$\begin{aligned}
&\sum_{j=1}^{3} u_{i,j}^2 = 1, && \forall i \in [1,3], \\
&\sum_{l=1}^{3} u_{i,l}u_{j,l} = 0, && \forall (i,j) \in [1,3]^2 \text{ and } i \neq j, \\
&\sum_{j=1}^{3} u_{j,2}\lambda_{j,1}^{PC} = 0, && \\
&\sum_{j=1}^{3} u_{j,3}\lambda_{j,1}^{PC} = 0 &&
\end{aligned}$$

We normalize the columns of $\tilde{F}^{PC} = F^{PC} \times U$ so that the different factors (namely the *Timing*, *FG*, and the *QE*), are positively correlated with a unit root effect with the six-month, the two-year, and the ten-year OIS rates, respectively.

### 1.10.2. The Bank Balance Sheet Dataset

In this section, we explain how we build the different explanatory variables that we use in our empirical exercise.

Table 1.6 shows the different items present in this dataset.

| **Assets** | **Liabilities** |
|---|---|
| Cash | |
| Deposit at Eurosystem | Borrowing from Eurosystem |
| Loans | Total Deposits |
| *Monetary and Financial Institutions* | *Monetary and Financial Institutions* |
| *Financial Corporations* | *Financial Corporations* |
| *Non-Financial Corporations* | *Non-Financial Corporations* |
| *Households* | *Households* |
| Securities | Debt securities issued |
| *Debt securities* | |
| *Shares in MMF* | |
| *Equity and Non-MMF investment funds shares* | |
| Reverse Repurchase Agreements | Repurchase Agreements |
| Remaining Assets (incl. Fixed Assets) | Remaining Liabilities |
| | Capital and Reserves |

Figure 1.6: Different balance sheet items present in the IBSI dataset.

We define the different balance sheet components of interest for bank $b$ at time $t$ as follows:

- the size as the log of total assets, $(\text{Size})_{b,t} = \log(\text{Total Assets})_{b,t}$,
- the equity-to-asset ratio, $(\text{E/A})_{b,t} = \left(\frac{\text{Capital and Reserves}}{\text{Total Assets}}\right)_{b,t}$,
- the share of liquid assets, $(\text{Share Liquid Assets})_{b,t} = \left(\frac{\text{Cash+Securities+Deposit at Eurosystem}}{\text{Total Assets}}\right)_{b,t}$ as in Kashyap & Stein (2000),
- the share of deposit liabilities, $(\text{Share of Dep. Liabilities})_{b,t} = \left(\frac{TotalDeposits}{\text{Total Liabilities}}\right)_{b,t}$.

| **Balance Sheet Component** | **Mean** | **Median** | **Standard Deviation** | **$25^{th}$-percentile** | **$75^{th}$-percentile** |
|---|---|---|---|---|---|
| *Dependent Variables* | | | | | |
| $\Delta$(Log(Loans)) (in %) | 0.46 | 0 | 0.372 | −0.392 | 1.23 |
| $\Delta$(Log(NFC Loans) (in %)) | 0.29 | 0.15 | 0.325 | −0.93 | 1.35 |
| *Explanatory Variables* | | | | | |
| Size | 11.28 | 11.35 | 1.43 | 10.35 | 12.4 |
| E/A (in %) | 8.46 | 6.43 | 11.46 | 3.86 | 9.48 |
| Share Liquid Assets (in %) | 19.22 | 17.35 | 16.04 | 10.01 | 24.65 |
| Share of Deposit Liabilities (in %) | 46.02 | 43.78 | 26.99 | 26.77 | 66.73 |

Figure 1.7: Summary Statistics for the different balance sheet components considered.

# Chapter 2

# Common Factors, Order Flows, and Exchange Rate Dynamics

**Joint Work With Dagfinn Rime, Lucio Sarno, Maik Schmeling and Adrien Verdelhan**

## 2.1. Introduction

At intraday frequencies, no economic variable is known to describe exchange rate dynamics, except for their associated order flows, a quantity-based measure of buyer-initiated and seller-initiated orders. In this chapter, we show that common, currency-based factors describe exchange rate dynamics at intraday frequencies at least as well as order flows. The same factors describe exchange rates over a large spectrum of frequencies, from 30-second to one-month.

Our results are based on the largest exchange rate dataset ever assembled. The sample covers the spot prices and order flows of 19 currency pairs over the last 15 years measured on Reuters and EBS, the main two trading platforms. The size of the database is not driven by hubris but by our methodology: we extract information from the cross-section of exchange rates in order to describe each bilateral exchange rate.

Building on a recent literature in macro-finance, we construct two exchange rate factors — the carry and the dollar factors. The carry factor corresponds to the change in exchange rates between baskets of high and low interest rate currencies, while the dollar factor corresponds to the average change in the exchange rate between the U.S. dollar and all other currencies. All exchange rates are defined here with respect to the U.S. dollar. We regress changes in exchange rates on the carry factor, the same carry factor multiplied by the country-specific interest rate difference (the latter is referred to as "conditional carry"), and the dollar factor. The change in bilateral exchange rate on the left-hand side of these regressions is measured between $t$ and $t+1$; on the right-hand side, the carry and dollar factors correspond to changes between $t$ and $t+1$ too, while the domestic and foreign interest rates are known at date $t$. The order flows correspond to the net of buyer and seller-initiated transactions between $t$ and $t+1$. The carry and dollar factors do not include the bilateral exchange rate that is the dependent variable; there is thus no mechanical link between the left-hand and the right-hand sides.

**Endogeneity.** As soon as prices and quantities are jointly considered, a clear endogeneity issue arises: order flows used as explanatory variables could themselves be determined by bilateral exchange rates, common factors, and any shocks that affect spot rates. To address this issue, we rely on the heteroskedasticy-based estimation (HBE) methods developed by Rigobon (2003) and Rigobon & Sack (2004). Non-farm payroll announcements provide the exogenous changes in volatilities. We find that the endogeneity issue is limited: slope coefficients in the regressions above appear close to their OLS estimates. Spot rates appear to have little impact on contemporaneous order flows. Thus, in the rest of the chapter, we focus on OLS estimates and uncover a new moment of intraday exchange rates.

**Factor Structure.** The two exchange rate factors account for a substantial share of individual exchange rate time-series. Among G10 currencies, common factors account for 12% to 55% of exchange rate dynamics at the 30-second frequency and from 29% to 62% at the five-minute frequency. These large $R^2s$ are obtained using only variables that are known to proxy for risk at lower frequencies: the carry factor accounts for the cross-section of interest rate-sorted currency portfolios (Lustig *et al.* (2011)) while the dollar factor accounts for the cross-section of dollar beta-sorted currency portfolios (Verdelhan (2018)).

Order flows account for 3% to 16% at the 30-second frequency and from 4% to 16% at the five-minute frequency. Taken together, common factors and order flows account for 23% to 56% of the exchange rate dynamics at the 30-second frequency and from 36% to 66% at the five-minute frequency. For example, they describe 66% of the change in the euro/U.S. dollar exchange rate at the five-minute frequency over the last 15 years. Order flows and common factors are correlated. On the one hand, one can consider that a share of the factors' variation should be attributed to order flows. On the other hand, one can consider that only the part of order flows that is not present in global factors really speaks to the trading frictions. We do not take a stand on this debate and considers both alternatives.

To measure the additional information contained in order flows that is not in prices, we focus on the orthogonalized order flows, obtained as residuals in regressions of the raw order flows on the factor structure. In that case, the descriptive power of order flows decreases significantly. For most G10 currencies, with the exception of the Japanese Yen, common factors explain a much larger share of exchange rate dynamics than the orthogonalized order flows. In other words, exchange rates are correlated across countries, and most of the information embedded in order flows is present in other exchange rates. This finding does not mean that order flows are useless: they are still the best predictive variables at high frequency. But the focus of this chapter is on contemporaneous, not predictive regressions. To establish a lower bound on the role played by the common factors (and an upper bound on the role of order flows), we consider the component of the common factors that is orthogonal to order flows. Even in that case, common factors still account for a large share of the intraday exchange rate variations.

In all our contemporaneous regressions, a clear difference between common factors and order flows appears across frequencies. While the share of exchange rate dynamics described by the common factors is higher at the daily frequency than intraday, the opposite happens for order flows. At the daily and monthly frequency, the marginal descriptive power of order flows is negligible.

We perform several robustness checks around our main results. We run similar tests at each hour of the day and for each month in our sample. The $R^2$s appear relatively stable throughout the day and drop for most currencies after 9:00 PM GMT. While we observe variation across months, our results are not driven by a particular month of our sample.

Our simple experiment provides a new systematic moment of exchange rates. It is well-know that exchange rate volatilities are persistent. Our experiment shows that currency betas are persistent too. To study this persistence, we obtain currency betas on non-overlapping windows, using our 30-second or 5-min data to build currency betas at the daily and weekly frequency. Thanks to our high frequency series, these betas are very precisely estimated. At the daily frequency, they exhibit autocorrelation coefficients of 0.5. At the weekly frequency, the autocorrelation coefficients increase to 0.7. Clearly, currency betas are not random. This is our key finding. There is no mechanical reason why the betas obtained on two non-overlapping samples should be persistent.

The time-series of currency betas represents a clear empirical challenge for anyone interested in exchange rates — the largest market in the world. Explaining the cross-section and time-series variation in these betas will go a long way to explaining exchange rates themselves because the currency factors describe a large share of the exchange rate variation, even intraday. As a very modest contribution to this quest, we show that the currency betas vary significantly with their corresponding bond yields.

## 2.2. Related Literature

Our chapter builds on two different large literatures: the microstructure and macro-finance approaches of exchange rates. Under rational expectations, exchange rates respond to macroeconomic news and instantaneously adjust to the new equilibrium level implied by macroeconomic news. The literature has generally struggled to find hard evidence that this mechanism works. The typical finding is that many news announcements have no perceptible effect on exchange rates, although the early literature was using data at a fairly low frequency, which may be lack power in this context. Almeida *et al.* (1998) address this question by using high-frequency data on the dollar-mark exchange rate and find that the length of the time interval does affect the significance of the response to some announcements. More recently, Andersen *et al.* (2003) use similar high-frequency data and again find a significant and very fast response of exchange rates to several U.S. macroeconomic news announcements. Evans & Lyons (2008) and Love & Payne (2008) report a larger impact of news on exchange rates by taking into account the response of order flows to macroeconomic surprises.

Order flows have a strong explanatory power on different asset prices, from equity (Chordia *et al.* (2002)), to bonds (Brandt & Kavajecz (2004)), and currencies. In a seminal contribution, Evans & Lyons (2002) document a strong relation between order flows and daily exchange rate changes in the Deutsche Mark and Japanese Yen versus the U.S. dollar over the May 1 to August 31, 1996 sample. The title of our chapter is an hommage to their work. Subsequent research have shown this to be a remarkable strong and robust finding across both frequencies (from intraday to quarterly) and currencies (in developed and emerging markets)[1]. The consensus in the microstructure literature is that roughly two-thirds of macroeconomic news are transmitted to exchange rates through order flows, thereby contradicting the simple Walrasian auctioneer textbook model of price determination (Evans & Lyons (2008), Love & Payne (2008)). We find that order flows account for less than 10% of the exchange rate variations. This lower share is due to our more restrictive approach: we only consider macroeconomic news, not all Bloomberg messages, and we focus on contemporaneous order flows, not including the past and future order flows in a defined range. It is still possible that a large fraction of news is impounded into prices through order flows and that we do not observe the relevant order flows as some of the trading does not take place on Reuters and EBS.

A number of papers further investigate the mechanism via which order flow impacts on exchange rate returns. Evans (2010) studies how order flow aggregates information on macroeconomic fundamentals (aggregated from micro entities such as firms and households) that are not observable in real time. Similarly, Dominguez & Panthaki (2006), Berger *et al.* (2008), Love & Payne (2008), and Evans & Lyons (2008) have linked the information content of order flow to macroeconomic news. Rime *et al.* (2010) confirm the link between macro news and order flow, and show that order flow also contains predictive information, not just contemporaneous information, for currency returns. Likewise, Evans & Lyons (2005) show that order flow forecasts exchange rates in an out-of-sample setting (without linking this predictability to macro fundamentals, though). Finally, it seems reasonable that order flow also captures information about (shocks to) liquidity and risk-aversion which are not observable in real time. In short, order flow can impact on exchange rate returns for at least three reasons: pure demand pressure (liquidity); by capturing new information about macro fundamentals; and by capturing variation in risk premia.

Our chapter is part of a growing literature that relies on currency portfolios to study currency risk. Previous research on currency portfolios shows that the carry factor accounts for the cross-section of currency excess returns sorted by interest rates: covariances of the carry factor with currency returns align with the cross-section of average excess returns, and the carry factor can be proxied by measures of global volatility on equity (Lustig *et al.* (2011)) or on currency markets (Menkhoff *et al.* (2012)), or by measures of downside equity risk (Lettau *et al.* (2014)). Lustig *et al.* (2014) study the predictability of the dollar risk factor (thus focusing on one single currency portfolio),

[1]Evans (2002) and Payne (2003) study intraday data. Berger *et al.* (2008) study frequencies from intraday to quarterly, and find a strong relation at all frequencies, although weaker at lower frequencies Chinn & Moore (2011) document a persistent impact using monthly data. See King *et al.* (2013) for a recent overview of the literature.

while Maggiori (2013) uses a conditional-Capital Asset Pricing Model to price the dollar excess return. Our chapter is closest to Verdelhan (2018) who runs similar regressions of exchange rates on the carry and dollar factors at the daily, monthly, and quarterly frequencies. Verdelhan (2018) shows that the dollar factor accounts for the cross-section of dollar-beta sorted currency returns. But he does not consider intraday frequencies, order flows, or macroeconomic news. Lustig & Richmond (2017) take up the key challenge of explaining the cross-country differences in betas and show that the dollar betas are significantly related to the distance between the foreign country and the U.S.

The rest of this chapter is organized as follows. Section 2.3. introduces a general framework and the definition of the currency factors and betas. Section 2.4. presents our data. Section 2.5. revisits the heteroscedasticity-based estimation of the share of news impounded directly into prices. Section 2.6. reports the results of our benchmark regressions of exchange rates on order flows and common factors and studies the characteristics of the time-varying currency betas. Section 2.7. concludes. Details on the construction of the data set and robustness checks are reported in the Appendix.

## 2.3. Theoretical Framework

We follow Lustig & Verdelhan (2019) to set up a very general model of exchange rates and bond prices when financial markets are incomplete. Let $M$ and $M^i$ denote the domestic and foreign SDFs that satisfy the Euler equations for the domestic and foreign returns:

$$E_t\left(M_{t+1}R_{t+1}\right) = 1, \tag{2.1}$$

$$E_t\left(M^i_{t+1}R^i_{t+1}\right) = 1, \tag{2.2}$$

where $R^i_{t+1}$ represents the foreign return expressed in units of foreign currency, while $R_{t+1}$ denotes the domestic return, expressed in units of the domestic currency. Throughout the chapter, lower case letters denote natural logarithms and $x^i$ denotes a foreign variable expressed in units of foreign currency. Following Lustig & Verdelhan (2019), we then introduce a wedge $\eta^i$ that reconciles the log change in exchange rates with the difference in log SDFs. The log changes of the exchange rate is thus

$$\Delta s_{t+1}^{i} = \eta_{t+1}^{i} + m_{t+1}^{i} - m_{t+1}, \tag{2.3}$$

where $S_t^i$ denotes the nominal exchange rate in domestic currency (e.g., U.S. dollars) per unit of foreign currency. When $S_t^i$ increases, the foreign currency appreciates and the U.S. dollar depreciates. When markets are complete, the wedge is zero.

We make two assumptions to pin down the form of the wedge.

**Assumption 1.** *We assume that the log domestic and foreign stochastic discount factors, $m$ and $m^i$, and the wedge $\eta^i$ are jointly normal and that the log domestic and foreign stochastic discount factors, $m$ and $m^i$, follow a simple Cox* et al. *(1985) process.*

The log-normality assumption delivers clear closed-form solutions. The domestic and foreign SDFs are driven by local and global shocks. We focus on global shocks to the SDF, denoted $u_{t+1}^g$ and $u_{t+1}^w$, but country-specific shocks can be added easily. The laws of motion of the SDFs are:

$$\begin{aligned}
-\log M_{t+1} &= \alpha + \chi z_t + \kappa z_t^\star + \sqrt{\gamma z_t}\, u_{t+1}^g + \sqrt{\delta z_t^\star}\, u_{t+1}^w, \\
-\log M_{t+1}^i &= \alpha + \chi z_t + \kappa z_t^\star + \sqrt{\gamma^i z_t}\, u_{t+1}^g + \sqrt{\delta^i z_t^\star}\, u_{t+1}^w, \\
z_{t+1} &= (1-\phi)\theta + \phi z_t - \sigma\sqrt{z_t}\,\epsilon_{t+1}, \\
z_{t+1}^\star &= (1-\phi)\theta + \phi z_t^\star - \sigma\sqrt{z_t^\star}\,\zeta_{t+1}
\end{aligned}$$

The SDFs are heteroscedastic because the log currency risk premium depends on the difference in volatilities of the log SDFs, and empirically the currency risk premium is time-varying. The state variables $z_t$ and $z_t^\star$ govern the necessary time-variation in volatility. We introduce two state variables because we find that the first two principal components of all G10 currency volatilities describe close to 80% of the volatility dynamics. In the classic CIR model, shocks to the SDF are the same as the shocks to the state variable, but this assumption can be easily relaxed.

**Assumption 2.** *We assume that there exists a risk-free asset at home and abroad that can be bought and sold freely by both domestic and foreign investors.*

Assumption 2 is not necessarily verified in practice or in all models: the recent models of Gabaix & Maggiori (2015), Schmitt-Grohé & Uribe (2016), Farhi & Werning (2017), Amador *et al.* (2017)), and Itskhoki & Mukhin (2017) do not satisfy Assumption 2. Yet, as Lustig & Verdelhan (2019) show, this simple assumption is very powerful: it allows us to define exchange rates without taking a stand on source of market incompleteness. Assumption 2 implies that four Euler equations have to hold simultaneously: the domestic investor's Euler equation for domestic and foreign risk-free assets, and the foreign investor's Euler equation for the domestic and foreign risk-free assets:

$$
\begin{aligned}
E_t\left(M_{t+1}R_t^f\right) &= 1, & (2.4)\\
E_t\left(M_{t+1}\frac{S_{t+1}^i}{S_t^i}R_t^{f,i}\right) &= E_t\left(M_{t+1}^i\exp(\eta_{t+1}^i)R_t^{f,i}\right)=1, & (2.5)\\
E_t\left(M_{t+1}^iR_t^{f,i}\right) &= 1, & (2.6)\\
E_t\left(M_{t+1}^i\frac{S_t^i}{S_{t+1}^i}R_t^f\right) &= E_t\left(M_{t+1}\exp(-\eta_{t+1}^i)R_t^f\right)=1. & (2.7)
\end{aligned}
$$

When markets are incomplete, these Euler equations imply that the wedge $\eta_{t+1}^i$ has to take the form:

$$
\eta_{t+1}^i = \psi^i z_t + \tau^i z_t^\star + \sqrt{\lambda^i z_t}\, u_{t+1}^g + \sqrt{\lambda^{i,\star} z_t^\star}\, u_{t+1}^w + \sqrt{\chi^i z_t}\,\epsilon_{t+1}^i + \sqrt{\chi^{i,\star} z_t^\star}\,\epsilon_{t+1}^i.
$$

where $\epsilon_{t+1}^i \sim \mathcal{N}(0,1)$ are i.i.d. shocks, and where the parameters $\psi$, $\tau$, $\lambda$, $\lambda^\star$, $\chi$, and $\chi^\star$ describe all potential incomplete market models and satisfy some conditions (linked to the SDF parameters, see proof in the Appendix).

To summarize, the exchange rate is driven by the priced global shocks $u_{t+1}^g$ and $u_{t+1}^w$ and by wedge shocks $\epsilon_{t+1}^i$. Its volatility is governed by two state variables, $z_t$ and $z_t^\star$. To simplify, we will denote its law of motion as:

$$
\Delta s_{t+1}^i = \psi z_t + \tau z_t^\star + \left(\sqrt{\gamma z_t} - \sqrt{\gamma^i z_t}\right) u_{t+1}^g + \left(\sqrt{\delta z_t^\star} - \sqrt{\delta^i z_t^\star}\right) u_{t+1}^w + \sqrt{\chi z_t}\,\epsilon_{t+1}^i + \sqrt{\chi^\star z_t^\star}\,\epsilon_{t+1}^i.
$$

where we bunched the global shocks stemming from the wedge with those stemming from the SDFs (and redefine $\gamma^i$ and $\delta^i$ accordingly).

The dollar risk factor is by definition the average of all $N$ exchange rates expressed in terms of U.S. dollars, and thus corresponds to

$$
Dollar_{t+1} = \frac{1}{N}\sum_i \Delta s_{t+1}^i. \tag{2.8}
$$

The carry risk factor is by definition the average exchange rate of high- versus low-interest rate currencies,

$$Carry_{t+1} = \frac{1}{N_H} \sum_{i \in H} \Delta s^i_{t+1} - \frac{1}{N_L} \sum_{i \in L} \Delta s^i_{t+1}, \tag{2.9}$$

where $N_H$ ($N_L$) denotes the number of high (low) interest rate currencies in the sample. We assume that there are enough currencies for the law of large numbers to apply for the non-priced shocks: $\frac{1}{N}\sum_i \sqrt{\chi z_t}\epsilon^i_{t+1} = \frac{1}{N}\sum_i \sqrt{\chi^\star z^\star_t}\epsilon^i_{t+1} = 0$. In this case, the Dollar factor only reflects global shocks:

$$Dollar_{t+1} = \psi z_t + \tau z^\star_t + \left(\sqrt{\gamma} - \overline{\sqrt{\gamma^i}}\right)\sqrt{z_t}u^g_{t+1} + \left(\sqrt{\delta} - \overline{\sqrt{\delta^i}}\right)\sqrt{z^\star_t}u^w_{t+1} \tag{2.10}$$

The dollar betas are thus:

$$\begin{aligned} \beta^i_{Dollar,t} &= \frac{cov_t(\Delta s^i_{t+1}, Dollar_{t+1})}{var_t(Dollar_{t+1})} \\ &= \frac{\left(\sqrt{\gamma} - \sqrt{\gamma^i}\right)\left(\sqrt{\gamma} - \overline{\sqrt{\gamma^i}}\right) z_t + \left(\sqrt{\delta} - \sqrt{\delta^i}\right)\left(\sqrt{\delta} - \overline{\sqrt{\delta^i}}\right) z^\star_t}{\left(\sqrt{\gamma} - \overline{\sqrt{\gamma^i}}\right)^2 z_t + \left(\sqrt{\delta} - \overline{\sqrt{\delta^i}}\right)^2 z^\star_t} \end{aligned} \tag{2.11}$$

The dollar betas vary across countries and over time because of different exposures to the state variables $z_t$ and $z^\star_t$. A similar approach applies to the carry betas.

## 2.4. Data

In this section, we first describe our exchange rate prices and then turn to the order flow quantities. We finally rapidly describe the macroeconomic news data and the construction of the currency factors.

### 2.4.1. Exchange Rates

Our data consist of tick-by-tick exchange rates against the U.S. Dollar for the following 19 currencies: the Australian Dollar (AUD), the Brazilian Peso (BRL), the Canadian Dollar (CAD), the Swiss Franc (CHF), the euro (EUR), the U.K. pound (GBP), the Hong-Kong Dollar (HKD), the Israeli Shekel (ILS), the Indian Roupie (INR), the Japanese Yen (JPY), the Korean won (KRW), the Mexican Peso (MXN), the Malaysian Ringgit (MYR), the New Zealand Dollar (NZD), the Russian

Rubble (RUB), the Swedish Krona (SEK), the Singapore Dollar (SGD), the Turkish Lira (TRY), and the South African Dollar (ZAR). All exchange rates are quoted as the U.S. Dollar price of foreign currency, i.e., a higher exchange rate corresponds to an appreciation of the foreign currency.

Tick-by-tick quotes are recorded on Reuters and EBS, the two main trading platforms of the inter-dealer market. Data for the EUR, JPY, and CHF come from EBS (where most transactions occur) whereas exchange rates for the other currencies are sourced from Reuters. The same filter, described in the Appendix, is applied to both sources in order to remove outliers.[2]

The sample period is from January $1^{th}$, 1999 to December $31^{st}$, 2014. We focus on the 8:00 AM to 8:00 PM hours (GMT), where most trading occurs, and discard overnight hours. We also exclude the non-business days in the U.S. and the U.K. Importantly, we assume that quotes are only valid for up to one minute, thus ensuring that our data correspond to actionable prices. We sample exchange rates at different frequencies, from 30 seconds to one month. A trading day ends – and a new trading day starts – at the London 4:00 PM fix, the standard convention used in currency markets (which is also mirrored in databases such as Datastream and Bloomberg). To check the accuracy of our data, we use the daily exchange rates published by the Federal Reserve (measured at noon, Eastern time), as well as quotes from Olsen and Associates at the five-minute frequency. They represent a set of high-quality intraday exchange rate quotations which are cleaned for outliers. For each currency, we have the Olsen and Associates bid, ask, high, low, and mid prices. The discrepancies are minimal and do not appear systematic.

We complement these data with daily one-month forward rates. To convert forward rates to higher frequencies, we use values of the previous trading day (4pm London time) for all high frequency intervals of the next trading day.

### 2.4.2. Currency Factors

Using exchange rates, we build two factors: the dollar and the carry factors. As noted, the dollar factor is the cross-country average over all exchange rate returns (log spot exchange rate changes) at each point in time. We build a separate dollar risk factor for each individual currency by dropping the respective currency from the sample. For example, the dollar risk factor for Australian dollars

[2]Figures 2.7 and 2.8 in the Appendix report the fraction of observations removed. We only delete very few observations, corresponding to 0.0001% to 0.1% of the number of quotes, depending on the hour of the day and currency. Despite this very limited filter, the distribution of the exchange rate data appears reasonable. Tables 2.7 and 2.8 in the Appendix report the distributions of the 30-sec and 5-min exchange rate log returns.

is the average exchange rate change of all currencies against the USD except for the change of the AUD against USD itself.

To construct carry portfolios, we follow the same principle and build one carry factor per currency (always dropping the respective currency from our sample) and attach positive portfolio weights to high interest rate currencies and negative portfolio weights to low interest rate currencies. We sort countries by the level of their short-term nominal interest rates into four portfolios.[3] The portfolios are rebalanced every month. Countries in each portfolio are equally-weighted. The carry factor corresponds to the exchange rate of the last portfolio minus the exchange rate of the first portfolio.

### 2.4.3. Order Flows

The Reuters database does not report order flows. As in the literature, we build order flow indicators, $I_k$, where $I_k$ is $+1$ ($-1$) for trade $k$ if the trade was initiated by the buyer (seller) of foreign currency. By assumption, a trade is buyer-initiated if the transaction occurs at the ask price. Killeen *et al.* (2006) show that most trades on Reuters are for \$1 million. The EBS database reports traded volume and order flow magnitudes directly.

In addition, our data also include the number of trades for each time minute interval, $N_t$, and, hence, we can distinguish between periods when no trade take place and periods when trades are executed but order flows aggregate to zero. Again, since trade sizes tend to be fairly standardized, we will refer to the number of trades as "volume" in the rest of the chapter. Finally, to make order flows comparable across currencies and over time within the same currency pair, we will frequently make use of scaled order flow, i.e. we divide order flow by the number of transactions during the time interval $(OF_t/N_t)$.

[3]The carry portfolio construction relies on daily interest rate differentials (forward discounts). We sort on forward discounts of the previous day and define a day from 4pm (yesterday) to 4pm (today). For example, on May 5th, the timing convention is as follows: First, we compute the forward discount for May 5th (one month forward contract) by using the end-of-day forward and spot rate for May 5th, 4 pm. Then, this forward discount is used to build a carry portfolio from May 5th 4:05 pm to May 6th 4pm.

## 2.5. Heteroscedasticity-based Estimation

Our first goal is to evaluate the relative importance of order flows and common factors in describing exchange rate changes. Yet, as soon as prices and quantities are jointly considered, a clear endogeneity issue potentially appears. In this section, we review this issue and describe our application of the heteroscedasticity-based method of Rigobon (2003) to address it.

### 2.5.1. Endogeneity

Prices and quantities are clearly endogenous:

$$\begin{aligned} p_t &= \beta q_t + \varepsilon_t, \\ q_t &= \alpha p_t + \eta_t. \end{aligned}$$

Prices affect quantities and vice-versa. In the context of our study, the price $p$ corresponds to the change in exchange rate $\Delta s$, while the quantity $q$ corresponds to the net order flow $OF$. To know the direct impact of one on the other, we would like to recover the coefficients $\alpha$ and $\beta$. Yet, even if one assumes that the structural shocks are not correlated: $\sigma_{\varepsilon,\eta} = 0$, one can only estimate the covariance matrix:

$$\hat{\Omega} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ & \omega_{22} \end{bmatrix} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \beta^2\sigma_\eta^2 + \sigma_\varepsilon^2 & \beta\sigma_\eta^2 + \alpha\sigma_\varepsilon^2 \\ & \sigma_\eta^2 + \alpha^2\sigma_\varepsilon^2 \end{bmatrix}.$$

The challenge is thus clear: there are three moments ($\sigma_p^2$, $\sigma_q^2$, and $\sigma_{pq}$) but four unknowns ($\alpha$, $\beta$, $\sigma_\varepsilon^2$, $\sigma_\eta^2$).

The heteroscedasticity-based method of Rigobon (2003) starts from the assumption that there are two regimes in the variances of the structural shocks: $\sigma_{\eta,s}^2, \sigma_{\varepsilon,s}^2,\ s \in \{1,2\}$ and assumes that the slope coefficients $\alpha$ and $\beta$ are the same in the two regimes. In this case, one can recover the coefficients $\beta$ and $\alpha$, which satisfy:

$$\begin{aligned} \beta &= \frac{\omega_{12,s} - \alpha\omega_{11,s}}{\omega_{22,s} - \alpha\omega_{12,s}} \\ [\omega_{11,1}\omega_{12,2} - \omega_{12,1}\omega_{11,2}]\,\alpha^2 &- [\omega_{11,1}\omega_{22,2} - \omega_{22,1}\omega_{11,2}]\,\alpha + [\omega_{12,1}\omega_{22,2} - \omega_{22,1}\omega_{12,2}] = 0 \end{aligned}$$

The second-order equation has a real solution if $\omega_{11,1}\omega_{12,2} - \omega_{11,2}\omega_{11,1} \neq 0$. The system is then identified up to row permutations of the original model: if $(\alpha,\ \beta)$ is a solution, then $(1/\beta,\ 1/\alpha)$ is also a solution.

Evans and Lyons (2008) and Love and Payne (2008) apply the heteroscedasticity-based method of Rigobon (2003) to study the share of news impounded into prices through order flows. In essence, their estimation is based on two volatility regimes: the exchange rate volatility is high when surprises (e.g. macroeconomic data) are announced.[4] We follow the same methodology, taking into account the potential common currency factors. The full system is thus:

$$p_t = \beta q_t + \gamma_p F_t + \varepsilon_t, \tag{2.12}$$

$$q_t = \alpha p_t + \gamma_q F_t + \eta_t, \tag{2.13}$$

### 2.5.2. Heteroscedasticity-Based Estimation with Common Factors

We assume that the risk factors are exogenous in the price and quantity equations, or in other words:

$$E[F_t \varepsilon_t] = 0 \text{ and } E[F_t \eta_t] = 0.$$

Under the assumptions above, we can still identify the system of Equations (2.12) and (2.13) with $N$ common factors by including just two or more volatility regimes. To show this, let us introduce the following notation: $Y_t = [p_t, q_t]'$, and $\nu_t = [\varepsilon_t, \eta_t]'$. The system can be written in the form $AY_t = BF_t + \nu_t$, where

$$A = \begin{bmatrix} 1 & -\beta \\ -\alpha & 1 \end{bmatrix} \text{ and } B = [\gamma_q \quad \gamma_p]'.$$

The reduced form is $Y_t = A^{-1}BF_t + \xi_t$. Under the exogeneity of $F_t$ this system is identified by OLS. In the first stage the coefficients $\widehat{A^{-1}B}$ are estimated by OLS. The residuals $\xi_t$ satisfy $A\xi_t = \nu_t$. Therefore for each volatility regime $s$, the following moment condition holds:

$$A\Omega_{\xi,s}A' - \Omega_{\nu,s} = 0,$$

[4]They report a stunning result: two-thirds of the impact of macroeconomic news surprises is impounded into prices through order flows. In essence, their key finding pertains to the fraction of exchange rates driven by order flows:

$$\frac{\sigma^2_{(\beta q)}}{\sigma^2_p} = \frac{\beta^2(\sigma^2_\eta + \alpha^2\sigma^2_\varepsilon)}{\beta^2\sigma^2_\eta + \sigma^2_\varepsilon}.$$

where $\widehat{\Omega_{\xi,s}}$ can be estimated from the empirical variance-covariance matrix of the reduced form residuals $\widehat{\xi_t}$. Meanwhile, because of the assumption of no correlation across error terms, the matrix $\Omega_{\nu,s}$ satisfies

$$\Omega_{\nu,s} = \begin{bmatrix} \sigma^2_{\varepsilon,s} & 0 \\ 0 & \sigma^2_{\eta,s} \end{bmatrix}$$

One could use the entire moment condition $A\Omega_{\xi,s}A' - \Omega_{\nu,s} = 0$, which would require estimation of the residual parameters $\sigma^2_{\varepsilon,s}$ and $\sigma^2_{\eta,s}$, but this is not necessary. Taking an off-diagonal element from each regime provides the moment conditions needed to identify the parameters $\alpha$ and $\beta$ in $A$. Therefore the moment condition becomes

$$\text{offdiag}\left(A\Omega_{\xi,s}A' - \Omega_{\nu,s}\right) = 0,$$

for each regime $s$.[5] As the matrix is symmetric, the off-diagonal elements provide only one unique moment condition (hence the need for at least two regimes to identify $\alpha$ and $\beta$). Having estimated $\widehat{A}$ from this moment condition via GMM, the matrix $B$ can be estimated by taking $\widehat{B} = \widehat{A}\widehat{A^{-1}B}$ (where again $\widehat{A^{-1}B}$ was obtained from the OLS estimation of the reduced form of the system).[6]

Let us repeat here the assumptions needed for this experiment to work: (i) the residuals are orthogonal; (ii) the slope coefficients $\alpha$ and $\beta$ do not change across regimes; and, (iii) the factors are exogenous in the price and quantity equations. Note that we do not actually need to impose that the factors have the same impact across regimes. One could also estimate separately the reduced form for each of the $S$ regimes to get $\widehat{A^{-1}B_1}, ..., \widehat{A^{-1}B_S}$ and then recover $\widehat{B}_1, ..., \widehat{B}_S$ in the exact same manner.

Assumption (i) may at first not seem plausible, as the residuals may be correlated: in other words, there could be one unobservable shock $\nu_t$ that is affecting both $\varepsilon_t$ and $\eta_t$, thus adding at least two unknowns. Proposition 2 of Rigobon (2003) shows that in this case the method fails. It must be that the residuals are orthogonal or at least that their covariance is constant. This assumption though pertains to residuals obtained after taking into account the common factors; if those factors summarize all the relevant information, assumption (i) is plausible.

Assumption (ii) deserves further scrutiny. A potential robustness check would be to redo the exper-

[5]The authors thank Roberto Rigobon for pointing this out.

[6]As in the case without common factors, this system is identified up to row permutations of the original model, so that there are two potential solutions to the model. We impose some sign and magnitude restrictions (based on simple OLS coefficients) on the $\alpha$ and $\beta$ coefficients to prevent the GMM estimation from oscillating between the two solutions. Standard errors are computed for all estimated parameters via bootstrap.

iment for large and very large volatility regimes, using for example the size of the macroeconomic surprises as a conditioning variable. One could also test the robustness of the results to the assumption that the slope coefficients scale up with volatility.

Assumption (iii) seems easiest to defend in a large cross-section of currencies, where the country-specific shocks average out, and when the factors summarize all the global shocks affecting exchange rates.

### 2.5.3. Results

Figure 2.1 shows that volatility spikes up when non-farm payroll data are released. The figure compares the exchange rate log return volatilities over non-overlapping 5-min windows on days with and without US non-farm payroll announcements for AUD, CAD, CHF, EUR, GBP, and JPY using data at the 30-second frequency. We pick these currencies because the volatility pattern is clear and conditioning on non-farm payroll announcements clearly deliver two volatility regimes. In Figure 2.1, time is measured from the minute when announcements are released (1:30pm GMT). With the exception of the Canadian dollar, the release of the non-farm payroll data corresponds to a volatility spike that is two to three times bigger than any other average volatility increase. The Canadian dollar exhibits a second volatility spikes one hour and half before the non-farm payroll data are announced; we do not use that volatility change and focus on the non-farm payroll announcements.

[INSERT FIGURE 2.1]

Tables 2.1 and 2.2 report the estimation of the following system:

$$\begin{aligned}\Delta s_{t+1} &= \alpha_1 \mathrm{OF}_{t+1} + \beta_1 \mathrm{Dollar}_{t+1} + \gamma_1 \mathrm{Carry}_{t+1} + \delta_1 (i_t^* - i_t)\mathrm{Carry}_{t+1} + \tau_1 (i_t^* - i_t) + \varepsilon_{t+1}, \\ \mathrm{OF}_{t+1} &= \alpha_2 \Delta s_{t+1} + \beta_2 \mathrm{Dollar}_{t+1} + \gamma_2 \mathrm{Carry}_{t+1} + \delta_2 (i_t^* - i_t)\mathrm{Carry}_{t+1} + \tau_2 (i_t^* - i_t) + \nu_{t+1},\end{aligned}$$

where $\Delta s_{t+1}$ denotes the bilateral exchange rate in U.S. dollar per foreign currency, $(i_t^* - i_t)$ is the interest rate differential between foreign country and the U.S., $Carry_{t+1}$ denotes the dollar-neutral average exchange rate change obtained by going long a basket of high interest rate currencies and short a basket of low interest rate currencies (excluding currency $j$ itself), $Dollar_{t+1}$ corresponds to the average change in exchange rates against the U.S. dollar (except for the foreign currency itself), and $OF_{t+1}$ denotes order flow (net buying pressure of the foreign currency).

[INSERT TABLES 2.1 AND 2.2 ]

Table 2.1 focuses on the first equation, while Table 2.2 focuses on the second. Table 2.1 shows that the direct impact of order flows on exchange rates is close to its OLS estimate for most G10 currencies.The coefficients increase for the AUD, CHF, EUR, GBP, JPY and decrease for CAD and NZD. These coefficients are highly significant. Likewise, the share of exchange rate variation accounted by order flows appear similar in the OLS and HBE estimation, ranging from 4 to 13%.[7] The slope coefficients on the dollar and carry factors appear very similar in the OLS and HBE procedures.

Table 2.2 shows that bilateral exchange rates account for less than 3% of the order flows dynamics on the G10 currencies. This limited role for spot prices in determining contemporaneous quantities is in line with most microstructure models.

## 2.6. Common Factors, Order Flows, and Exchange Rate Dynamics

Since the endogeneity bias of order flows appears limited, we rely on simple OLS regressions in the rest of the chapter and describe now how the factor structure evolves across frequencies and over time.

### 2.6.1. The Factor Structure Across Frequencies

We run time-series regressions of exchange rate changes on the factors and order flows, separately for each currency. Tables 2.3 and 2.4 report the results for data sampled at 30-second and five-minute frequencies.

[INSERT TABLES 2.3 AND 2.4]

[7]The Swedish and Norwegian Kronas are exceptions: the estimates of the impact of order flows goes respectively from 0.6 (OLS) to 0.06 (HBE) and from 0.7 to 0. This result is certainly due to our data construction. For these two currencies, we use order flows on the euro-based transactions instead of the dollar-based ones because the market is much more liquid in euros. These order flows do not seem to describe exchange rates once their endogeneity is taken into account.

Adjusted R-squares, denoted $\overline{R}^2$, range from 3% (for the Korean won, which is pegged to the U.S. dollar) to 56% (for the Swiss franc) at the 30-second frequency and from 4% (Korean won again) to 66% (for the euro) at the five-minute frequency. For example, common factors and order flows jointly describe 46% of the change in the euro/U.S. dollar exchange rate and 31% of the change in the pound/dollar exchange rate at the 30-second frequency. $R^2$s for the non G10 currencies are on average lower, but the comparison across currencies is limited by the shorter time-window of developing markets. Common factors appear significant for all currencies. Order flows appear significant for all currencies, except the Korean won. Puzzlingly, they appear with a negative sign for BRL, KRW, and RUB, but are positive in all other cases. Order flows seem to convey additional information that is not present in the common factors (and vice versa).

We turn now to a systematic comparison across frequencies. While the heteroscedasticity-based estimation suggests that the OLS give a reasonable description of the descriptive power of order flows and factors, we entertain two additional polar cases in order to be conservative. First, we give all the possible explanatory power to order flows and only consider common factors that are orthogonal to the order flows. The $R^2$s of such regressions give a lower bound on the explanatory power of common factors. They correspond to the blue bars in Figure 2.2. Intuitively, we assume here that the Dollar and carry factors are partly driven by the currency order flows. Second, we consider the alternative, giving all the possible explanatory power to the common factors, only considering order flows that are orthogonal to the factors. The $R^2$s of such regressions give a lower bound on the explanatory power of order flows. They correspond to the red bars in Figure 2.2. Intuitively, we assume here that the information that shows up across exchange rates is not order flow-specific. The truth has to be between these two polar cases: from the simple OLS regressions of exchange rates on order flows and common factors, we obtain the $R^2$s that could be attributed to one or the other.

As an example, take AUD. At the 5-min frequency, Table 2.4 shows that order flows and common factors jointly account for 39% of the exchange rate variation. We find that the part of the common factors that is orthogonal to order flows account for 24% of the exchange rate variation, while the part of the order flows that is orthogonal to the common factors accounts for 5%. Thus the part that could be attributed to order flows or exchange rates is $39 - 24 - 5 = 10\%$. Common factors account at least for 24% of the exchange rate variation and at most for 34%. Order flows describe at least 5% and at most 15%. The heteroscedasticity-based estimation suggests that the explanatory power of order flows is close to the lower value.

Figure 2.2 shows that the factor structure appears at intraday frequencies and that its importance grows as we consider lower frequencies. The opposite happens for order flows. The information content of order flows is most powerful at very short frequencies but loses importance once we move to lower frequencies. Berger *et al.* (2008) report similar results for order flows on EUR and JPY against USD for the period 1999-2005.

[INSERT FIGURE 2.2]

### 2.6.2. The Factor Structure Over Time

We next explore the time-variation in the factor structure (and order flow), first across the different hours of the day and then over time. Our primary objective is to check that the strong results reported above are not driven by some specific time windows or outliers.

Figure 2.3 plots the $R^2$s from regressions of spot exchange rate changes on the currency factors and order flows obtained at a 5-minute frequency and separately for each hour of the day. Again, the $R^2$ is decomposed into three components: in blue, the portion of the $R^2$ attributable to the component of the factor structure that is orthogonal to order flows; in red, the portion attributable to the component of order flows that is orthogonal to the factor structure; in purple, the portion attributable to the shared component of the factor structure and order flows.

[INSERT FIGURE 2.3]

As Figure 2.3 shows, from 8am to 8pm (our benchmark sample), the share of exchange rate variation described by order flows and common factors is fairly stable. Our results are not driven by some specific hour of the day. For most currencies, the $R^2$s are slightly higher during the 13:00-16:00 GMT window, which coincides with the most active trading hours of the day for developed currencies (when both London and New York are open). The factor structure seems to capture a larger share of exchange rate variation during times of more active trading, with sharpe declines in $R^2$s for most currencies after 22:00 GMT (5:00pm ET).

We now turn to the strength of the factor structure over time, running the same tests for each month in our sample. Figure 2.4 shows the $R^2$s from regressions of spot exchange rate changes on the currency factors and order flows based on monthly non-overlapping windows of data at a 5-min frequency. Two results emerge. First, our benchmark findings are not driven by a particular month of the sample. Second, the explanatory power of order flows appears much larger in the first half of the sample (2000 to 2007) and greatly reduced afterwards. It is possible that order flows observed on other trading platforms, introduced in the second half of our sample, convey more information. Overall, the time-variation in the $R^2$s suggest that the factor betas could be persistent. We now explore this characteristic in more details.

[INSERT FIGURE 2.4]

### 2.6.3. The Persistence of Betas

As an example, Figure 2.5 shows the time-series of dollar betas obtained over weekly non-overlapping windows for the AUD and EUR. These time series do not look random.

To be more systematic, Table 2.5 reports the results from the panel regressions of daily betas on lagged daily betas (left panel) and weekly betas on lagged weekly betas (right panel), without or with currency fixed effects (CCY FE), day/week fixed effects (Time FE), or both. At the daily frequency, with currency fixed effects, the dollar and carry betas exhibit a first-order autoregressive coefficient, denoted AR(1), of 0.55. This coefficient increases to 0.7 at the weekly frequency. Even without any fixed effect, past daily dollar (carry) betas account for 58% (71%) of the variation in dollar (carry) betas.

[INSERT TABLE 2.5]

Figure 2.6 reports the slope estimates for regressions of weekly betas on lagged weekly betas by currency. The persistence in the dollar betas are low for NZD, SEK, and NOK (around 0.5), but are all around 0.75 for the other currencies (and up to 0.85). There is less heterogeneity in the persistence of carry betas.

[INSERT TABLE 2.6]

### 2.6.4. Betas and Interest Rates

As a preliminary test, we report the link between currency betas and bond yields. Table 2.6 reports regression results of detrended FX betas on detrended 10-year bond yields, where both series are detrended by a 22-trading day moving average. In almost all cases, the betas appear significantly related to bond yields. Their co-movement, however, appears to change sign over time. Panel A shows results for the pre-crisis period (2000/01 – 2007/06) while Panel B shows results for the post-crisis period (after 2007/06). Regression coefficients switch sign across periods.

[INSERT TABLE 2.6]

## 2.7. Conclusion

This chapter shows that common, price-based factors describe exchange rate dynamics at high frequencies at least as well as the quantity-based order flows. The same factors describe exchange rates over a large spectrum of frequencies, from 30 seconds to one month. While the descriptive power of order flows decreases when frequencies decrease, the descriptive power of common factors increases. The factor betas are precisely estimated over daily or weekly horizons. They appear very persistent, far from random, and thus offer a novel characteristic of exchange rates. The challenge in the years to come is to account for the cross-section and time-variation in these betas. They hold the key to our understanding of a large fraction of the exchange rate dynamics.

Table 2.1: OLS vs Heteroskedasticity-based Estimation (Equation 1)

This table reports results of estimating Equation (1) in the following system:

$$\Delta s_{t+1} = \alpha_1 \mathrm{OF}_{t+1} + \beta_1 \mathrm{Dollar}_{t+1} + \gamma_1 \mathrm{Carry}_{t+1} + \delta_1 (i_t^* - i_t)\mathrm{Carry}_{t+1} + \tau_1 (i_t^* - i_t) + \varepsilon_{t+1}, \quad (1)$$

$$\mathrm{OF}_{t+1} = \alpha_2 \Delta s_{t+1} + \beta_2 \mathrm{Dollar}_{t+1} + \gamma_2 \mathrm{Carry}_{t+1} + \delta_2 (i_t^* - i_t)\mathrm{Carry}_{t+1} + \tau_2 (i_t^* - i_t) + \nu_{t+1}. \quad (2)$$

using OLS and the Rigobon (2003) heteroskedasticity-based estimation (HBE). The sample includes observations between 8 am and 8 pm on non-holidays for both US and UK. Observations occurring in the 30 minutes following and at the time of U.S. non-farm payroll macroeconomic news announcements are constitue the "high-volatility" regime. Newey-West $t$-stats for OLS estimates and bootstrapped $t$-stats for HBE estimates are included in parentheses. The columns $R^2_{OLS}$ and $R^2_{HBE}$ denote the fraction of exchange rate variation explained by contemporaneous order flows using respectively the OLS and HBE estimates. Additionally, $N1$ and $N2$ are the respectively the number of observations in the post-announcement and the non-announcement regime. The data are sampled at the 30-sec frequency.

| | $\widehat{\alpha}_{1OLS}$ | $\widehat{\alpha}_{1HBE}$ | $\widehat{\beta}_{1OLS}$ | $\widehat{\beta}_{1HBE}$ | $\widehat{\gamma}_{1OLS}$ | $\widehat{\gamma}_{1HBE}$ | $\widehat{\delta}_{1OLS}$ | $\widehat{\delta}_{1HBE}$ | $\widehat{\tau}_{1OLS}$ | $\widehat{\tau}_{1HBE}$ | $R^2_{OF}$(OLS) | $R^2_{OF}$(HBE) | N1 | N2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AUD | 1.10 | 1.17 | 0.58 | 0.57 | 0.01 | 0.01 | 0.63 | 0.67 | 0.06 | 0.06 | 0.11 | 0.13 | 9,760 | 3,024,940 |
| | (302.43) | (47.42) | (60.61) | (84.42) | (0.62) | (0.98) | (0.11) | (0.18) | (5.73) | (5.52) | | | | |
| CAD | 0.81 | 0.66 | 0.71 | 0.73 | -0.16 | -0.16 | 28.71 | 29.99 | -0.04 | -0.04 | 0.10 | 0.06 | 9,694 | 2,692,003 |
| | (220.67) | (26.07) | (62.44) | (83.80) | (-44.35) | (-55.74) | (8.14) | (9.83) | (-3.43) | (-2.89) | | | | |
| CHF | 0.29 | 0.40 | 1.36 | 1.34 | -0.58 | -0.57 | -13.94 | -13.73 | 0.02 | 0.03 | 0.01 | 0.02 | 10,394 | 3,465,068 |
| | (40.83) | (10.17) | (80.02) | (90.46) | (-85.69) | (-96.50) | (-4.29) | (-5.31) | (3.65) | (3.25) | | | | |
| EUR | 0.58 | 0.81 | 0.94 | 0.91 | -0.32 | -0.31 | 6.60 | 6.31 | 0.00 | -0.00 | 0.04 | 0.09 | 10,665 | 4,911,015 |
| | (94.17) | (46.93) | (67.14) | (90.77) | (-54.64) | (-73.53) | (2.16) | (2.23) | (0.16) | (-0.12) | | | | |
| GBP | 0.65 | 0.78 | 0.65 | 0.63 | -0.19 | -0.18 | -0.19 | -0.01 | -0.03 | -0.03 | 0.08 | 0.12 | 10,544 | 3,725,930 |
| | (191.19) | (37.30) | (68.26) | (80.66) | (-27.25) | (-29.65) | (-0.05) | (-0.00) | (-4.35) | (-4.58) | | | | |
| JPY | 0.61 | 0.74 | 0.55 | 0.54 | -0.35 | -0.34 | -14.93 | -14.84 | -0.02 | -0.02 | 0.06 | 0.10 | 10,624 | 4,331,825 |
| | (238.65) | (55.16) | (80.95) | (122.45) | (-96.45) | (-121.46) | (-14.40) | (-17.40) | (-4.92) | (-5.29) | | | | |
| NZD | 0.99 | 0.91 | 1.32 | 1.34 | 0.47 | 0.47 | -85.46 | -85.21 | -0.02 | -0.01 | 0.04 | 0.04 | 7,147 | 1,499,723 |
| | (68.53) | (9.99) | (45.21) | (42.90) | (8.59) | (11.21) | (-4.94) | (-6.29) | (-0.62) | (-0.41) | | | | |
| SEK | 0.61 | 0.06 | 2.17 | 2.20 | -0.47 | -0.47 | 41.80 | 45.83 | -0.01 | 0.00 | 0.02 | 0.00 | 4,799 | 1,085,958 |
| | (43.85) | (0.70) | (15.31) | (20.35) | (-17.81) | (-23.78) | (3.90) | (5.99) | (-0.58) | (0.07) | | | | |
| NOK | 0.74 | -0.00 | 2.10 | 2.13 | -0.51 | -0.52 | 95.82 | 102.49 | 0.02 | -0.01 | 0.02 | 0.00 | 4,128 | 938,821 |
| | (54.66) | (-0.00) | (13.34) | (24.70) | (-13.08) | (-23.17) | (5.75) | (8.40) | (0.83) | (-0.42) | | | | |

Table 2.2: OLS vs Heteroskedasticity-based Estimation (Equation 2)

This table reports results of estimating Equation (2) in the following system:

$$\Delta s_{t+1} = \alpha_1 \mathrm{OF}_{t+1} + \beta_1 \mathrm{Dollar}_{t+1} + \gamma_1 \mathrm{Carry}_{t+1} + \delta_1 (i_t^* - i_t)\mathrm{Carry}_{t+1} + \tau_1 (i_t^* - i_t) + \varepsilon_{t+1}, \quad (1)$$

$$\mathrm{OF}_{t+1} = \alpha_2 \Delta s_{t+1} + \beta_2 \mathrm{Dollar}_{t+1} + \gamma_2 \mathrm{Carry}_{t+1} + \delta_2 (i_t^* - i_t)\mathrm{Carry}_{t+1} + \tau_2 (i_t^* - i_t) + \nu_{t+1}. \quad (2)$$

using OLS and the Rigobon (2003) heteroskedasticity-based estimation (HBE). The sample includes observations between 8 am and 8 pm on non-holidays for both US and UK. Observations occurring in the 30 minutes following and at the time of U.S. non-farm payroll macroeconomic news announcements are constitue the "high-volatility" regime. Newey-West $t$-stats for OLS estimates and bootstrapped $t$-stats for HBE estimates are included in parentheses. The columns $R^2_{OLS}$ and $R^2_{HBE}$ denote the fraction of order flows variation explained by contemporaneous exchange rates using respectively the OLS and HBE estimates. Additionally, $N1$ and $N2$ are the respectively the number of observations in the post-announcement and the non-announcement regime. The data are sampled at the 30-sec frequency.

| | $\widehat{\alpha_{2OLS}}$ | $\widehat{\alpha_{2HBE}}$ | $\widehat{\beta_{2OLS}}$ | $\widehat{\beta_{2HBE}}$ | $\widehat{\gamma_{2OLS}}$ | $\widehat{\gamma_{2HBE}}$ | $\widehat{\delta_{2OLS}}$ | $\widehat{\delta_{2HBE}}$ | $\widehat{\tau_{2OLS}}$ | $\widehat{\tau_{2HBE}}$ | $R^2_{\Delta s}$(OLS) | $R^2_{\Delta s}$(HBE) | N1 | N2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AUD | 0.11 | -0.01 | 0.03 | 0.12 | -0.01 | -0.01 | -0.51 | -0.50 | -0.05 | -0.05 | 0.14 | 0.00 | 9,760 | 3,024,940 |
| | (88.13) | (-2.75) | (29.14) | (52.77) | (-9.96) | (-8.26) | (-0.85) | (-1.17) | (-12.65) | (-13.82) | | | | |
| CAD | 0.15 | 0.03 | 0.03 | 0.12 | -0.01 | -0.03 | 3.05 | 7.13 | 0.03 | 0.03 | 0.14 | 0.01 | 9,694 | 2,692,003 |
| | (61.05) | (6.46) | (18.16) | (31.54) | (-10.99) | (-26.02) | (6.56) | (11.76) | (3.69) | (4.31) | | | | |
| CHF | 0.07 | -0.03 | 0.09 | 0.22 | -0.03 | -0.09 | -0.90 | -2.24 | -0.03 | -0.03 | 0.04 | 0.01 | 10,394 | 3,465,068 |
| | (41.49) | (-2.99) | (37.72) | (17.80) | (-30.02) | (-16.07) | (-2.27) | (-5.47) | (-7.31) | (-8.09) | | | | |
| EUR | 0.13 | -0.06 | 0.01 | 0.19 | -0.00 | -0.07 | 0.32 | 1.65 | 0.01 | 0.01 | 0.12 | 0.02 | 10,665 | 4,911,015 |
| | (141.51) | (-13.38) | (13.84) | (40.14) | (-13.87) | (-37.87) | (1.40) | (2.23) | (2.14) | (2.67) | | | | |
| GBP | 0.15 | -0.04 | 0.04 | 0.18 | -0.01 | -0.05 | -1.16 | -1.35 | 0.03 | 0.03 | 0.12 | 0.01 | 10,544 | 3,725,930 |
| | (91.78) | (-6.47) | (35.72) | (41.74) | (-12.38) | (-33.30) | (-1.96) | (-2.20) | (7.69) | (8.10) | | | | |
| JPY | 0.14 | -0.03 | 0.03 | 0.14 | -0.01 | -0.08 | 1.40 | -1.18 | 0.03 | 0.03 | 0.10 | 0.01 | 10,624 | 4,331,825 |
| | (116.03) | (-9.34) | (41.82) | (59.52) | (-23.36) | (-54.34) | (9.88) | (-5.65) | (14.40) | (16.11) | | | | |
| NZD | 0.06 | 0.01 | 0.09 | 0.17 | -0.05 | -0.02 | 7.72 | 3.36 | 0.05 | 0.05 | 0.08 | 0.00 | 7,147 | 1,499,723 |
| | (29.26) | (1.00) | (30.94) | (20.55) | (-13.54) | (-6.40) | (6.15) | (3.54) | (5.53) | (7.28) | | | | |
| SEK | 0.05 | 0.04 | -0.05 | -0.04 | 0.01 | 0.01 | 5.03 | 5.23 | 0.02 | 0.02 | 0.05 | 0.04 | 4,799 | 1,085,958 |
| | (7.13) | (8.48) | (-7.04) | (-3.15) | (5.94) | (4.27) | (5.65) | (8.41) | (2.44) | (3.53) | | | | |
| NOK | 0.04 | 0.05 | -0.04 | -0.05 | 0.01 | 0.01 | 4.67 | 4.21 | -0.04 | -0.04 | 0.04 | 0.05 | 4,128 | 938,821 |
| | (5.31) | (12.64) | (-3.83) | (-6.34) | (3.08) | (5.84) | (3.54) | (4.81) | (-4.14) | (-6.21) | | | | |

Table 2.3: Common Factors and Order Flows: 30-second Frequency

This table reports results from regressions of the form:

$$\Delta s_{t+1} = \alpha + \beta(i_t^* - i_t) + \gamma(i_t^* - i_t)\text{Carry}_{t+1} + \delta\text{Carry}_{t+1} + \tau\text{Dollar}_{t+1} + \psi\text{OF}_{t+1} + \varepsilon_{t+1}$$

where $\Delta s_{t+1}$ (in % ) denotes the bilateral exchange rate in U.S. dollar per foreign currency, $(i_t^* - i_t)$ is the interest rate difference between the foreign country and the U.S., $\text{Carry}_{t+1}$ denotes the dollar-neutral average exchange rate change obtained by going long a basket of high interest rate currencies and short a basket of low interest rate currencies, $\text{Dollar}_{t+1}$ corresponds to the average change in exchange rates against the U.S. dollar, and $\text{OF}_{t+1}$ is the interbank order flow (normalized by volume and divided by 100). $\overline{R}^2$ denotes the adjusted regression $R^2$, $\overline{R}^2_{FS}$ denotes the adjusted $R^2$ from a regression of exchange rates on only the factor structure, and $R^2_{OF}$ denotes the $R^2$ from a regression of exchange rates on order flow alone.

| | $\beta$ | $\gamma$ | $\delta$ | $\tau$ | $\psi$ | $\overline{R}^2$ | $\overline{R}^2_{FS}$ | $R^2_{OF}$ | N |
|---|---|---|---|---|---|---|---|---|---|
| | | | | **Panel A: G10 Currencies** | | | | | |
| AUD | 0.06 | 0.71 | 0.01 | 0.58 | 1.10 | 0.23 | 0.12 | 0.15 | 3,037,268 |
| | (5.79) | (0.12) | (0.63) | (60.63) | (302.63) | | | | |
| CAD | -0.04 | 28.64 | -0.16 | 0.71 | 0.81 | 0.30 | 0.20 | 0.16 | 2,703,058 |
| | (-3.43) | (8.13) | (-44.31) | (62.38) | (220.29) | | | | |
| CHF | -0.02 | -14.10 | -0.58 | 1.36 | 0.27 | 0.56 | 0.55 | 0.08 | 3,476,697 |
| | (-3.38) | (-4.33) | (-85.82) | (80.22) | (40.85) | | | | |
| EUR | 0.04 | 6.92 | -0.33 | 0.95 | 0.50 | 0.46 | 0.42 | 0.11 | 4,924,526 |
| | (9.06) | (2.19) | (-55.01) | (67.73) | (92.59) | | | | |
| GBP | -0.03 | -0.16 | -0.19 | 0.65 | 0.65 | 0.31 | 0.23 | 0.14 | 3,739,378 |
| | (-4.35) | (-0.04) | (-27.26) | (68.31) | (191.38) | | | | |
| JPY | -0.13 | -14.95 | -0.35 | 0.56 | 0.55 | 0.31 | 0.25 | 0.11 | 4,344,730 |
| | (-37.18) | (-14.34) | (-97.05) | (81.43) | (234.69) | | | | |
| NZD | -0.02 | -85.56 | 0.47 | 1.32 | 0.99 | 0.35 | 0.31 | 0.11 | 1,508,256 |
| | (-0.54) | (-4.94) | (8.60) | (45.25) | (68.62) | | | | |
| SEK | -0.01 | 41.89 | -0.47 | 2.17 | 0.61 | 0.42 | 0.40 | 0.03 | 1,091,766 |
| | (-0.54) | (4.00) | (-17.87) | (15.33) | (43.83) | | | | |
| NOK | 0.02 | 95.81 | -0.51 | 2.10 | 0.74 | 0.31 | 0.28 | 0.03 | 943,865 |
| | (0.80) | (5.76) | (-13.09) | (13.35) | (54.73) | | | | |
| | | | | **Panel B: Other Currencies** | | | | | |
| BRL | -0.02 | -21.23 | 1.31 | 1.46 | -0.16 | 0.36 | 0.36 | 0.00 | 105,486 |
| | (-0.35) | (-1.23) | (9.40) | (26.27) | (-9.54) | | | | |
| HKD | 0.02 | -17.37 | -0.02 | 0.02 | 0.12 | 0.08 | 0.01 | 0.08 | 161,781 |
| | (1.04) | (-1.92) | (-2.51) | (3.20) | (72.31) | | | | |
| ILS | -0.09 | 332.07 | -0.58 | 2.58 | 1.17 | 0.25 | 0.23 | 0.05 | 183,225 |
| | (-0.49) | (8.15) | (-7.74) | (15.37) | (31.19) | | | | |
| INR | -0.01 | 74.08 | -0.10 | 0.38 | -0.09 | 0.09 | 0.08 | 0.00 | 195,761 |
| | (-0.38) | (13.67) | (-4.85) | (12.38) | (-16.32) | | | | |
| KRW | -0.00 | 24.27 | -0.07 | 0.17 | 0.00 | 0.03 | 0.03 | 0.00 | 59,736 |
| | (-0.13) | (1.51) | (-3.08) | (3.31) | (0.78) | | | | |
| MYR | 0.10 | 57.58 | -0.07 | 0.28 | -0.00 | 0.03 | 0.03 | 0.00 | 23,098 |
| | (1.12) | (8.25) | (-8.36) | (13.97) | (-0.21) | | | | |
| MXN | -0.01 | 21.92 | 0.09 | 0.57 | 0.93 | 0.24 | 0.16 | 0.12 | 1,724,549 |
| | (-0.45) | (2.31) | (2.71) | (31.54) | (115.56) | | | | |
| SGD | -0.02 | 104.46 | -0.19 | 0.53 | 0.55 | 0.26 | 0.19 | 0.12 | 653,962 |
| | (-0.79) | (1.88) | (-13.77) | (14.52) | (36.17) | | | | |
| RUB | 0.06 | 70.75 | -0.13 | 0.46 | -0.16 | 0.16 | 0.15 | 0.00 | 647,880 |
| | (4.69) | (5.66) | (-2.72) | (21.36) | (-39.29) | | | | |
| TRY | 0.03 | 61.84 | 1.25 | 1.62 | -0.57 | 0.51 | 0.50 | 0.02 | 260,867 |
| | (1.02) | (5.48) | (13.45) | (16.22) | (-36.96) | | | | |

Table 2.4: Common Factors and Order Flows: 5-minute Frequency

This table reports results from regressions of the form:

$$\Delta s_{t+1} = \alpha + \beta(i_t^* - i_t) + \gamma(i_t^* - i_t)\text{Carry}_{t+1} + \delta\text{Carry}_{t+1} + \tau\text{Dollar}_{t+1} + \psi\text{OF}_{t+1} + \varepsilon_{t+1}$$

where $\Delta s_{t+1}$ (in % ) denotes the bilateral exchange rate in U.S. dollar per foreign currency, $(i_t^* - i_t)$ is the interest rate difference between the foreign country and the U.S., $\text{Carry}_{t+1}$ denotes the dollar-neutral average exchange rate change obtained by going long a basket of high interest rate currencies and short a basket of low interest rate currencies, $\text{Dollar}_{t+1}$ corresponds to the average change in exchange rates against the U.S. dollar, and $\text{OF}_{t+1}$ is the interbank order flow (normalized by volume and divided by 100). $\overline{R}^2$ denotes the adjusted regression $R^2$, $\overline{R}^2_{FS}$ denotes the adjusted $R^2$ from a regression of exchange rates on only the factor structure, and $R^2_{OF}$ denotes the $R^2$ from a regression of exchange rates on order flow alone.

| | $\beta$ | $\gamma$ | $\delta$ | $\tau$ | $\psi$ | $\overline{R}^2$ | $\overline{R}^2_{FS}$ | $R^2_{OF}$ | N |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: G10 Currencies** | | | | | | | | | |
| AUD | 0.18 | 16.02 | 0.11 | 0.96 | 4.22 | 0.39 | 0.33 | 0.15 | 438,775 |
| | (3.23) | (2.13) | (6.97) | (94.94) | (130.94) | | | | |
| CAD | -0.13 | 10.05 | -0.06 | 0.78 | 3.31 | 0.36 | 0.29 | 0.16 | 421,104 |
| | (-1.70) | (1.54) | (-10.83) | (104.16) | (152.16) | | | | |
| CHF | -0.05 | -53.16 | -0.63 | 1.37 | 0.57 | 0.65 | 0.65 | 0.07 | 514,992 |
| | (-1.66) | (-10.63) | (-59.13) | (171.01) | (30.07) | | | | |
| EUR | 0.21 | 7.10 | -0.38 | 1.33 | 2.30 | 0.66 | 0.65 | 0.13 | 526,970 |
| | (5.99) | (3.83) | (-87.27) | (157.25) | (71.09) | | | | |
| GBP | -0.16 | -4.78 | -0.21 | 0.91 | 2.94 | 0.43 | 0.38 | 0.15 | 500,979 |
| | (-3.52) | (-1.48) | (-41.58) | (148.78) | (133.42) | | | | |
| JPY | -0.75 | -18.23 | -0.53 | 0.57 | 2.90 | 0.38 | 0.34 | 0.13 | 525,240 |
| | (-26.79) | (-5.54) | (-54.87) | (69.57) | (108.83) | | | | |
| NZD | -0.21 | -78.60 | 0.45 | 1.31 | 2.10 | 0.44 | 0.42 | 0.09 | 326,567 |
| | (-2.00) | (-4.52) | (8.84) | (98.89) | (67.07) | | | | |
| SEK | -0.06 | 43.10 | -0.35 | 1.74 | 1.96 | 0.54 | 0.52 | 0.04 | 278,422 |
| | (-1.46) | (4.61) | (-18.16) | (42.32) | (71.75) | | | | |
| NOK | 0.09 | 58.69 | -0.41 | 1.69 | 2.17 | 0.48 | 0.45 | 0.04 | 251,942 |
| | (1.71) | (8.02) | (-29.33) | (72.37) | (103.82) | | | | |
| **Panel B: Other Currencies** | | | | | | | | | |
| BRL | 0.07 | 30.10 | 0.81 | 1.18 | -0.30 | 0.43 | 0.43 | 0.00 | 83,340 |
| | (0.45) | (1.96) | (6.28) | (37.63) | (-7.49) | | | | |
| HKD | 0.06 | -1.74 | -0.01 | 0.01 | 0.23 | 0.09 | 0.00 | 0.09 | 44,878 |
| | (1.04) | (-0.65) | (-2.60) | (5.94) | (54.31) | | | | |
| ILS | -0.58 | 76.71 | -0.16 | 0.81 | 1.93 | 0.16 | 0.13 | 0.06 | 61,392 |
| | (-1.67) | (3.55) | (-6.59) | (24.80) | (39.51) | | | | |
| INR | -0.13 | 52.28 | -0.08 | 0.35 | 0.07 | 0.09 | 0.09 | 0.00 | 111,516 |
| | (-2.64) | (8.57) | (-4.67) | (40.59) | (4.32) | | | | |
| KRW | -0.23 | 45.67 | -0.09 | 0.15 | -0.02 | 0.04 | 0.04 | 0.00 | 47,921 |
| | (-0.93) | (2.71) | (-6.01) | (6.85) | (-0.86) | | | | |
| MYR | 0.06 | 48.01 | -0.04 | 0.26 | 0.29 | 0.07 | 0.06 | 0.01 | 20,271 |
| | (0.36) | (5.63) | (-4.72) | (19.71) | (11.01) | | | | |
| MXN | 0.09 | -9.54 | 0.43 | 0.63 | 3.01 | 0.36 | 0.30 | 0.14 | 310,881 |
| | (2.21) | (-1.14) | (11.85) | (41.40) | (72.81) | | | | |
| SGD | -0.04 | 45.53 | -0.09 | 0.44 | 1.09 | 0.34 | 0.29 | 0.15 | 173,059 |
| | (-0.55) | (8.76) | (-16.73) | (72.48) | (86.91) | | | | |
| RUB | 0.06 | 52.50 | -0.17 | 0.64 | -0.32 | 0.24 | 0.24 | 0.00 | 209,463 |
| | (1.00) | (4.51) | (-3.70) | (56.94) | (-19.28) | | | | |
| TRY | 0.01 | 5.26 | 0.78 | 1.00 | 0.12 | 0.35 | 0.35 | 0.00 | 152,086 |
| | (0.20) | (0.22) | (3.97) | (43.84) | (4.65) | | | | |
| ZAR | 0.57 | 30.78 | 0.57 | 1.16 | 3.40 | 0.48 | 0.44 | 0.16 | 274,728 |
| | (6.14) | (2.43) | (7.88) | (68.39) | (58.84) | | | | |

Table 2.5: Panel Regressions: Persistence in Dollar and Carry Betas

This table reports results for panel regressions of daily betas on lagged daily betas (left panel) and regressions of weekly betas on lagged weekly betas (right panel). $\rho$ denotes the slope coefficient in these regressions. Panel A reports results for dollar betas, panel B for carry betas. We report four specifications for each regression: pooled, with currency fixed effects (CCY FE), with day/week fixed effects (Time FE), or with currency and day/week fixed effects. Standard errors for all specifications are double-clustered at the currency and day level. The sample of countries is AUD, CAD, CHF, EUR, GBP, JPY, NZD, SEK, NOK, MXN, and ZAR. The $t$-stats denoted $t$ do not take into account the uncertainty from their first-stage estimates at the 5-minute frequency. The sample period is 1/1/1999 – 12/31/2014.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | **Panel A: Dollar betas** | | | | |
| | Daily frequency | | | | Weekly frequency | | | |
| $\rho$ | 0.76 | 0.55 | 0.76 | 0.50 | 0.85 | 0.68 | 0.85 | 0.63 |
| $t$ | [18.90] | [11.54] | [16.32] | [8.53] | [22.21] | [11.98] | [20.15] | [9.57] |
| $R^2$ | 57.72 | 62.83 | 62.83 | 67.20 | 71.94 | 74.45 | 73.88 | 77.18 |
| CCY FE | NO | YES | NO | YES | NO | YES | NO | YES |
| Time FE | NO | NO | YES | YES | NO | NO | YES | YES |
| | | | | **Panel B: Carry betas** | | | | |
| | Daily frequency | | | | Weekly frequency | | | |
| $\rho$ | 0.84 | 0.53 | 0.85 | 0.49 | 0.92 | 0.70 | 0.92 | 0.66 |
| $t$ | [32.48] | [17.16] | [28.88] | [19.26] | [56.39] | [29.15] | [49.90] | [29.01] |
| $R^2$ | 70.68 | 75.57 | 72.69 | 78.20 | 84.00 | 85.77 | 85.28 | 87.21 |
| CCY FE | NO | YES | NO | YES | NO | YES | NO | YES |
| Time FE | NO | NO | YES | YES | NO | NO | YES | YES |

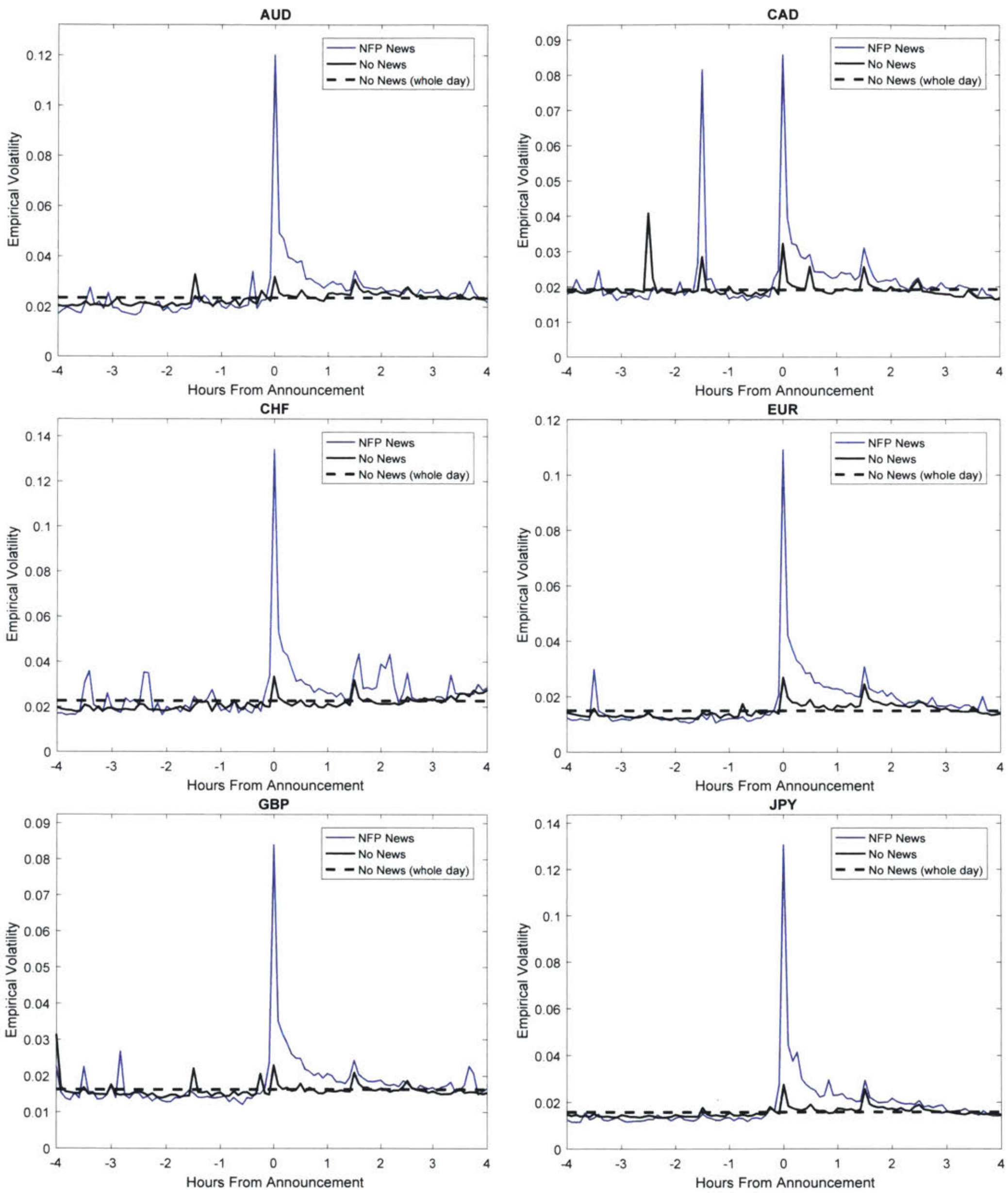
Table 2.6: Currency Betas and Bond Yields

This table reports results for regressions of detrended FX betas on detrended 10-year bond yields. Both betas and yields are detrended by a 22-trading day moving average. The frequency is daily and the sample of countries is AUD, CAD, CHF, EUR, GBP, JPY, NZD, SEK, NOK, MXN, and ZAR. Panel A shows results for the pre-crisis period (2000/01 – 2007/06) and Panel B shows results for the post-crisis period (after 2007/06).

| | Dollar betas | | | | Carry betas | | | |
|---|---|---|---|---|---|---|---|---|
| | slope | $t$ | $R^2$ | $N$ | slope | $t$ | $R^2$ | $N$ |
| **Panel A: Pre-crisis period** | | | | | | | | |
| AUD | -0.29 | [-8.08] | 13.86 | 1,615 | 0.17 | [8.20] | 13.72 | 1,615 |
| CAD | -0.31 | [-20.20] | 52.62 | 1,599 | 0.09 | [18.14] | 60.59 | 1,599 |
| CHF | -0.21 | [-11.33] | 23.35 | 1,812 | 0.17 | [14.43] | 45.49 | 1,812 |
| EUR | -0.22 | [-13.77] | 31.42 | 1,725 | 0.18 | [20.67] | 65.35 | 1,725 |
| GBP | -0.29 | [-6.95] | 13.64 | 1,675 | 0.25 | [11.63] | 33.04 | 1,675 |
| JPY | -0.11 | [-2.10] | 1.93 | 1,812 | -0.02 | [-1.11] | 0.42 | 1,812 |
| NZD | 0.85 | [6.14] | 29.90 | 966 | 0.69 | [4.84] | 23.04 | 966 |
| SEK | 0.07 | [4.90] | 7.41 | 1,357 | 0.23 | [21.72] | 76.05 | 1,357 |
| NOK | 0.03 | [0.87] | 0.68 | 704 | 0.27 | [14.91] | 74.77 | 704 |
| MXN | -0.02 | [-1.92] | 2.58 | 822 | -0.02 | [-2.67] | 3.60 | 822 |
| ZAR | -0.11 | [-5.17] | 13.21 | 563 | -0.03 | [-2.61] | 2.63 | 563 |
| **Panel B: Post-crisis period** | | | | | | | | |
| AUD | 0.08 | [5.14] | 9.93 | 1,806 | 0.05 | [7.44] | 16.51 | 1,806 |
| CAD | 0.23 | [15.14] | 40.42 | 1,806 | -0.13 | [-11.58] | 28.10 | 1,806 |
| CHF | 0.13 | [8.87] | 32.95 | 1,771 | -0.03 | [-3.02] | 2.02 | 1,771 |
| EUR | 0.06 | [5.65] | 10.69 | 1,771 | 0.02 | [3.73] | 5.87 | 1,771 |
| GBP | 0.05 | [4.89] | 8.62 | 1,806 | 0.05 | [9.81] | 26.97 | 1,806 |
| JPY | 0.07 | [1.03] | 0.50 | 1,771 | -0.17 | [-6.80] | 14.76 | 1,771 |
| NZD | 0.12 | [9.79] | 25.53 | 1,797 | 0.06 | [8.29] | 22.75 | 1,797 |
| SEK | 0.07 | [6.75] | 11.69 | 1,623 | 0.00 | [0.38] | 0.04 | 1,623 |
| NOK | 0.10 | [9.59] | 20.65 | 1,577 | 0.03 | [3.11] | 3.80 | 1,577 |
| MXN | -0.13 | [-10.94] | 30.81 | 1,806 | 0.00 | [-0.22] | 0.02 | 1,806 |
| ZAR | -0.05 | [-1.93] | 1.90 | 1,692 | 0.03 | [1.24] | 1.17 | 1,692 |

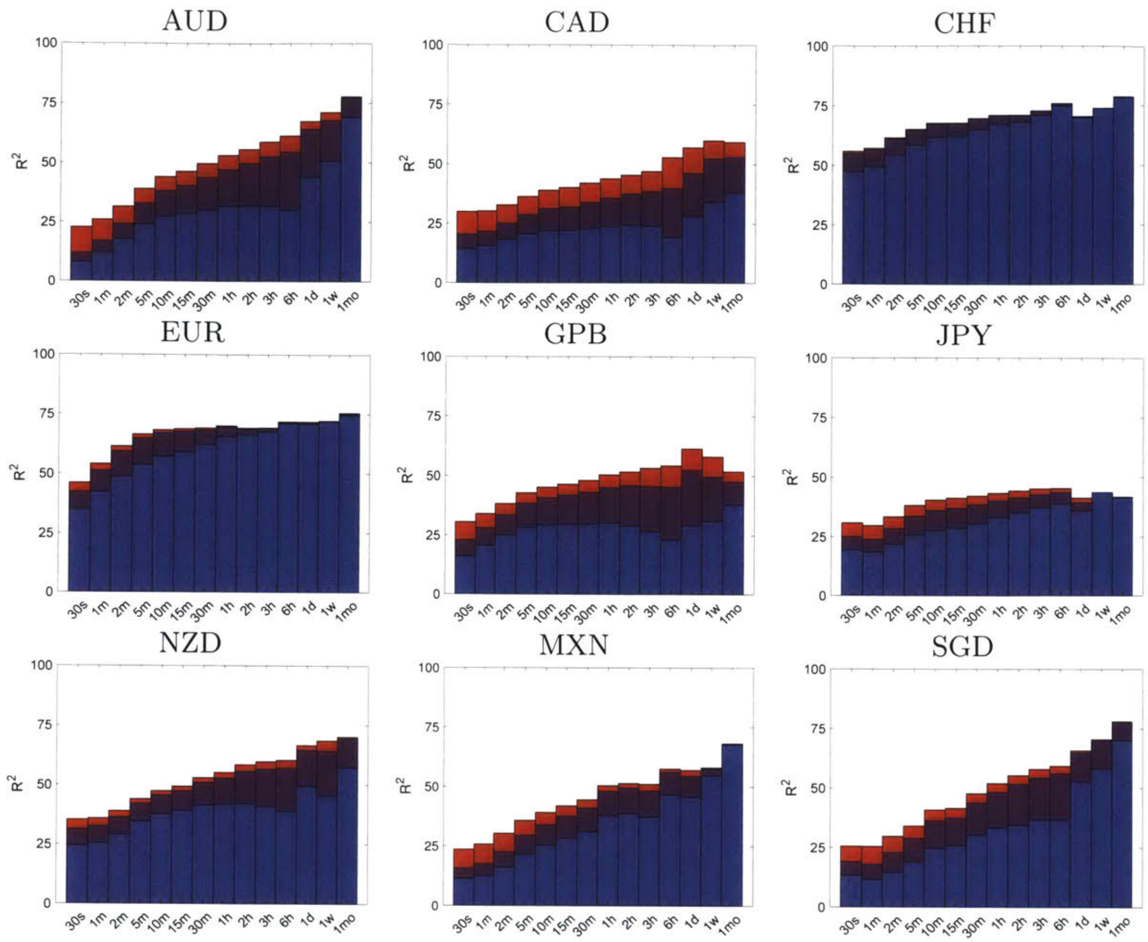
## 2.9. Figures

Figure 2.1: Exchange Rate Return Volatilities on Non-Farm Payroll Announcement and Non-Announcement Days



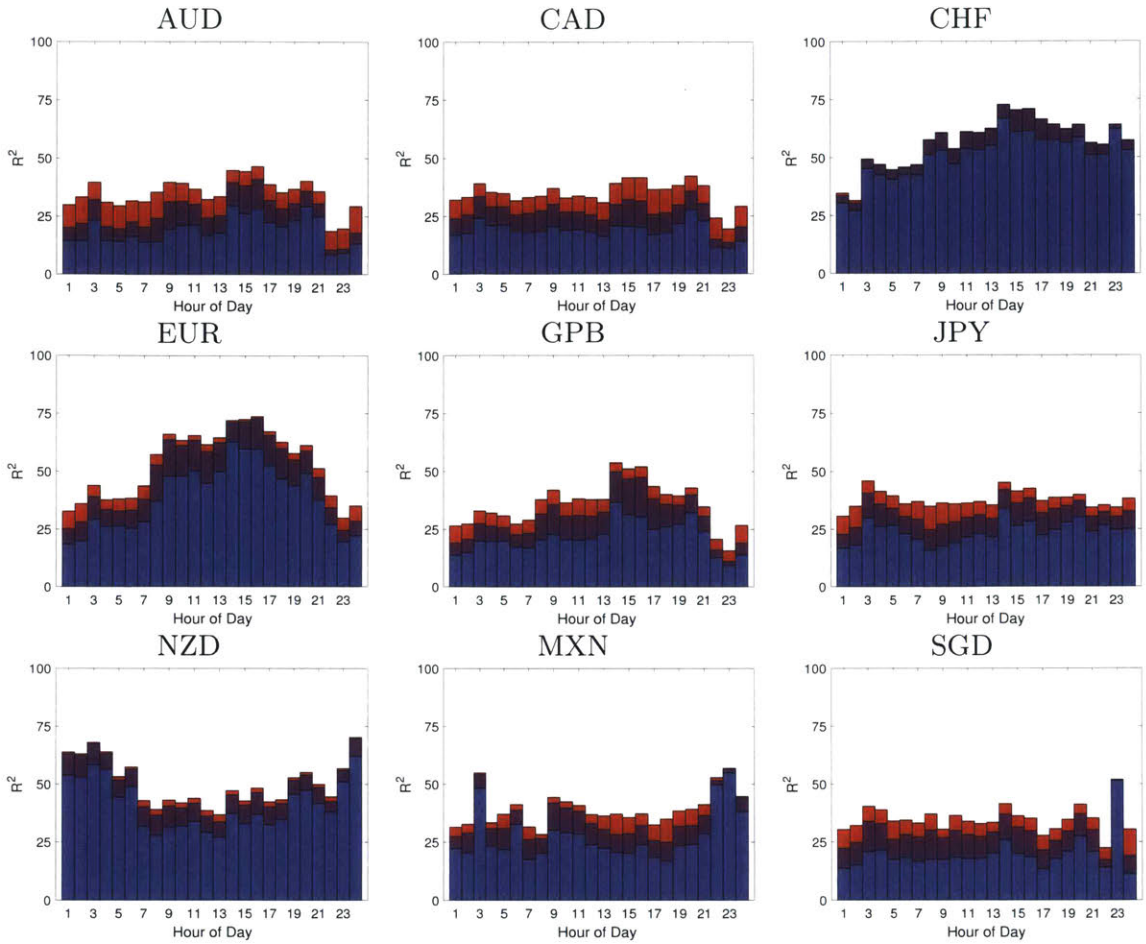

This figure compares the exchange rate log return volatilities on days with and without US non-farm payroll announcements for AUD, CAD, CHF, EUR, GBP, and JPY using data at the 30-second frequency. Time is measured from the minute when announcements are released. Volatilities are computed using non-overlapping 5-min windows. The announcements occur at 1:30 pm GMT. The sample period is 1/1/1999 – 12/31/2014.

Figure 2.2: Common Factors and Order Flows: $R^2$s Across Frequencies



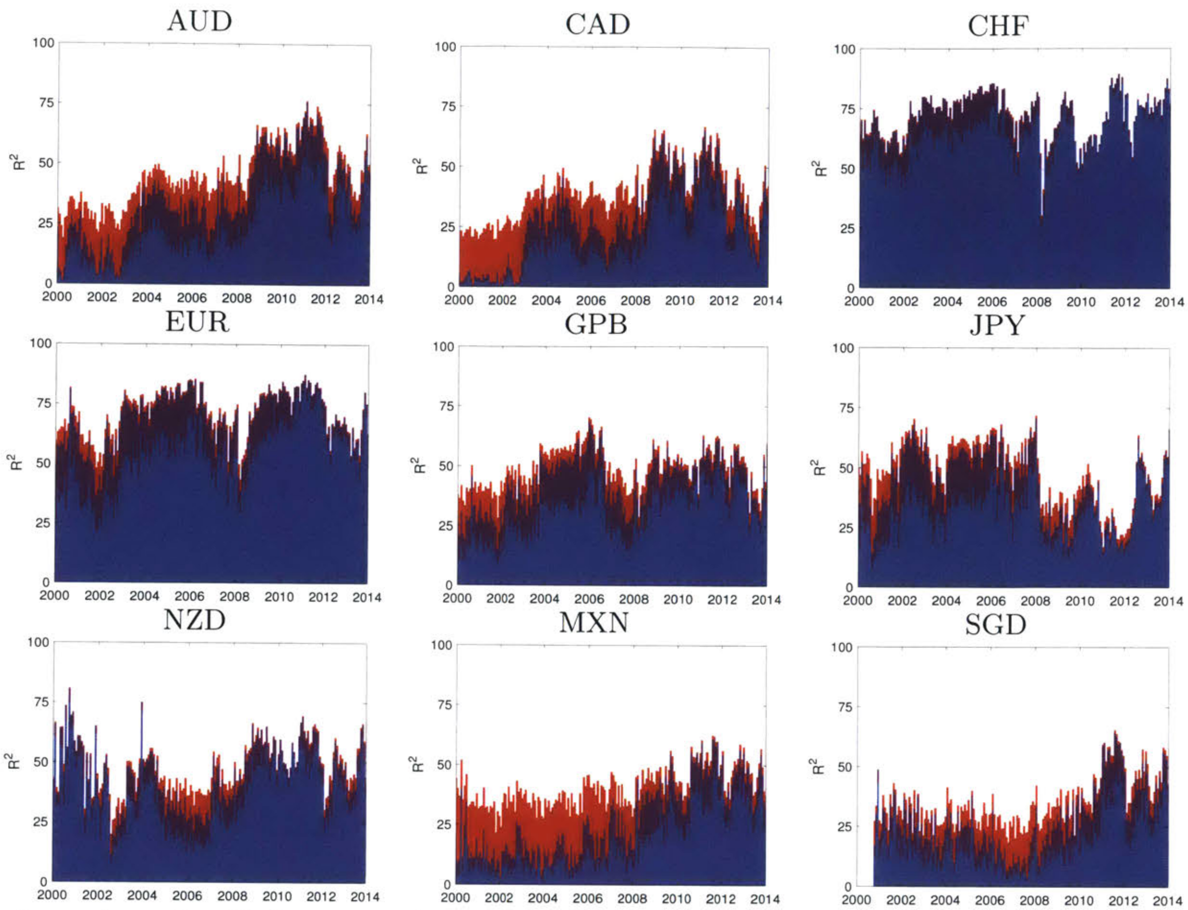

This figure shows the $R^2$ of the factor structure and order flows for different frequencies ranging from 30 seconds to one month (30-sec, one-min, two-min, five-min, 10-min, 15-min, 30-min, one-hour, two-hour, three-hour, six-hour, one-day, one-week, and one-month frequencies). The $R^2$ is decomposed into three components in OLS estimations: in blue, the portion of the $R^2$ attributable to the component of the factor structure that is orthogonal to order flows; in red, the portion attributable to the component of order flows that is orthogonal to the factor structure; in purple, the portion attributable to the shared component of the factor structure and order flows. The sample period is 1/1/1999 – 12/31/2014.

Figure 2.3: Common Factors and Order Flows: $R^2$s Intraday



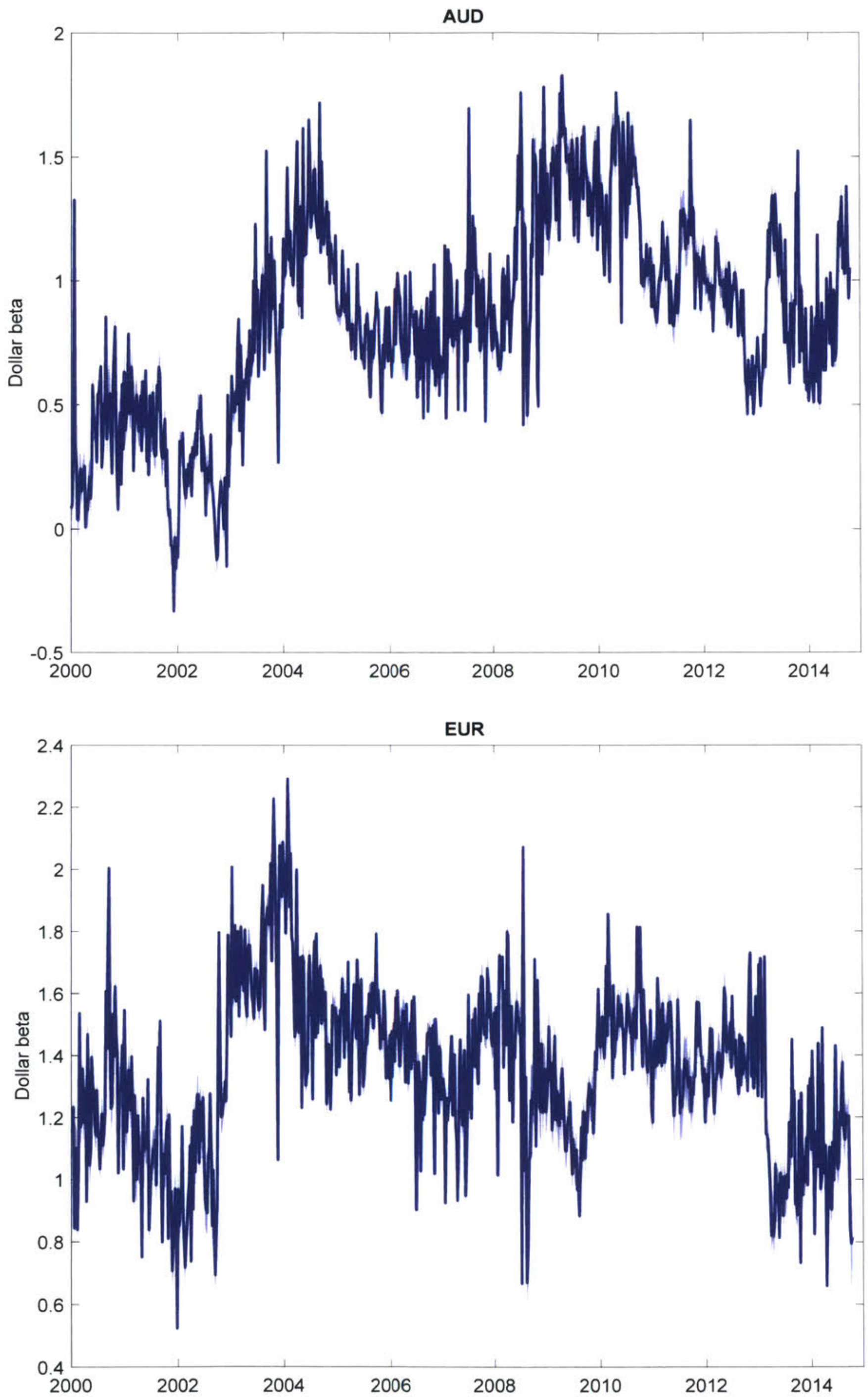

This figure shows the $R^2$s from regressions of spot exchange rate changes on the currency factors and order flows obtained at a 5-minute frequency and separately for each hour of the day. The $R^2$ is decomposed into three components: in blue, the portion of the $R^2$ attributable to the component of the factor structure that is orthogonal to order flows; in red, the portion attributable to the component of order flows that is orthogonal to the factor structure; in purple, the portion attributable to the shared component of the factor structure and order flows. The sample period is 1/1/1999 – 12/31/2014.

Figure 2.4: Common Factors and Order Flows: $R^2$s Over Time



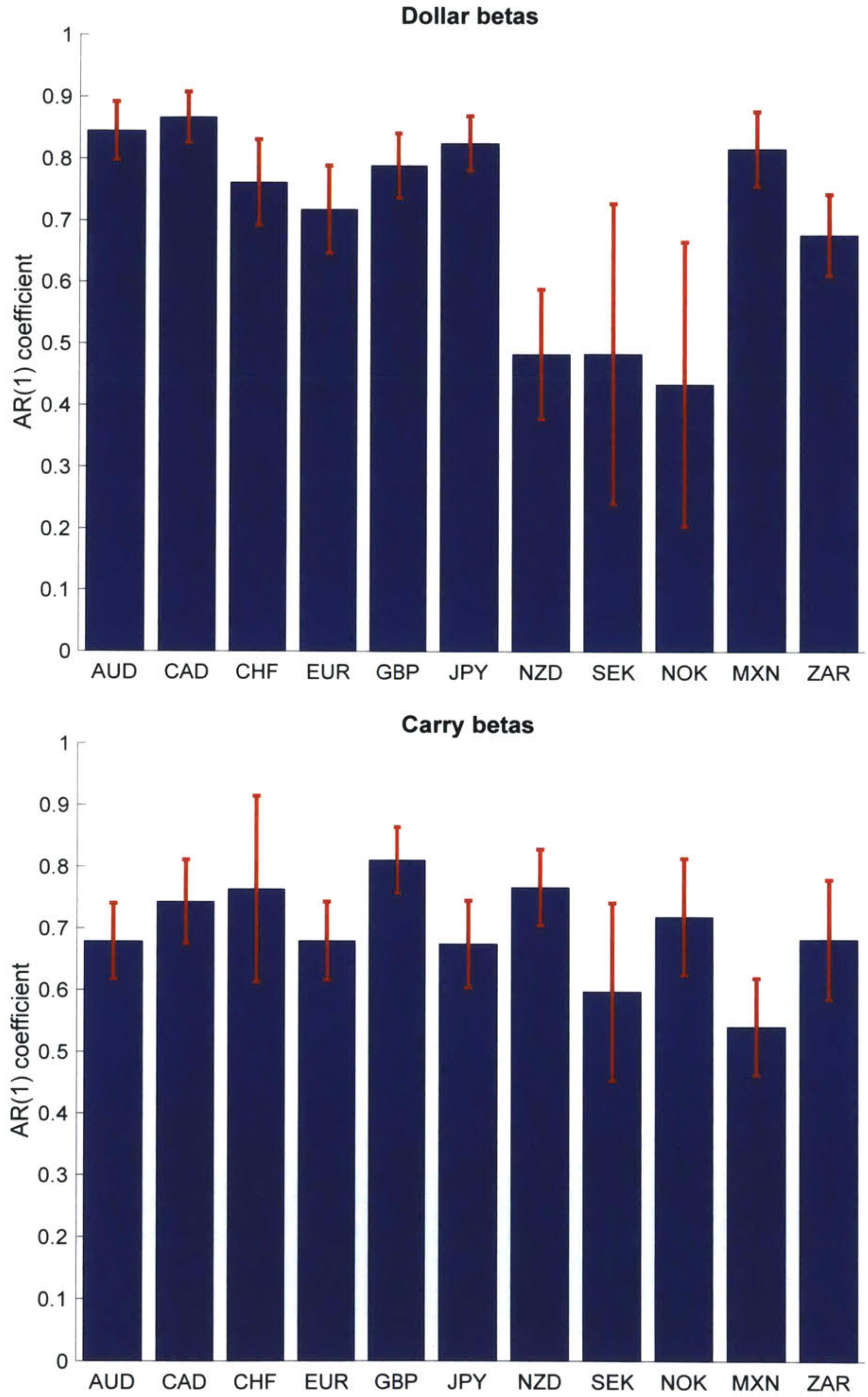

This figure shows the $R^2$s from regressions of spot exchange rate changes on the currency factors and order flows based on monthly non-overlapping windows of data at a 5-min frequency. The $R^2$ is decomposed into three components: in blue, the portion of the $R^2$ attributable to the component of the factor structure that is orthogonal to order flows; in red, the portion attributable to the component of order flows that is orthogonal to the factor structure; in purple, the portion attributable to the shared component of the factor structure and order flows. The sample period is 1/1/1999 – 12/31/2014.

Figure 2.5: Weekly Betas




This figure shows the weekly dollar betas obtained with 5-min data. The sample period is 1/1/1999 – 12/31/2014.

Figure 2.6: Time-series regressions: Persistence in betas




This figure shows slope estimates for regressions of weekly betas on lagged weekly betas. Red error bars show 95% confidence intervals for the AR(1) coefficients based on Newey-West standard errors. The sample period is 1/1/1999 – 12/31/2014.

# 2.10. Appendix

## 2.10.1. Theoretical Framework: Proofs

The proof follows Lustig and Verdelhan (2017). Equations (2.4) and (2.7) need to hold simultaneously, as do Equations (2.5) and (2.6). As a result, under Assumptions 1 and 2, when the exchange rate change is $\Delta s^i_{t+1} = \eta^i_{t+1} + m^i_{t+1} - m_{t+1}$, then the wedge $\eta^i_{t+1}$ satisfies:

$$
\begin{aligned}
covar_t\left(m^i_{t+1}, \eta^i_{t+1}\right) &= -E_t\left(\eta^i_{t+1}\right) - \frac{1}{2} var_t\left(\eta^i_{t+1}\right), && (2.14)\\
covar_t\left(m_{t+1}, \eta^i_{t+1}\right) &= -E_t\left(\eta^i_{t+1}\right) + \frac{1}{2} var_t\left(\eta^i_{t+1}\right), && (2.15)
\end{aligned}
$$

where $E_t\left(\eta^i_{t+1}\right)$ satisfies these additional restrictions:

$$
\begin{aligned}
-E_t\left(\eta^i_{t+1}\right) &\leq std_t\left(\eta^i_{t+1}\right)\left(std_t\left(m^i_{t+1}\right) + \frac{1}{2} std_t\left(\eta^i_{t+1}\right)\right), \textit{ when } E_t\left(\eta^i_{t+1}\right) \leq -\frac{1}{2} var_t\left(\eta^i_{t+1}\right),\\
E_t\left(\eta^i_{t+1}\right) &\leq std_t\left(\eta_{t+1}\right)\left(std_t\left(m^i_{t+1}\right) - \frac{1}{2} std_t\left(\eta^i_{t+1}\right)\right), \textit{ when } E_t\left(\eta^i_{t+1}\right) \geq -\frac{1}{2} var_t\left(\eta^i_{t+1}\right),\\
E_t\left(\eta^i_{t+1}\right) &\leq std_t\left(\eta^i_{t+1}\right)\left(std_t\left(m_{t+1}\right) + \frac{1}{2} std_t\left(\eta^i_{t+1}\right)\right), \textit{ when } E_t\left(\eta^i_{t+1}\right) \geq \frac{1}{2} var_t\left(\eta^i_{t+1}\right),\\
-E_t\left(\eta^i_{t+1}\right) &\leq std_t\left(\eta^i_{t+1}\right)\left(std_t\left(m_{t+1}\right) - \frac{1}{2} std_t\left(\eta^i_{t+1}\right)\right), \textit{ when } E_t\left(\eta^i_{t+1}\right) \leq \frac{1}{2} var_t\left(\eta^i_{t+1}\right),\\
std_t\left(\eta^i_{t+1}\right) &\leq std_t\left(m^i_{t+1} - m_{t+1}\right), \textit{ everywhere.}
\end{aligned}
$$

Recall that the law of motion of the SDFs in the CIR model is:

$$
\begin{aligned}
-m_{t+1} &= \alpha + \chi z_t + \kappa z^\star_t + \sqrt{\gamma z_t}\, u^g_{t+1} + \sqrt{\delta z^\star_t}\, u^w_{t+1},\\
-m^i_{t+1} &= \alpha + \chi z_t + \kappa z^\star_t + \sqrt{\gamma^i z_t}\, u^g_{t+1} + \sqrt{\delta^i z^\star_t}\, u^w_{t+1},\\
z_{t+1} &= (1-\phi)\theta + \phi z_t - \sigma\sqrt{z_t}\,\epsilon_{t+1},\\
z^\star_{t+1} &= (1-\phi)\theta + \phi z^\star_t - \sigma\sqrt{z^\star_t}\,\zeta_{t+1}
\end{aligned}
$$

The wedge $\eta^i_{t+1}$ has to take the form:

$$
\eta^i_{t+1} = \psi^i z_t + \tau^i z^\star_t + \sqrt{\lambda^i z_t}\, u^g_{t+1} + \sqrt{\lambda^{i,\star} z^\star_t}\, u^w_{t+1} + \sqrt{\chi^i z_t}\, \epsilon^i_{t+1} + \sqrt{\chi^{i,\star} z^\star_t}\, \epsilon^i_{t+1}.
$$

where $\epsilon_{t+1} \sim \mathbb{N}(0,1)$ and $\epsilon^*_{t+1} \sim \mathbb{N}(0,1)$ are i.i.d., and where the parameters $\psi^i$, $\tau^i$, $\lambda^i$, $\lambda^{i,\star}$, $\chi^i$, and $\chi^{i,\star}$ describe all potential incomplete market models and satisfy the conditions (2.14) and (2.15):

$$\begin{aligned}
covar_t\left(m^i_{t+1}, \eta^i_{t+1}\right) &= -\sqrt{\gamma^i}\sqrt{\lambda^i}z_t - \sqrt{\delta^i}\sqrt{\lambda^{i,\star}}z^\star_t \\
-E_t\left(\eta^i_{t+1}\right) - \frac{1}{2}var_t\left(\eta^i_{t+1}\right) &= -\psi^i z_t - \tau^i z^\star_t - \frac{1}{2}\left[\lambda^i + \chi\right] z_t - \frac{1}{2}\left[\lambda^{i,\star} + \chi^{i,\star}\right] z^\star_t \\
covar_t\left(m_{t+1}, \eta^i_{t+1}\right) &= -\sqrt{\gamma}\sqrt{\delta}z_t - \sqrt{\delta}\sqrt{\lambda^{i,*}}z^\star_t \\
-E_t\left(\eta_{t+1}\right) + \frac{1}{2}var_t\left(\eta_{t+1}\right) &= -\psi^i z_t - \tau^i z^\star_t + \frac{1}{2}\left[\lambda^i + \chi^i\right] z_t + \frac{1}{2}\left[\lambda^{i,\star} + \chi^{i,\star}\right] z^\star_t
\end{aligned}$$

Thus the wedge parameters $\psi^i$, $\tau^i$, $\lambda^i$, $\lambda^{i,\star}$, $\chi^i$, and $\chi^{i,\star}$ have to satisfy:

$$\begin{aligned}
-\sqrt{\gamma^i}\sqrt{\lambda^i} &= -\psi^i - \frac{1}{2}\left[\lambda^i + \chi^i\right] \\
-\sqrt{\delta^i}\sqrt{\lambda^{i,*}} &= -\tau - \frac{1}{2}\left[\lambda^{i,\star} + \chi^{i,\star}\right] \\
-\sqrt{\gamma}\sqrt{\lambda} &= -\psi^i + \frac{1}{2}\left[\lambda^i + \chi^i\right] \\
-\sqrt{\delta}\sqrt{\lambda^*} &= -\tau^i + \frac{1}{2}\left[\lambda^{i,\star} + \chi^{i,\star}\right]
\end{aligned}$$

The wedge $\eta^i_{t+1}$ can be driven by additional shocks orthogonal to the SDF shocks $u^g$ and $u^g$, but the volatility of these additional shocks has to be drive by the same two state variables $z_t$ and $z^\star_t$.

### 2.10.2. From Tick-by-Tick to Sampled Data

#### 2.10.2.1. The Reuters Database

The following exchange rates are extracted from the Thomson Reuters Tick History database: AUD, BRL, CAD, GBP, HKD, ILS, INR, KRW, MYR, MXN, NZD, RUB, SGD, TRY and ZAR for the currencies quoted, directly or indirectly, against the USD and EUR/SEK and EUR/NOK for the currencies quoted against the EUR. Since the market for USD/SEK and USD/NOK is not liquid, we focus on EUR/SEK and EUR/NOK where the Swedish and Norwegian Kronas are mostly traded. All the currencies, except AUD, GBP and NZD, are quoted indirectly against the USD, meaning that the value observed corresponds to the number of units of foreign currency of one unit of U.S. dollar.

The Reuters Database contains trading prices and quotes. The transaction prices do not specify which side of the order book has been hit or on the quantity traded. The quotes correspond to a bid or a ask price, or both. The bid and ask prices correspond to the best buy and sale prices at which any investor can buy or sell the currency. Each new quote on either the bid, the ask or both prices is taken into account. On either side of the order book, the price is set as a missing if the previous quote appeared more than one minute before.

The Reuters Database does not contain order flows. Following the literature, we infer order flows from transaction prices. For each transaction, if it takes places at the ask (bid) price, order flow is recorded as $+1$ $(-1)$. Regardless of whether the transaction occurs at the bid or the ask price, the volume is $+1$. All trades are by assumption normalized to $\$1,000,000$.

#### 2.10.2.2. The EBS Database

The following exchange rates are extracted from the EBS database: CHF, EUR and JPY. The EBS database contains traded volumes and actual order flows. Actual trade sizes are very often of $\$1M$ with little heterogeneity across currencies and time.

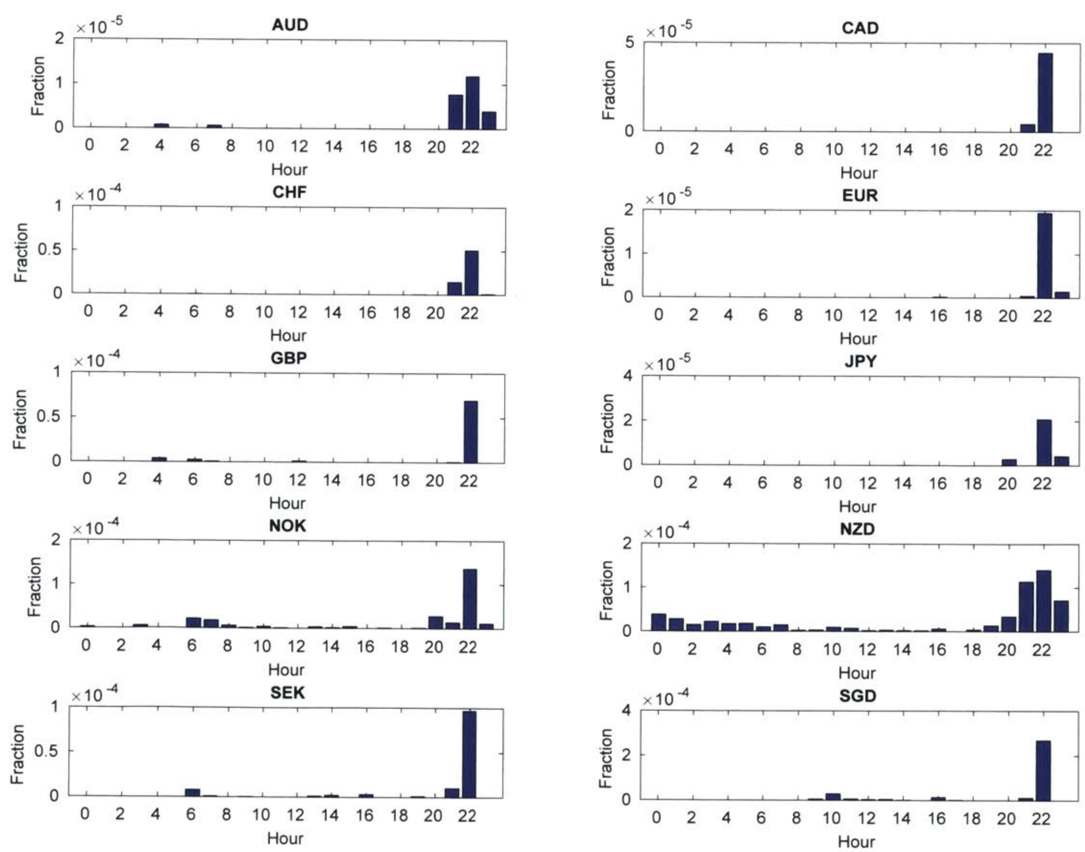
#### 2.10.2.3. Filter

To get rid of clear outliers in the time series of quotes, often referred as "fat fingers" by financial practitioners, we remove bid and ask prices that are below and above a time-varying threshold. To determine the threshold, we first record the daily minimum and maximum values of the bid and ask prices on the tick-by-tick data, focusing only on business days and the time period between 7:00:00AM and 6:00:00PM GMT to avoid taking into account extreme observations and erratic jumps occurring overnight. We consider a rolling window of 30 days before and after each observation and use the maximum value of all daily maxima during that rolling window in order to determine the maximum threshold. A similar procedure applies to the minima. Quotes that are more than 10% above the maximum or below the minimum are removed. Thus, for any tick-by-tick quoted price $p_{i,d^*,t^*}$ (either bid or ask price observed on day $d^*$ at time $t^*$, for currency $i$), if $p_{i,d^*,t^*} \geq 1.1 \times \max_{d \in [d^*-30,d^*-1], d \in [d^*+1,d^*+30]} \left\{ \max_t p_{i,d,t} \right\}$, or if $p_{i,d^*,t^*} \leq 1.1 \times \min_{d \in [d^*-30,d^*-1], d \in [d^*+1,d^*+30]} \left\{ \min_t p_{i,d,t} \right\}$, then $p_{i,d^*,t^*}$ is set as missing.

We check that our filter deletes few and abnormal observations. Figures 2.7 and 2.8 report, for each currency and for each hour of the day, the fraction of tick-by-tick quoted prices that are removed.

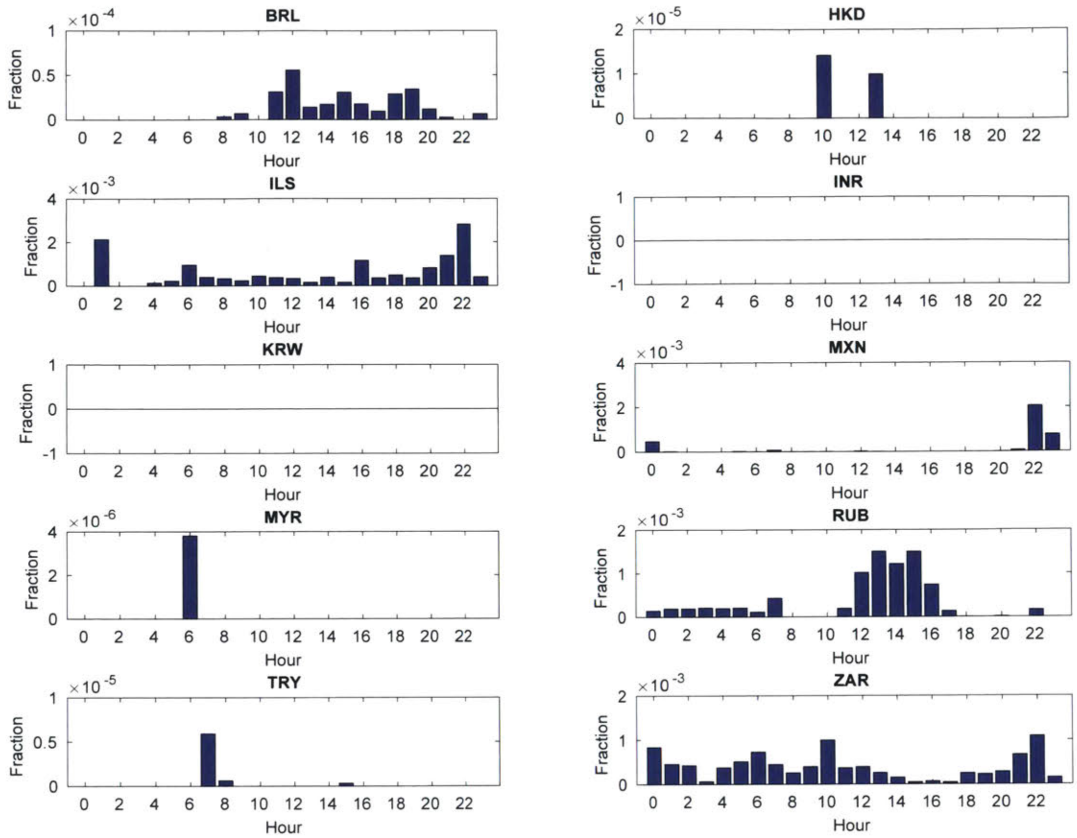
For developed countries, the majority of the tick-by-tick observations removed are overnight (with reference to British Summer Time), i.e. when markets are less liquid. They only represent on average $10^{-5}$ of total observations. For emerging countries, more tick-by-tick quoted prices observed during the day are filtered out. Nevertheless, the number of observations removed is still negligible: they represent between $10^{-6}$ and $10^{-3}$ of total observations. Our filter thus appears to remove much less observations than a classic winsorizing procedure at the usual 0.5% level.

Figure 2.7: Fraction of Filtered Tick-by-Tick Observations, Developed Countries




This figure displays for each currency and each hour of the day the fraction of tick-by-tick quoted prices on the bid and ask sides that have been removed.

Figure 2.8: Fraction of Filtered Tick-by-Tick Observations, Emerging countries




This figure displays for each currency and each hour of the day the fraction of tick-by-tick quoted prices on the bid and ask sides that have been removed.

#### 2.10.2.4. Sampling Procedure

The data are then sampled at the 30 sec-, 1 min-, 2 min-, 5 min-, 10 min-, 15 min, 30 min-, 1 hour-, 2 hour, 3 hour-, 6 hour-, 12 hour-, daily, weekly and monthly frequencies. We focus on non overlapping time intervals. For instance, at the hourly frequency, the time series correspond to time stamps at 12:00pm, 1:00pm, 2:00pm, etc. For the 12-hour frequency, the data are sampled at 4 AM and 4 PM. For the daily, weekly and monthly frequency, the observations correspond to $4:00$pm. Moreover, overnight (between 6:00:00pm GMT and 7:00:00am GMT) observations and those on non-business days are removed from the datasets before starting the sampling procedure at these low frequencies. For the weekly frequency, the observations correspond to 4pm on Fridays (if a business day, otherwise the last business day of the week). Over each sub-period (of length 30 seconds, 1 minute, 2 minutes, 5 minutes, etc.), the data correspond to the last quote if recorded less than one-minute before, and nothing otherwise. For instance, at the 15-min frequency, assume we observe a quote at 3:52:41pm and then nothing until 4:00:00pm, then the value for the sub-period between 3:45:00 PM and 4:00:00 PM is set as missing. For transactions, only the last trade price over the sub-period is reported. For order flows and volumes, the series correspond to the sum over each sub-period.

#### 2.10.2.5. Construction of risk factors

The two risk factors, the dollar and the carry factors, are built for each frequency.

We consider both common and currency-specific dollar factors. The common dollar factor is the same for all currencies and is computed as the average of the log returns of all currencies with respect to the US dollar. The currency-specific dollar factor relies on the same idea except that there is a dollar factor for each currency since computed as the average of the log returns over all currencies excluding the currency in question.

At each point in time, currencies are ranked according to their interest rate differentials with respect to the U.S. interest rate, $i_t^* - i_t$. The interest rate differential is recovered from the one-month forward and spot foreign exchange rates for each currency against the U.S dollar: $S_t = F_{t,T} e^{-(i_t^* - i_t)(T-t)}$ where $i_t^*$ denotes the interest rate prevailing between $t$ and $T > t$ in the foreign country, $i_t$ the interest rate between $t$ and $T$ in the US, $S_t$ the spot exchange rate (with the convention that when $S_t$ increases, it correspond to an appreciation of the foreign currency, i.e. $S_t$ corresponds to the amount of U.S. dollars that can be obtained with one unit of the foreign currency) and $F_{t,T}$ the forward price prevailing at time $t$ with delivery date $T$. We take $T - t$ equal to one month. For BRL, ILS and RUB, we use interest rates instead of forward rates because of missing observations.

Once currencies are ranked according to their interest rate differentials, different portfolios are created. The carry factor is then computed as the average of the log returns of the currencies with the highest interest rate differentials minus the average of the log returns of the currencies with the lowest interest rate differentials. As in the case of the dollar factor, we consider both common and currency-specific carry factors. In the case of the common carry factor, there is only one carry factor computed at each point in time and common to all currencies. For the currency-specific carry factor, the procedure is similar except that the currency in question is excluded from the interest differential ranking and therefore its log returns do not appear in the high minus low interest rate differential portfolios log returns.

#### 2.10.2.6. Distributions

Table 2.7 and 2.8 report the distributions of the 30-sec and 5-min exchange rate log returns.

#### 2.10.2.7. Comparison to the Federal Reserve Data

Table 2.9 reports the mean, standard deviation, median and maximum absolute value of the spread between our data and the Federal Reserve Data. The spread is scaled by the current value of the exchange rate and reported in basis points. The Federal Reserve data are noon buying rates in New York for cable transfers payable in foreign currencies. The average spread is less than 3 basis points, with a standard deviation of at most 16 basis points. The maximum spreads in absolute values range from 5 basis points (Hong Kong Dollar) to 430 basis points (Brazilian Real).

#### 2.10.2.8. Exchange Rate Volatilities

Table 2.10 reports the principal components analysis of daily currency return volatilities. Daily volatilities are computed either from 30-second returns (Panel A) or from 5-minute returns (Panel B), i.e., we use non-overlapping return for each day in our sample to compute daily volatilities. The frequency is daily and the sample of countries is AUD, CAD, CHF, EUR, GBP, JPY, NZD, SEK, NOK, MXN, and ZAR. Two principal components account for 70% (using 30-sec data) to 77% (using 5-min data) of the volatility dynamics.

Table 2.7: Distribution of Exchange Rate Returns: 30-sec Frequency

Returns are expressed in percentage terms. The sample excludes observations occurring on non-U.S. and U.K. business days and when reported trading volume is zero over the 30-second time interval. The sample period runs from January 2000 to December 2014.

| **Currency** | **Min** | **0.001** | **0.01** | **0.1** | **1** | **5** | **50** | **95** | **99** | **99.9** | **99.99** | **99.999** | **Max** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AUD | -2.77 | -0.64 | -0.31 | -0.14 | -0.06 | -0.03 | 0.00 | 0.03 | 0.06 | 0.14 | 0.29 | 0.64 | 2.41 |
| CAD | -2.35 | -0.45 | -0.22 | -0.11 | -0.05 | -0.03 | 0.00 | 0.03 | 0.05 | 0.11 | 0.21 | 0.47 | 3.47 |
| CHF | -2.42 | -0.82 | -0.47 | -0.18 | -0.06 | -0.03 | 0.00 | 0.03 | 0.06 | 0.18 | 0.47 | 0.83 | 3.02 |
| EUR | -1.06 | -0.31 | -0.15 | -0.08 | -0.04 | -0.02 | 0.00 | 0.02 | 0.04 | 0.08 | 0.16 | 0.35 | 1.31 |
| GBP | -1.65 | -0.43 | -0.21 | -0.10 | -0.04 | -0.02 | 0.00 | 0.02 | 0.04 | 0.10 | 0.21 | 0.43 | 2.31 |
| JPY | -1.67 | -0.43 | -0.18 | -0.09 | -0.04 | -0.02 | 0.00 | 0.02 | 0.04 | 0.09 | 0.18 | 0.40 | 2.90 |
| NZD | -6.28 | -1.99 | -0.80 | -0.28 | -0.10 | -0.05 | 0.00 | 0.05 | 0.10 | 0.29 | 0.79 | 2.06 | 5.98 |
| SEK | -9.79 | -2.57 | -0.76 | -0.23 | -0.08 | -0.04 | 0.00 | 0.04 | 0.08 | 0.23 | 0.84 | 2.51 | 9.73 |
| NOK | -6.59 | -2.75 | -0.77 | -0.24 | -0.09 | -0.04 | 0.00 | 0.04 | 0.08 | 0.24 | 0.78 | 3.50 | 9.70 |
| BRL | -3.92 | -2.92 | -0.66 | -0.37 | -0.15 | -0.07 | 0.00 | 0.07 | 0.15 | 0.36 | 0.69 | 1.44 | 1.59 |
| HKD | -0.52 | -0.19 | -0.07 | -0.02 | -0.01 | -0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.07 | 0.23 | 0.57 |
| ILS | -5.66 | -5.50 | -1.89 | -0.62 | -0.19 | -0.07 | 0.00 | 0.07 | 0.18 | 0.62 | 1.55 | 3.19 | 4.21 |
| INR | -2.82 | -1.99 | -1.01 | -0.24 | -0.06 | -0.03 | 0.00 | 0.02 | 0.06 | 0.16 | 0.37 | 0.86 | 2.06 |
| KRW | -1.60 | -1.24 | -0.41 | -0.16 | -0.05 | -0.02 | 0.00 | 0.02 | 0.05 | 0.16 | 0.50 | 1.12 | 2.04 |
| MYR | -1.22 | -1.13 | -0.30 | -0.14 | -0.07 | -0.03 | 0.00 | 0.03 | 0.07 | 0.13 | 0.31 | 0.55 | 0.56 |
| MXN | -4.87 | -1.23 | -0.42 | -0.17 | -0.07 | -0.03 | 0.00 | 0.03 | 0.07 | 0.16 | 0.46 | 1.27 | 7.51 |
| SGD | -3.44 | -0.66 | -0.26 | -0.11 | -0.05 | -0.02 | 0.00 | 0.02 | 0.04 | 0.11 | 0.27 | 0.78 | 3.57 |
| RUB | -3.69 | -1.45 | -0.44 | -0.15 | -0.07 | -0.04 | 0.00 | 0.04 | 0.07 | 0.15 | 0.41 | 0.96 | 2.21 |
| TRY | -2.91 | -1.49 | -0.51 | -0.31 | -0.20 | -0.12 | 0.00 | 0.12 | 0.21 | 0.33 | 0.52 | 1.05 | 1.71 |
| ZAR | -5.96 | -2.23 | -0.86 | -0.34 | -0.14 | -0.07 | 0.00 | 0.06 | 0.14 | 0.34 | 0.86 | 2.32 | 7.66 |

Table 2.8: Distribution of Exchange Rate Returns: 5-min Frequency

Returns are expressed in percentage terms. The sample excludes observations occurring on non-U.S. and U.K. business days and when reported trading volume is zero over the 5-min time interval. The sample period runs from January 2000 to December 2014.

| **Currency** | **Min** | **0.001** | **0.01** | **0.1** | **1** | **5** | **50** | **95** | **99** | **99.9** | **99.99** | **99.999** | **Max** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AUD | -2.73 | -1.32 | -0.73 | -0.36 | -0.16 | -0.08 | 0.00 | 0.08 | 0.16 | 0.35 | 0.69 | 1.12 | 1.96 |
| CAD | -1.08 | -0.81 | -0.48 | -0.25 | -0.13 | -0.07 | 0.00 | 0.07 | 0.13 | 0.26 | 0.48 | 0.77 | 1.26 |
| CHF | -4.46 | -1.10 | -0.63 | -0.31 | -0.14 | -0.07 | 0.00 | 0.07 | 0.14 | 0.31 | 0.65 | 1.08 | 3.26 |
| EUR | -1.55 | -0.69 | -0.41 | -0.22 | -0.11 | -0.06 | 0.00 | 0.06 | 0.11 | 0.22 | 0.42 | 0.89 | 2.71 |
| GBP | -1.31 | -0.93 | -0.42 | -0.24 | -0.12 | -0.06 | 0.00 | 0.06 | 0.12 | 0.23 | 0.44 | 0.71 | 1.22 |
| JPY | -2.88 | -0.90 | -0.50 | -0.24 | -0.11 | -0.06 | 0.00 | 0.06 | 0.11 | 0.24 | 0.50 | 1.10 | 2.86 |
| NZD | -5.32 | -2.68 | -1.06 | -0.50 | -0.20 | -0.10 | 0.00 | 0.10 | 0.20 | 0.49 | 1.06 | 2.50 | 4.94 |
| SEK | -6.55 | -3.65 | -1.11 | -0.41 | -0.19 | -0.10 | 0.00 | 0.10 | 0.19 | 0.42 | 1.05 | 3.43 | 6.55 |
| NOK | -6.15 | -3.51 | -1.12 | -0.42 | -0.19 | -0.10 | 0.00 | 0.10 | 0.19 | 0.42 | 1.02 | 3.25 | 6.10 |
| BRL | -3.92 | -3.44 | -1.54 | -0.74 | -0.31 | -0.15 | 0.00 | 0.15 | 0.31 | 0.79 | 1.73 | 4.54 | 5.45 |
| HKD | -0.49 | -0.45 | -0.10 | -0.03 | -0.01 | -0.01 | 0.00 | 0.01 | 0.01 | 0.04 | 0.15 | 0.38 | 0.39 |
| ILS | -4.68 | -4.56 | -2.49 | -0.71 | -0.25 | -0.11 | 0.00 | 0.11 | 0.24 | 0.68 | 2.15 | 5.01 | 5.32 |
| INR | -3.00 | -2.36 | -1.46 | -0.78 | -0.15 | -0.06 | 0.00 | 0.06 | 0.12 | 0.28 | 0.49 | 0.91 | 1.11 |
| KRW | -5.85 | -4.83 | -2.05 | -0.57 | -0.16 | -0.06 | 0.00 | 0.06 | 0.16 | 0.57 | 1.74 | 5.65 | 5.92 |
| MYR | -0.84 | -0.84 | -0.38 | -0.19 | -0.11 | -0.06 | 0.00 | 0.06 | 0.12 | 0.23 | 0.39 | 0.56 | 0.56 |
| MXN | -5.31 | -3.84 | -1.01 | -0.39 | -0.16 | -0.08 | 0.00 | 0.08 | 0.16 | 0.37 | 1.06 | 2.53 | 3.01 |
| SGD | -1.73 | -0.58 | -0.29 | -0.16 | -0.08 | -0.04 | 0.00 | 0.04 | 0.08 | 0.17 | 0.35 | 0.73 | 2.63 |
| RUB | -2.19 | -1.97 | -1.20 | -0.41 | -0.13 | -0.07 | 0.00 | 0.07 | 0.14 | 0.37 | 1.02 | 2.31 | 4.45 |
| TRY | -3.90 | -2.93 | -1.09 | -0.51 | -0.27 | -0.16 | 0.00 | 0.16 | 0.27 | 0.50 | 1.06 | 1.65 | 1.87 |
| ZAR | -5.22 | -2.39 | -1.30 | -0.58 | -0.27 | -0.14 | 0.00 | 0.14 | 0.27 | 0.60 | 1.29 | 3.45 | 4.24 |

Table 2.9: Percent Differences Between EBS/Reuters and Federal Reserve Data

The table reports the mean, standard deviation, median and maximum absolute value of the spread between our data and the Federal Reserve Data. The spread is scaled by the current value of the exchange rate and reported in basis points. The Federal Reserve data are noon buying rates in New York for cable transfers payable in foreign currencies. The sample period runs from January 2000 to December 2014.

| **Currency** | **N** | **Mean** | **Std Dev.** | **Median** | **Max Abs.** |
|---|---|---|---|---|---|
| AUD | 3,684 | -0.123 | 5.897 | -0.885 | 74.712 |
| CAD | 3,684 | 0.138 | 5.645 | 0.488 | 134.937 |
| CHF | 3,684 | 0.120 | 5.173 | 0.763 | 110.619 |
| EUR | 3,684 | -0.084 | 4.422 | -0.367 | 75.125 |
| GBP | 3,684 | -0.045 | 5.068 | -0.563 | 135.948 |
| JPY | 3,684 | 0.333 | 5.316 | 0.453 | 167.854 |
| NZD | 3,684 | -0.697 | 7.817 | -1.459 | 87.935 |
| SEK | 3,684 | 1.782 | 9.713 | 1.922 | 275.169 |
| NOK | 3,684 | 2.367 | 9.993 | 2.586 | 246.601 |
| BRL | 3,684 | 1.183 | 12.301 | 2.254 | 427.537 |
| HKD | 3,684 | 0.229 | 0.507 | 0.258 | 4.706 |
| INR | 2,825 | 1.559 | 13.723 | 2.527 | 257.908 |
| KRW | 3,684 | 1.892 | 16.314 | 3.081 | 269.115 |
| MYR | 3,684 | 2.882 | 9.094 | 1.462 | 88.601 |
| MXN | 3,684 | 0.260 | 6.565 | 0.730 | 187.879 |
| SGD | 3,499 | 0.900 | 2.839 | 1.176 | 23.192 |

Table 2.10: Daily Currency Return Volatilities

This table reports the principal components analysis of daily currency return volatilities. Daily volatilities are computed either from 30-second returns (Panel A) or from 5-minute returns (Panel B), i.e., we use non-overlapping return for each day in our sample to compute daily volatilities. The frequency is daily and the sample of countries is AUD, CAD, CHF, EUR, GBP, JPY, NZD, SEK, NOK, MXN, and ZAR.

| | Panel A: 30-sec frequency | | | | | Panel B: 5-min frequency | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| PC #/Currency | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| AUD | 0.31 | 0.14 | 0.21 | -0.11 | -0.07 | 0.32 | 0.12 | 0.12 | 0.00 | -0.34 |
| CAD | 0.18 | 0.05 | 0.03 | -0.15 | -0.10 | 0.19 | 0.04 | -0.11 | -0.19 | -0.55 |
| CHF | 0.20 | 0.13 | -0.12 | -0.07 | -0.55 | 0.21 | 0.09 | 0.00 | -0.24 | 0.08 |
| EUR | 0.19 | 0.12 | -0.11 | -0.02 | -0.28 | 0.21 | 0.12 | -0.02 | -0.15 | 0.14 |
| GBP | 0.16 | 0.09 | -0.03 | -0.01 | -0.21 | 0.19 | 0.12 | -0.06 | -0.13 | -0.12 |
| JPY | 0.19 | 0.08 | 0.03 | -0.19 | -0.51 | 0.17 | 0.06 | 0.03 | -0.25 | -0.54 |
| NZD | 0.39 | 0.19 | 0.79 | 0.27 | 0.15 | 0.42 | 0.07 | 0.82 | 0.24 | 0.13 |
| SEK | 0.36 | 0.28 | -0.37 | 0.19 | 0.18 | 0.37 | 0.30 | -0.27 | -0.07 | 0.27 |
| NOK | 0.37 | 0.29 | -0.41 | 0.28 | 0.30 | 0.39 | 0.25 | -0.28 | -0.18 | 0.36 |
| MXN | 0.27 | 0.03 | 0.00 | -0.85 | 0.39 | 0.25 | 0.08 | -0.35 | 0.84 | -0.19 |
| ZAR | 0.49 | -0.85 | -0.09 | 0.13 | 0.00 | 0.43 | -0.88 | -0.13 | -0.06 | 0.09 |
| Var% | 56.69 | 14.06 | 9.35 | 5.24 | 4.34 | 64.79 | 12.74 | 8.11 | 3.86 | 3.12 |

# Chapter 3

# Financial Distress, Dealers' Behavior and Asset Pricing in the Foreign Exchange Market

## 3.1. Introduction

A quick search on Google Scholar with the entry words "Intermediary Asset Pricing" yields more than 350 research papers. This metric, even though not exhaustive and not exactly representative of where research in asset pricing stands these days, says a lot about the amount of attention that the academic sphere has dedicated to the role of financial intermediaries in determining equilibrium asset prices over the last decade. Many theoretical models incorporating this specific feature, namely that financial intermediaries' limited risk-bearing capital can directly affect financial asset prices, have emerged.[1] Numerous empirical papers have in the meantime tried to corroborate the diverse empirical implications predicted by these models. Some of them find strong negative correlation between broker dealers's capital and asset returns. Nevertheless, empirically identifying the role played by financial intermediaries in asset price dynamics in a causal way is still a challenge that has to be tackled.[2]

[1]Some examples are Froot & O' Connell (2008), Pedersen *et al.* (2007), He & Krishnamurthy (2013), Brunnermeier & Sannikov (2014) and Duffie & Strulovici (2012), among others.

[2]Siriwardane (2015) is one of the few papers which successfully tackles these identification issues when looking at the impact of dealers'capital fluctuations on CDS prices dynamics.

Using a tick-by-tick dealer-specific quotes database on the foreign exchange (FX) market, I build daily currency specific time-series of bid and ask quotes posted by each financial intermediary. I argue that the CDS spread of a financial intermediary can be considered as a proxy for its financial wealth.[3] To test the effects of deterioration in intermediary financial wealth on FX quotes, I run a panel regression of bid-ask spreads on the CDS spread of the corresponding financial intermediary who posted these quotes. Empirical identification is the main challenge here. Indeed, fluctuations in intermediaries'wealth are concomitant with aggregate global shocks that might also have a direct impact on FX market liquidity and in particular on bid-ask spreads. As a result, not controlling for these global shocks could lead to wrongfully attribute increase in bid-ask spread size to deterioration in intermediaries'financial wealth. The use of currency-by-time and intermediary fixed effects in my estimation allows me to mitigate such concerns. The core findings of my chapter are that when financial intermediaries'health worsens, the bid-ask spreads they quote in the FX market increase in times of high volatility and low competition. In a nutshell, I show that when exchange rate volatility is high, a 1% increase in intermediary's default probability does translate into a 4 bps increase in the bid-ask spread that she quotes. When competition is low, a similar deterioration in financial wealth leads to a 6.4 bps increase in bid-ask spread size.

From this micro dataset, I then build a time-varying measure of currency-specific intermediary financial distress by computing the average CDS spread of the different dealers quoting in the market for each currency each day. I show that in the case of emerging country currencies, this *financial distress* measure is a statistically significant variable explaining the volatility of the idiosyncratic component of the currency risk premium. More surprisingly, the cross-sectionnal variance of the CDS spreads across financial intermediaries quoting in the market is an important determinant of this volatility for a large set of emerging country currencies. This seems to suggest that distributional effects are a key determinant of exchange rate dynamics.

In order to analyze how dealers behave in the FX market, I use the Thomson Reuters Tick History Database where tick-by-tick quotes posted by each player in the different FX spot markets for the sample period 2000-2015[4] are available. The richness of this database, where more than 1,100 mar-

[3]This measure can be directly linked to the notion of risk-bearing capital of an intermediary, empirically exploited by Siriwardane (2015).

[4]When I mention different FX spot markets, I refer to the FX spot markets for the different currencies.

ket participants quote across currencies and with more than 400 million observations, allows me to look in depth at the ask (selling) and bid (buying) prices at which each dealer is willing to trade a specific currency. To the best of my knowledge, I am the first to analyze this database in details.

Through this data, I discover a salient feature of FX markets: they are dominated by a handful of dealers who post the large majority of the quotes available each day for trading. As a result, the FX displays a strong oligopolistic structure. Another interesting feature is that, even if some major dealers are omnipresent, i.e. frequently quote across all currencies, some are very specialized and only quote on one or two markets. This is especially the case for big domestic banks. For instance, Banco Itau who merged with Unibanco in 2008 is extremely active in the Brazilian Real market but never quotes in the other markets. The FX market is therefore characterized by some strong features of both globalization and specialization.

To measure the financial distress of an intermediary, I use its Credit Default Swaps (CDS) spread. These are securities whose payoffs are conditional on the firm defaulting on its debt, so their price reflects the expected probability that a firm enters bankruptcy. Because they are much more liquid than the bonds of the respective companies, they provide the most current measure of companies' financial distress. CDS spreads present the advantage to deliver measures of intermediary financial distress and to a certain extent risk-bearing capital at a relatively high frequency. The higher the CDS spread, the more constrained the financial intermediary is. Consequently, it is plausible to argue that a dealer whose holding company faces a higher CDS spread might face more stringent borrowing constraints and therefore be subject to higher financial frictions. Hence, I treat the CDS spread of the dealer's holding company as the relevant state variable for explaining dealer's behavior in the FX market.

At the micro level, I find that a more financially distressed dealer[5] does actually tend to be more conservative by quoting larger bid-ask spreads compared to her competitors when the volatility of the underlying traded asset is high or when market competition is low. Most of intermediary-based asset pricing models explores and focuses on non-linear relationships between risk-bearing capital

[5]Any microstructure model with risk-averse agents would predict that she would quote larger bid-ask spreads assuming that facing stricter financial constraints makes her more risk-averse (see Biais (1993), Ho & Stoll (1981) and Stoll (1978)).

and asset prices dynamics. To a certain extent, my first empirical result can be considered as a prediction of these non-linearities: the level of intermediary financial distress only seems to matter for quoting behavior when the quantity of risk is large enough. Moreover, a significant positive shock to a dealer's CDS spread does not significantly increase the probability for this dealer not to quote the following day. On the other hand, a much more striking result is that an intermediary experiencing harsher financial conditions quotes significantly much more often than her peers do. Even though one cannot rule the potential explanation that such a dealer is more cautious and therefore simply tries to test the market more often, a model of rational inattention can potentially rationalize this type of change in dealer behavior when hit by a financial shock (see Sims (2003) and Sims (2006)).

Since intermediaries are marginal investors in the FX market, an highly decentralized over-the-counter market, their financial wealth is a plausible major state variable for explaining exchange rate dynamics as advocated by He *et al.* (2017). Based on the detailed information contained in my FX database, and in particular about the identity of the financial intermediaries present in each spot market, I build a currency specific time-varying measure of *intermediary financial distress*, denoted $\kappa_{i,t}$ as the average of the CDS spreads of the financial intermediaries quoting on day $t$ for the currency $i$:

$$\kappa_{i,t} = \frac{1}{|\Omega_{i,t}|} \sum_{j \in \Omega_{i,t}} CDS_{i,j,t} \tag{3.1}$$

where $\Omega_{i,t}$ is the set of intermediaries quoting on day $t$ for currency $i$ and $|\Omega_{i,t}|$, the cardinality of this set. Building upon the empirical framework proposed by Verdelhan (2018), I regress the weekly log change in bilateral exchange rate on the carry factor, the same carry factor multiplied by the country-specific interest rate difference (the latter is referred to as "conditional carry"), and the dollar factor. The carry factor corresponds to the change in exchange rates between baskets of high and low interest rate currencies, while the dollar factor corresponds to the average change in the exchange rate between the U.S. dollar and all other currencies. All exchange rates are defined here with respect to the U.S. dollar. I show that change in this *financial distress* measure is not correlated with the residuals from the regression mentioned previously and which correspond to the idiosyncratic component observed in exchange rate returns. However, I find that unsurprisingly its level explains well the magnitude of this idiosyncratic shock volatility: the more financially constrained intermediaries are, the higher the quantity of risk in the exchange rate market. My empirical strategy relies on the fact that there does not exist a single representative intermediary common to all FX spot markets but rather several, one for each FX market segment. I therefore introduce the notion of *segmented intermediary asset pricing.*

## 3.2. Related Literature

This chapter is part of a burgeoning literature that studies asset prices dynamics when financial intermediaries are limited in their ability to efficiently and frictionlessly allocate capital supply emanating from savers to capital demand (investment opportunities). The list of theoretical papers which try to incorporate this feature to explain asset prices dynamics is extremely long and includes not exhaustively He & Krishnamurthy (2012), He & Krishnamurthy (2013), Brunnermeier & Sannikov (2014), Allen & Gale (1994), Basak & Cuoco (1998), Gromb & Vayanos (2002), Xiong (2001), Kyle & Xiong (2001), Vayanos (2004), Pavlova & Rigobon (2007), Brunnermeier & Pedersen (2009), Duffie (2010), Adrian & Shin (2014), Garleanu & Pedersen (2011), Adrian & Boyarchenko (2012), Basak & Pavlova (2013). More specifically related to exchange rate dynamics, Gabaix & Maggiori (2015) proposes a theoretical framework in which alterations to financial intermediary balance sheets might change their required compensation for holding currency risk and impair their capacity to absorb global imbalances. This paper can serve as a theoretical background to my work. On the empirical side, there are also many papers trying to confront these theories to the data. Froot & O' Connell (2008) studies the effects of slow-moving intermediary capital in the catastrophe insurance market, Gabaix *et al.* (2007) focuses on the mortgage-backed securities market; Bates (2003), Garleanu *et al.* (2009) on the option market. My chapter is closely related to the work of Siriwardane (2015) which demonstrates the effect of intermediary capital losses on CDS spreads. In exchange rate literature, Adrian *et al.* (2011) and Hong & Yogo (2012) show that financier's positions are useful in predicting expected currency returns. My work departs from the empirical strategies implemented in these papers in several dimensions. First, I test whether cross-sectional variation in terms of financial distress across financial intermediaries can explain differences in the quoting behavior of these intermediaries. Second, by clearly identifying the financial intermediaries present in each FX market, I am able to build a currency-specific *intermediary financial distress* measure allowing me to test whether perform some cross-sectional asset pricing tests.

This chapter also add to the microstructure literature. One of the earliest theoretical works trying to link bid-ask spreads and dealers'risk aversion, by Ho & Stoll (1981) shows that the spread is a positive function of single transaction size (order size), the dealer's degree of risk aversion, and the security return variance. Stoll (1978) and Biais (1993) have developed similar models. In particular, Biais (1993) considers CARA competitive dealers and shows that the quoted bid-ask spread is an increasing function of dealers'risk aversion coefficient but does not depend on the dealer's inventory. On the empirical side, using intraday high-frequency data, Bollerslev & Melvin (1994) provide some strong evidence that the size of the bid-ask spread in the foreign exchange market is positively correlated with the exchange rate volatility. Huang & Masulis (1999) find that bid-ask spreads in the FX market decrease with an increase in competition, primarily measured by the number of dealers active in the market, and this even after controlling for the effects of volatility. To my knowledge, I am the first looking at the relationship between intermediary financial condition and their quoting behavior.

The remainder of the chapter proceeds as follows. Section 3.3. gives a description of the data used in this chapter. Section 3.4. presents the main stylized facts about the FX market and in particular highlights the high degree of concentration of this relatively opaque market. Section 3.5. establishes my three main core findings about how financial distress can have an impact at the micro level on dealer's behavior in the cross-section. Section 3.6. tries to explore the link between intermediary financial distress and asset price dynamics in the FX market. Finally, Section 3.7. concludes.

## 3.3. Data Description

In this section, I first describe the foreign exchange dataset used primarily in this chapter. I then give a brief description of the CDS database used to extract time series of shocks to the financial distress/conditions of each financial intermediary present in the foreign exchange market and considered in my sample.

### 3.3.1. Foreign Exchange Rate Dataset

As mentioned before, the data for this chapter comes from the Thomson Reuters Tick History database. This database provides tick-by-tick data. In particular, in the case of foreign exchange, the electronic database reports tick-by-tick quotes posted by each major player present in the Reuters InterDealer Trading System. Each tick-by-tick observation displays the best selling (ask price) and buying (bid price) prices at which a specific entity is willing to trade the exchange rate in question. In this aspect, these prices are purely indicative and do not correspond to traded prices. These tradable rates are quality checked and then streamed into the continuously updating spot FX rate by Reuters.

In order to have the most liquid market possible for each currency, the exchange rates considered in this chapter are all against the U.S. dollar (USD). My sample contains 20 currencies from both developed and emerging countries: the Australian Dollar (AUD), the Brazilian Real (BRL), the Swiss Franc (CHF), the Canadian Dollar (CAD), the Euro (EUR), the British Pound (GBP), the Japanese Yen (JPY), the Hong-Kong Dollar (HKD), the Israeli New Shekel (ILS), the Indian Rupee (INR), the South Korean Won (KRW), the Mexican Peso (MXN), the Malaysian Ringgit (MYR), the Norwegian Krone (NOK), the New-Zealand Dollar (NZD), the Russian Ruble (RUB), the Swedish Krone (SEK), the Singapore Dollar (SGD), the Turkish Lira (TRY) and the South African Rand (ZAR).

The sample in this study covers 16 years of tick-by-tick data, from January $1^{st}$ 2000 to December $31^{st}$ 2015. However, for any empirical specification run, I restrict myself to the sample from January $1^{st}$ 2004 to December $31^{st}$ 2015 to make sure that there exists some CDS data available for some entities. There is over a thousand entity names referenced in the whole database (i.e. across all currencies). Some of them are banks, some are private dealers specialized in the foreign exchange business, some are insurance companies.[6] However, the analysis only focuses on financial institutions for which data on their CDS is available to be able to measure the effect of their own distress on their behavior in terms of quotations in the FX market. The names of all the players active in the FX market can be obtained upon request.

Each observation on a quote lists the time of the day, the Reuters code for the name of the dealer, the city where the dealer is located, together with the bid and ask prices posted by the dealer in question. To illustrate, consider the following five consecutive quotes for AUD/USD on January $8^{th}$ 2014 between 11:11 A.M. and 4 seconds and 11:11 A.M and 7 seconds:

[6] The list of all the players quoting in the foreign exchange market for the different currencies mentioned above can be available upon request.

| Currency | Date | Time | GMT Offset | Type | Ex/Cntrb.ID | Bid Price | Ask Price |
|---|---|---|---|---|---|---|---|
| AUD= | 8-Jan-14 | 11 : 11 : 04.8 | 0 | OTC Quote | SOC GENERALE PAR | 0.8927 | 0.893 |
| AUD= | 8-Jan-14 | 11 : 11 : 04.9 | 0 | OTC Quote | RBS FFT | 0.8927 | 0.8929 |
| AUD= | 8-Jan-14 | 11 : 11 : 06.2 | 0 | OTC Quote | WGZ BANK DUS | 0.8927 | 0.8932 |
| AUD= | 8-Jan-14 | 11 : 11 : 06.7 | 0 | OTC Quote | DANSKE BANK COP | 0.8927 | 0.8928 |
| AUD= | 8-Jan-14 | 11 : 11 : 07.5 | 0 | OTC Quote | RBS LON | 0.8927 | 0.893 |

The time of the day is GMT (Greenwich Meridian Time). The first observation of this list displays the bid price, the price expressed in US Dollars at which the desk in Paris of Sociètè Gènèrale is willing to buy 1 AUD and which is 0.8927 and the ask price at which the same desk is willing to sell 1 AUD and which is 0.893. The second and last observations correspond to quotes issued by Royal Bank of Scotland (RBS) but in two different locations, one is in Frankfurt (FFT) and the other one is in London (LON). I classify all branches of the same bank dealer as a single dealer such that the second and the fourth observations in the previous example would correspond, both of them, to quotes issued by RBS.
This dataset is enormous and contains over 400 million tick-by-tick quotes and represents more than 100 GB of data. To be as precise as possible, I have carefully documented each step of my data processing in the next section where I explore in more details the main features of the foreign exchange market. When necessary, I also provide additional details about the underlying data in the empirical analysis contained in the main text.

**A Comment on the Sample of Selected Currencies.** In this chapter, I only focus on the twenties currencies mentioned previously. The main reason for limiting our attention to these currencies comes from the fact that the market for other currencies is highly illiquid and might lead to inappropriate inference. Some currencies are more heavily traded on another inter-dealer trading platform, the EBS (Electronic Brokerage System) platform. This is the case for EUR, JPY, and CHF. Since I do not have access to the individual quotes posted by financial intermediaries on this platform, I compared the average daily bid-ask spreads and the midquote prices at 4pm to check whether or not there are some significant discrepancies across platforms. The differences are very minor and therefore we can reasonably assume that the Reuters platform is a valid database to look at for EUR, JPY and CHF. Details about this comparison are available upon request.

**A Comment on Inverted Quotes.** It is important to point out that some of the currencies in the Reuters database are indirectly quoted compared to the pool of other currencies, i.e. the value of the exchange rate displayed corresponds to the value of one unit of the currency in question expressed in USD. This is the case for EUR, GBP, AUD and NZD. The majority of our currencies are directly quoted. As a result, for any empirical exercise where I look at the link between financial distress of the intermediaries quoting in the market for a specific currency and the return on this currency, I first invert the quote and then compute the return. For the tests run on the bid-ask spread, I take to take the inverts of the ask and the bid prices to avoid adding any noise since the way a currency is quoted does not really matter for analyzing transaction costs.

### 3.3.2. The CDS Dataset

To measure intermediaries' financial distress levels, I use Credit Default Swaps (CDS) spreads. These are securities whose payoffs are conditional on the firm defaulting on its debt, so their price reflects the expected probability that a firm enters bankruptcy. Because they are much more liquid than the bonds of the respective companies, they provide the most current measure of companies' financial distress at a relatively high frequency. Following the strategy implemented in He *et al.* (2017) and for some obvious reasons about data availability, I measure financial distress at the holding company level for the FX dealers and not at the broker-dealer subsidiary level and even less at the desk level.[7] Consequently my definition of an intermediary is broader than in Adrian *et al.* (2014) in the sense that I treat the entire holding company as the observation of interest.[8]

I obtain the daily time series of CDS with five-year maturity from Bloomberg for all the financial intermediaries for which CDS data is available. Bloomberg merges over-the-counter data on CDS from two main sources:

- CMA, which provides data (CMA DataVision (TM)) for more than 2,000 single name CDS,

[7]For instance, Citibank is one of the broker-dealer subsidiaries which operate in the foreign exchange market on behalf of Citigroup Inc. Moreover, Citibank owns several desks over the world: one in Singapore (CITIBANK SGP), one in Moscow (CITIBANK MOS) and one in London (CITIBANK LON) for instance. All these entities which are referred under different Reuters codes are aggregated at the holding company level and are all labelled CITIGROUP.

[8]The main argument for running the whole analysis at the holding company level is well supported by (He *et al.* , 2017) and relies on the role of internal capital markets. A well established view in corporate finance is that internal capital markets within a conglomerate are likely to diversify and transmit adverse financial shocks across divisions (e.g. Stein 1997; Scharfstein & Stein 2000). If internal capital markets are important sources of funds for broker-dealer subsidiaries, then the CDS of the intermediary's holding company is the economically relevant measure of financial distress. There exist several papers in the banking literature which support this idea, Houston *et al.* (1997) and Houston & James (1998). The interested reader can look at He *et al.* (2017), which mentions two anecdotes, the Lehman Brothers failure in 2008 and the bankruptcy case of the Drexel Burnham Lambert Group in 1990, where internal capital markets seem to have played a crucial role.

indices and tranches uniquely delivered by 5pm London and 5pm New York time,

- CME Group, which reports daily quotes for a large number of reference entities.

More specifically, the dataset consists of end-of-the-day observed prices. When there is no quote available for a specific entity on a particular day, for some obvious liquidity and information issues arising with a non-updated price, I decided to consider it as a missing observation. The list of all the single name entities (97 worldwide financial institutions) used in this chapter can be found in Table 3.10 in the Appendix. Figure 3.2 plots the CDS time series for six major financial intermediaries: AIG, Bank of America, Citigroup, HSBC, Société Générale, UBS. The prices are in basis points, which can be interpreted under risk neutrality as default probability. Major crisis episodes, such as the subprime and the euro sovereign bond crises which started at the end of 2009, clearly appear in the the CDS time series.

I then match the appropriate CDS series to the foreign exchange data using the financial intermediary code in the Reuters database. The matching of CDS data and FX quotes yields a matched database containing 724,737 individual daily observations. Table 3.9 in the Appendix contains the descriptive statistics on CDS in basis points reported currency by currency for the final matched data. The data reflect significant variation in CDS not only over the whole sample (the standard deviation goes from 67 bps for KRW to 262 bps for GBP) but also after controlling with time fixed effects. Indeed, the cross-section volatility statistics which to a certain extent corresponds to the average daily cross-sectional variation over the different intermediaries quoting in the market goes from 39 bps to 242 bps. Such a finding suggests that the volatility over the whole sample is not entirely driven by significant time series variations but also by important differences across FX intermediaries at each point in time.

## 3.4. The Features of the Foreign Exchange Market

Before exploring how dealer's financial distress affects his behavior in the FX market in Section 3.5., I first document the main features of the FX market notably in terms of traded volume and quote concentration.

Table 3.1: **Average Daily Turnover by Currency.** This table reports the self-reported FX average daily turnover against the US Dollar on the spot market from all the FX actors. All the data are extracted from the BIS Triennal surveys (2007, 2010, 2013).

| **Currency** | **2007** | | **2010** | | **2013** | |
|---|---|---|---|---|---|---|
| | Volume (in millions of USD) | Fraction (in %) | Volume (in millions of USD) | Fraction (in %) | Volume (in millions of USD) | Fraction (in %) |
| AUD | 38,594 | 4.88 | 83,869 | 7.06 | 143,003 | 8.46 |
| BRL | - | - | 8,223 | 0.69 | 10,308 | 0.61 |
| CAD | 33,480 | 4.23 | 65,148 | 5.49 | 74,946 | 4.43 |
| CHF | 49,245 | 6.23 | 50,793 | 4.28 | 45,641 | 2.70 |
| EUR | 265,062 | 33.54 | 468,891 | 39.48 | 494,041 | 29.2 |
| GBP | 102,572 | 12.98 | 139,582 | 11.75 | 156,810 | 9.27 |
| HKD | - | - | 13,440 | 1.13 | 16,597 | 0.98 |
| ILS | - | - | - | - | - | - |
| INR | - | - | 12,525 | 1.05 | 14,773 | 0.87 |
| JPY | 140,355 | 17.76 | 183,108 | 15.41 | 447,859 | 26.48 |
| KRW | - | - | 20,280 | 1.7 | 18,322 | 1.08 |
| MXN | - | - | - | - | 54,170 | 3.20 |
| MYR | - | - | - | - | - | - |
| NOK | - | - | - | - | 6,374 | 0.38 |
| NZD | - | - | - | - | 26,426 | 1.56 |
| RUB | - | - | 8,223 | 0.70 | 34,970 | 2.07 |
| SEK | 6,038 | 0.76 | 5,441 | 0.46 | 7,868 | 0.47 |
| SGD | - | - | - | - | 17,209 | 1.02 |
| TRY | - | - | - | - | 13,931 | 0.82 |
| ZAR | - | - | 7,023 | 0.59 | 17,564 | 1.04 |
| Total | 790,233 | - | 1,187,699 | - | 1,691,238 | - |

### 3.4.1. Main Facts and Institutional Framework

The foreign exchange market is a decentralized over-the-counter multiple-dealer market with no common trading floor or single trading system. The spot FX market is similar to the bond market by nature. There are three main distinctions between the FX market and any other market: (i) trading volume is enormous; (ii) trade between dealers account for most of this volume and (iii) trade transparency is low (see (Lyons, 2001) for an interesting discussion).

**Traded Volume.** The FX market as a whole (spot, forward, and option contracts) is the world's biggest market in terms of daily turnover. According to the BIS Triennal Survey, the total average daily turnover in April 2013 amounts to 5,344 billions of USD and 35% higher than in 2010. Therefore, each day the sum of both France and Germany annual GDP is traded in the FX market. Transactions on spot exchange rates accounts for 38.3% of this daily turnover. The vast majority (83%) of these spot transactions involves the US Dollar whereas the second mostly traded currency, the Euro, represents only 33% of total daily volume. Table 3.1 summarizes the information collected and provided by the BIS Triennal Survey in terms of traded volume currency by currency. In April 2013, the EUR and JPY correspond to roughly two thirds of the total volume of spot transactions against the USD dollar. Such figures highlight the significant differences in terms of traded volume across currencies.

**Market Structure.** For decades, the spot FX market had a three-layer structure (see Figure 3.1). Indeed, there used to three distinct categories of market participants. The most actively traded part of the market corresponded to the direct interdealer trading market where large dealers traded relatively high volumes among themselves. The database used in this chapter focuses on this part of the market, which is still extremely liquid and which allows me to extract information about relatively large dealers' behavior in this market. Another part of the market was the brokered interdealer market: smaller players (small banks, pension funds, insurance companies, hedge funds, etc.) used to contact a broker who would then match their buy (sell) order with the sell (buy) order of a big dealer, in exchange for some fees. The last layer represented customer-dealer trading. These customers (non-financial companies, institutional investors, central banks, etc.) were generally non-financial companies who were excluded to the FX market but had to trade currencies to run their daily business.

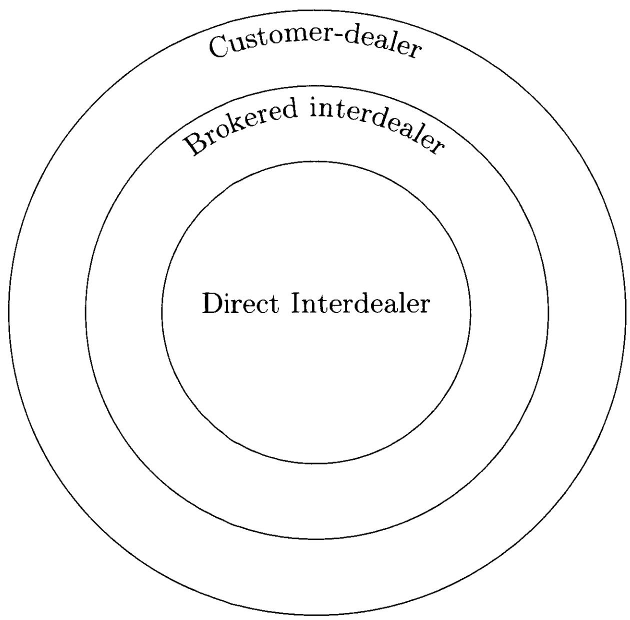



Figure 3.1: FX Market structure

Over the last decade, the FX market structure has considerably evolved. The BIS reports that in April 2013 interdealer trading represents only 42% of daily turnover.[9] The majority (56%) of these trades is executed through electronic systems.[10]

[9]"The FX market has become less dealer-centric, to the point where there is no longer a distinct inter-dealer-only market. A key driver has been the proliferation of prime brokerage[$\cdots$], allowing smaller banks, hedge funds and other players to participate more actively.", (Rime & Schrimpf, 2013)

[10]Only 16% of the electronically executed trades goes through the two major electronic brokerage systems, Reuters and EBS. In particular, the last decade has witnessed an explosion of the use of single-bank trading platforms. A

### 3.4.2. A Concentrated and Segmented Market

There are many hypothetical ways to measure the concentration of dealers in the foreign exchange market. A natural and ideal way to properly measure FX concentration would be to look at the volume traded by each dealer in the market. Given the data limitation, I measure concentration in the FX market by computing the number of quotes posted by every dealer each day. This measure can be interpreted as the market share of quote activity. Each quote is indicative and tradable: even though in reality not every quote is hit by a trade, in theory it can be. Thus, each quote reflects the price at which a dealer is willing to trade and therefore the risk she might take.

Before computing the daily quote share of each dealer for every currency, I filter the tick-by-tick dataset. I remove all the observations for which the intermediary's Reuters code was not identifiable. As said in section 3.3.1., the whole database across currencies lists more than 1,000 different dealer names. These dealers are implemented in major financial centers located in countries all around the globe. Some of them cannot be identified in the sense that there exists no public information mentioning them [11]. Approximatively, 10% of the observations are therefore erased this way. I also apply a very basic filter on the quotes for which the bid-ask spread is zero or strictly negative. Such a quote would mean that a dealer is willing to buy a certain currency at a higher price than at which she is willing to sell and therefore makes little sense.

The FX market is extremely concentrated in terms of the market share of quotes posted by each dealer. Figures 3.3 and 3.4 display the cumulative quote market share as a function of number of banks present in the market. For most currencies, only a handful of dealers dominates the market. It is especially true for emerging countries where only 20 (even less for some currencies like ILS) dealers are responsible for all the quotes in the market. The markets for EUR and JPY are less concentrated, suggesting a more intense competition for these highly liquid currencies.

Table 3.11 lists the main 30 traders present in each market and are ranked according to their quote

single-bank trading platform corresponds to an electronic brokerage system developed by a major bank to automatize its transactions with its clients (non-financial customers but also other dealers) in a totally opaque way. The most famous single-bank trading platforms are BARX (Barclays), Autobahn (Deutsche Bank), Velocity (Citigroup).

[11] I checked all the dealer names on the Internet, consulting any publicly relevant website. For some of them, the dealer's name was simply undecipherable and for some, I was unable to find any information on them

market share. It reveals a striking characteristic of FX market. It is relatively segmented in the sense that even if some major dealers (RBS, UBS, Citigroup, HSBC, Barclays, Société Générale, etc.) are present in all FX markets and quote relatively frequently, some national dealers are among the most active players for some currencies, especially the ones which are less liquid.

## 3.5. Cross-sectional evidence of intermediary financial condition on microstructure behaviour

The fundamental question of interest in this chapter is to test whether the financial situation of an intermediary has an impact on the way it behaves in the FX market. More specifically, I test whether a financial intermediary which experiences a more distressed financial situation, measured by an higher CDS spread compared to its competitors in the FX market quotes larger bid-ask spreads.

The main core findings of this chapter are: (i) an high CDS spread does lead to a larger quoted bid-ask spread but only when interacted with the spot midquote volatility, suggesting that non-linearities in financial matter to explain intermediary behavior, (ii) when the competition is low, the more financially constrained dealers quote larger bid-ask spreads, (iii) intermediaries which are hit by a positive shock on their perceived probability of default do not stop quoting in the market, (iv) there is a strong negative correlation between the number of quotes posted by a dealer and its financial situation. In this section, I develop all these points empirically.

### 3.5.1. Do more financially constrained dealers quote larger bid-ask spreads?

The first finding of my chapter is that bid-ask spread which is one of the natural measures of liquidity seems not to depend on the financial situation of the intermediary quoting this bid-ask spread. The intermediary financial condition only affects the bid-ask spread when the spot volatility is high, i.e. the quantity of risk is high.

From the microstructure theory, the bid-ask spread quoted by each dealer should be an increasing function in her degree of risk-aversion (see Biais (1993), Ho & Stoll (1981) and Stoll (1978)). If we assume that shocks to a dealer'd risk-bearing capacity translate into an higher risk-aversion for this dealer, a plausible theoretical prediction would be that a deterioration in a dealer's financial condition would push her to quote larger bid-ask spreads.

To test the hypothesis whether or not dealer financial condition is a key determinant to the bid-ask spread that she or he quotes, I run the following panel regression of bid-ask spreads on financial intermediary CDS spread:

$$\log(\text{Bid-Ask spread}_{i,t,j}) = \alpha_j + \gamma_i + \delta_j + \beta \log(CDS_{i,t}) + \zeta' X_{it} + \varepsilon_{i,j,t} \tag{3.2}$$

where Bid-Ask spread$_{i,t,j}$ corresponds to the daily average bid-ask spread quoted by financial intermediary $i$ for currency $j$ on day $t$, $CDS_{i,t}$ is the CDS spread obtained from Bloomberg for financial intermediary $i$ at time $t$. $\alpha_t$ is a time fixed effect that absorbs any global shock occurring at time $t$. This time-fixed effect allows me to capture all the public news (macro shocks, global imbalances, global uncertainty, etc.) available at time $t$ which may convey information for the determinants of the bid-ask spread on average. $\gamma_i$ is a financial intermediary fixed effect that absorbs any time invariant intermediary characteristics whereas $\delta_j$ is a currency fixed effect which controls for the specificities associated to each currency (e.g. differences in average traded volume, market depth). I also consider some other currency-level variables , $X_{it}$, which will be specified in the following subsections.

In some specifications, I replace the time and currency fixed effects, $\alpha_t$ and $\delta_j$ by a single currency by time fixed effect, $\mu_{j,t}$ to capture currency specific shock occurring to currency $j$ at time $t$. In such regressions, I obviously do not include the currency-level control variables, which would be redundant with the currency-time fixed effect. The bid-ask spreads are expressed in basis points whereas the CDS are expressed in percentage points. I work in logs to avoid econometric issues that arise from the fact that the bid-ask spreads are bounded below by zero.

I am interested in estimating $\beta = \frac{\partial \log(\text{Bid-Ask spread}_{i,t,j})}{\partial \log(CDS_{i,t})}$, with the expectation that $\beta > 0$. This estimator corresponds to the elasticity of bid-ask spread to intermediary CDS, the measure of intermediary financial distress considered in this chapter. Because this regression accounts for intermediary time invariant characteristics (via $\gamma_i$) and macroeconomic factors (via $\alpha_t$ and $\delta_j$ or the combination of both fixed effects in $\mu_{j,t}$), I argue that this regression enables me to assess the impact of intermediary financial distress on bid-ask spread.

**Comments on Identification Issues.** There are several identification issues with this specification. One natural concern is the fact that there might be a reverse causality problem: do more financially constrained dealers quote larger bid-ask spreads or does an intermediary who quotes large bid-ask spreads in the FX market experience a harsher financial situation, which notably translates into an higher CDS spread? The answer seems to be contained in the question. It appears difficult to argue that by quoting larger bid-ask spreads in the FX market an intermediary would face losses, large enough to increase significantly the CDS at the holding company level. Another worry might be the presence of omitted variables. One variable which is not observable and which might potentially explain the cross-section differences in terms of bid-ask spreads is the inventory held by each intermediary. However, since I look at daily averages, it seems highly improbable that inventories matter at this frequency. Lyons (1995) and Bjønnes & Rime (2005) show that every dealer finishes her trading day with no net position in all the days considered in their studies and that within the day, the half-life of the gap between a dealer's current position and zero is only between 10 and 40 minutes depending on the currencies.[12]

### 3.5.1.1. Financial Distress and Uncertainty

Table 3.2 contains the results of regression 3.2, where the control variable is the midquote volatility, $Vol_{j,t}$, of currency $j$ at day $t$. Column (1) of Table 3.2 can be considered as a benchmark. It is a regression of log of the bid-ask spreads on fixed effects. The bottom line from Column (1) is that all the fixed effects captures 68.3% percent of bid-ask spread variation on their own, which is relatively high but not surprising. When taking into account currency-time fixed effect, the adjusted $R^2$ jumps from 68.3% to 76.25%, suggesting that currency specific shocks are a key determinant to the level of bid-ask spread (in log terms).

Column (3) adds the log of the CDS spreads to the baseline regression with intermediary, time and currency fixed effects taken separately. As it is clear from the point estimate and its standard errors, the log of CDS spread does not add any statistical power to explain the cross-section variations in the log of the bid-ask spreads quoted in the market. At the same time, the adjusted $R^2$ does not increase significantly as well. Such a finding suggests that dealer financial condition seems not to have any impact on the way she quotes in terms of bid-ask spreads.

[12] I also run all the regressions considered in this chapter by considering the daily median of the dependent variable, i.e. the median of the bid-ask spread to obtain a daily measure less contaminated by potential outliers which might bias the results. The results are extremely similar.

Column (4) adds to the regression run in Column (3) the midquote volatility, $Vol_{j,t}$ and the interaction of the log of intermediary CDS and this volatility, $\log(CDS_{i,t}) \times Vol_{j,t}$.[13]This specification allows to take into account any non-linearity between a dealer's financial situation and the quantity of risk present in the market which might have an impact on the spread quoted. It tries to capture whether an intermediary being in a financially distressed situation tends to quote differently, notably by quoting larger bid-ask spreads when the volatility of the underlying asset is high. The first result which is not surprising is that the midquote volatility is of first importance when explaining the average bid-ask spread. The other result which is more striking is that when the volatility is high, an higher CDS spread translates into an higher bid-ask spread. The result holds even when I add currency-time fixed effect.

Columns (5) and (6) reports the same baseline regression except that now an extra variable, $\log(CDS_{i,t}) \times \mathbb{1}_{Vol_{j,t} \geq Vol^{q\%}_{j,t}}$, is added and correspond to the log of the intermediary CDS conditional on the state of market in terms of midquote volatility. The idea behind these regressions is to test whether when the quantity of risk is high, the intermediary financial condition matters for explaining the width of the bid-ask spreads. In my regressions, I considered two different threshold levels for $q$: when the midquote volatility for currency $j$ is above its 75% level and it is above its 90% level. The results show that indeed when the volatility is high, differences in terms of financial distress will translate into differences of bid-ask spreads. More specifically, when the volatility of the midquote of the traded asset is high (above its 75% or 90% over time value), an increase of 1% in a financial intermediary's CDS (which is a little bit less than one standard deviation of the intermediary CDS over the whole sample) leads to a 4 bps increase in the bid-ask spread she quotes.

As a result, more financially constrained dealers tend to quote larger spreads when the uncertainty with respect to the traded asset is high. It is however difficult to rule out that the intermediary financial condition does not affect the dealer behavior even in normal times since maybe my measure of financial distress might be not the most appropriate one and it could be more powerful to rather consider measures at the dealer level.

[13]To be more specific, for each currency, I normalize the $Vol_{j,t}$ variable by its over time mean $\bar{V}_j$ over the whole sample such that for each currency on average it is equal to 1.

Table 3.2: Effect of Financial Distress on Quoted Bid-Ask Spreads: the Role of Uncertainty

| Dep. Variable | log(Bid-Ask spread$_{i,t,j}$) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $\log(CDS_{i,t})$ | | | 0.014 | 0.012 | .017 | 0.13 | 0.11 |
| | | | (0.97) | (0.24) | (0.04) | (0.032) | (0.022) |
| $Vol_{j,t}$ | | | | 0.052* | Omitted | | |
| | | | | (2.08) | since Red. | | |
| $\log(CDS_{i,t}) \times Vol_{j,t}$ | | | | 0.026** | 0.04** | | |
| | | | | (2.51) | (2.2) | | |
| $\log(CDS_{i,t}) \times \mathbb{1}_{Vol_{j,t} \geq Vol_{j,t}^{75\%}}$ | | | | | | 0.05** | |
| | | | | | | (2.31) | |
| $\log(CDS_{i,t}) \times \mathbb{1}_{Vol_{j,t} \geq Vol_{j,t}^{90\%}}$ | | | | | | | 0.06** |
| | | | | | | | (2.67) |
| Intermediary FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time, Currency FE | Yes | No | Yes | Yes | No | No | No |
| Time $\times$ Currency FE | No | Yes | No | No | Yes | Yes | Yes |
| $\bar{R}^2$ | 68.3 | 76.25 | 68.6 | 72.4 | 79.4 | 77.1 | 76.87 |
| Nobs | 724,586 | 722,006 | 724,586 | 724,532 | 722,006 | 722,006 | 722,006 |

This table reports results for regressions of the form

$$\log(\text{Bid-Ask spread}_{i,t,j}) = \alpha_j + \gamma_i + \delta_j + \beta \log(CDS_{i,t}) + \zeta' X_{it} + \varepsilon_{i,j,t}$$

where Bid-Ask spread$_{i,j,t}$ denotes the daily average relative bid-ask spread (average of bid-ask spread divided by midquote and in basis points) quoted by player $i$ on day $t$ for currency $j$, $CDS_{i,t}$ is the CDS premium (in percentage points) associated to player $i$ at time $t$. The point estimates are reported along with their t-stat. All standard errors are triple-clustered by time, currency and intermediary. In the case of currency by time fixed effect, the standard errors are double clustered. **,* indicates coefficient is statistically different than zero at the 5 percent and 10 percent confidence level, respectively. $\overline{R}^2$ denotes the adjusted regression $R^2$. The frequency is daily and the panel dataset which is unbalanced spans from January 2004 to December 2015.

#### 3.5.1.2. Financial Distress and Competition

In this section, I am interested in testing how competition among dealers make them more vulnerable in the way they quote bid-ask spreads when they are financially constrained. In other words, when the competition is intense among dealers, does a more constrained intermediary quote larger bid-ask spreads? The measure of competition I consider is given by:

$$\text{Conc}_{j,t} = \frac{1}{Nbanks_{j,t}}$$

where $Nbanks_{j,t}$ corresponds to the number of financial intermediaries quoting in the FX market for currency $j$ on day $t$. The higher $Conc_{j,t}$, the higher the competition in the market since the lower the number of dealers present. By construction, this variable is bounded between 0 and 1.[14] Table 3.3 shows the results of regression 3.2 with the competition measure mentioned above.

[14] Likewise for the volatility control variable in the previous section, I decide to normalize $\text{Conc}_{j,t}$ by $\overline{\text{Conc}_j}$ its over time mean, currency by currency.

Table 3.3: Effect of Financial Distress on Quoted Bid-Ask Spreads: the Role of Competition

| Dep. Variable | log(Bid-Ask spread$_{i,t,j}$) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\log(CDS_{i,t})$ | -0.022 | -0.056 | -0.064 | -0.071 |
| | (-0.40) | (-0.95) | (-1.13 ) | (-1.25) |
| $\text{Conc}_{j,t}$ | -0.14 | Omitted | | |
| | (-0.23) | since Red. | | |
| $\log(CDS_{i,t}) \times \text{Conc}_{j,t}$ | 0.041** | 0.065** | | |
| | ( 2.29 ) | (2.50) | | |
| $\log(CDS_{i,t}) \times \mathbb{1}_{\text{Conc}_{j,t} \geq \text{Conc}^{75\%}_{j,t}}$ | | | 0.064** | |
| | | | (2.29) | |
| $\log(CDS_{i,t}) \times \mathbb{1}_{\text{Conc}_{j,t} \geq \text{Conc}^{90\%}_{j,t}}$ | | | | 0.062** |
| | | | | (2.42) |
| Intermediary FE | Yes | Yes | Yes | Yes |
| Time, Currency FE | Yes | No | No | No |
| Time $\times$ Currency FE | No | Yes | Yes | Yes |
| $\bar{R}^2$ | 72.01 | 76.29 | 77.43 | 76.86 |
| Nobs | 724,586 | 722,006 | 722,006 | 722,006 |

This table reports results for regressions of the form

$$\log(\text{Bid-Ask spread}_{i,t,j}) = \alpha_j + \gamma_i + \delta_j + \beta \log(CDS_{i,t}) + \zeta' X_{it} + \varepsilon_{i,j,t}$$

where Bid-Ask spread$_{i,j,t}$ denotes the daily average relative bid-ask spread (average of bid-ask spread divided by midquote and in basis points) quoted by player $i$ on day $t$ for currency $j$, $CDS_{i,t}$ is the CDS premium (in percentage points) associated to player $i$ at time $t$. The point estimates are reported along with their t-stat. All standard errors are triple-clustered by time, currency and intermediary. In the case of currency by time fixed effect, the standard errors are double clustered. **,* indicates coefficient is statistically different than zero at the 5 percent and 10 percent confidence level, respectively. $\overline{R}^2$ denotes the adjusted regression $R^2$. The frequency is daily and the panel dataset which is unbalanced spans from January 2004 to December 2015.

As shown previously, the financial condition of the intermediary does not have any impact on the bid-ask spread quoted in general. However, when the log of the CDS spread is interacted with my competition measure, there is some variation in the bid-ask spread depending on the intermediary financial condition. Columns (1) and (2) only differ in the choice of fixed effects considered. This interesting result holds even when I introduce currency-time fixed effects, suggesting that such a feature is relatively robust. The fact that *only* when market competition is low, intermediaries which temporarily face more difficult financial conditions tend to quote wider bid-ask spreads is not easy to interpret. One way to explain it can be that when the competition is less intense, discrimination between dealers in terms of their financial condition can occur. Two reasons can explain why there seems to be no effect of financial condition on bid-ask spreads when the competition is high: when hit by a large shock, dealers can either be forced to quote narrow spreads, at least narrower spreads than what they would optimally quote, due to the competitive pressure or they might decide not to quote at all and be excluded from the market. In other words, if there are more dealers present in the market, it is more difficult for a financially distressed intermediary to quote larger bid-ask spreads. Since all my results so far have been conditional on the fact that the dealer quotes in the market at time $t$, the effect I try to measure here might therefore be underestimated overall if dealers decide not to participate in the market if competition is intense. The next section tries to answer this question by looking at the probability that a dealer which usually quotes in the market is still present in the days following a deterioration of its financial situation.

### 3.5.2. Market Exit and Financial Distress

This section tries to test whether if a financial intermediary which experiences a shock to its financial situation, measured through a shock occurring to its CDS spread tends to not quote in the market the following day. Let me first explain the measure of intermediary financial shock I consider here and then I will explore the different results.

#### 3.5.2.1. Measure of shock to financial condition

In the same vein as in He *et al.* (2017), I construct the intermediary financial shock hitting intermediary $i$ at time $t$, denoted $z_{i,t}$, as follows. I estimate it as the innovation in the auto-regression

Table 3.4: Probability of Entry and Exit

| State at time $t-1$ | Probability of quoting at time $t$ | Nobs |
|---|---|---|
| Quote | 88.8% | 751,355 |
| No Quote | 7.90% | 665,252 |

This table reports the probability of quoting in the market at time $t$ depending on whether the financial intermediary quoted at time $t-1$. Here, only the observations for which the variable Treatment$_{i,t}$, which means that only the observations for which a CDS value is available at time $t-1$ and time $t$.

applied to the log of CDS in levels,

$$\log(CDS_{i,t}) = \mu_i + \rho_i \log(CDS_{i,t}) + z_{i,t}$$

This innovation term can be seen as the shock to the probability of default to the intermediary at the holding company level. Then, I assign a value 0 to the variable Treatment$_{i,t}$ if the shock is below a certain threshold (in the baseline scenario when it is below its median) and 1 if it is above, therefore when the intermediary experiences a negative financial shock. The observations for which Treatment$_{i,t} = 1$ can be considered as "treated" observations in the view of the randomized controlled trial literature.

#### 3.5.2.2. Exit and Financial Distress

In the sample, there are some financial intermediaries which quote at time $t-1$ but do not quote in the market at time $t$. The idea is to see whether a bank decides not to quote the next day if it has experienced a large financial shock, in the sense of the one described in the previous section or not.

Table 3.4 reports the summary statistics about the probability for a financial intermediary to quote in the FX at time $t$ conditional on the fact that the same financial intermediary quoted or not at time $t-1$. These statistics show how stable the quoting behavior is: when a dealer quotes in the FX market, there is an extremely high probability that she will quote the following day, as well. Such a finding suggests that the financial condition of a dealer seems not to matter for her quoting decision.

To test whether a deterioration in a dealer's financial condition lead her to stop quoting in the FX market, I run the following regression:

$$\pi_{i,j,t} = \mu_{jt} + \gamma_i + \beta \text{Treatment}_{i,t} + \varepsilon_{i,j,t} \tag{3.3}$$

where $\mu_{j,t}$ and $\gamma_i$ are the previously mentioned time-currency and intermediary fixed effects, $\pi_{i,j,t} \in \{0,1\}$ is the binary outcome which takes value 1 if intermediary $i$ quotes on day $t$ for currency $j$, $\text{Treatment}_{i,t} \in \{0,1\}$ is the treatment variable which takes 1 if intermediary is hit by a shock, $z_{i,t}$, greater than a certain percentile. I considered three different levels of percentiles, 50%, 75% and 90%, to measure the different effects depending on the severity of the shock.

A significant large financial shock hitting an intermediary does not prevent it from quoting in the market. Indeed, the results in Table 3.5 show that a dealer whose holding company is hit by a negative financial shock does not have less probability to quote in the FX market than any other competitor whose financial condition did not deteroriate. The parameter of interest in the previous regression, $\beta$, is never significant. It is even the case when I make the distinction between developed and emerging countries (see Table 3.12 in the Appendix). The main argument given in the previous section to explain why when there is intense competition there is no evidence that more financially constrained intermediaries tend to quote larger bid-ask spreads, which was that when there is too much competition, these dealers tend to be excluded from the market seems not to hold.

### 3.5.3. Do financially distressed intermediaries tend to quote more often?

So far, this chapter has not provided some strong evidence that dealers who are more financially constrained tend to change the way they quote in the FX market.

I analyze another variable of adjustment that dealers can use to change their behavior, namely the frequency at which they quote. For every day and every currency, I count the number of quotes posted by each financial intermediary. I then divide it by the number of desks that each financial intermediary has in order to avoid misleadingly inflating the number of quotes posted by each financial intermediary if it has a large number of desks.

I then estimate a panel regression similar to the one implemented in to determine the effect of

Table 3.5: Effect of Financial Distress on Market Exit

| Dep. Variable | | $\pi_{i,t,j}$ | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\text{Treatment}_{i,t}^{50\%}$ | 0.002 | | |
| | (1.21) | | |
| $\text{Treatment}_{i,t}^{75\%}$ | | 0.002 | |
| | | (1.16) | |
| $\text{Treatment}_{i,t}^{90\%}$ | | | .0003 |
| | | | (0.01) |
| Intermediary FE | Yes | Yes | Yes |
| Time $\times$ Currency FE | Yes | Yes | Yes |
| $\bar{R}^2$ | 15.72 | 15.83 | 15.54 |
| Nobs | 716,957 | 716,957 | 716,957 |

This table reports results for regressions of the form

$$\pi_{i,j,t} = \mu_{jt} + \gamma_i + \beta \text{Treatment}_{i,t} + \varepsilon_{i,j,t}$$

where $\mu_{j,t}$ and $\gamma_i$ are the previously mentioned time-currency and intermediary fixed effects, $\pi_{i,j,t} \in \{0,1\}$ is the binary outcome which takes value 1 if intermediary $i$ quotes on day $t$ for currency $j$, $\text{Treatment}_{i,t} \in \{0,1\}$ is the treatment variable which takes 1 if intermediary is hit by a shock, $z_{i,t}$, greater than a certain percentile. The point estimates are reported along with their t-stat. All standard errors are double clustered. **,* indicates coefficient is statistically different than zero at the 5 percent and 10 percent confidence level, respectively. $\overline{R}^2$ denotes the adjusted regression $R^2$. The frequency is daily and the panel dataset which is unbalanced spans from January 2004 to December 2015.

financial distress on quoting frequency:

$$\text{Number of Quotes}_{i,t,j} = \alpha_j + \gamma_i + \delta_j + \beta \log(CDS_{i,t}) + \varepsilon_{i,j,t} \tag{3.4}$$

with the usual fixed effects mentioned previously. The parameter of interest is $\beta$.

Table 3.6: Effect of Financial Distress on Quoting Frequency

| Dep. Variable | log(Bid-Ask spread$_{i,t,j}$) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\log(CDS_{i,t})$ | | 597.7** | 513.86 ** | 651.2** |
| | | (2.11) | ( 2.00) | (2.00) |
| $\log(CDS_{i,t}) \times \mathbb{1}_{\text{Emerging}}$ | | | | -290.7 |
| | | | | -0.84 |
| Intermediary FE | Yes | Yes | Yes | Yes |
| Time, Currency FE | Yes | Yes | No | No |
| Time × Currency FE | No | No | Yes | Yes |
| $\bar{R}^2$ | 33.4 | 35.3 | 37.8 | 37.1 |
| Nobs | 978,261 | 724,735 | 724,586 | 24,586 |

This table reports results for regressions of the form

$$\text{Number of Quotes}_{i,t,j} = \alpha_j + \gamma_i + \delta_j + \beta \log(CDS_{i,t}) + \zeta' X_{it} + \varepsilon_{i,j,t}$$

where Bid-Ask spread$_{i,j,t}$ denotes the daily average relative bid-ask spread (average of bid-ask spread divided by midquote and in basis points) quoted by player $i$ on day $t$ for currency $j$, $CDS_{i,t}$ is the CDS premium (in percentage points) associated to player $i$ at time $t$. The point estimates are reported along with their t-stat. All standard errors are triple-clustered by time, currency and intermediary. In the case of currency by time fixed effect, the standard errors are double clustered. **,* indicates coefficient is statistically different than zero at the 5 percent and 10 percent confidence level, respectively. $\overline{R}^2$ denotes the adjusted regression $R^2$. The frequency is daily and the panel dataset which is unbalanced spans from January 2004 to December 2015.

The results displayed in Table 3.6 sheds light on a salient feature of the FX market. A financial intermediary which experiences some financial distress in the sense that its CDS is high, has the tendency to quote much more often than the average of the others players in the market (see Column(2)). Such a finding is extremely strong since even controlling for time by currency fixed effect, the point estimate is statistically and economically significant: for every 1% increase in a CDS spread, a dealer quotes approximately 600 more times than the average dealer in the market. I have shown in section 3.5.1. that more financially distressed intermediaries do not tend to quote narrower bid-ask spreads. An increase in her CDS spread does not make a dealer more competitive in terms of transaction costs, therefore there is no reason for her to adjust more often her quotes because a transaction hits one side of her book. Such a behavior might potentially find an explanation in the rational inattention literature (see Sims (2003) and Sims (2006) for the most representative papers on this topic). Given a fixed cost of attention common to every dealer, the loss function that each FX player tries to minimize, like in any rational inattention model, could be increasing in the level of financial distress this dealer is. As a result, a more financially distressed dealer would have more incentives to pay the price of "being attentive" and consequently adjusts her quotes more often, every time she receives some new information from the market or from outside the market. I intend to explore this direction more formally in the future.

# 3.6. Segmented intermediary asset pricing

In this section, I explore how the financial conditions of FX intermediaries can explain the exchange rate dynamics. I first introduce the measure of currency-specific *intermediary financial distress*. I then test whether or not adding this new variable can explain both the level and the volatility of the idiosyncratic component of the currency risk premium.

## 3.6.1. Measure of currency-specific intermediary financial distress

Based on the detailed information contained in my FX database, and in particular about the identity of the financial intermediaries present in each spot market, I build a currency specific time-varying measure of *intermediary financial distress*, denoted $\kappa_{j,t}$ as the average of the CDS spreads of the financial intermediaries quoting on day $t$ for the currency $j$:

$$\kappa_{j,t} = \frac{1}{|\Omega_{j,t}|} \sum_{i \in \Omega_{j,t}} CDS_{i,j,t} \tag{3.5}$$

where $\Omega_{j,t}$ is the set of intermediaries quoting on day $t$ for currency $j$ and $|\Omega_{j,t}|$, the cardinality of this set.

Figure 3.5 plots the time series of the *financial distress* measure and without any surprise these time series comove a lot. The average correlation is 0.95.

Moreover, I also construct an *dispersion* measure, denoted $\nu_{i,t}$ and which tries to capture some higher-order moments (in reality the second-one) of the distribution of intermediary financial conditions:

$$\nu_{j,t} = \sqrt{\frac{1}{|\Omega_{j,t}|} \sum_{i \in \Omega_{j,t}} (CDS_{i,j,t} - \kappa_{j,t})^2} \tag{3.6}$$

### 3.6.2. Financial Distress and Currency Risk Premium

#### 3.6.2.1. Does average intermediary financial distress explain the idiosyncratic component of currency risk premium?

Building upon the empirical framework proposed by Verdelhan (2018), I run the weekly time-series regressions of exchange rate changes on the factors and change in the previously introduced *intermediary financial distress* measure, separately for each currency $j$:

$$\Delta s_{j,t+1} = \alpha + \beta(i^*_{j,t} - i_t) + \gamma(i^*_{j,t} - i_t)\text{Carry}_{j,t+1} + \delta\text{Carry}_{j,t+1} + \tau\text{Dollar}_{j,t+1} + \psi\Delta\kappa_{j,t+1} + \varepsilon_{t+1} \tag{3.7}$$

where $\Delta s_{j,t+1}$ denotes the bilateral exchange rate in U.S. dollar per foreign currency $j$, $(i^*_{j,t} - i_t)$ is the interest rate differential between foreign country $j$ and the U.S., $\text{Carry}_{j,t+1}$ denotes the dollar-neutral average exchange rate change obtained by going long a basket of high interest rate currencies and short a basket of low interest rate currencies (excluding currency $j$ itself), $\text{Dollar}_{j,t+1}$ corresponds to the average change in exchange rates against the U.S. dollar (except for currency $j$ itself).

Table 3.13 in Appendix reports the results of regression 3.7 run at the weekly frequency. In these tables, $R^2$ denotes the adjusted regression $R^2$, $R^2_{FS}$ denotes the adjusted $R^2$ from a regression of exchange rates on the carry and dollar factors. Clearly, this new factor, the *intermediary financial distress* does not have any power in explaining the exchange rate dynamics after controlling for global shocks, embedded in the factor structure. The coefficient $\psi$ is never statistically different from 0 except for two currencies, INR and HKD. This is consistent with the findings of He *et al.* (2017) who does not find strong evidence that financial intermediary capital ratio is correlated with returns on the 6 currency portfolios sorted on the interest rate differential proposed by Lettau *et al.* (2014) and on the 6 currency portfolios sorted on momentum from Menkhoff *et al.* (2012).

#### 3.6.2.2. Financial distress and volatility of the currency risk premium idiosyncratic component

In this subsection, I extract first the underlying volatility process of the idiosyncratic component of the currency risk premium. More specifically, the ultimate goal is to measure the volatility, $\sigma_{j,t}$ of the residuals $\varepsilon_{j,t}$, corresponding to the residuals from the regression which consists in regressing the change in the log of exchange rates on the factor structure. These residuals correspond to the idiosyncratic component of the currency risk premium.
I estimate the volatility time series for each currency $j$ assuming that it follows a standard GARCH(1,1) process. I denote this estimated volatility by $\hat{\sigma}_{j,t}$. To quantify the link between intermediary financial distress and volatility of the the currency risk premium idiosyncratic component, I then run the simple regression of

$$\log \hat{\sigma}_{j,t} = \alpha + \rho \log \hat{\sigma}_{j,t-1} + \theta \kappa_{j,t} + \eta_{j,t}$$

where I use log values to avoid potential econometric issues stemming from the fact that $\hat{\sigma}_{j,t}$ for each currency $j$. I run a similar regression and consider the measure of *financial distress dispersion*, $\nu_{j,t}$ introduced previously as the explanatory variable.

Tables 3.7 and 3.8 report the main results for these two regressions run currency by currency. Apart from the fact that the volatility process displays a strong autocorrelation, the results shed light on an interesting feature of the FX market. The financial distress of the intermediaries quoting in a market seems to have some explanatory power with respect to the evolution of the volatility of the idiosyncratic component of exchange rate dynamics. The $\theta$ coefficient is statistically significant at 5% for the majority (7 out of 11) of emerging country currencies. More surprisingly, my *financial distress dispersion* measure is significantly correlated with the volatility process at the 10% level in 8 out of 11 cases for emerging country currencies, highlighting the importance of the variance in terms of intermediary financial situation in a market to explain the evolution of the quantity of idiosyncratic risk associated to exchange rate dynamics.

Table 3.7: Financial Distress and Currency Risk Premium Volatility

This table reports results from regressions of the form:

$$\log \hat{\sigma}_{j,t} = \alpha + \rho \log \hat{\sigma}_{j,t-1} + \theta \kappa_{j,t} + \eta_{j,t}$$

where $\log \hat{\sigma}_{j,t}$ denotes the estimated volatility of the idiosyncratic component of the currency risk premium and $\kappa_{j,t}$ (in bps), the *intermediary financial distress* measure. $\overline{R}^2$ denotes the adjusted regression $R^2$. The estimated coefficient $\theta$ is multiplied by 10000 and all the standard errors are robustly estimated according to the Newey-West procedure.

| | $\rho$ | $\theta$ | $\overline{R}^2$ | $N$ |
|---|---|---|---|---|
| | **Panel A: G10 Currencies** | | | |
| AUD | 0.92 | 0.09 | 0.85 | 543 |
| | (47.31) | (0.19) | | |
| CAD | 0.98 | -0.35 | 0.96 | 515 |
| | (122.50) | (-1.26) | | |
| CHF | 0.95 | 0.85 | 0.89 | 541 |
| | (78.44) | (0.86) | | |
| EUR | 0.94 | 3.38 | 0.92 | 543 |
| | (65.04) | (2.46) | | |
| GBP | 0.95 | -0.16 | 0.91 | 543 |
| | (52.85) | (-0.30) | | |
| JPY | 0.94 | 0.92 | 0.90 | 543 |
| | (75.75) | (1.69) | | |
| NOK | 0.95 | 0.37 | 0.90 | 542 |
| | (67.50) | (0.81) | | |
| NZD | 0.97 | -0.17 | 0.94 | 543 |
| | (119.03) | (-0.89) | | |
| SEK | 0.96 | 0.93 | 0.93 | 543 |
| | (95.04) | (1.63) | | |
| | **Panel B: Other Currencies** | | | |
| BRL | 0.89 | 1.19 | 0.79 | 527 |
| | (38.81) | (2.01) | | |
| HKD | 0.96 | 0.12 | 0.92 | 541 |
| | (88.36) | (1.08) | | |
| ILS | 0.97 | 0.42 | 0.95 | 542 |
| | (106.17) | (2.49) | | |
| INR | 0.95 | 2.56 | 0.94 | 533 |
| | (65.30) | (2.58) | | |
| KRW | 0.96 | 1.98 | 0.94 | 514 |
| | (76.50) | (1.42) | | |
| MXN | 0.93 | 1.52 | 0.88 | 539 |
| | (69.86) | (1.77) | | |
| MYR | 0.72 | 4.47 | 0.56 | 458 |
| | (19.89) | (2.74) | | |
| RUB | 0.94 | 6.84 | 0.95 | 519 |
| | (42.19) | (1.98) | | |
| SGD | 0.90 | 2.04 | 0.86 | 542 |
| | (48.40) | (2.83) | | |
| TRY | 0.93 | 2.43 | 0.86 | 528 |
| | (56.99) | (1.78) | | |
| ZAR | 0.97 | 3.66 | 0.94 | 537 |
| | (131.50) | (2.13) | | |

Table 3.8: Financial Distress Dispersion and Currency Risk Premium Volatility

This table reports results from regressions of the form:

$$\log \hat{\sigma}_{j,t} = \alpha + \rho \log \hat{\sigma}_{j,t-1} + \theta \nu_{j,t} + \eta_{j,t}$$

where $\log \hat{\sigma}_{j,t}$ denotes the estimated volatility of the idiosyncratic component of the currency risk premium and $\nu_{j,t}$ (in bps), the *dispersion* measure mentioned previously. $\overline{R}^2$ denotes the adjusted regression $R^2$. The estimated coefficient $\theta$ is multiplied by 10000 and all the standard errors are robustly estimated according to the Newey-West procedure.

| | $\rho$ | $\theta$ | $\overline{R}^2$ | $N$ |
|---|---|---|---|---|
| | **Panel A: G10 Currencies** | | | |
| AUD | 0.92 | -0.24 | 0.85 | 543.00 |
| | (47.27) | (-0.32) | | |
| CAD | 0.98 | -0.89 | 0.96 | 515.00 |
| | (116.21) | (-1.87) | | |
| CHF | 0.95 | 0.59 | 0.89 | 541.00 |
| | (83.60) | (0.52) | | |
| EUR | 0.94 | 3.11 | 0.92 | 543.00 |
| | (55.81) | (1.80) | | |
| GBP | 0.95 | -0.43 | 0.91 | 543.00 |
| | (53.19) | (-0.92) | | |
| JPY | 0.95 | 0.30 | 0.90 | 543.00 |
| | (78.52) | (0.67) | | |
| NOK | 0.95 | 0.01 | 0.90 | 542.00 |
| | (68.07) | (0.02) | | |
| NZD | 0.97 | -0.20 | 0.94 | 543.00 |
| | (121.12) | (-1.12) | | |
| SEK | 0.97 | 0.42 | 0.93 | 543.00 |
| | (101.68) | (0.75) | | |
| | **Panel B: Other Currencies** | | | |
| BRL | 0.89 | 1.61 | 0.79 | 527 |
| | (38.83) | (1.48) | | |
| HKD | 0.96 | 2.35 | 0.92 | 541 |
| | (87.35) | (2.22) | | |
| ILS | 0.97 | 1.47 | 0.95 | 542 |
| | (89.13) | (0.68) | | |
| INR | 0.95 | 3.81 | 0.93 | 533 |
| | (68.68) | (2.13) | | |
| KRW | 0.96 | 3.52 | 0.94 | 514 |
| | (50.50) | (2.26) | | |
| MXN | 0.93 | 1.88 | 0.88 | 539 |
| | (68.31) | (1.83) | | |
| MYR | 0.73 | 7.80 | 0.56 | 458 |
| | (19.76) | (2.00) | | |
| RUB | 0.95 | 6.96 | 0.94 | 519 |
| | (49.27) | (1.92) | | |
| SGD | 0.88 | 4.34 | 0.86 | 542 |
| | (41.38) | (2.95) | | |
| TRY | 0.93 | -0.21 | 0.86 | 528 |
| | (56.86) | (-0.33) | | |
| ZAR | 0.97 | 2.11 | 0.94 | 537 |
| | (127.30) | (1.72) | | |

## 3.7. Conclusion

Using a tick-by-tick dealer-specific quotes database on the foreign exchange (FX) market, this chapter explores how cross-sectional variations in intermediary financial conditions, measured through financial intermediary's CDS spreads, may impact dealer quoting behavior in a differential way. More specifically, this chapter tests whether a financial intermediary experiencing an idiosyncratic deterioration in its financial condition does or does not quote differently from its competitors. In an nutshell, I show that an increase in a dealer's CDS spread does not lead her to adopt a different behavior compared to the rest of the cohort in general, except that she has the tendency to quote more frequently.

From this micro dataset, I then build a time-varying measure of currency-specific intermediary financial distress by computing the average CDS spread of the different dealers quoting in the market for each currency each day. Even if the change in this *financial distress* measure is not correlated with the idiosyncratic shock observed in exchange rate returns, the one obtained after controlling for global shocks, I show that at least for emerging countries, its level explains the magnitude of this shock volatility for emerging country currencies. More surprisingly, variation in terms of financial conditions across financial intermediaries quoting in the market is a good predictor for the shock volatility of a large set of emerging country currencies, suggesting that distributional effects are a key determinant of exchange rate dynamics, especially when market is characterized by a certain illiquidity. My empirical strategy relies on the fact that there does not exist a single representative intermediary common to all FX spot markets but rather several, one for each FX market segment. I therefore introduce the notion of *segmented intermediary asset pricing.*

## 3.8. Appendix

Table 3.9: Summary statistics for CDS (in basis points) by currency. All the statistics are computed currency by currency over the whole sample for which both CDS and foreign exchange data for each single-name entity is available. The autocorrelation statistics, $\rho$ is computed according to the following panel regression: $CDS_{i,t} = \alpha_i + \rho CDS_{i,t-1} + \varepsilon_{i,t}$, where $\alpha_i$ is a financial intermediary fixed effect. The cross-section volatility statistics corresponds to the volatility of the residuals, $\varepsilon_{i,t}$ extracted from the following panel regression: $CDS_{i,t} = \alpha_t + \varepsilon_{i,t}$, where $\alpha_t$ is a time fixed effect.

| Currency | Mean | Standard Deviation | Auto-Correlation | Median | Cross-Section Volatility | Quantiles | | | | | | | Min | Max | Nobs |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 1% | 5% | 25% | 75% | 90% | 95% | 99% | | | |
| AUD | 107.997 | 105.267 | 0.996 | 87.450 | 70.214 | 5.833 | 8.000 | 28.000 | 143.386 | 221.365 | 300.000 | 503.13 | 1.500 | 1239.095 | 51914 |
| BRL | 94.042 | 84.604 | 0.997 | 77.257 | 44.485 | 5.686 | 8.143 | 21.167 | 131.268 | 214.146 | 269.546 | 378.08 | 3.000 | 487.501 | 16888 |
| CAD | 103.854 | 99.533 | 0.995 | 85.810 | 67.476 | 5.156 | 8.000 | 26.686 | 136.692 | 209.081 | 283.675 | 480.84 | 1.500 | 950.000 | 42504 |
| CHF | 127.837 | 156.582 | 0.998 | 93.400 | 125.925 | 6.418 | 9.521 | 42.667 | 150.710 | 252.557 | 370.000 | 839.91 | 1.500 | 1796.200 | 54213 |
| EUR | 119.320 | 166.734 | 1.007 | 82.135 | 141.016 | 5.857 | 8.375 | 22.333 | 144.162 | 240.319 | 361.872 | 838.61 | 1.500 | 5952.870 | 78253 |
| GBP | 137.896 | 262.356 | 0.987 | 85.920 | 241.998 | 6.036 | 8.667 | 29.000 | 146.980 | 273.234 | 395.000 | 1201.69 | 1.500 | 8649.980 | 64879 |
| HKD | 115.376 | 145.779 | 0.998 | 86.845 | 115.641 | 5.188 | 8.000 | 24.917 | 142.044 | 232.354 | 319.600 | 724.51 | 3.000 | 1739.051 | 41067 |
| ILS | 99.363 | 81.390 | 0.997 | 83.911 | 43.891 | 5.047 | 9.000 | 38.500 | 136.838 | 201.586 | 250.244 | 360.56 | 3.964 | 665.532 | 13391 |
| INR | 134.962 | 115.784 | 0.997 | 103.720 | 85.989 | 6.350 | 9.643 | 55.500 | 187.845 | 300.000 | 361.820 | 526.38 | 4.222 | 1794.000 | 40107 |
| JPY | 107.784 | 133.230 | 0.999 | 81.447 | 105.884 | 6.000 | 8.281 | 22.840 | 137.500 | 212.660 | 305.000 | 667.25 | 1.500 | 1796.200 | 65678 |
| KRW | 70.830 | 66.562 | 0.997 | 65.000 | 38.991 | 6.500 | 8.665 | 18.825 | 93.309 | 139.847 | 172.120 | 356.81 | 4.222 | 665.532 | 8866 |
| MXN | 96.500 | 99.431 | 0.997 | 73.744 | 61.862 | 5.500 | 8.175 | 24.250 | 131.810 | 209.325 | 268.521 | 450.00 | 3.964 | 950.000 | 21430 |
| MYR | 98.500 | 69.988 | 0.996 | 88.380 | 43.861 | 6.500 | 10.111 | 59.835 | 127.325 | 180.000 | 222.995 | 341.13 | 4.375 | 665.532 | 17062 |
| NOK | 119.499 | 131.274 | 0.998 | 88.621 | 101.483 | 5.625 | 8.300 | 49.815 | 155.000 | 235.802 | 312.912 | 710.00 | 1.500 | 1796.200 | 34086 |
| NZD | 129.203 | 152.692 | 0.997 | 97.516 | 120.346 | 5.625 | 7.938 | 45.375 | 159.930 | 268.021 | 358.625 | 771.05 | 2.000 | 1739.051 | 41919 |
| RUB | 129.138 | 132.834 | 0.993 | 91.677 | 105.657 | 5.188 | 8.500 | 56.700 | 165.513 | 279.725 | 368.248 | 583.25 | 3.916 | 2225.000 | 15071 |
| SEK | 117.908 | 129.321 | 0.999 | 87.942 | 99.889 | 5.500 | 8.000 | 44.772 | 153.385 | 237.181 | 314.658 | 677.20 | 1.500 | 1796.200 | 36898 |
| SGD | 101.405 | 89.190 | 0.998 | 86.934 | 57.910 | 6.168 | 8.830 | 44.602 | 135.904 | 191.334 | 250.863 | 405.08 | 1.500 | 950.000 | 31160 |
| TRY | 142.702 | 185.872 | 0.998 | 97.000 | 151.730 | 6.000 | 7.571 | 26.250 | 179.883 | 302.955 | 400.275 | 1068.19 | 4.937 | 1739.051 | 22046 |
| ZAR | 123.856 | 169.117 | 0.998 | 82.088 | 129.606 | 5.862 | 8.111 | 24.300 | 157.480 | 258.300 | 350.000 | 947.31 | 4.089 | 1739.051 | 27303 |

Table 3.10: **Biggest players from the Bloomberg CDS database.** This table reports all the biggest foreign exchange players for which CDS data is available on Bloomberg. The entity code corresponds to the generic name given here in this chapter to a particular financial intermediary. The country columns reports the country (ISO code) in which the headquarters of the corresponding financial intermediary are located.

| Entity Code | Financial Intermediary | Country | Entity Code | Financial Intermediary | Country |
|---|---|---|---|---|---|
| ABN AMRO | ABN Amro | NLD | GOLDMAN SACHS | Goldman Sachs Group | USA |
| ADCB | Abu Dhabi Commercial Bank | UAE | HSBC | HSBC Holdings PLC | GBR |
| ALFA BANK | Alfa Group | RUS | HALYK BANK | Halyk Bank | KAZ |
| AIB | Allied Irish Banks | IRL | ICICI BANK | Industrial Credit and Investment Corporation of India | IND |
| ALPHA BANK | Alpha Bank | GRC | IDBI BANK | Industrial Development Bank of India | IND |
| AMERICAN EXPRESS | American Express | USA | ING | ING Group | NLD |
| AIG | AIG | USA | ICBC | Industrial and Commercial Bank of China | CHN |
| ANZ | Australia and New Zealand Group | AUS | BANCA INTESA | Banca Intesa | ITA |
| BBK | Bank of Bahrain and Kuwait | BHR | JPM CHASE | JPMorgan Chase | USA |
| BBVA BANCOMER | BBVA Bancomer | ESP | KBC | KBC Bank | BEL |
| BNP PARIBAS | BNP Paribas | FRA | KOOKMIN BANK | Kookmin Bank | KOR |
| BMPS | Banca Monte dei Paschi di Siena | ITA | LBBW | Landesbank Baden-Württemberg | DEU |
| BANCA NAZIONALE LAVORO | Banca Nazionale del Lavoro | ITA | LLOYDS BANK | Lloyds Bank | GBR |
| BANCA POPOLARE DE MILANO | Banca Popolare de Milano | ITA | MACQUARIE | Macquarie Group | AUS |
| BBVA | BBVA Bancomer | ESP | MERRILL LYNCH | Merrill Lynch | USA |
| BRADESCO | Brandesco | BRA | MIZUHO BANK | Mizuho Financial Group | JPN |
| BCP | Banco Comercial Portugues | PRT | MORGAN STANLEY | Morgan Stanley | USA |
| BANCO POPOLARE | Banco Popolare | ITA | NAB | National Australia Bank | AUS |
| BANCO POPULAR | Banco Popular Espanol | ESP | NATIXIS | Natixis | FRA |
| SANTANDER | Santander Group | ESP | NOMURA | Nomura | JPN |
| BANCO SABADELL | Banco de Sabadell | ESP | NORDEA | Nordea Bank | SWE |
| BANCO DO BRASIL | Banco do Brasil | BRA | PIRAEUS BANK | Piraeus Bank | GRC |
| BANK OF AMERICA | Bank of America | USA | WEST LB | West LB Bank | DEU |
| BANK OF CHINA | Bank of China | CHN | RBG | Raiffeisen Banking Group | AUT |
| BEA | Bank of East Asia | HKG | RBS | Royal Bank of Scotland | GBR |
| BANK INDIA | Bank of India | IND | SBERBANK | Sberbank | RUS |
| BANK IRELAND | Bank of Ireland | IRL | SHINHAN BANK | Shinhan Bank | KOR |
| BANK OF MOSCOW | Bank of Moscow | RUS | SHINSEI BANK | Shinsei Bank | NLD |
| BANK SCOTLAND | Bank of Scotland | GBR | SEB | Skandinaviska Enskilda Banken | SWE |
| BTMU | Bank of Tokyo and Mitsubishi | JPN | SOCGEN | Société Générale | FRA |
| BARCLAYS | Barclays | GBR | STANDCHART | Standard Chartered | GBR |
| BAYERN LB | Bayerische Landesbank | DEU | SBI | State Bank of India | IND |
| BEAR STERNS | Bear Sterns | USA | SMBC | Sumitomo Mitsui Banking Corporation | JPN |
| CTBC FINANCIAL HOLDING | CTBC Financial Holding | TWN | SUNCORP GROUP | Suncorp Group | AUS |
| CGD | Caixa Geral de Depositos | PRT | SVENSKA HANDELSBANKEN | Svenska Handelsbanken | SWE |
| CITIGROUP | Citigroup | USA | SWEDBANK | Swedbank | SWE |
| COMMERZBANK | Commerzbank | DEU | UBS | Union Bank of Switzerland | CHE |
| CBA | Commonwealth Bank of Australia | CBA | UNICREDIT GROUP | Unicredit Group | ITA |
| RABOBANK | Rabobank | NLD | VTB BANK | VTB Bank | RUS |
| CREDIT AGRICOLE | Crédit Agricole | FRA | WELLS FARGO | Wells Fargo | RUS |
| CREDIT SUISSE | Credit Suisse | CHE | WESTPAC | Western-Pacific | AUS |
| DNB NOR | Den Norkse Bank | NOR | YAPI KREDI | Yapi Kredi | TUR |
| DZ BANK | DZ Bank | DEU | BES BANK | Banco Espirito Santo | PRT |
| DANSKE BANK | Danske Bank | DNK | GAZPROMBANK | Gazprombank | RUS |
| DEUTSCHE BANK | Deutsche Bank | DEU | BTM | Bank of Tokyo and Mitsubishi | JPN |
| DEXIA | Dexia | BEL/FRA | SMTH | Sumitomo Mitsui Trust Holdings | JPN |
| ERSTE BANK | Erste Group | AUT | UOB | United Overseas Bank | SGP |
| EUROBANK ERGASIAS GROUP | Eurobank Ergasias Group | GRC | | | |

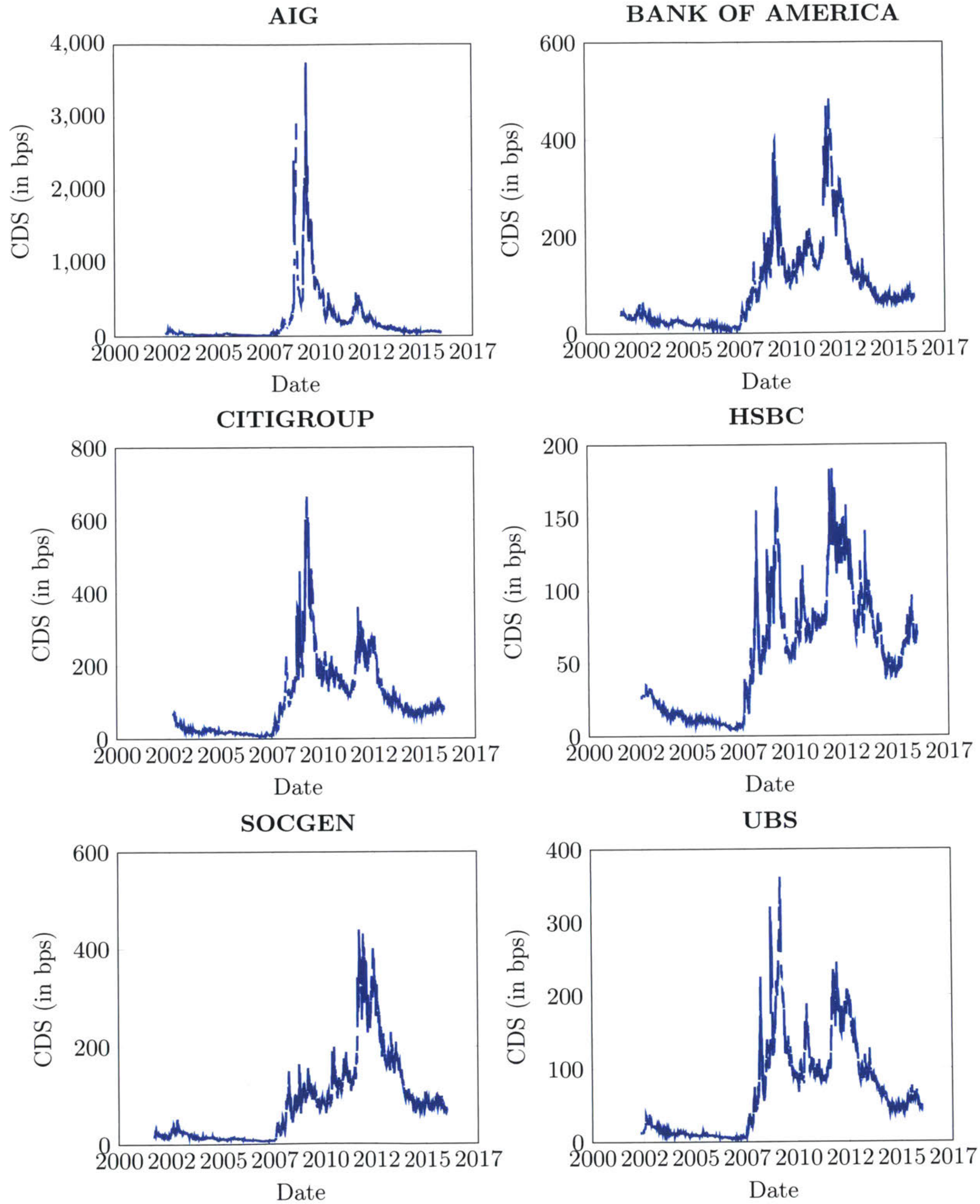



Figure 3.2: Financial Intermediary CDS Spreads (2000-2015).

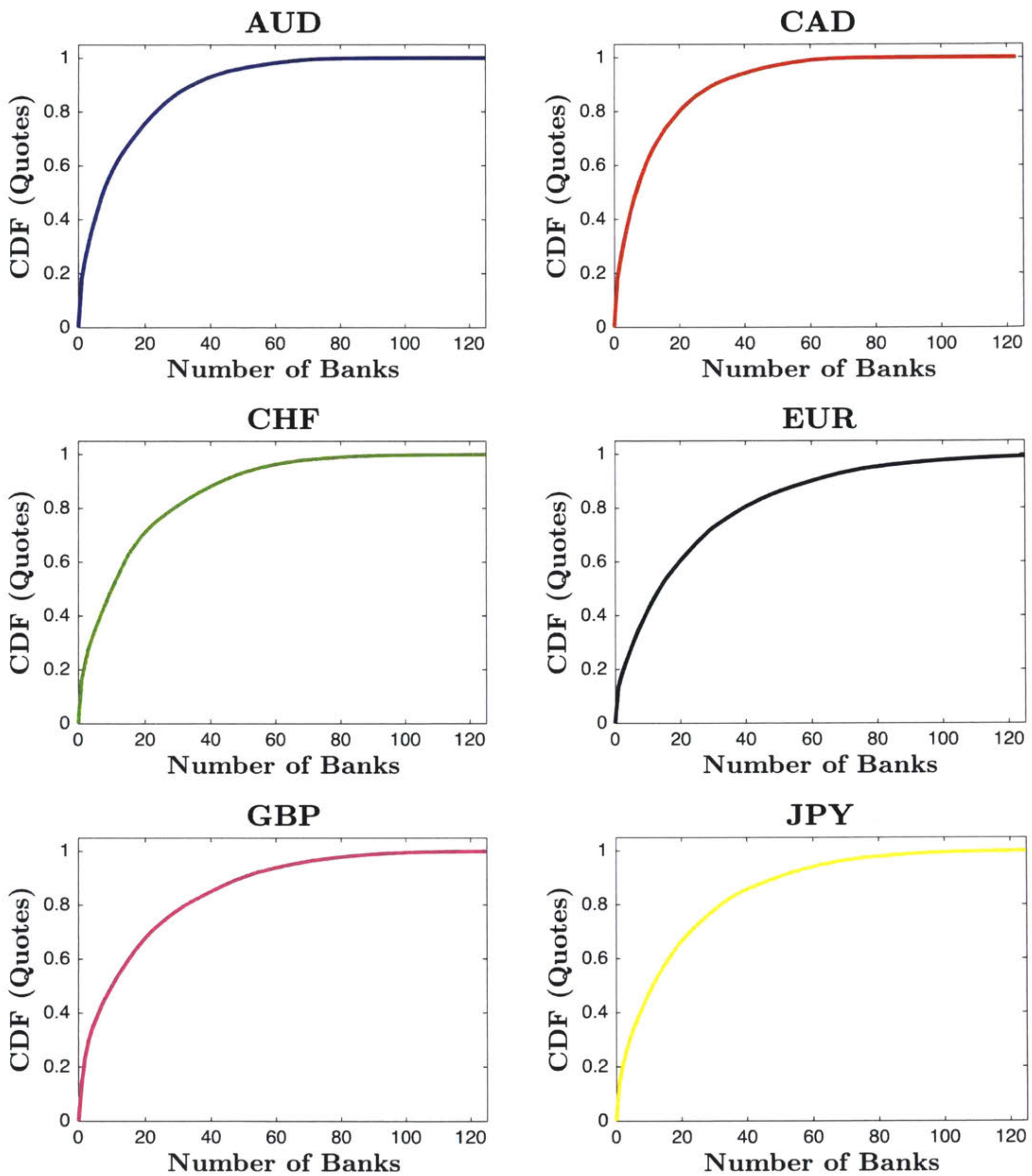



Figure 3.3: Market Quote Share (2000-2015), Developed Countries.

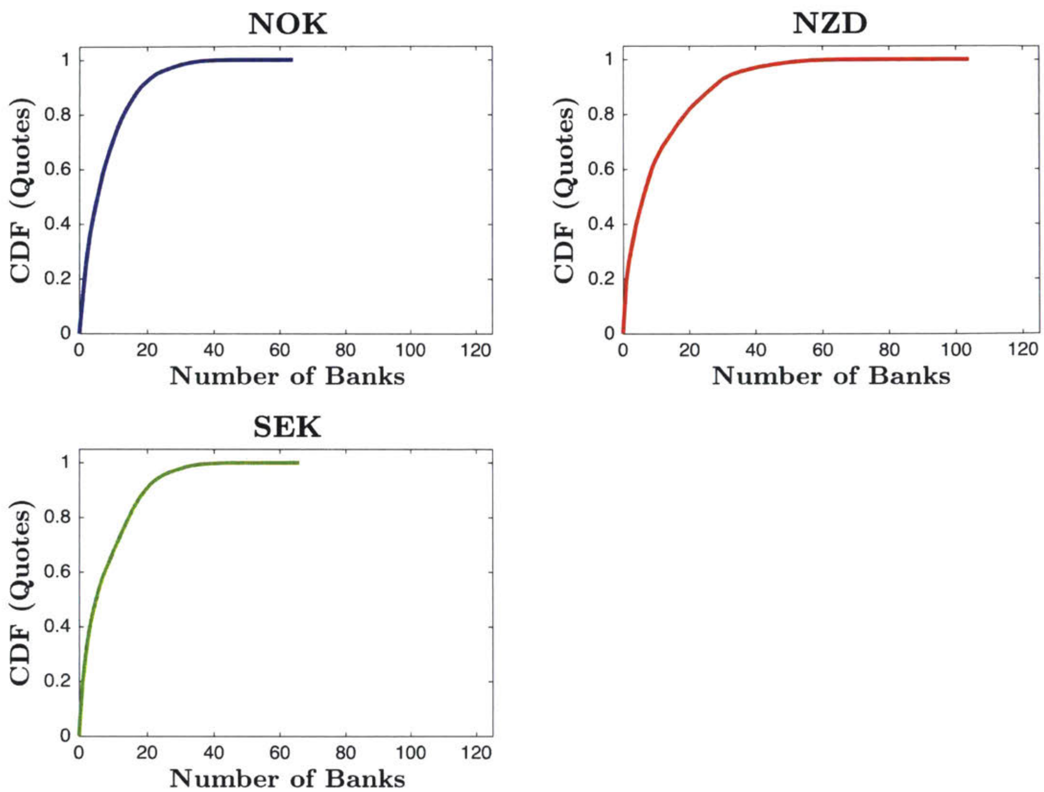



Figure 3.3: Market Quote Share (2000-2015), Developed Countries, Continued.

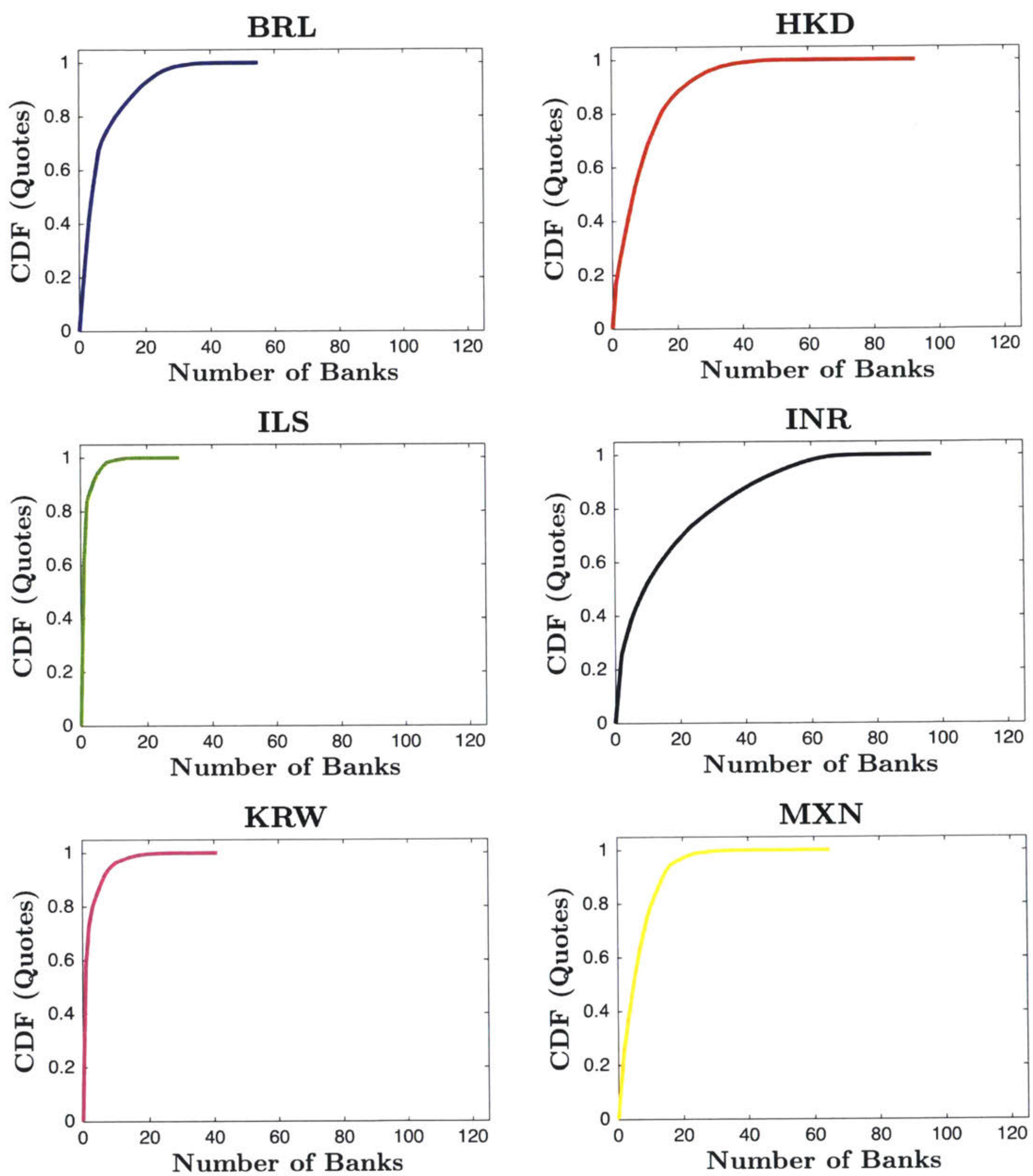



Figure 3.4: Market Quote Share (2000-2015), Emerging Countries.

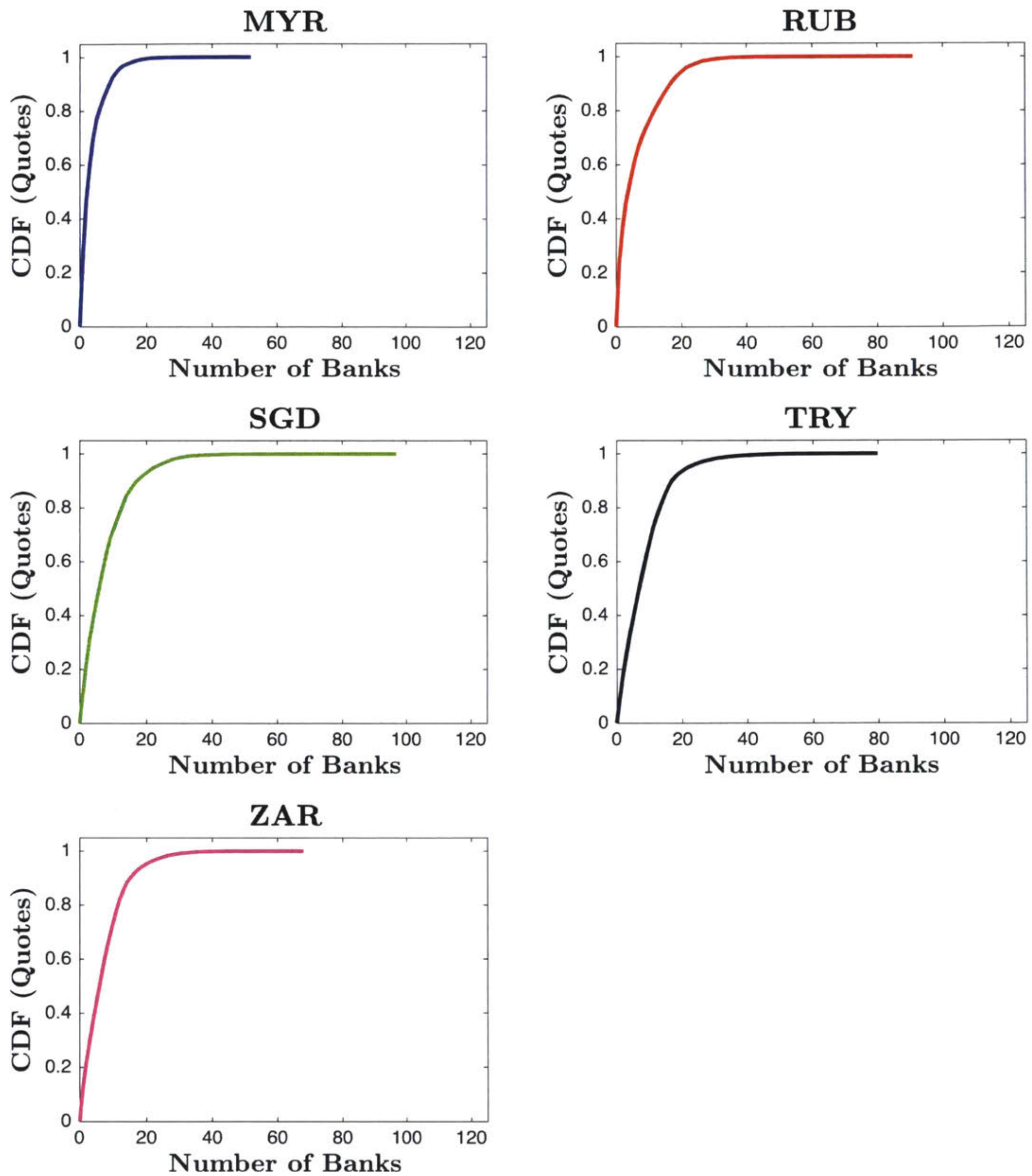



Figure 3.4: Market Quote Share (2000-2015), Emerging Countries, Continued.

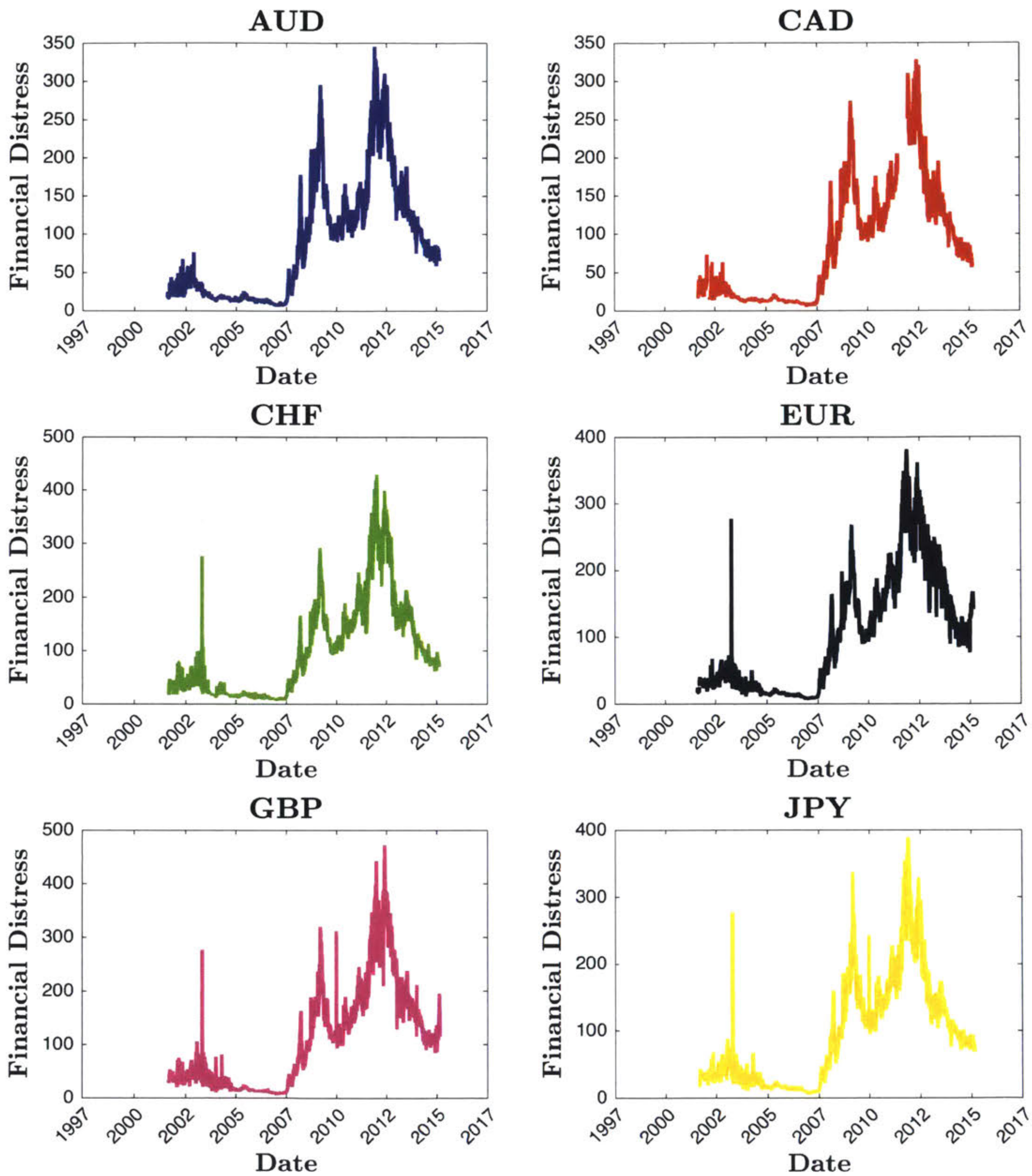



Figure 3.5: Financial Distress (2000-2015), Developed Countries. This figure plots the currency specific financial distress measure, $\kappa_{i,t} = \dfrac{1}{|\Omega_{i,t}|} \sum_{j \in \Omega_{i,t}} CDS_{i,j,t}$, introduced in Section 3.6.1.. This corresponds to the average of the CDS spreads of financial intermediaries quoting in the FX spot market for currency $i$.

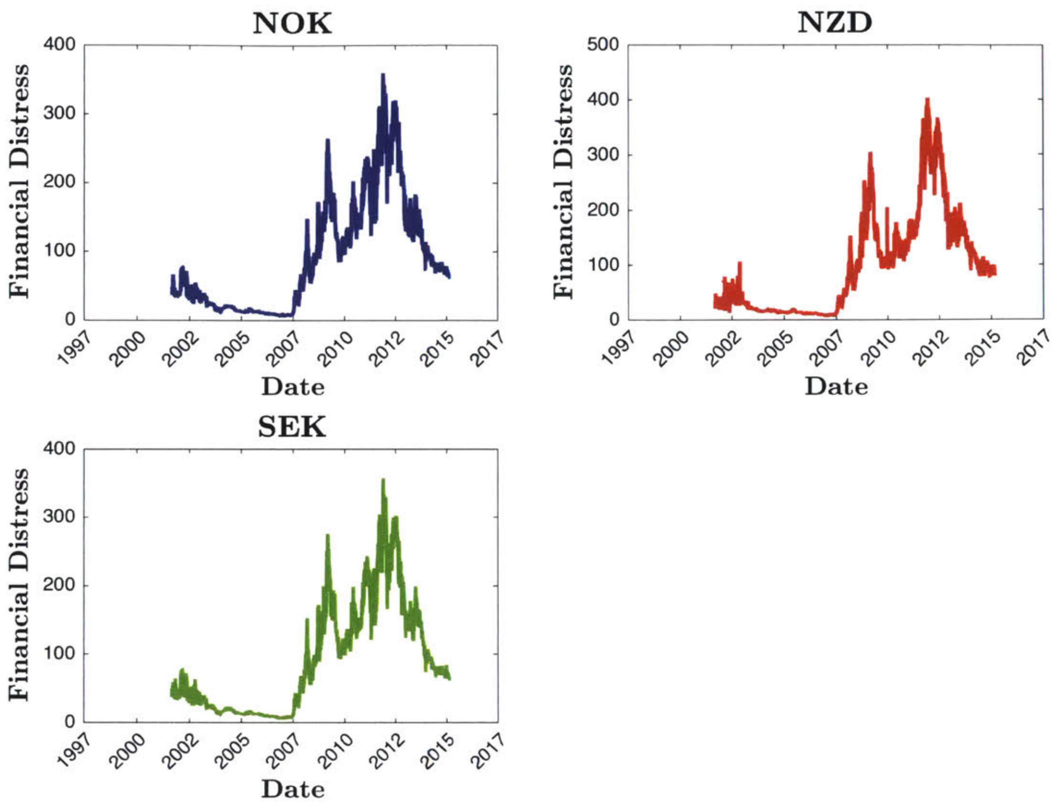



Figure 3.5: Financial Distress (2000-2015), Developed Countries, Continued. This figure plots the currency specific financial distress measure, $\kappa_{i,t} = \frac{1}{|\Omega_{i,t}|} \sum_{j \in \Omega_{i,t}} CDS_{i,j,t}$, introduced in Section 3.6.1.. This corresponds to the average of the CDS spreads of financial intermediaries quoting in the FX spot market for currency $i$.

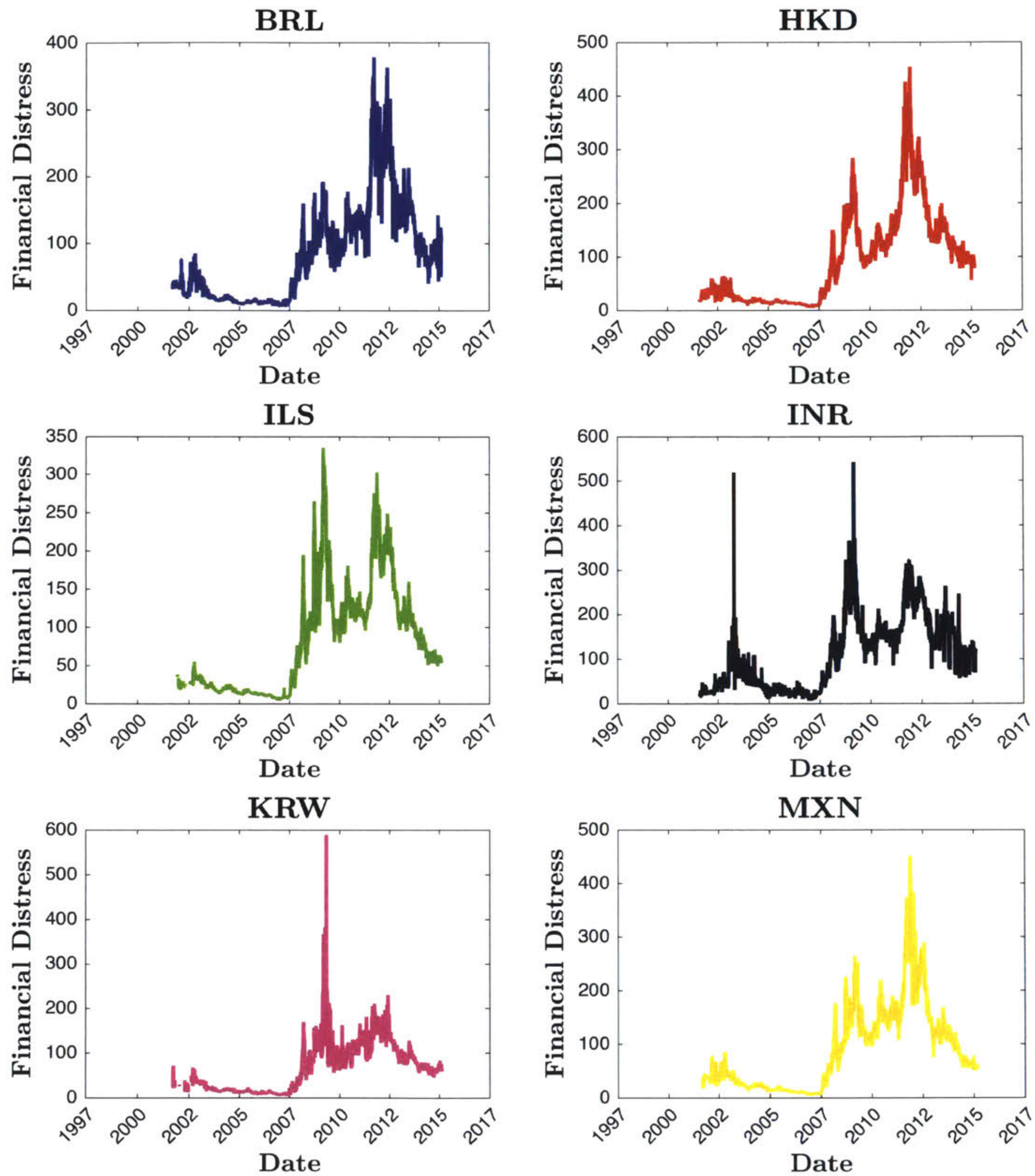



Figure 3.6: Financial Distress (2000-2015), Emerging Countries. This figure plots the currency specific financial distress measure, $\kappa_{i,t} = \frac{1}{|\Omega_{i,t}|} \sum_{j \in \Omega_{i,t}} CDS_{i,j,t}$, introduced in Section 3.6.1.. This corresponds to the average of the CDS spreads of financial intermediaries quoting in the FX spot market for currency $i$.

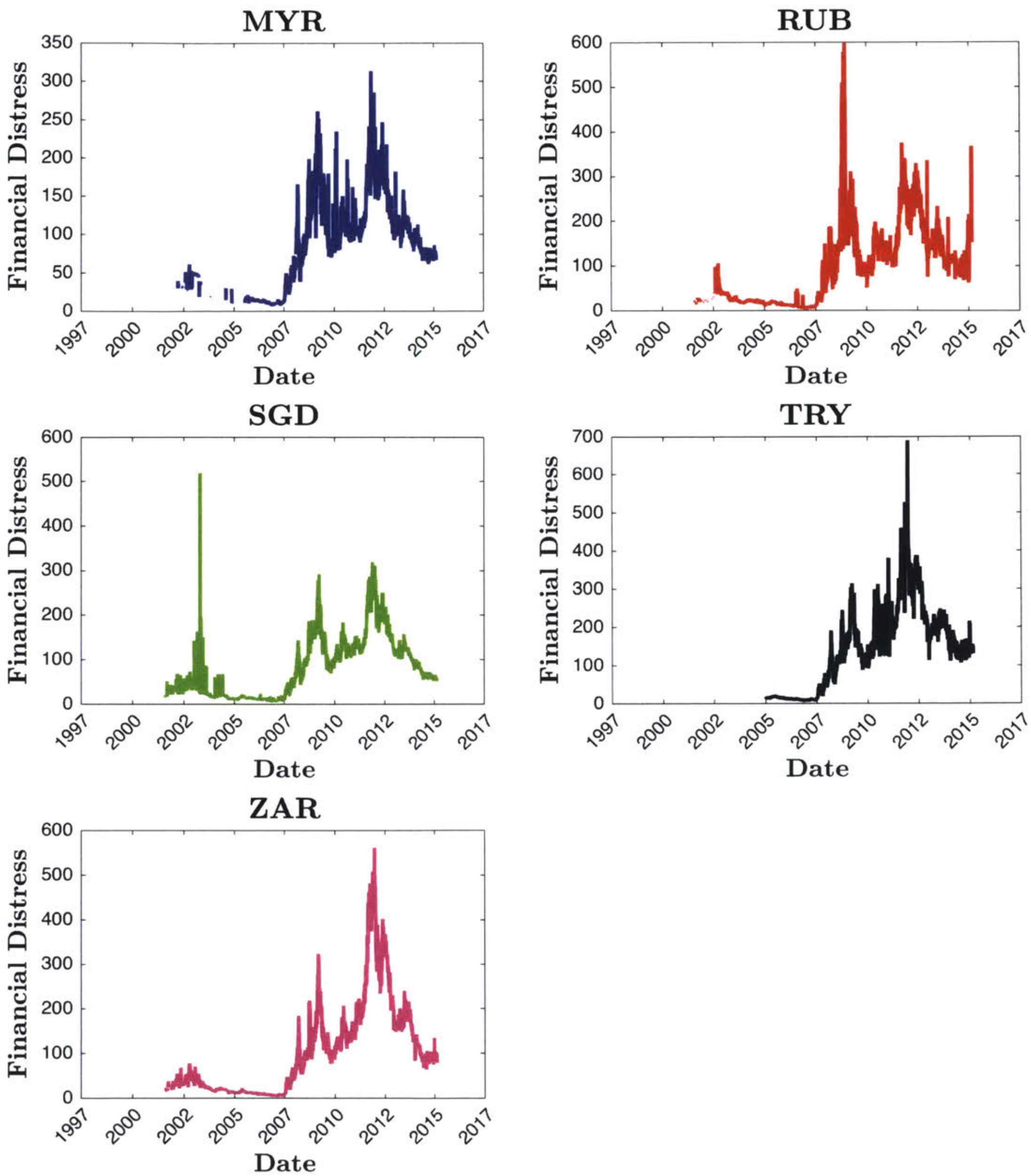



Figure 3.6: Financial Distress (2000-2015), Emerging Countries, Continued. This figure plots the currency specific financial distress measure, $\kappa_{i,t} = \frac{1}{|\Omega_{i,t}|} \sum_{j \in \Omega_{i,t}} CDS_{i,j,t}$, introduced in Section 3.6.1.. This corresponds to the average of the CDS spreads of financial intermediaries quoting in the FX spot market for currency $i$.

Table 3.11: **Biggest players in the foreign exchange market.** Market participants are ranked according to the number of quotes they have posted in the inter-dealer market between January $1^{st}$, 2000 and February, $28^{th}$ 2016. The table displays the 30 biggest players. The market fraction corresponds to the ratio of quotes posted by each market participant over the total number of quotes for each currency.

| **AUD** | | **BRL** | | **CAD** | |
|---|---|---|---|---|---|
| **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** |
| RBS | 18.037 | HSBC | 14.387 | RBS | 17.895 |
| SOCGEN | 7.145 | SANTANDER | 13.774 | BARCLAYS | 7.398 |
| BARCLAYS | 5.585 | BANCO ITAU | 13.386 | SOCGEN | 6.578 |
| CIBC | 5.116 | CITIGROUP | 9.626 | SANTANDER | 5.573 |
| UBS | 4.32 | RBS | 8.223 | CIBC | 5.037 |
| DANSKE BANK | 4.27 | STANDCHART | 7.918 | SEB | 4.505 |
| WGZ BANK | 4.155 | BSN | 3.58 | UBS | 3.923 |
| CBA | 3.441 | BNP PARIBAS | 2.554 | BROWN BROS | 3.908 |
| HSBC | 2.824 | BRADESCO | 2.239 | KASPI BANK | 3.204 |
| BANK OF AMERICA | 2.706 | BCSUL | 2.058 | CBA | 3.083 |
| CIMB | 2.397 | DEUTSCHE BANK | 1.993 | RABOBANK | 2.567 |
| JPM CHASE | 2.234 | SOCGEN | 1.675 | JPM CHASE | 2.521 |
| BTM | 1.993 | BANCO MODAL | 1.602 | NORDEA | 2.156 |
| NORDEA | 1.763 | BANK OF CHINA | 1.501 | ZUERCHER KB | 1.918 |
| RABOBANK | 1.733 | RBC | 1.482 | BNY MELLON | 1.873 |
| TORONTO DOM | 1.656 | CAIXA ECONOMICA FEDERAL | 1.401 | WGZ BANK | 1.852 |
| ZUERCHER KB | 1.59 | PIONEER | 1.352 | LEHMAN BROTHERS | 1.526 |
| BROWN BROS | 1.561 | JPM CHASE | 1.344 | COMMERZBANK | 1.442 |
| DNB | 1.546 | CREDIT AGRICOLE | 1.301 | RABOBANK | 1.437 |
| RABOBANK | 1.53 | BNY MELLON | 1.041 | WESTPAC | 1.432 |
| BNY MELLON | 1.389 | ING | 0.99 | HSBC | 1.362 |
| KBC | 1.358 | DAYCOVAL | 0.963 | RUSSKY SLAVIANSKY BANK | 1.169 |
| LEHMAN BROTHERS | 1.257 | BANCO DO BRASIL | 0.871 | ICBC | 1.113 |
| WESTPAC | 1.225 | RABOBANK | 0.865 | BHF BANK | 1.021 |
| SEB | 1.181 | ABN AMRO | 0.657 | KBC | 1.005 |
| KASPI BANK | 1.14 | WEST BRAZIL | 0.554 | CREDIT AGRICOLE | 0.894 |
| COMMERZBANK | 1.008 | MORGAN STANLEY | 0.502 | BANK OF COMM | 0.8 |
| ICBC | 0.972 | NATIXIS | 0.395 | BANK BPH | 0.778 |
| RUSSKY SLAVIANSKY BANK | 0.931 | CREDIT SUISSE | 0.373 | HANG SENG BANK | 0.77 |
| BANCO POPOLARE | 0.929 | MERRILL LYNCH | 0.246 | RBC | 0.695 |

Table 3.11: **Biggest players in the foreign exchange market.** Market participants are ranked according to the number of quotes they have posted in the inter-dealer market between January $1^{st}$, 2000 and February, $28^{th}$ 2016. The table displays the 30 biggest players. The market fraction corresponds to the ratio of quotes posted by each market participant over the total number of quotes for each currency.

| CHF | | EUR | | GBP | |
|---|---|---|---|---|---|
| **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** |
| RBS | 16.178 | RBS | 13.422 | RBS | 14.307 |
| BARCLAYS | 6.022 | CITIGROUP | 4.565 | NEDBANK | 9.605 |
| SOCGEN | 5.502 | SOCGEN | 3.774 | BARCLAYS | 5.861 |
| WGZ BANK | 3.628 | COMMERZBANK | 3.206 | CIBC | 4.173 |
| UBS | 3.356 | RABOBANK | 3.193 | UBS | 3.091 |
| COMMERZBANK | 3.224 | HSBC | 3.097 | WGZ BANK | 3.075 |
| DANSKE BANK | 3.203 | BARCLAYS | 3.035 | AIB | 2.996 |
| NEDBANK | 2.983 | WGZ BANK | 2.622 | JPM CHASE | 2.46 |
| BCP | 2.963 | UBS | 2.601 | BROWN BROS | 2.26 |
| JPM CHASE | 2.761 | AIB | 2.433 | COMMERZBANK | 2.245 |
| HSBC | 2.686 | DBS BANK | 2.338 | HSBC | 2.218 |
| BROWN BROS | 2.676 | FORTIS BANK | 2.332 | KASPI BANK | 2.032 |
| CIBC | 2.574 | BROWN BROS | 2.143 | SEB | 1.875 |
| KASPI BANK | 2.518 | QIB | 1.947 | DANSKE BANK | 1.838 |
| CBA | 2.407 | JPM CHASE | 1.87 | RABOBANK | 1.819 |
| ZUERCHER KB | 1.867 | KASPI BANK | 1.719 | SANTANDER | 1.74 |
| NORDEA | 1.701 | SEB | 1.591 | DNB | 1.676 |
| LEHMAN BROTHERS | 1.69 | BANK LEU | 1.541 | NORDEA | 1.538 |
| BANK LEU | 1.657 | CIBC | 1.466 | ZUERCHER KB | 1.474 |
| DNB | 1.345 | DANSKE BANK | 1.43 | RABOBANK | 1.469 |
| BNY MELLON | 1.338 | LEHMAN BROTHERS | 1.393 | LEHMAN BROTHERS | 1.317 |
| NBP | 1.239 | BMPS | 1.371 | BNY MELLON | 1.311 |
| HANG SENG BANK | 1.118 | BTM | 1.363 | ING | 1.106 |
| AKROS BANK | 1.083 | NEDBANK | 1.307 | CBA | 1.06 |
| BTM | 0.942 | BHF BANK | 1.269 | YAPI KREDI | 1.057 |
| WESTPAC | 0.911 | YAPI KREDI | 1.216 | BTM | 1.015 |
| BANCA POPOLARE DE MILANO | 0.896 | CBA | 1.197 | KBC | 1.011 |
| CREDIT SUISSE | 0.885 | NORDEA | 1.182 | WESTPAC | 0.938 |
| KBC | 0.862 | BNY MELLON | 1.149 | BCP | 0.922 |
| DNB NOR | 0.818 | PIRAEUS BANK | 0.896 | BMCE BANK | 0.813 |

Table 3.11: **Biggest players in the foreign exchange market.** Market participants are ranked according to the number of quotes they have posted in the inter-dealer market between January $1^{st}$, 2000 and February, $28^{th}$ 2016. The table displays the 30 biggest players. The market fraction corresponds to the ratio of quotes posted by each market participant over the total number of quotes for each currency.

| HKD | | ILS | | INR | |
|---|---|---|---|---|---|
| **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** |
| BANK OF NEW YORK | 16.424 | FIRST INT BANK | 60.685 | SBI | 13.164 |
| BARCLAYS | 7.057 | CITIGROUP | 23.31 | HSBC | 12.431 |
| RABOBANK | 6.035 | UBS | 3.669 | ING | 4.501 |
| UOB | 5.941 | DEUTSCHE BANK | 3.42 | SAKO FOREX | 4.279 |
| BHF BANK | 5.736 | RBS | 2.725 | CBA | 4.135 |
| BROWN BROS | 5.607 | HSBC | 1.853 | CITIGROUP | 3.267 |
| DBS BANK | 5.55 | BANK MIZRAHI-TEFAHOT | 1.543 | BANK BARODA | 2.752 |
| BCP | 4.275 | UBANK | 1.12 | SYNDICATE BANK | 2.676 |
| RABOBANK | 4.015 | UNION BANK | 0.397 | CANARA BANK | 2.545 |
| HSBC | 3.915 | ISRAEL DISCOUNT BANK | 0.318 | JPM CHASE | 2.475 |
| DANSKE BANK | 3.874 | BANK HAPOALIM | 0.289 | PUNJAB NATIONAL BANK | 2.064 |
| CBA | 2.981 | BANK LEUMI | 0.217 | STANDCHART | 1.928 |
| ICBC | 2.809 | MARITIME BANK | 0.206 | UNION BANK | 1.879 |
| RBS | 2.744 | BROWN BROS | 0.134 | BANK OF MAHARASHTRA | 1.739 |
| STANDCHART | 2.667 | INVESTEC | 0.045 | ADCB | 1.676 |
| CITIGROUP | 2.319 | JPM CHASE | 0.032 | FEDERAL BANK | 1.6 |
| BANK OF COMM | 1.548 | CREDIT AGRICOLE | 0.022 | ABN AMRO | 1.555 |
| SOCGEN | 1.518 | COUGAR | 0.012 | CENTURION BANK | 1.473 |
| CIMB | 1.385 | DRESDNER BANK | 0.005 | CORPORATION BANK | 1.41 |
| KBC | 1.303 | BNP PARIBAS | 0.002 | DEUTSCHE BANK | 1.348 |
| BTM | 1.192 | INTL FCSTONE | 0.002 | BANK OF NEW YORK | 1.325 |
| CREDIT AGRICOLE | 0.948 | MIZUHO BANK | 0.002 | UCO BANK | 1.274 |
| BNY MELLON | 0.945 | AMERICAN EXPRESS | 0.001 | KARNATAKA BANK | 1.225 |
| ING | 0.914 | ABN AMRO | 0.001 | SARASWAT BANK | 1.192 |
| DEUTSCHE BANK | 0.868 | BANK OF AMERICA | 0.001 | HDFC BANK | 0.998 |
| BANK OF CHINA | 0.78 | LEHMAN BROTHERS | 0.001 | DCB BANK | 0.993 |
| HANG SENG BANK | 0.755 | IDBI BANK | 0.001 | KARUR VYSYA BANK | 0.988 |
| BANCA INTESA | 0.666 | NORTHERN TRUST | 0.001 | AXIS BANK | 0.956 |
| LLOYDS BANK | 0.662 | NAB | 0.001 | BBK | 0.928 |
| CARL KLIEM | 0.594 | MORGAN STANLEY | 0.001 | JK BANK | 0.895 |

Table 3.11: **Biggest players in the foreign exchange market.** Market participants are ranked according to the number of quotes they have posted in the inter-dealer market between January $1^{st}$, 2000 and February, $28^{th}$ 2016. The table displays the 30 biggest players. The market fraction corresponds to the ratio of quotes posted by each market participant over the total number of quotes for each currency.

| **JPY** | | **KRW** | | **MXN** | |
|---|---|---|---|---|---|
| **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** |
| RBS | 14.388 | SMBC | 57.387 | HSBC | 13.788 |
| SOCGEN | 5.983 | BANK OF NEW YORK | 15.555 | CIBANCO | 12.843 |
| BARCLAYS | 4.827 | BNP PARIBAS | 6.702 | DEUTSCHE BANK | 8.767 |
| BANK OF AMERICA | 4.229 | HSBC | 3.753 | RBS | 7.965 |
| SEB | 3.389 | DEUTSCHE BANK | 3.242 | CITIGROUP | 7.832 |
| NEDBANK | 3.282 | CITIGROUP | 3.043 | BANAMEX | 6.644 |
| UBS | 2.89 | ING | 2.557 | SANTANDER | 6.254 |
| BROWN BROS | 2.723 | KEB | 1.845 | BROWN BROS | 5.292 |
| AIB | 2.684 | JPM CHASE | 1.181 | UBS | 5.212 |
| JPM CHASE | 2.665 | RBS | 1.124 | BNP PARIBAS | 4.077 |
| KASPI BANK | 2.38 | CREDIT LYONNAIS | 0.54 | GF BANORTE | 2.969 |
| CBA | 2.299 | NAB | 0.515 | BNS | 2.935 |
| DBS BANK | 2.242 | KORAM BANK | 0.453 | INTERCAM | 2.91 |
| WGZ BANK | 1.989 | LEHMAN BROTHERS | 0.432 | BNY MELLON | 2.667 |
| RABOBANK | 1.867 | KOOKMIN BANK | 0.355 | BBVA BANCOMER | 2.279 |
| LEHMAN BROTHERS | 1.862 | BARCLAYS | 0.302 | RBC | 1.756 |
| BANK LEU | 1.817 | CREDIT AGRICOLE | 0.244 | DEXIA | 0.939 |
| COMMERZBANK | 1.691 | ANZ | 0.174 | NOMURA | 0.676 |
| BTM | 1.643 | SOCGEN | 0.133 | CREDIT AGRICOLE | 0.65 |
| HSBC | 1.42 | STANDCHART | 0.108 | BARCLAYS | 0.646 |
| RABOBANK | 1.369 | DBS BANK | 0.087 | JPM CHASE | 0.491 |
| DEUTSCHE POSTBANK | 1.368 | SVENSKA HANDELSBANKEN | 0.076 | BASE INTL | 0.455 |
| NORDEA | 1.281 | NACF | 0.05 | LEHMAN BROTHERS | 0.419 |
| MIZUHO BANK | 1.181 | CTBC FINANCIAL HOLDING | 0.049 | STANDCHART | 0.354 |
| DANSKE BANK | 1.173 | BANK OF AMERICA | 0.042 | BANCO INTERACCIONES | 0.222 |
| BNY MELLON | 1.114 | COUGAR | 0.023 | ING | 0.151 |
| DNB | 1.102 | RADA FOREX | 0.022 | STATE STREET CORPORATION | 0.143 |
| KBC | 1.044 | INTL FCSTONE | 0.009 | FLEET BANK | 0.129 |
| BANCA POPOLARE DE MILANO | 1.043 | NORTHERN TRUST | 0.003 | BMO | 0.107 |
| ZUERCHER KB | 1.035 | UBS | 0.003 | BBVA | 0.092 |

Table 3.11: **Biggest players in the foreign exchange market.** Market participants are ranked according to the number of quotes they have posted in the inter-dealer market between January $1^{st}$, 2000 and February, $28^{th}$ 2016. The table displays the 30 biggest players. The market fraction corresponds to the ratio of quotes posted by each market participant over the total number of quotes for each currency.

| MYR | | NOK | | NZD | |
|---|---|---|---|---|---|
| **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** |
| STANDCHART | 27.805 | BARCLAYS | 13.175 | RBS | 19.216 |
| HONG LEONG BANK | 19.652 | RBS | 12.653 | ANZ | 8.37 |
| OCBC BANK | 12.585 | SEB | 9.357 | BNZ | 6.272 |
| MAYBANK | 9.707 | DANSKE BANK | 6.89 | BARCLAYS | 6.167 |
| HSBC | 6.965 | CIBC | 5.941 | BCP | 4.724 |
| RHB BANK | 4.11 | BROWN BROS | 5.48 | CBA | 4.351 |
| CIMB | 3.573 | AIB | 5.453 | KASPI BANK | 4.208 |
| DEUTSCHE BANK | 3.145 | CBA | 4.167 | DANSKE BANK | 4.021 |
| CITIGROUP | 2.862 | JPM CHASE | 3.908 | HSBC | 3.932 |
| JPM CHASE | 2.551 | NORDEA | 3.616 | JPM CHASE | 2.567 |
| UOB | 1.564 | COMMERZBANK | 3.519 | BROWN BROS | 2.317 |
| RBS | 1.425 | LEHMAN BROTHERS | 3.134 | ZUERCHER KB | 2.183 |
| AMBANK | 0.997 | DNB | 2.659 | CIBC | 1.825 |
| PUBLIC BANK BERHAD | 0.512 | ZUERCHER KB | 2.419 | KBC | 1.805 |
| ABMB | 0.484 | BNP PARIBAS | 2.067 | WGZ BANK | 1.779 |
| AFFIN BANK | 0.476 | DEUTSCHE BANK | 2.034 | RABOBANK | 1.76 |
| ABN AMRO | 0.385 | BNY MELLON | 1.902 | CIMB | 1.733 |
| BTMU | 0.327 | HSBC | 1.636 | WESTPAC | 1.543 |
| EON BANK | 0.239 | POHJOLA BANK | 1.206 | BNY MELLON | 1.515 |
| CBA | 0.196 | UBN | 1.114 | TORONTO DOM | 1.51 |
| BNS | 0.133 | DNB NOR | 1.089 | COMMERZBANK | 1.229 |
| BIMB | 0.092 | SANTANDER | 0.917 | SEB | 1.203 |
| BTM | 0.05 | BHF BANK | 0.852 | ICBC | 1.16 |
| ING | 0.03 | KBC | 0.532 | LEHMAN BROTHERS | 1.114 |
| KFH | 0.027 | BANCA INTESA | 0.521 | BANCO POPOLARE | 1.109 |
| DBS BANK | 0.021 | LBBW | 0.463 | DBS BANK | 1.056 |
| BNP PARIBAS | 0.021 | SVENSKA HANDELSBANKEN | 0.435 | BHF BANK | 1.052 |
| LEHMAN BROTHERS | 0.019 | STANDARD BANK | 0.397 | RABOBANK | 1.052 |
| OSK | 0.012 | BANK OF AMERICA | 0.395 | RUSSKY SLAVIANSKY BANK | 1.045 |
| ECM LIBRA | 0.011 | DRESDNER BANK | 0.391 | BANK OF COMM | 0.992 |

Table 3.11: **Biggest players in the foreign exchange market.** Market participants are ranked according to the number of quotes they have posted in the inter-dealer market between January $1^{st}$, 2000 and February, $28^{th}$ 2016. The table displays the 30 biggest players. The market fraction corresponds to the ratio of quotes posted by each market participant over the total number of quotes for each currency.

| RUB | | SEK | | SGD | |
|---|---|---|---|---|---|
| **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** |
| CITIGROUP | 23.718 | RBS | 18.823 | UOB | 11.137 |
| HSBC | 12.158 | BARCLAYS | 11.414 | BARCLAYS | 11.037 |
| RBG | 9.407 | SEB | 8.697 | HSBC | 8.906 |
| JPM CHASE | 6.43 | SWEDBANK | 6.094 | CBA | 7.044 |
| SBERBANK | 5.773 | DANSKE BANK | 5.052 | BROWN BROS | 6.65 |
| RBS | 5.036 | BROWN BROS | 4.632 | UBS | 6.152 |
| COMMERZBANK | 4.086 | JPM CHASE | 3.612 | ZUERCHER KB | 6.078 |
| ING | 3.561 | AIB | 3.061 | DBS BANK | 5.786 |
| MORGAN STANLEY | 3.077 | DBS BANK | 2.941 | STANDCHART | 5.057 |
| NORDEA | 2.49 | CIBC | 2.935 | RBS | 3.566 |
| KASPI BANK | 2.461 | NORDEA | 2.907 | BANK OF NEW YORK | 3.461 |
| ROSBANK | 2.335 | COMMERZBANK | 2.813 | KBC | 3.304 |
| DANSKE BANK | 2.254 | CBA | 2.768 | SEB | 3.225 |
| BANK OF MOSCOW | 2.146 | DEUTSCHE BANK | 2.633 | MIZUHO BANK | 3.043 |
| DEUTSCHE BANK | 1.916 | LEHMAN BROTHERS | 2.556 | CIMB | 1.942 |
| DRESDNER BANK | 1.843 | HSBC | 2.532 | BNY MELLON | 1.762 |
| BANCA INTESA | 1.717 | SVENSKA HANDELSBANKEN | 2.107 | COMMERZBANK | 1.647 |
| OTP BANK | 1.632 | POHJOLA BANK | 1.99 | CITIGROUP | 1.117 |
| PROMSVYAZBANK | 1.296 | BNP PARIBAS | 1.598 | BHF BANK | 1.072 |
| VTB BANK | 1.028 | ZUERCHER KB | 1.532 | CREDIT AGRICOLE | 0.979 |
| CREDIT SUISSE | 1.019 | BNY MELLON | 1.469 | ING | 0.915 |
| EVROFINANCE | 0.832 | DNB | 1.05 | MAYBANK | 0.888 |
| POHJOLA BANK | 0.519 | DNB NOR | 0.923 | LEHMAN BROTHERS | 0.642 |
| CREDIT AGRICOLE | 0.509 | SANTANDER | 0.771 | LLOYDS BANK | 0.589 |
| ROSINTERBANK | 0.463 | BHF BANK | 0.734 | DEXIA | 0.532 |
| SAMPO BANK | 0.453 | SOCGEN | 0.614 | CARL KLIEM | 0.513 |
| PETROCOMMERCE BANK | 0.329 | KBC | 0.435 | DRESDNER BANK | 0.51 |
| ALFA BANK | 0.219 | BANCA INTESA | 0.429 | BTM | 0.491 |
| MDM BANK | 0.203 | NOMURA | 0.412 | UFJ BANK | 0.313 |
| GAZPROMBANK | 0.181 | DRESDNER BANK | 0.393 | SOCGEN | 0.268 |

Table 3.11: **Biggest players in the foreign exchange market.** Market participants are ranked according to the number of quotes they have posted in the inter-dealer market between January $1^{st}$, 2000 and February, $28^{th}$ 2016. The table displays the 30 biggest players. The market fraction corresponds to the ratio of quotes posted by each market participant over the total number of quotes for each currency.

| **TRY** | | **ZAR** | |
|---|---|---|---|
| **Ranking** | **Market Fraction** | **Ranking** | **Market Fraction** |
| UBS | 9.276 | FIRST RAND BANK | 12.94 |
| FINANSBANK | 8.913 | BARCLAYS | 8.977 |
| GARANTI BANK | 7.334 | STANDARD BANK | 7.916 |
| RBS | 7.218 | INVESTEC | 7.313 |
| BCP | 5.917 | UBS | 6.794 |
| TEB | 5.904 | CBA | 6.764 |
| VAKIFBANK | 5.895 | NEDBANK | 6.7 |
| YAPI KREDI | 5.762 | BCP | 6.025 |
| ISBANK | 5.58 | HSBC | 5.167 |
| ZIRAAT BANK | 5.202 | BROWN BROS | 4.897 |
| CITIGROUP | 4.799 | RBS | 4.747 |
| ING | 3.974 | ABSA | 4.041 |
| AK BANK | 3.506 | LEHMAN BROTHERS | 3.062 |
| HALK BANK | 3.297 | COMMERZBANK | 2.896 |
| DENIZBANK | 2.811 | BHF BANK | 1.648 |
| TSKB | 2.559 | SOCGEN | 1.445 |
| CREDIT SUISSE | 2.206 | BNY MELLON | 1.341 |
| SANTANDER | 1.38 | KBC | 1.047 |
| COMMERZBANK | 1.181 | BANCA INTESA | 0.829 |
| RBG | 0.801 | CREDIT AGRICOLE | 0.77 |
| MERRILL LYNCH | 0.797 | ZUERCHER KB | 0.617 |
| JPM CHASE | 0.744 | RBG | 0.607 |
| DEUTSCHE BANK | 0.535 | CITIGROUP | 0.482 |
| ANADOLUBANK | 0.535 | DRESDNER BANK | 0.429 |
| HSBC | 0.411 | FORTIS BANK | 0.406 |
| CREDIT AGRICOLE | 0.409 | BANK OF NEW YORK | 0.367 |
| ABANK | 0.375 | NOMURA | 0.29 |
| TEKSTILBANK | 0.314 | STANDCHART | 0.259 |
| A&T BANK | 0.272 | BNP PARIBAS | 0.22 |
| SOCGEN | 0.264 | DEUTSCHE BANK | 0.218 |

Table 3.12: Effect of Financial Distress on Market Exit: Distinction between Developed and Emerging Countries

| Dep. Variable | | $\pi_{i,t,j}$ | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\text{Treatment}_{i,t}^{50\%}$ | 0 .003* | | |
| | (1.81) | | |
| $\text{Treatment}_{i,t}^{50\%} \times \mathbb{1}_{\text{Emerging}}$ | -0.003 | | |
| | (-1.18) | | |
| $\text{Treatment}_{i,t}^{75\%}$ | | 0.002 | |
| | | (0.76) | |
| $\text{Treatment}_{i,t}^{75\%} \times \mathbb{1}_{\text{Emerging}}$ | | 0.001 | |
| | | (0.35) | |
| $\text{Treatment}_{i,t}^{90\%}$ | | | 0.0014 |
| | | | (0.48) |
| $\text{Treatment}_{i,t}^{90\%} \times \mathbb{1}_{\text{Emerging}}$ | | | -0.004 |
| | | | (-1.03) |
| Intermediary FE | Yes | Yes | Yes |
| Time × Currency FE | Yes | Yes | Yes |
| $\bar{R}^2$ | 15.72 | 15.81 | 15.55 |
| Nobs | 716,957 | 716,957 | 716,957 |

This table reports results for regressions of the form

$$\pi_{i,j,t} = \mu_{jt} + \gamma_i + \beta \text{Treatment}_{i,t} + \delta \text{Treatment}_{i,t} \times \mathbb{1}_{\text{Emerging}} + \varepsilon_{i,j,t}$$

where $\mu_{j,t}$ and $\gamma_i$ are the previously mentioned time-currency and intermediary fixed effects, $\pi_{i,j,t} \in \{0,1\}$ is the binary outcome which takes value 1 if intermediary $i$ quotes on day $t$ for currency $j$, $\text{Treatment}_{i,t} \in \{0,1\}$ is the treatment variable which takes 1 if intermediary is hit by a shock, $z_{i,t}$, greater than a certain percentile. The point estimates are reported along with their t-stat. All standard errors are double clustered. **,* indicates coefficient is statistically different than zero at the 5 percent and 10 percent confidence level, respectively. $\overline{R}^2$ denotes the adjusted regression $R^2$. The frequency is daily and the panel dataset which is unbalanced spans from January 2004 to December 2015.

Table 3.13: Financial Distress and Factor Structure

This table reports results from regressions of the form:

$$\Delta s_{t+1} = \alpha + \beta(i_t^\star - i_t) + \gamma(i_t^\star - i_t)Carry_{t+1} + \delta Carry_{t+1} + \tau Dollar_{t+1} + \psi\Delta\kappa_{j,t+1} + \varepsilon_{t+1}$$

where $\Delta s_{t+1}$ (in %) denotes the bilateral exchange rate in U.S. dollar per foreign currency, $(i_t^\star - i_t)$ is the interest rate difference between the foreign country and the U.S., $Carry_{t+1}$ denotes the dollar-neutral average exchange rate change obtained by going long a basket of high interest rate currencies and short a basket of low interest rate currencies, $Dollar_{t+1}$ corresponds to the average change in exchange rates against the U.S. dollar, and $\Delta\kappa_{j,t+1}$ is the weekly change of the *intermediary financial distress* measure for currency $j$ between $t$ and $t+1$ (expressed in percentage points). $\overline{R}^2$ denotes the adjusted regression $R^2$, $\overline{R}^2_{FS}$ denotes the adjusted $R^2$ from a regression of exchange rates on only the factor structure.

| | $\beta$ | $\gamma$ | $\delta$ | $\tau$ | $\psi$ | $\overline{R}^2$ | $\overline{R}^2_{FS}$ | $N$ |
|---|---|---|---|---|---|---|---|---|
| | | | | **Panel A: G10 Currencies** | | | | |
| AUD | 8.33 | 68.49 | 0.08 | 1.39 | -0.01 | 0.77 | 0.74 | 543 |
| | (0.29) | (1.12) | (0.60) | (25.42) | (-0.44) | | | |
| CAD | -69.86 | 4.36 | 0.13 | 0.89 | -0.02 | 0.58 | 0.55 | 515 |
| | (-1.46) | (0.07) | (2.53) | (16.47) | (-0.69) | | | |
| CHF | 23.91 | -149.55 | -1.09 | 1.57 | 0.02 | 0.66 | 0.65 | 541 |
| | (1.04) | (-3.07) | (-7.15) | (12.75) | (0.77) | | | |
| EUR | -19.15 | -54.78 | -0.45 | 1.32 | 0.01 | 0.71 | 0.75 | 543 |
| | (-0.84) | (-1.71) | (-9.51) | (22.17) | (0.58) | | | |
| GBP | -40.80 | 135.87 | -0.22 | 0.97 | -0.03 | 0.48 | 0.52 | 543 |
| | (-1.02) | (2.90) | (-3.70) | (14.92) | (-0.48) | | | |
| JPY | -23.69 | 35.96 | -0.80 | 0.64 | 0.07 | 0.47 | 0.43 | 543 |
| | (-1.14) | (0.75) | (-9.11) | (5.48) | (1.61) | | | |
| NOK | -20.22 | 28.49 | -0.32 | 1.55 | 0.04 | 0.71 | 0.72 | 542 |
| | (-0.77) | (0.75) | (-6.78) | (16.55) | (1.04) | | | |
| NZD | -68.35 | -24.24 | 0.27 | 1.44 | 0.04 | 0.66 | 0.66 | 543 |
| | (-1.28) | (-0.67) | (2.12) | (22.03) | (0.79) | | | |
| SEK | -4.13 | -7.53 | -0.37 | 1.60 | 0.01 | 0.71 | 0.72 | 543 |
| | (-0.23) | (-0.16) | (-6.24) | (20.75) | (0.41) | | | |
| | | | | **Panel B: Other Currencies** | | | | |
| BRL | 24.52 | 25.87 | 0.40 | 0.94 | -0.05 | 0.64 | 0.62 | 527 |
| | (1.07) | (0.99) | (1.73) | (12.02) | (-0.39) | | | |
| HKD | 1.18 | 19.06 | 0.00 | 0.02 | -0.01 | 0.12 | 0.12 | 541 |
| | (0.19) | (2.19) | (0.96) | (5.05) | (-3.17) | | | |
| ILS | 42.56 | 0.52 | -0.06 | 0.75 | 0.01 | 0.35 | 0.36 | 542 |
| | (0.86) | (0.02) | (-1.28) | (14.17) | (0.06) | | | |
| INR | -0.13 | 43.94 | -0.04 | 0.54 | -0.11 | 0.45 | 0.43 | 533 |
| | (-0.01) | (3.31) | (-0.66) | (11.74) | (-2.34) | | | |
| KRW | 12.01 | -62.00 | 0.07 | 1.15 | -0.16 | 0.56 | 0.45 | 514 |
| | (0.24) | (-0.75) | (0.66) | (8.25) | (-1.11) | | | |
| MXN | -1.92 | 69.00 | 0.28 | 0.68 | -0.08 | 0.66 | 0.62 | 539 |
| | (-0.09) | (2.09) | (3.01) | (11.14) | (-0.70) | | | |
| MYR | 2.78 | 57.02 | -0.00 | 0.61 | 0.08 | 0.55 | 0.53 | 458 |
| | (0.21) | (5.00) | (-0.15) | (14.86) | (0.94) | | | |
| RUB | -24.56 | 46.84 | -0.13 | 0.80 | 0.13 | 0.39 | 0.45 | 519 |
| | (-1.30) | (2.56) | (-1.98) | (9.73) | (1.62) | | | |
| SGD | 9.82 | 19.49 | -0.10 | 0.65 | -0.06 | 0.73 | 0.73 | 542 |
| | (0.56) | (1.20) | (-5.12) | (29.77) | (-1.46) | | | |
| TRY | 39.22 | 66.52 | 0.05 | 0.95 | 0.01 | 0.68 | 0.66 | 528 |
| | (2.77) | (3.67) | (0.35) | (11.81) | (0.23) | | | |
| ZAR | 67.26 | -25.88 | 0.70 | 1.41 | 0.06 | 0.70 | 0.68 | 537 |
| | (2.16) | (-1.09) | (5.32) | (16.26) | (0.74) | | | |

# Bibliography


Adrian, Tobias, & Boyarchenko, Nina. 2012. Intermediary leverage cycles and financial stability. *Becker Friedman Institute for Research in Economics Working Paper.*

Adrian, Tobias, & Shin, Hyun Song. 2014. Procyclical leverage and value-at-risk. *Review of Financial Studies*, **27**(2), 373–403.

Adrian, Tobias, Etula, Erkko, & Groen, Jan JJ. 2011. Financial amplification of foreign exchange risk premia. *European Economic Review*, **55**(3), 354–370.

Adrian, Tobias, Etula, Erkko, & Muir, Tyler. 2014. Financial Intermediaries and the Cross-Section of Asset Returns. *The Journal of Finance*, **69**(6), 2557–2596.

Allen, Franklin, & Gale, Douglas. 1994. Limited market participation and volatility of asset prices. *The American Economic Review*, 933–955.

Almeida, Alvaro, Goodhart, Charles, & Payne, Richard. 1998. The Effects of Macroeconomic News on High Frequency Exchange Rate Behavior. *Journal of Financial and Quantitative Analysis*, **33**(3), 383–408.

Altavilla, Carlo, Brugnolini, Luca, Gurkaynak, Refet S., Motto, Roberto, & Ragusa, Giuseppe. 2019. Measuring euro area monetary policy. *Journal of Monetary Economics*, **108**, 162 – 179.

Amador, Manuel, Bianchi, Javier, Bocola, Luigi, & Perri, Fabrizio. 2017. *Exchange rate policies at the zero lower bound.* Tech. rept. National Bureau of Economic Research.

Andersen, Torben G., Bollerslev, Tim, Diebold, Francis X., & Vega, Clara. 2003. Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *The American Economic Review*, **93**, 38–62.

Andrade, Philippe, Cahn, Christophe, Fraisse, Henri, & Mésonnier, Jean-Stéphane. 2018. Can the Provision of Long-Term Liquidity Help to Avoid a Credit Crunch? Evidence from the Eurosystem?s LTRO. *Journal of the European Economic Association*, **17**(4), 1070–1106.

Basak, Suleyman, & Cuoco, Domenico. 1998. An equilibrium model with restricted stock market participation. *Review of Financial Studies*, **11**(2), 309–341.

Basak, Suleyman, & Pavlova, Anna. 2013. Asset Prices and Institutional Investors. *The American Economic Review*, **103**(5), 1728–58.

Bates, David S. 2003. Empirical option pricing: A retrospection. *Journal of Econometrics*, **116**(1), 387–404.

Berger, D.W., Chaboud, A.P., Chernenko, S.V., Howorka, E., & Wright, J.H. 2008. Order Flow and Exchange Rate Dynamics in Electronic Brokerage System Data. *Journal of International Economics*, **75**, 93–109.

Bernanke, Ben S., Boivin, Jean, & Eliasz, Piotr. 2005. Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *The Quarterly Journal of Economics*, **120**(1), 387–422.

Biais, Bruno. 1993. Price formation and equilibrium liquidity in fragmented and centralized markets. *The Journal of Finance*, **48**(1), 157–185.

Bjønnes, Geir Høidal, & Rime, Dagfinn. 2005. Dealer behavior and trading systems in foreign exchange markets. *Journal of Financial Economics*, **75**(3), 571–605.

Bollerslev, Tim, & Melvin, Michael. 1994. Bid-ask spreads and volatility in the foreign exchange market: An empirical analysis. *Journal of International Economics*, **36**(3-4), 355–372.

Brand, Claus, Buncic, Daniel, & Turunen, Jarkko. 2010. The Impact of ECB Monetary Policy Decisions and Communication on the Yield Curve. *Journal of the European Economic Association*, **8**(6), 1266–1298.

Brandt, Michael W., & Kavajecz, Kenneth A. 2004. Price Discovery in the U.S. Treasury Market: The Impact of Orderflow and Liquidity on the Yield Curve. *The Journal of Finance*, **59**, 2623–2654.

Brunnermeier, Markus K., & Koby, Yann. 2019 (June). *The Reversal Interest Rate*. IMES Discussion Paper Series 19-E-06. Institute for Monetary and Economic Studies, Bank of Japan.

Brunnermeier, Markus K, & Pedersen, Lasse Heje. 2009. Market liquidity and funding liquidity. *Review of Financial studies*, **22**(6), 2201–2238.

Brunnermeier, Markus K, & Sannikov, Yuliy. 2014. A Macroeconomic Model with a Financial Sector. *The American Economic Review*, **104**(2), 379–421.

Campello, Murillo. 2002. Internal Capital Markets in Financial Conglomerates: Evidence from Small Bank Responses to Monetary Policy. *The Journal of Finance*, **57**(6), 2773–2805.

Chinn, Menzie D., & Moore, Michael. 2011. Order Flow and the Monetary Model of Exchange Rates: Evidence from a Novel Data Set. *Journal of Money, Credit and Banking*, **43**, 1599–1624.

Chordia, Tarun, Roll, Richard, & Subrahmanyam, Avanidhar. 2002. Order imbalance, liquidity, and market returns. *Journal of Financial Economics*, **65**(1), 111–130.

Christiano, Lawrence J., Eichenbaum, Martin, & Evans, Charles L. 2005. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy*, **113**(1), 1–45.

Cieslak, Anna, & Schrimpf, Andreas. 2019. Non-monetary news in central bank communication. *Journal of International Economics*, **118**, 293 – 315.

Cochrane, John H., & Piazzesi, Monika. 2002. The Fed and Interest Rates - A High-Frequency Identification. *The American Economic Review*, **92**(2), 90–95.

Cook, Timothy, & Hahn, Thomas. 1989. The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics*, **24**(3), 331–351.

Cox, J., Ingersoll, J., & Ross, S. 1985. An Intertemporal General Equilibrium Model of Asset Pricing. *Econometrica*, **53**, 363–384.

Cragg, John G., & Donald, Stephen. 1997. Inferring the rank of a matrix. *Journal of Econometrics*, **76**(1-2), 223–250.

Di Maggio, Marco, Kermani, Amir, Keys, Benjamin J., Piskorski, Tomasz, Ramcharan, Rodney, Seru, Amit, & Yao, Vincent. 2017. Interest Rate Pass-Through: Mortgage Rates, Household Consumption, and Voluntary Deleveraging. *The American Economic Review*, **107**(11), 3550–88.

Diamond, Douglas W, & Dybvig, Philip H. 1983. Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, **91**(3), 401–419.

Dominguez, Kathryn M.E., & Panthaki, Freyan. 2006. What Defines News in Foreign Exchange Markets? *Journal of International Money and Finance*, **25**, 168–198.

Drechsler, Itamar, Savov, Alexi, & Schnabl, Philipp. 2017. The Deposits Channel of Monetary Policy*. *The Quarterly Journal of Economics*, **132**(4), 1819–1876.

Duffie, Darrell. 2010. Presidential Address: Asset Price Dynamics with Slow-Moving Capital. *The Journal of Finance*, **65**(4), 1237–1267.

Duffie, Darrell, & Strulovici, Bruno. 2012. Capital mobility and asset pricing. *Econometrica*, **80**(6), 2469–2509.

English, William B., den Heuvel, Skander J. Van, & Zakrajsek, Egon. 2018. Interest rate risk and bank equity valuations. *Journal of Monetary Economics*, **98**, 80 – 97.

Evans, Martin D. 2002. FX Trading and Exchange Rate Dynamics. *The Journal of Finance*, **57**(6), 2405–2447.

Evans, Martin D. 2010. Order Flows and the Exchange Rate Disconnect Puzzle. *Journal of International Economics*, **80**, 58–71.

Evans, Martin D., & Lyons, Richard K. 2002. Order Flow and Exchange Rate Dynamics. *Journal of Political Economy*, **110**, 170–180.

Evans, Martin D., & Lyons, Richard K. 2005. Meese-Rogoff Redux: Micro-Based Exchange Rate Forecasting. *The American Economic Review, Papers and Proceedings*, **95**, 405–414.

Evans, Martin D., & Lyons, Richard K. 2008. How Is Macro News Transmitted to Exchange Rates? *Journal of Financial Economics*, **88**, 26–50.

Farhi, Emmanuel, & Werning, Iván. 2017. Fiscal unions. *The American Economic Review*, **107**(12), 3788–3834.

Froot, Kenneth A, & O' Connell, Paul GJ. 2008. On the pricing of intermediated risks: Theory and application to catastrophe reinsurance. *Journal of Banking & Finance*, **32**(1), 69–85.

Gabaix, Xavier, & Maggiori, Matteo. 2015. International Liquidity and Exchange Rate Dynamics. *The Quarterly Journal of Economics*, **130**(3), 1369–1420.

Gabaix, Xavier, Krishnamurthy, Arvind, & Vigneron, Olivier. 2007. Limits of Arbitrage: Theory and Evidence from the Mortgage-Backed Securities Market. *The Journal of Finance*, **62**(2), 557–595.

Garleanu, Nicolae, & Pedersen, Lasse Heje. 2011. Margin-based asset pricing and deviations from the law of one price. *Review of Financial Studies*, **24**(6), 1980–2022.

Garleanu, Nicolae, Pedersen, Lasse Heje, & Poteshman, Allen M. 2009. Demand-based option pricing. *Review of Financial Studies*, **22**(10), 4259–4299.

Gomez, Matthieu, Landier, Augustin, Sraer, David, & Thesmar, David. 2016 (June). *Banks' exposure to interest rate risk and the transmission of monetary policy*. ESRB Working Paper Series 13. European Systemic Risk Board.

Gorton, Gary, & Pennacchi, George. 1990. Financial Intermediaries and Liquidity Creation. *Journal of Finance*, **45**(1), 49–71.

Gromb, Denis, & Vayanos, Dimitri. 2002. Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics*, **66**(2), 361–407.

Gürkaynak, Refet S, Sack, Brian, & Swanson, Eric. 2005. Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking*, **1**(1).

Hanson, Samuel G., Shleifer, Andrei, Stein, Jeremy C., & Vishny, Robert W. 2015. Banks as patient fixed-income investors. *Journal of Financial Economics*, **117**(3), 449 – 469.

He, Zhigu, & Krishnamurthy, Arvind. 2012. A model of capital and crises. *The Review of Economic Studies*, **79**(2), 735–777.

He, Zhiguo, & Krishnamurthy, Arvind. 2013. Intermediary Asset Pricing. *The American Economic Review*, **103**(2), 732–70.

He, Zhiguo, Kelly, Bryan, & Manela, Asaf. 2017. Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, **126**(1), 1 – 35.

Heider, Florian, Saidi, Farzad, & Schepens, Glenn. 2019. Life below Zero: Bank Lending under Negative Policy Rates. *The Review of Financial Studies*, **32**(10), 3728–3761.

Ho, Thomas, & Stoll, Hans R. 1981. Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics*, **9**(1), 47–73.

Hong, Harrison, & Yogo, Motohiro. 2012. What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, **105**(3), 473–490.

Houston, Joel, James, Christopher, & Marcus, David. 1997. Capital market frictions and the role of internal capital markets in banking. *Journal of Financial Economics*, **46**(2), 135–164.

Houston, Joel F, & James, Christopher. 1998. Do bank internal capital markets promote lending? *Journal of Banking & Finance*, **22**(6), 899–918.

Huang, Roger D, & Masulis, Ronald W. 1999. FX spreads and dealer competition across the 24-hour trading day. *Review of Financial Studies*, **12**(1), 61–93.

Itskhoki, Oleg, & Mukhin, Dmitry. 2017. *Exchange rate disconnect in general equilibrium*. Tech. rept. National Bureau of Economic Research.

Jardet, Caroline, & Monks, A. 2014. *Euro Area monetary policy shocks: impact on financial asset prices during the crisis?* Working papers. Banque de France.

Jimenez, Gabriel, Ongena, Steven, Peydro, Jose-Luis, & Saurina, Jesus. 2012. Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications. *The American Economic Review*, **102**(01), 2301–2326.

Kashyap, Anil, & Stein, Jeremy. 1995. The impact of monetary policy on bank balance sheets. *Carnegie-Rochester Conference Series on Public Policy*, **42**(1), 151–195.

Kashyap, Anil K., & Stein, Jeremy C. 2000. What Do a Million Observations on Banks Say about the Transmission of Monetary Policy? *The American Economic Review*, **90**(3), 407–428.

Kashyap, Anil K., Rajan, Raghuram, & Stein, Jeremy C. 2002. Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-taking. *The Journal of Finance*, **57**(1), 33–73.

Khwaja, Asim Ijaz, & Mian, Atif. 2008. Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. *The American Economic Review*, **98**(4), 1413–42.

Killeen, William P., Lyons, Richard K., & Moore, Michael J. 2006. Fixed versus Flexible: Lessons from EMS Order Flow. *Journal of International Money and Finance*, **25**(4), 551–579.

King, Michael R., Osler, Carol L., & Rime, Dagfinn. 2013. The Market Microstructure Approach to Foreign Exchange: Looking Back and Looking Forward. *Journal of International Money and Finance*, **38**(Nov.), 95–119.

Kishan, Ruby P, & Opiela, Timothy. 2000. Bank Size, Bank Capital, and the Bank Lending Channel. *Journal of Money, Credit and Banking*, **32**(1), 121–41.

Kuttner, Kenneth. 2001. Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics*, **47**(3), 523–544.

Kyle, Albert S, & Xiong, Wei. 2001. Contagion as a wealth effect. *The Journal of Finance*, **56**(4), 1401–1440.

Lettau, Martin, Maggiori, Matteo, & Weber, Michael. 2014. Conditional Risk Premia in Currency Markets and Other Asset Classes. *Journal of Financial Economics*, **114**, 197–225.

Love, Ryan, & Payne, Richard. 2008. Macroeconomic News, Order Flows, and Exchange Rates. *Journal of Financial and Quantitative Analysis*, **43**, 467–488.

Lustig, Hanno, & Richmond, Robert J. 2017. *Gravity in FX R-Squared: Understanding the Factor Structure in Exchange Rates*. Tech. rept. National Bureau of Economic Research.

Lustig, Hanno, & Verdelhan, Adrien. 2019. Does Incomplete Spanning in International Financial Markets Help to Explain Exchange Rates? *The American Economic Review*, **109**(6), 2208–44.

Lustig, Hanno, Roussanov, Nikolai, & Verdelhan, Adrien. 2011. Common Risk Factors in Currency Markets. *Review of Financial Studies*, **24**, 3731–3777.

Lustig, Hanno, Roussanov, Nikolai L., & Verdelhan, Adrien. 2014. Countercyclical Currency Risk Premia. *Journal of Financial Economics*, **111**, 527–553.

Lyons, Richard K. 1995. Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics*, **39**(2), 321–351.

Lyons, Richard K. 2001. *The microstructure approach to exchange rates.* Vol. 333. Citeseer.

Maggiori, Matteo. 2013. *The U.S. Dollar Safety Premium.* Working Paper, Harvard University.

Menkhoff, Lukas, Sarno, Lucio, Schmeling, Maik, & Schrimpf, Andreas. 2012. Carry Trades and Global Foreign Exchange Volatility. *The Journal of Finance*, **67**, 681–718.

Nakamura, Emi, & Steinsson, Jón. 2018. High-Frequency Identification of Monetary Non-Neutrality: The Information Effect. *The Quarterly Journal of Economics*, **133**(3), 1283–1330.

Pavlova, Anna, & Rigobon, Roberto. 2007. Asset prices and exchange rates. *Review of Financial Studies*, **20**(4), 1139–1180.

Payne, Richard. 2003. Informed Trade in Spot Foreign Exchange Markets: An Empirical Investigation. *Journal of International Economics*, **61**, 307–329.

Pedersen, Lasse Heje, Mitchell, Mark, Pulvino, Todd, *et al.* . 2007. Slow Moving Capital. *The American Economic Review*, **97**(2), 215–220.

Rattier, Gabriel. 1951. Le Service Central des Risques Bancaires.

Rigobon, Robert. 2003. Identification through Heteroscedasticity. *Review of Economics and Statistics*, **85**, 777–792.

Rigobon, Roberto, & Sack, Brian. 2004. The Impact of Monetary Policy on Asset Prices. *Journal of Monetary Economics*, **51**, 1553–1575.

Rime, Dagfinn, & Schrimpf, Andreas. 2013. The anatomy of the global FX market through the lens of the 2013 Triennial Survey. *BIS Quarterly Review, December.*

Rime, Dagfinn, Sarno, Lucio, & Sojli, Elvira. 2010. Exchange Rates, Order Flow and Macroeconomic Information. *Journal of International Economics*, **80**, 72–88.

Rudebusch, Glenn. 1998. Do Measures of Monetary Policy in a VAR Make Sense? *International Economic Review*, **39**(4), 907–31.

Scharfstein, David S, & Stein, Jeremy C. 2000. The dark side of internal capital markets: Divisional rent-seeking and inefficient investment. *The Journal of Finance*, **55**(6), 2537–2564.

Schmitt-Grohé, Stephanie, & Uribe, Martin. 2016. Downward nominal wage rigidity, currency pegs, and involuntary unemployment. *Journal of Political Economy*, **124**(5), 1466–1514.

Sims, Christopher A. 2003. Implications of rational inattention. *Journal of monetary Economics*, **50**(3), 665–690.

Sims, Christopher A. 2006. Rational inattention: Beyond the linear-quadratic case. *The American Economic Review*, **96**(2), 158–163.

Siriwardane, Emil. 2015. Concentrated capital losses and the pricing of corporate credit risk. *Available at SSRN 2584043.*

Stein, Jeremy. 1998. An Adverse-Selection Model of Bank Asset and Liability Management with Implications for the Transmission of Monetary Policy. *RAND Journal of Economics*, **29**(3), 466–486.

Stein, Jeremy C. 1997. Internal capital markets and the competition for corporate resources. *The Journal of Finance*, **52**(1), 111–133.

Stoll, Hans R. 1978. The supply of dealer services in securities markets. *The Journal of Finance*, **33**(4), 1133–1151.

Swanson, Eric T. 2017 (April). *Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets.* Working Paper 23311. National Bureau of Economic Research.

Vayanos, Dimitri. 2004. *Flight to quality, flight to liquidity, and the pricing of risk.* Tech. rept. National Bureau of Economic Research.

Verdelhan, Adrien. 2018. The Share of Systematic Risk in Bilateral Exchange Rates. *The Journal of Finance*, **73**(1), 375–418.

Winberry, Thomas, & Ottonello, Pablo. 2017. *Financial Heterogeneity and the Investment Channel of Monetary Policy.* 2017 Meeting Papers 598. Society for Economic Dynamics.

Wong, Arlene. 2016. *Population aging and the transmission of monetary policy to consumption.* 2016 Meeting Papers 716. Society for Economic Dynamics.

Xiong, Wei. 2001. Convergence trading with wealth effects: an amplification mechanism in financial markets. *Journal of Financial Economics*, **62**(2), 247–292.