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

by

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Abstract

Exploiting a high frequency dealer-specific quote database in the FX market, I 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. I 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. I 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. I 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. More surprisingly, the dispersion in terms of financial wealth across financial intermediaries, measured as the variance of the financial intermediaries CDS spreads, is also an important determinant of this volatility for a large set of emerging country currencies.

Thesis Supervisor: Adrien Verdelhan
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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.

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.[2] 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.[3]

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.[4] 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 paper are

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

[3]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.

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

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[5] are available. The richness of this database, where more than 1,100 market 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

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

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[6] 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 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

[6]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)).

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.* (2016). 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:

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

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 (2015), 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.*

Related Literature. This paper 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 (2014) 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 paper 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 paper 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 paper proceeds as follows. Section 2. gives a description of the data used in this paper. Section 3. presents the main stylized facts about the FX market and in particular highlights the high degree of concentration of this relatively opaque market. Section 4. 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 5. tries to explore the link between intermediary financial distress and asset price dynamics in the FX market. Finally, Section 6. concludes.

2. Data Description

In this section, I first describe the foreign exchange dataset used primarily in this paper. 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.

2.1. Foreign Exchange Rate Dataset

As mentioned before, the data for this paper 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 dealable 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 paper 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.[7] 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.

[7]The list of all the players quoting in the foreign exchange market for the different currencies mentioned above can be available 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:

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 Sociêté Génêrale 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 paper, 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.

2.2. 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.* (2016) 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.[8] Consequently my

[8]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

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.[9]

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, 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 paper can be found in Table 10 in the Appendix. Figure 0-2 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

level and are all labelled CITIGROUP.

[9]The main argument for running the whole analysis at the holding company level is well supported by (He *et al.* , 2016) 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.* (2016), 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.

yields a matched database containing 724,737 individual daily observations. Table 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. The Features of the Foreign Exchange Market

Before exploring how dealer's financial distress affects his behaviour in the FX market in Section 4., I first document the main features of the FX market notably in terms of traded volume and quote concentration.

3.1. 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

Table 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	-

whereas the second mostly traded currency, the Euro, represents only 33% of total daily volume. Table 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 0-1). 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 paper focuses on this part of the market, which is still extremely liquid and which allows me to extract information about relatively large dealers' behaviour 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.

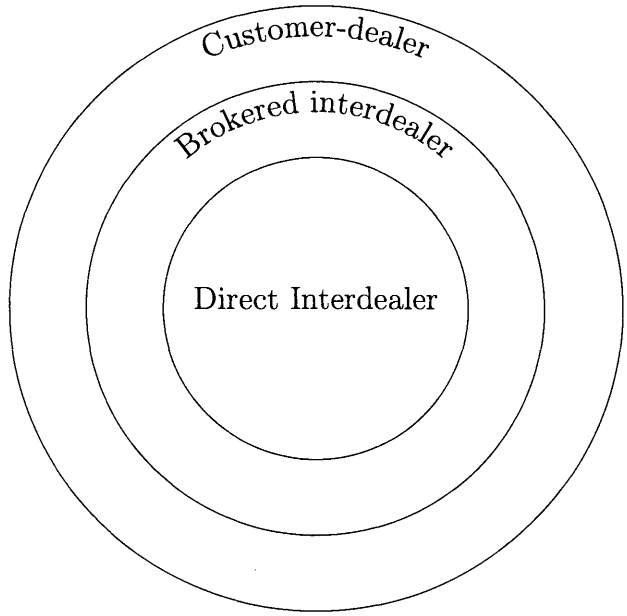

Figure 0-1: FX Market structure

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.[10] The majority

[10]"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)

(56%) of these trades is executed through electronic systems.[11]

3.2. 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 dealable: 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 2.1., 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 [12]. 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

[11]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 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).

[12]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

by each dealer. Figures 0-3 and 0-4 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 11 lists the main 30 traders present in each market and are ranked according to their quote 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.

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

The fundamental question of interest in this paper 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 paper 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.

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

The first finding of my paper 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:

$$\log(\text{Bid-Ask spread}_{i,t,j}) = \alpha_j + \gamma_i + \delta_j + \beta \log(CDS_{i,t}) + \zeta' X_{it} + \varepsilon_{i,j,t} \tag{2}$$

where Bid-Ask $\text{spread}_{i,t,j}$ 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. α_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. γ_i is a financial intermediary fixed effect that absorbs any time invariant intermediary characteristics whereas δ_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, α_t and δ_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 paper.

Because this regression accounts for intermediary time invariant characteristics (via γ_i) and macroeconomic factors (via α_t and δ_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.[13]

Financial Distress and Uncertainty

Table 2 contains the results of regression 2, where the control variable is the midquote volatility, $Vol_{j,t}$, of currency j at day t. Column (1) of Table 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.

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, $\log(CDS_{i,t}) \times Vol_{j,t}$.[14]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

[13] I also run all the regressions considered in this paper 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.

[14] 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.

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, $\log(CDS_{i,t}) \times \mathbb{1}_{Vol_{j,t} \geq Vol_{j,t}^{q\%}}$, 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.

Table 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.

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?

Consequently, the measure of competition I consider is given by:

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

where $Nbanks_{j,t}$ correspond to the number of different 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 new variable is bounded between 0 and 1.[15]

Table 3 contains the results of regression 2 along with the competition measure mentioned above. 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.

[15]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: 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.

4.2. 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.

Measure of shock to financial condition

In the same vein as in He *et al.* (2016), 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 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 $\text{Treatment}_{i,t}$ 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 $\text{Treatment}_{i,t} = 1$ can be considered as "treated" observations in the view of the randomized controlled trial literature.

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 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

Table 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 $\text{Treatment}_{i,t}$, which means that only the observations for which a CDS value is available at time $t-1$ and time t.

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:

$$\pi_{i,j,t} = \mu_{jt} + \gamma_i + \beta \text{Treatment}_{i,t} + \varepsilon_{i,j,t} \tag{3}$$

where $\mu_{j,t}$ and γ_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 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 deteriorate. The parameter of interest in the previous regression, β, is never significant. It is even the case when I make the distinction between developed and emerging countries (see Table 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.

Table 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 × 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 γ_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.

4.3. Do financially distressed intermediaries tend to quote more often?

So far, this paper 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 behaviour, 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 financial distress on quoting frequency:

$$\text{Number of Quotes}_{i,t,j} = \alpha_j + \gamma_i + \delta_j + \beta \log(CDS_{i,t}) + \varepsilon_{i,j,t} \tag{4}$$

with the usual fixed effects mentioned previously. The parameter of interest is β.

Table 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 $\times$ 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 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 4.1. 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 behaviour 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.

5. 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.

5.1. 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:

$$\kappa_{j,t} = \frac{1}{|\Omega_{j,t}|} \sum_{i \in \Omega_{j,t}} CDS_{i,j,t} \tag{5}$$

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 0-5 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:

$$\nu_{j,t} = \sqrt{\frac{1}{|\Omega_{j,t}|} \sum_{i \in \Omega_{j,t}} (CDS_{i,j,t} - \kappa_{j,t})^2} \tag{6}$$

5.2. Financial Distress and Currency Risk Premium

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

Building upon the empirical framework proposed by Verdelhan (2015), 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:

$$\Delta s_{j,t+1} = \alpha + \beta(i^*_{j,t} - i_t) + \gamma(i^*_{j,t} - i_t)\text{Carry}_{j,t+1} + \delta\text{Carry}_{j,t+1} + \tau\text{Dollar}_{j,t+1} + \psi\Delta\kappa_{j,t+1} + \varepsilon_{t+1} \tag{7}$$

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 13 in Appendix reports the results of regression 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 ψ is never statistically different from 0 except for two currencies, INR and HKD. This is consistent with the findings of He *et al.* (2016) 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).

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 7 and 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 θ 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.

6. Conclusion

Using a tick-by-tick dealer-specific quotes database on the foreign exchange (FX) market, this paper explore 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 paper tests whether a financial intermediary experiencing an idiosyncratic deterioration in its financial condition does or does not quote differently from its competitors. In an nutsell, 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.*

Table 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 θ is multiplied by 10000 and all the standard errors are robustly estimated according to the Newey-West procedure.

	ρ	θ	$\overline{R}^2$	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 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 θ is multiplied by 10000 and all the standard errors are robustly estimated according to the Newey-West procedure.

	ρ	θ	$\overline{R}^2$	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)		

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.

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. *American Economic Review*, **103**(5), 1728–58.

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

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.

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. *American Economic Review*, **104**(2), 379–421.

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.

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. 2014. International Liquidity and Exchange Rate Dynamics.

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.

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

Guillaume, Dominique M, Dacorogna, Michel M, Davé, Rakhal R, Müller, Ulrich A, Olsen, Richard B, & Pictet, Olivier V. 1997. From the bird's eye to the microscope: A survey of new stylized facts of the intra-daily foreign exchange markets. *Finance and stochastics*, **1**(2), 95–129.

He, Zhighuo, Kelly, Bryan, & Manela, Asaf. 2016. Intermediary Asset Pricing: New Evidence from Many Asset Classes. *Working Paper.*

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. *American Economic Review*, **103**(2), 732–70.

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.

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**(2), 197–225.

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.

Menkhoff, Lukas, Sarno, Lucio, Schmeling, Maik, & Schrimpf, Andreas. 2012. Carry trades and global foreign exchange volatility. *The Journal of Finance*, **67**(2), 681–718.

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

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

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

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.

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 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.

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

Verdelhan, Adrien. 2015. The Share of Systematic Variation in Bilateral Exchange Rates. *Journal of Finance, Forthcoming.*

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

7. Appendix

Table 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, ρ is computed according to the following panel regression: $CDS_{i,t} = \alpha_i + \rho CDS_{i,t-1} + \varepsilon_{i,t}$, where α_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 α_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 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 paper 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			

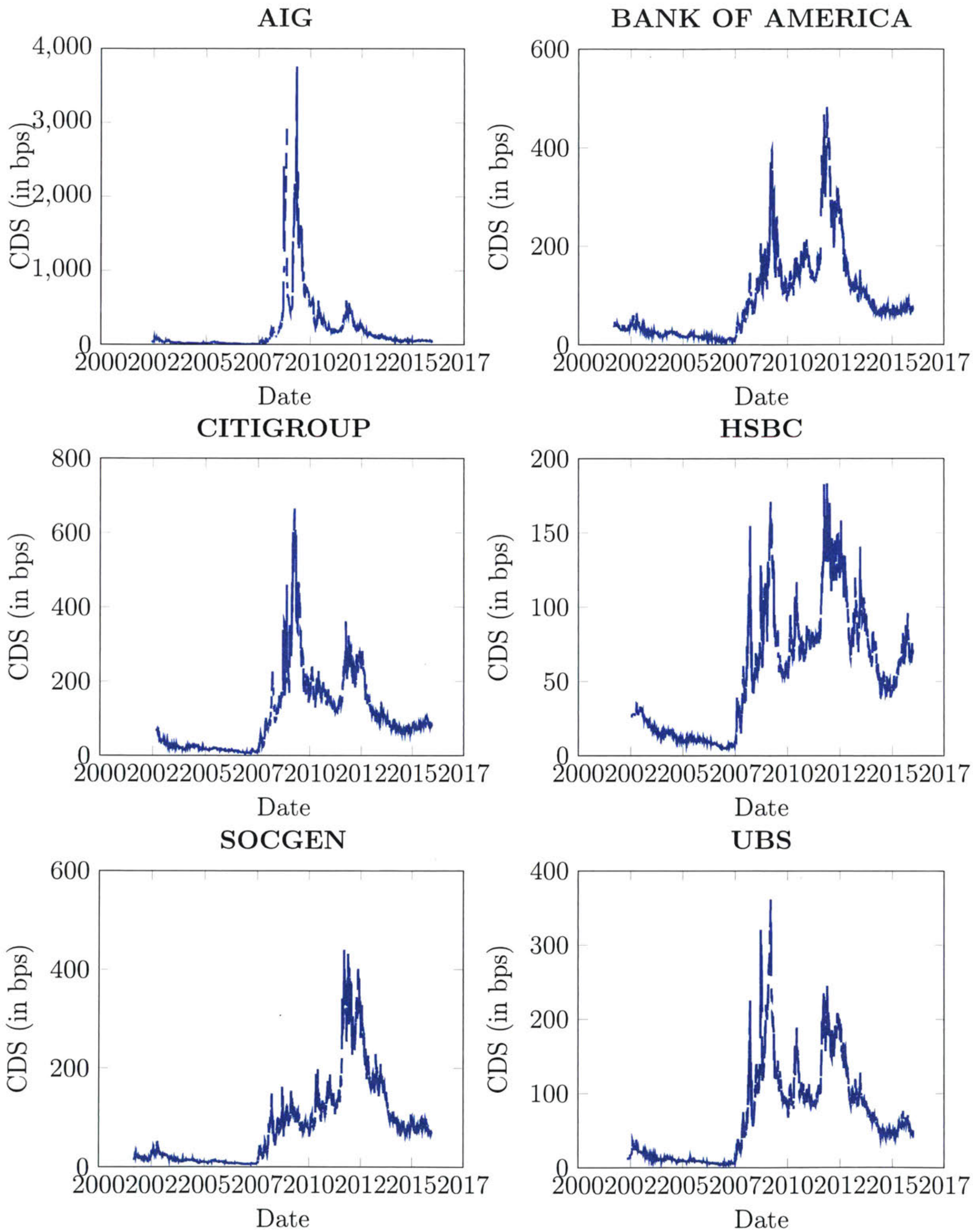

Figure 0-2: Financial Intermediary CDS Spreads (2000-2015).

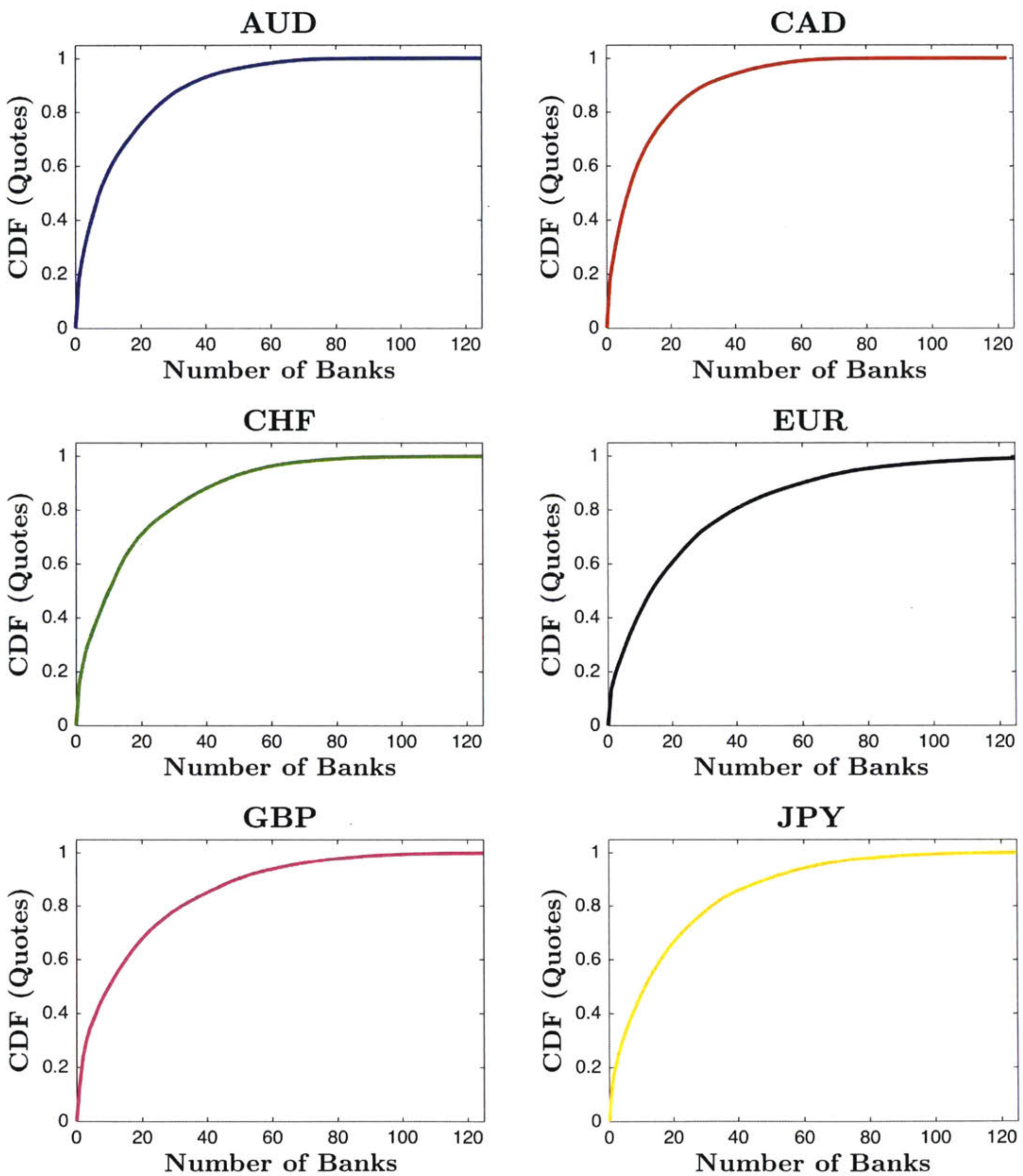

Figure 0-3: Market Quote Share (2000-2015), Developed Countries.

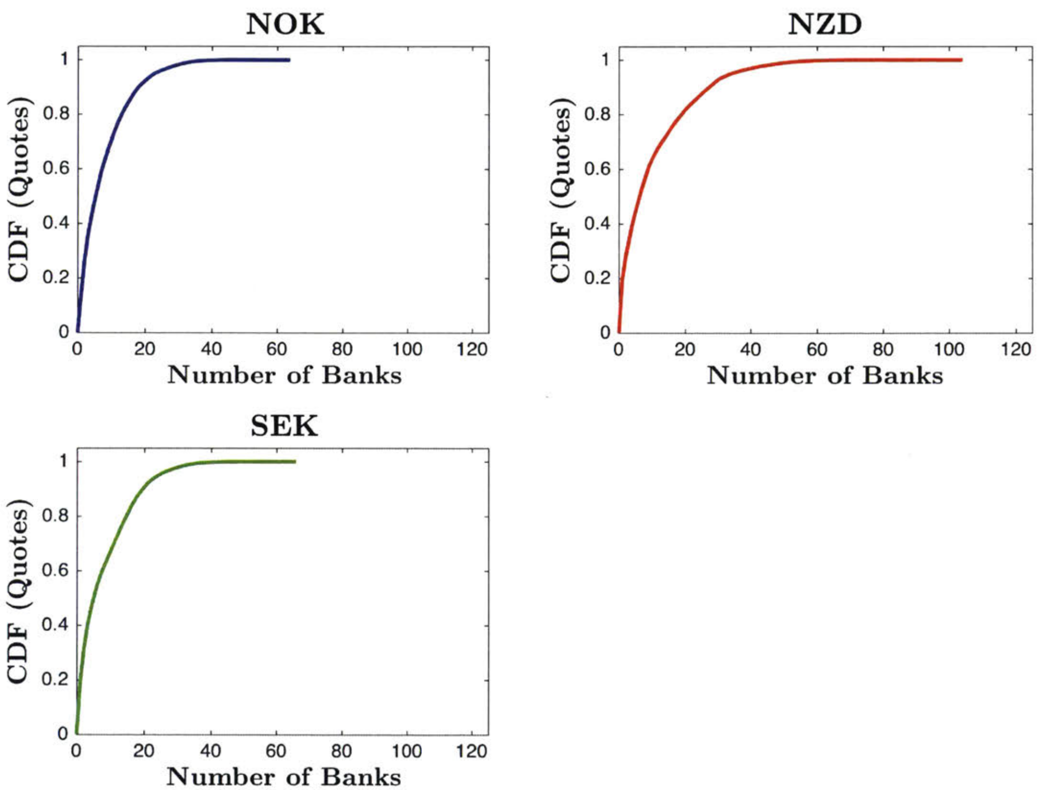

Figure 0-3: Market Quote Share (2000-2015), Developed Countries, Continued.

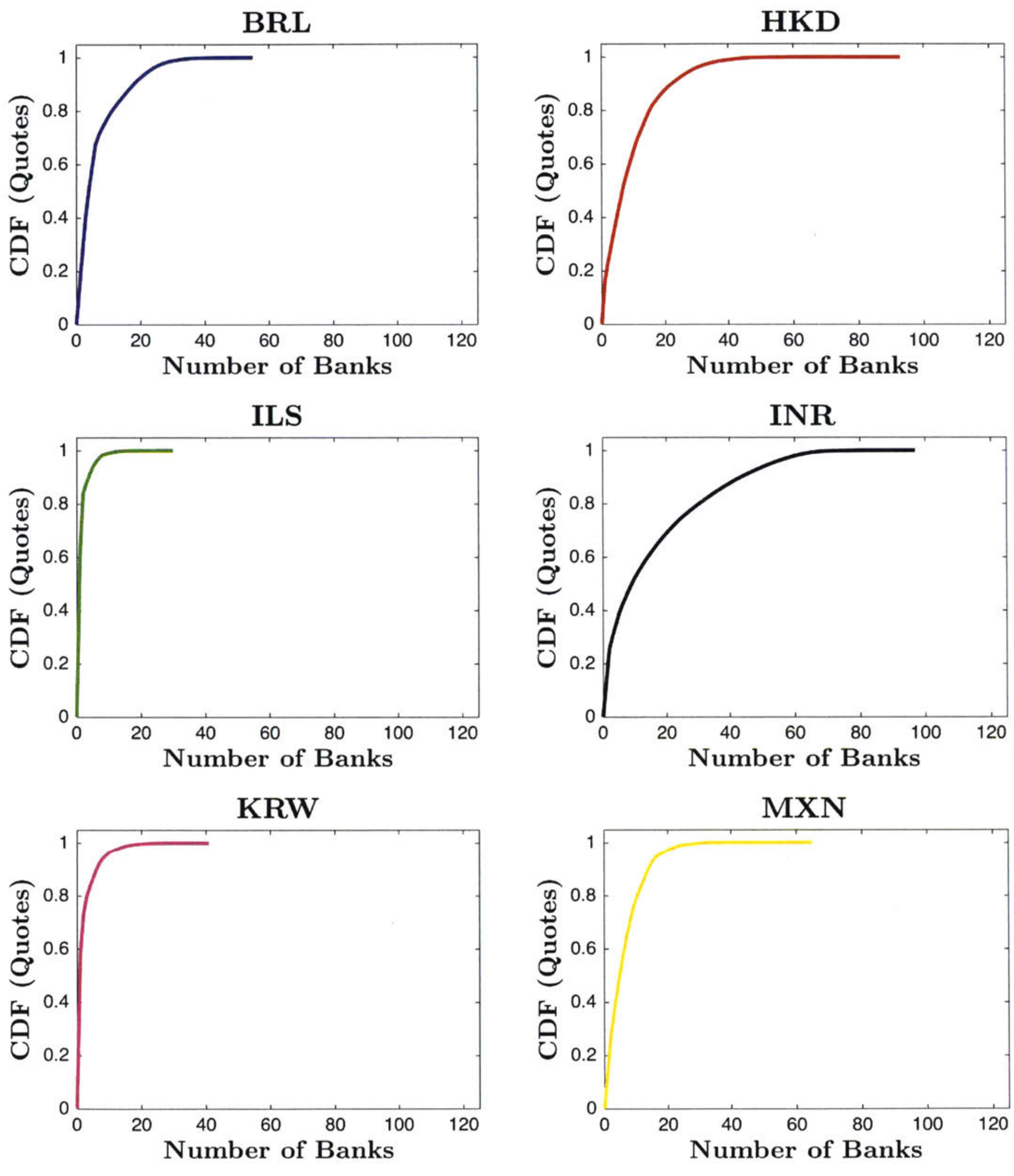

Figure 0-4: Market Quote Share (2000-2015), Emerging Countries.

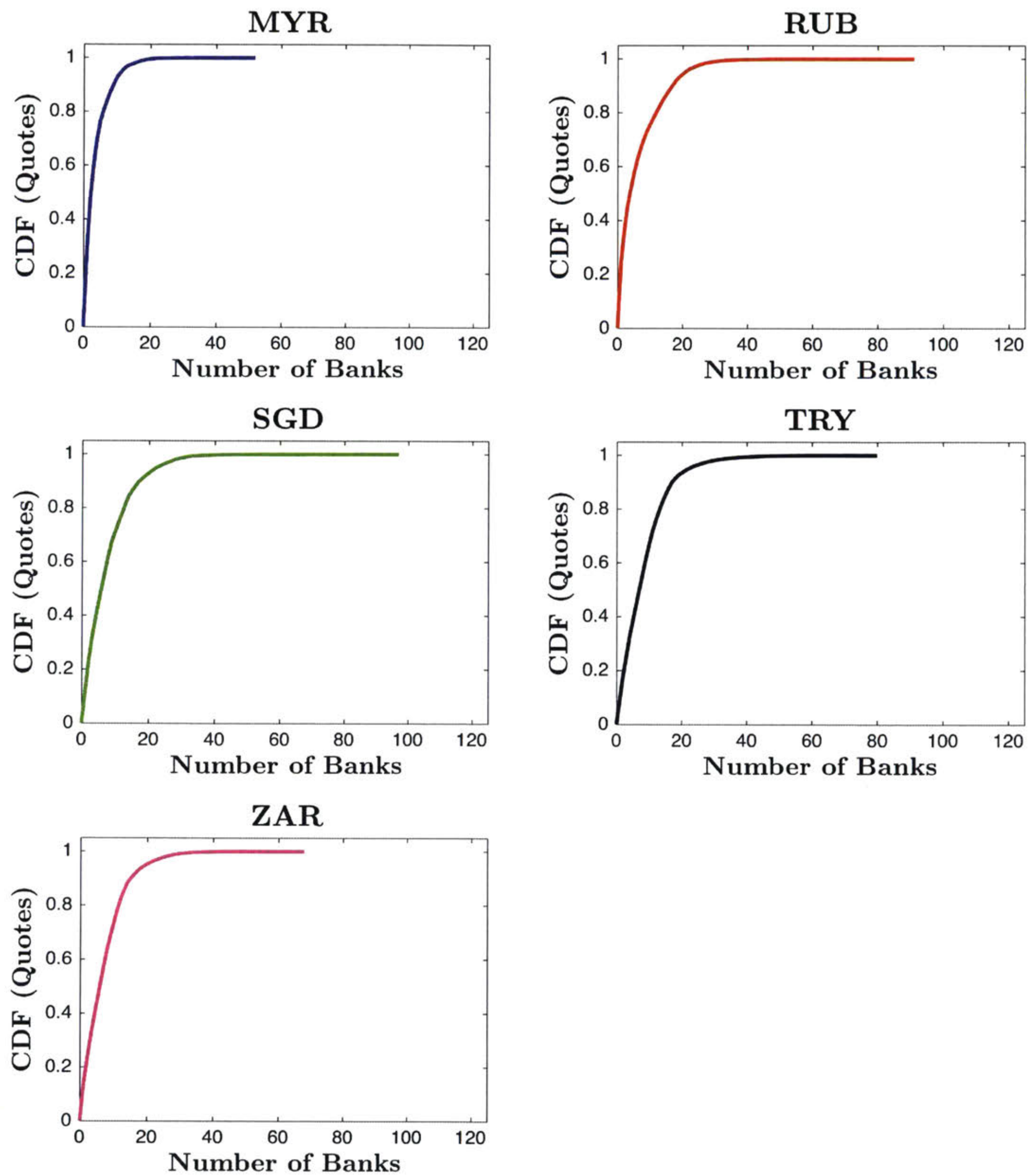

Figure 0-4: Market Quote Share (2000-2015), Emerging Countries, Continued.

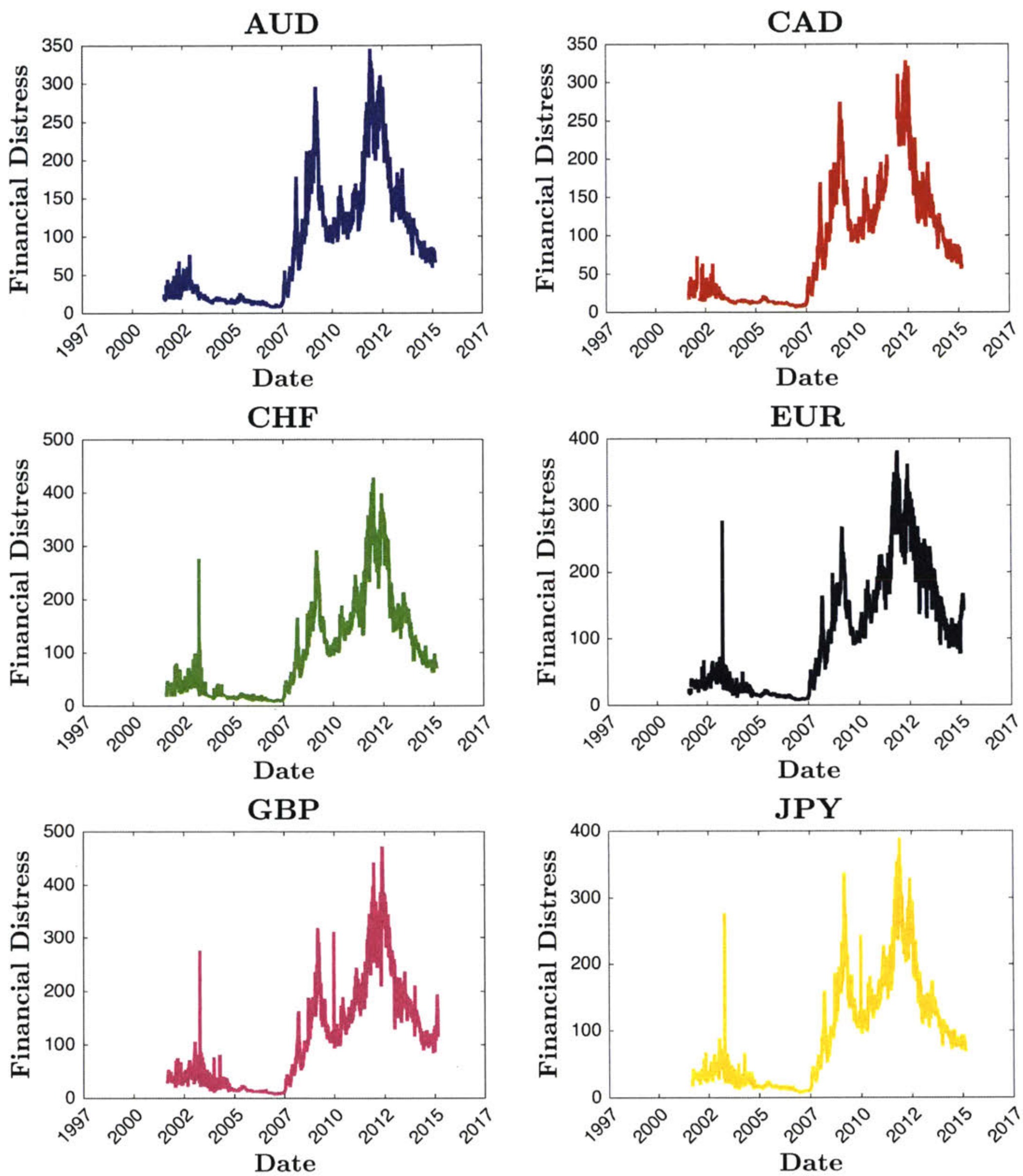

Figure 0-5: Financial Distress (2000-2015), Developed Countries. This figure plots the currency specific financial distress measure, $\kappa_{i,t} = \frac{1}{|\Omega_{i,t}|} \sum_{j \in \Omega_{i,t}} CDS_{i,j,t}$, introduced in Section 5.1.. This corresponds to the average of the CDS spreads of financial intermediaries quoting in the FX spot market for currency i.

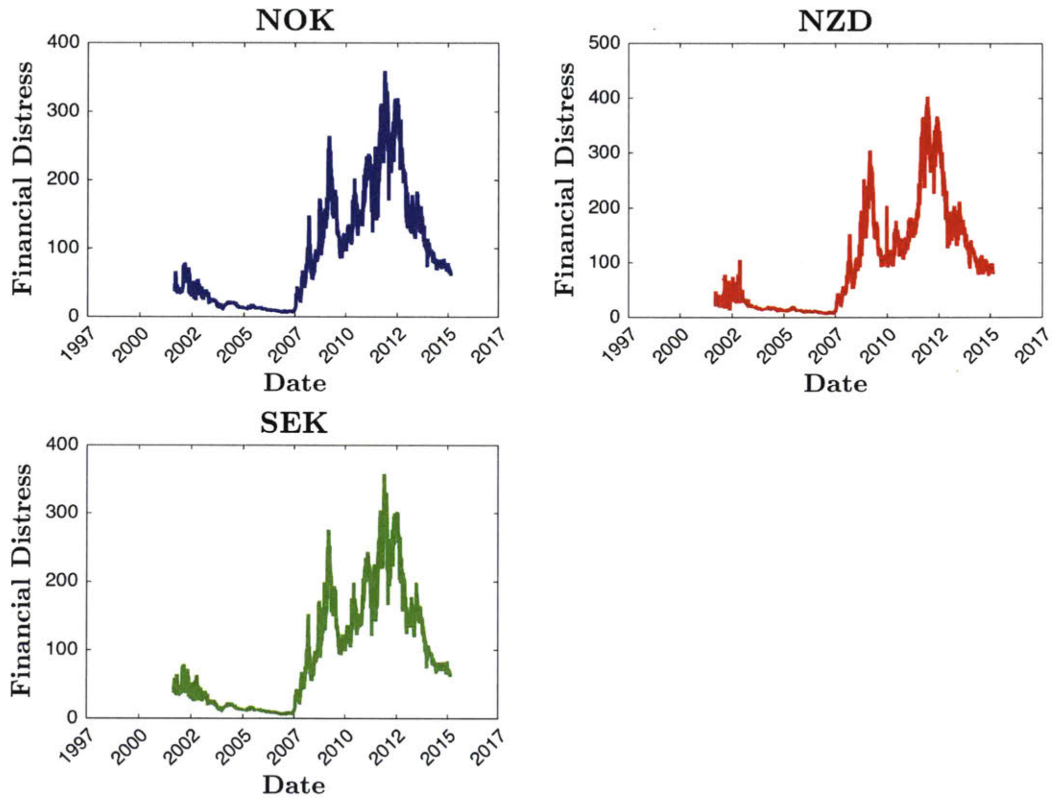

Figure 0-5: Financial Distress (2000-2015), Developed Countries, Continued. This figure plots the currency specific financial distress measure, $\kappa_{i,t} = \frac{1}{|\Omega_{i,t}|} \sum_{j \in \Omega_{i,t}} CDS_{i,j,t}$, introduced in Section 5.1.. This corresponds to the average of the CDS spreads of financial intermediaries quoting in the FX spot market for currency i.

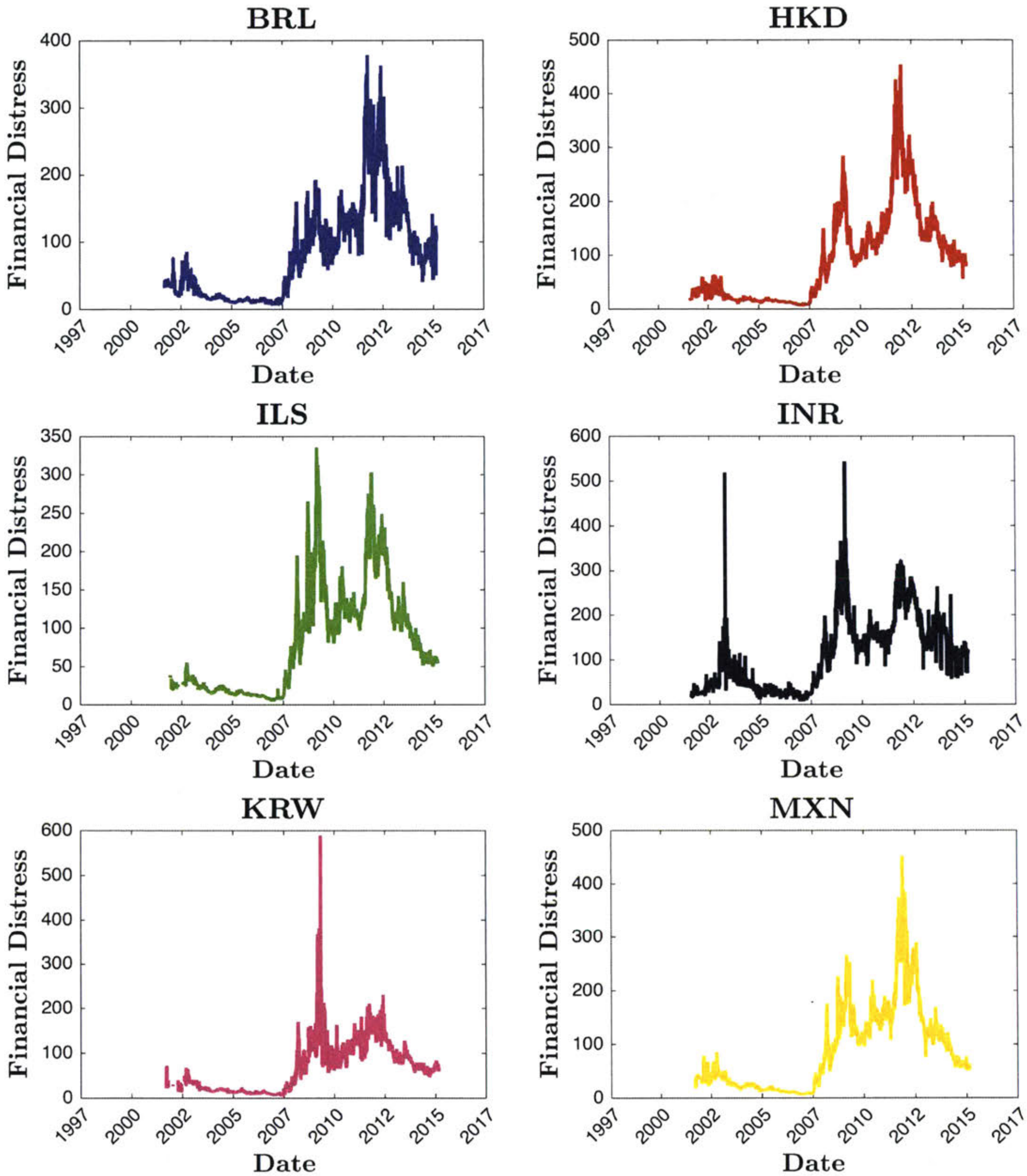

Figure 0-6: Financial Distress (2000-2015), Emerging Countries. This figure plots the currency specific financial distress measure, $\kappa_{i,t} = \dfrac{1}{|\Omega_{i,t}|} \sum_{j \in \Omega_{i,t}} CDS_{i,j,t}$, introduced in Section 5.1.. This corresponds to the average of the CDS spreads of financial intermediaries quoting in the FX spot market for currency i.

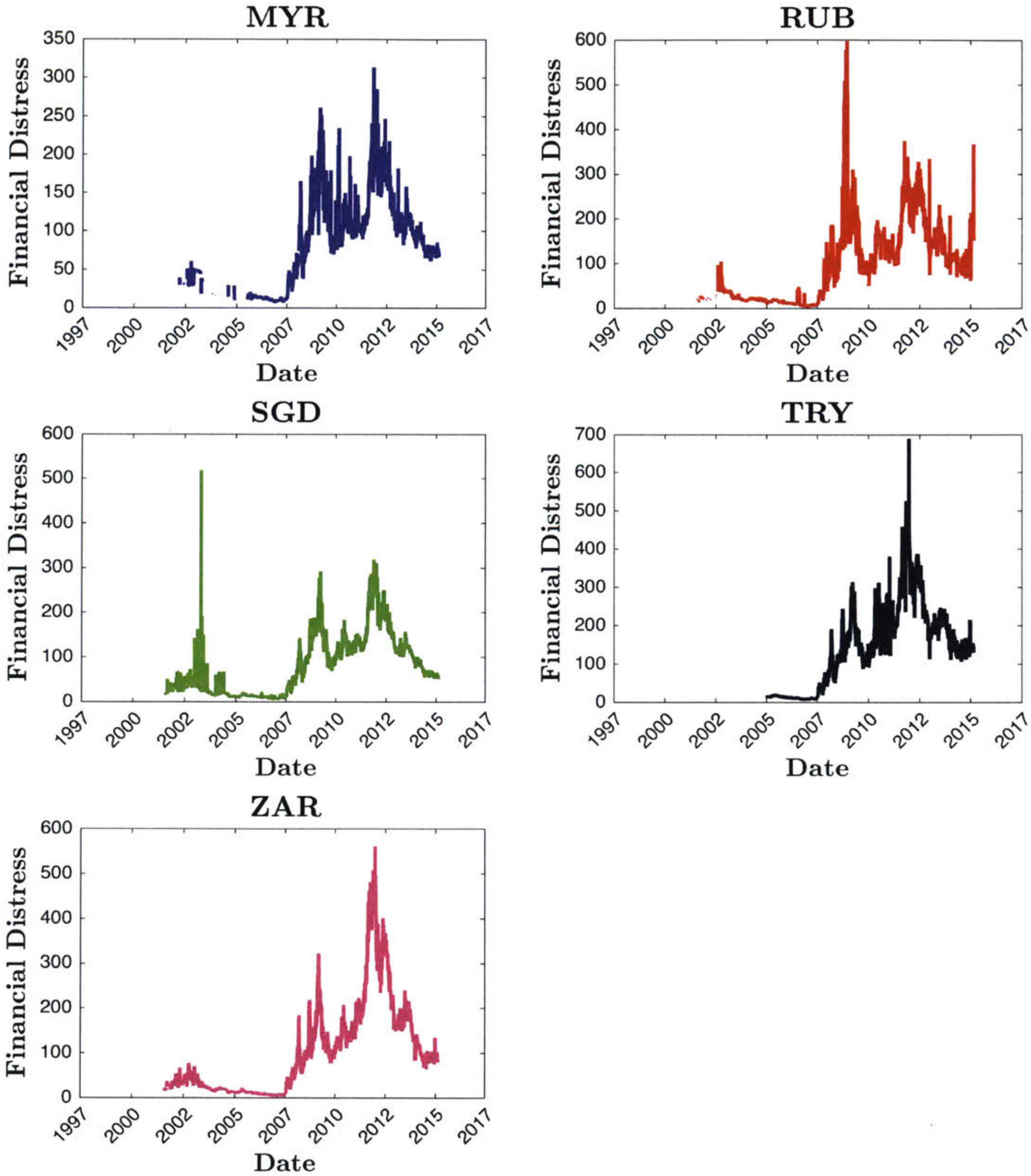

Figure 0-6: Financial Distress (2000-2015), Emerging Countries, Continued. This figure plots the currency specific financial distress measure, $\kappa_{i,t} = \frac{1}{|\Omega_{i,t}|}\sum_{j\in\Omega_{i,t}} CDS_{i,j,t}$, introduced in Section 5.1.. This corresponds to the average of the CDS spreads of financial intermediaries quoting in the FX spot market for currency i.

Table 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 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

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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 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 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

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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

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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 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 γ_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 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 Δs_{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.

	β	γ	δ	τ	ψ	$\overline{R}^2$	$\overline{R}^2_{FS}$	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)			