Essays on Financial Stability

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Abstract

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This dissertation studies covered interest parity, global dollar funding conditions, and the predictability of future financial crises using recent global data on the foreign exchange derivatives market and a historical macrofinancial database.

The first chapter examines how demand for FX swaps impacts persistent deviations from CIP. Using a novel dataset on FX swaps from the CLS Group, I analyze the factors driving CIP deviations across multiple interest rates and tenors. Specifically, I focus on non-bank demand for FX swaps and examine heterogeneity across industries and currency pairs. I estimate that on average, a 1% increase in FX swap volume results in a 2% widening of the CIP basis. As a result, a persistent dollar financing premium allows us to better understand why CIP does not hold in the data.

The second chapter extends on the first and analyzes the price impact of FX order flow for swaps and outright forwards. I find evidence of the substitution channel: market participants who draw on swap lines reduce demand for dollars via the FX swap and forward market. In times of financial stress, such as the COVID-19 Pandemic, swap lines can be beneficial by providing cross-border liquidity. During quarter-ends, demand rises and price makers adjust prices to adjust for higher order flow.

The third chapter studies the impacts balance sheet ratios on the probability of banking crises. I utilize the Jorda-Schularick-Taylor Macrohistory Database to predict

crises over a longer sample period incorporating macroprudential target ratios. I supplement these results using machine learning models in order to model non-linear relationships and decompose crisis probabilities using the Shapley value approach. I find that the Loan-To-Deposit ratio is a robust predictor of financial crises and outperforms other variables proposed in the literature, such as overall credit growth, asset price growth, or the yield curve.

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I would like to thank my advisor, Professor Eric Zivot, for his continued support throughout the dissertation process. I am grateful to my committee members Professor Philip Brock, Professor Dennis O'Dea, Professor Yu-Chin Chen, Professor Stephen Turnovsky, as well as my GSR, Professor Zack Almquist, for their useful suggestions and feedback on my work throughout my Ph.D.

DEDICATION

To my parents and Dash

Chapter 1

NONBANK FX SWAP DEMAND AND COVERED INTEREST PARITY DEVIATIONS

1.1 Introduction

Historically, many researchers have shown that covered interest parity (CIP) held, both across countries and across time, leading to the belief that CIP is one of the few binding laws in economics. Theoretically, converting the amount borrowed in a foreign currency using the foreign exchange (FX) spot market, and simultaneously hedging the resulting exchange rate risk using an FX forward contract, should result in the same overall cost for the investor as directly borrowing in the foreign currency. Prior to the Great Financial Crisis (GFC), CIP was known as one of the textbook relationships in international finance. Since 2008, deviations from CIP have become a regularity across currencies, tenors, and various asset classes. Specifically, these deviations are typically widest for the EUR/USD, CHF/USD, and JPY/USD pairs and have been persistent since the 2008 crisis. CIP has been well-known amongst economists and policymakers for being a barometer of international dollar funding conditions. The Federal Reserve has often monitored deviations from CIP in times of financial stress over the past two decades.

Explanations of CIP deviations are centered around risk, specifically that CIP is dependent on antiquated notions of counterparty and liquidity risk. Furthermore, perfect capital mobility and perfect substitutability of domestic and foreign assets are key assumptions that CIP has relied on which no longer hold post-2008. Higher counterparty and liqudity risks have resulted in deviations from CIP even in non-crisis periods. Specifically, the risks involved in an FX swap are no longer equivalent to those in the overnight money market. Dealers will no longer use CIP to set FX forward and swap rates and consider all these risks when setting prices. These fundamental changes in dollar funding conditions, along with balance sheet constraints by Basel III regulations, have ensured that CIP deviations persisted over the past 15 years.

In this paper, I analyze FX hedging demand using a novel dataset from the CLS group. This will bridge a major gap in the literature by providing a detailed look at the impact of non-bank demand in the dollar funding market. Using daily data, I examine the relationship between CIP deviations and non-bank investment demand and currency hedging decisions. Specifically, I focus on non-bank demand for FX swaps and examine heterogeneity across financial industries and currency pairs. The literature on this topic has documented CIP deviations extensively for various interest rates and tenors. However, the fundamental determinants of FX swap demand have been overlooked. It is important for policymakers to determine and anticipate the conditions of dollar funding markets, especially for nonbank entities that do not report their FX holdings on a regular basis. In the appendix, I utilize a portfolio choice model the relationship between a bank and an arbitrageur in order to rationalize the risk channel of CIP deviations. The first agent is a foreign bank that obtains direct and synthetic dollar funding via FX swaps. The second agent is a risk-averse arbitrageur who intends to profit from the CIP deviation and funds dollars in the swap market (hedge fund, FX trader, etc.). They face exchange rate and counterparty risk that is reflected empirically in the price of FX swaps. The supply of dollars by the arbitrageur and demand for dollars by the international bank form a market clearing condition. In order to take on higher risk, the arbitrageur raises the price of the FX swap and therefore raises the equilibrium CIP deviation.

1.2 Literature Review

Du and Schreger (2021) provide an excellent summary of the literature in the Handbook of International Economics. Cerutti, Obstfeld, and Zhou (2019) examine how various macrofinancial series are correlated with the CIP basis. Baba and Packer (2009) explain how counterparty risk during the financial crisis elevated CIP deviations. Higher balance sheet costs and capital requirements are studied by Du, Tepper, and Verdelhan (2018), Liao (2020), and Brauning and Puria (2017). Avdjiev et al. (2019) show a relationship between US dollar spot movements and CIP deviations. Andersen, Duffie, and Song (2019) introduce that funding value adjustment (FVA) costs have exacerbated CIP deviations. Borio, Iqbal, et al. (2018) show that imbalances in FX hedging demand add to the issue. My paper is most closely related to Rime, Schrimpf, and Syrstad (2020) and Wong, Leung, and Ng (2017) who point out that risk premia are not properly assesed in CIP deviation calculations.

Rime, Schrimpf, and Syrstad (2020) uses commercial paper rates to compute CIP deviations based on banks' true marginal funding costs. Wong and Zhang (2018) decompose CIP violations into counterparty credit and funding liquidity risk. Similarly, Kohler, Muller, et al. (2019) use cross-currency repo rates in order to capture this funding liquidity premia.The previous literature on risk in CIP has focused only on documenting deviationsfor various interest rates. My paper fills this gap by modeling why CIP deviations have persisted in order to compensate for liquidity risk and documenting nonbank demand for FX swaps . Most of the recent literature on modeling these deviations focuses on tightening balance sheet constraints or imposing an outside cost of capital (Vayanos and Vila (2009); Ivashina, Scharfstein, and Stein (2015); Liao (2020); Gabaix and Maggiori (2015); Avdjiev et al. (2019); Borio, McCauley, et al. (2016). I use a modified Viswanath-Natraj (2020) model in order to incorporate liquidity risks and generate CIP deviations. Furthermore, I make an empirical contribution to the literature by providing a detailed analysis of non-bank demand in the FX swap market using a novel dataset from the largest swap dealer internationally. Most of the focus has been on how global bank participation in the FX swap and dollar funding markets has impacted CIP. I find that short term spikes in CIP deviations in the past 5 years can be attributed to an increase in non-bank demand for FX swaps, specifically by mutual and hedge funds.

1.3 Motivation

Covered interest parity is a classic no-arbitrage relationship that implicitly postulates the pricing of an FX swap. Specifically, CIP states that the interest rates on two similar assets that differ only in their currency denomination should be identical after hedging for foreign exchange risk. For example, using USD and EUR, the theoretical CIP condition is defined as:

$$1 + i_{USD} = \frac{F}{S}(1 + i_{EUR}) \tag{1.1}$$

where i_{USD} is the interest rate in dollars, i_{USD} is the interest rate in euros, S is the spot exchange rate of USD in terms of EUR, and F is the forward exchange rate of USD in terms of EUR. Note that both interest rates and the forward exchange rate have the same maturity. Moreover, both of these interest-bearing monetary assets should, except for their currency denomination, also be similar in other dimensions, such as the credit risk profile and liquidity. After a logarithmic approximation, the CIP condition implies that the forward premium— the relative difference between the forward and spot exchange rate—is given by:

$$f := log(F/S) = i_{USD} - i_{EUR} \tag{1.2}$$

Equation (2) states that the cost of the FX swap equals the interest rate differential under the covered interest parity condition. Note that the forward premium f is a rate, such that that $f * 100$ measures the percentage cost of the notional value of the swap. Furthermore, the forward premium does not have to be greater than zero; a negative forward premium is also referred to as a forward discount.

Figure 1 illustrates the decisions an investor faces in the FX swap market when covered interest parity holds. Suppose Investor A has USD that she would like to invest either domestically or abroad. Assuming perfect capital mobility and asset substitutability, the return Investor A makes on a dollar-denominated asset should be equivalent to the return that she makes on a similar foreign asset with a higher interest rate. Under CIP, the costs associated with engaging in an FX swap to hedge the foreign exchange risk should offset any extra return that Investor A gains from investing in the foreign asset. A CIP deviation occurs if the cross-currency basis (ccb), defined as the approximate spread between the forward premium and the interest rate differential,

$$ccb := f - (i_{USD} - i_{EUR}) \tag{1.3}$$

is not equal to zero. For example, a positive cross-currency basis, as we have seen for most currencies against USD in recent periods, means that the cost of hedging exchange rate risk is larger than is implied by the CIP. Alternatively, one may interpret a positive basis as the excess cost of borrowing dollars through the swap market when compared to borrowing dollars directly in the money market.

Historically, the cross-currency basis has hovered near zero, as arbitrageurs have taken advantage of the mismatch between the money market and the FX swap market, driving the cross-currency basis down to zero. When credit risk and transaction costs are low, an investor can borrow an in-demand currency in the money market and sell the funds in the FX swap market. During periods when international capital mobility is almost frictionless, the CIP condition converges to zero, as all significant deviations in the cross- currency basis are arbitraged away by parties that have access to large amounts of in- demand currencies (for example, U.S. banks have easy access to dollars). Hence, the supply curve of swaps is perfectly elastic, meaning any volume in the swap market can be accommodated at a constant forward premium that is determined by the interest rate differential.

It is important to emphasize that the CIP conditions depend on the specific asset and maturity used in the CIP calculation, a fact that is not fully recognized in the previous literature. Figure 2 shows the three-month CIP deviation for EUR-USD computed using different interest rates. Given that banks are the most prominent participants in the swap market, using the interest rate paid on government securities may not be appropriate, as these rates may not represent the true marginal cost of funding for banks. Historically, Frenkel and Levich (1975) used interbank rates to evaluate the CIP condition, and the majority of papers thereafter have followed this practice. However, since the 2007–2008 global financial crisis, it became clear that London interbank offered rates (LIBOR rates) contain a significant credit risk premium that may bias CIP computations. Therefore, computing CIP conditions based on overnight index swap (OIS) rates seems more appropriate, as these rates contain little credit risk and liquidity risk premiums (see Liao 2016). Additionally, there is little consensus in the literature on the specific maturity that should be used to calculate the cross-currency basis. The three-month and five-year maturities are commonly used in recent papers. However, given a frictionless swap market,the CIP condition should hold for all maturities. As Figure 1 and 2 shows, deviations from CIP vary widely given the particular interest rate and maturity (the results for other currency pairs are similar). Indeed, the figure shows that the term structure of CIP deviations varies and has been strictly increasing by maturity only in the past few years, while during the global financial crisis and the European sovereign crisis, CIP violations were more pronounced for short maturities.

In the Handbook of International Macro (Du et al. 2021): the authors state that for non-banks, need to "have a better understanding of the relationship between CIP deviations and their investment demand and currency hedging decisions." The CLS data utilized in this paper will help to fill this gap in the literature. Furthermore. policymakers often worry if the CIP basis is a warning signal of greater financial stress. The literature has thoroughly tested CIP breakdown using various interest rates, we now need to understand why we see deviations and what is driving FX demand (see Maggiori 2021).

1.4 Methodology

In order to learn more about the composition of the FX swap market, I use a novel dataset on FX swap holdings from the Continuously Linked Settlement (CLS) service. Firms use the centralized CLS platform to settle their FX transactions and mitigate the settlement risk associated with their FX trades. After forming in 2002, CLS has rapidly increased its trading volume and by March 2017 was settling just over 50% of global FX transactions. In terms of FX Market Growth, CLS data acts as a very good proxy for the market as a whole and growth rates of FX swap turnover are comparable to other sources such as the Bank for International Settlements (BIS) Triennial Survey and the New York Fed Biannual FX Swap Report. CLS provides daily data on FX swap holdings, which to my knowledge has not been utilized before in the context of understanding CIP deviations and FX swap demand by currency pair.

The CLS FX Forward Flow dataset providing insights into directional sentiment of the FX outright forwards and swaps market. This unique dataset provides data illustrating aggregate flow between certain counterparty types: market makers and price takers; non-bank financial institutions and banks; funds and banks; and corporates and banks. The dataset comprises executed trade data for 10 major currency pairs settled by CLS. The underlying data is aggregated daily and processed to illustrate flow between trading parties by tenor. The data is adjusted to follow the reporting convention used by the Bank for International Settlements (BIS) and the local semi-annual foreign exchange committee market reports. These surveys only report the bought currency values, or one leg of the trade, to avoid double counting the total amount of trades. FX price takers and market makers are identified by CLS based on a statistical analysis of network data. The market makers are typically large G-SIB banks while the price takers are often mutual funds, hedge funds, insurance companies, and other non-bank financial institutions.

In this paper, I use a panel dataset by counterparty, tenor, and currency position from 6/1/2020-6/30/2021. The dataset includes 10 major currencies traded against the U.S. Dollar (USD) for 3 different tenors (1 week, 1 month, and 3 months). Unlike other public datasets such as the BIS Triennial Survey and the NY Fed FX Survey, the CLS data provides counterparty level aggregation (Buy Side, Corporate, Fund, or Non-Bank Financial) on a daily basis by FX instrument. This level of detail allows us to better understand non-banks' currency hedging demand, an open research topic proposed by Du and Schreger (2021).

Table 1 shows the daily summary statistics for swap volumes for each currency pairing. CLS reports all volumes from the price taker's perspective. Buy volume denotes the amount of foreign currency bought (in USD billions) and sell volume denotes the amount of domestic USD bought (in USD billions). Table 2 reports the FX swap volumes by tenors reported in CLS. The 1 month tenor takes the largest share of FX swap volume for the sample. Table 3 reports the trade counts for each currency on average. The EUR/USD pair is the most highly traded, followed by the GBP/USD pair.

The EUR/USD pair also has the highest trading volume on average in the sample. Figure 5 shows a pie chart of the trading volume, all currencies are paired against the dollar. Figure 6 reports the volume for the 5 highest currency pairs by date for the sample. As noted by Du et al. (2018), we see large quarter-end and month-end spikes in CIP deviations for all currency pairs and most prominently for the EUR/USD pair. This is mostly due to the face banks face tighter balance sheet constraints at the end of the quarter and investors rebalance their portfolios at the end of the month. These Basel III regulations are explored in Brauning and Puria (2017), including the Value at Risk (VaR) measures for FX swap holdings. Looking at Figure 7, I note that mutual and hedge funds account for the monthly spikes in the EUR/USD basis. This is a key finding, as the composition of FX demand by counterparty industry has not been identified thus far in the previous literature.

Data on FX forward rates, swap rates, and other controls are obtained from Bloomberg. The dollar broad index is downloaded from FRED.

CIP Panel Regressions: Libor Rates

The CIP basis is correlated with dollar market liquidity and intermediaries' risk taking. I start by presenting CIP basis regressions that revisit these results, along with incorporating the CLS FX swap volume in order to identify how changes in non-bank demand can impact CIP deviations across currencies and tenors. Table 4 presents panel regressions of the form:

$$\Delta Log(CIPDeviation)_{tenor,it} = \alpha + \beta_1 \Delta Log(CLSSwapVolume)_{tenor,it} + \beta_2 BroadDollarIndex_{it} + \beta_3 Log(VIX)_{it} + \beta_4 ForwardBidAsk_{tenor,it} + \gamma_i + \varepsilon_t \quad (1.4)$$

CIPDeviation is the absolute value of the percentage deviation from covered interest parity for a given currency pair, CLS Swap Volume is the amount of FX swap volume from the price taker's perspective, and the Broad Dollar Index is downloaded from the FRED database. VIX is the ticker symbol and the popular name for the Chicago Board Options Exchange's CBOE Volatility Index, and finally Forward Bid-Ask refers to the forward rate bid-ask spread in Bloomberg. I use these as controls in order to compare the results to the previous work of Du et al. (2018) and Cerutti et al. (2019). γ_i represents currency pair fixed effects.

Table 1.4 presents the results for the 1 month tenor for all currency pairs against the USD. Huber-White standard errors are used to calculate t-statistics. Column (4) reports the baseline results for the model above. All else equal, a 1% increase in FX swap volume for this tenor results in a 2% widening of the CIP basis. Tables 1.5 and 1.6 report the results for the 1 week and 3 month tenors respectively. The results are not significant for these tenors, as they are lower in volume compared to the 1 month tenor and therefore do not affect the basis as much.

Quarter-End and Month-End Effects of CIP Deviations

Tables 1.7 and 1.8 show the quarter-end and month-end effects on Libor CIP deviations across a panel of 10 currencies from 2000-2021, a topic first explored in Du et al. (2018). I run the following regression models for 3 seperate sample periods (2000-2021, Post-2007, and June 2020-June 2021) in the same spirit of Du et al. (2018):

$$CIPDeviation_t = \alpha + \beta_1 QuarterEnd + \varepsilon_t \tag{1.5}$$

$$CIPDeviation_t = \alpha + \beta_1 MonthEnd + \varepsilon_t \tag{1.6}$$

We see that for the level of CIP deviations, quarter-end effects are significant for the 2000-2021 and Post 2007 sample. The quarter-end effect for the log of CIP deviations is only significant for the entire sample period. Month-end effects, while prominent in the volume of FX swaps traded in CLS, are not significant for any time period. This result implies that for non-banks, month end demand does not have a significant impact on the size of CIP deviations.

CIP Panel Regressions: OIS Rates

I now use the same model in Equation 1.4 but calculate the CIP deviation using Overnight Index Swap (OIS) rates. In table 1.9, the key coefficient on $\Delta LogSwapVol$ is significant only at the 10% level for the 1 week and 1 month tenor. The key coefficient is not significant for the 3 month tenor. We see slightly different results here as for OIS CIP deviations often are lower in magnitude and are not as persistent as deviations using LIBOR rates for the CIP calculation.

1.5 Conclusion

The CIP relationship has fundamentally changed since the Great Financial Crisis. CIP deviations continue to persist due to liquidity risk as domestic and foreign deposits via money market rates are no longer considered equivalent. Although FX swaps are collateralized and therefore reduces counterparty risk, the underlying interest rates take on different risk profiles. Thus, short-term deviations from CIP are no longer a cause for alarm and reflect a different post-crisis trading environment. Finally, I examine a novel dataset from CLS to understand non-bank FX swap demand and the impact on CIP deviations. I find that funds account for short-term spikes in FX swap demand and that increases in FX volume result in short-term deviations from CIP.

1.6 Appendix: Model of FX Swap Demand

The model has two agents, an arbitrageur and an international bank. I consider an arbitrageur that seeks to profit from CIP deviations and a bank that seeks access to synthetic dollar funding in the FX swap market. The international bank can borrow directly via wholesale funding or can turn to the FX swap market at a higher cost. The bank chooses a level of funding that maximizes risk-adjusted return, while the arbitrageur supplies dollars in exchange for domestic currency. Arbitrageurs are risk averse and take on exchange rate risk that increases in the size of the swap position. The market clears when the forward rate ensures that the arbitrageur absorbs the demand for dollar funding by banks.

Arbitrageur

Following Viswanath et al.(2020), I model an arbitrageur that has expected exponential utility over the next period wealth W_{t+1}. The arbitrageur has utility $U_t = E_t[-e^{-\rho W_t+1}]$, where ρ is a risk aversion parameter. In terms of the swap, the arbitraguer exchanges the initial currency principal at the spot rate s_t dollars per unit of foreign currency, with an agreement to re-exchange the principals at the forward rate f_t at maturity. The arbitrageur takes on funding liquidity risk but not exchange rate risk as the swap is collateralized by both sides.

$$W_{t+1} = W_t\,(1+R_t) + (1-\theta)x_{\$,t}\,(f_t - s_t + R_t^* - R_t) \\ +\theta x_{\$,t}\,(s_{t+1} - s_t + R_t^* - R_t) + \gamma_t x_{\$,t} \tag{1.7}$$

There is a default risk where arbitrageur earns stochastic return based on the realized spot rate s_{t+1} instead of forward rate. Due to the collateralized nature of FX swaps, counterparty risk is usually small. The arbitrageur employs a funding liquidity surcharge of γ for swapping dollars with less liquid foreign currency, increasing in the position size.

Assuming $s_{t+1} \sim N(f_t, \sigma_s^2)$, the agent maximizes expected exponential utility, optimizing mean-variance preferences:

$$\max_{x_{\$,t}} \rho\left(W_t\,(1+R_t) + x_{\$,t}\Delta_t - \frac{1}{2}\rho x_{\$,t}^2\sigma^2\right) \tag{1.8}$$

The supply of dollars provided by the arbitrageur is given by the following:

$$x_{\$,t}^* = \frac{\Delta_t}{\rho\theta^2\sigma^2} \tag{1.9}$$

Note that:

$$U_t = -e^{-\rho(W_t(1+R_t)+x_{s,t}\Delta_t-\theta x_{s,t}f_t)}E_t e^{-\rho\theta x_{s,t}s_{t+1}} \tag{1.10}$$

Using the properties of the exponential distribution:

$$E_t e^{-\rho\theta x_{s},t^{s}t+1} = e^{-\rho\theta x_{s,t}-\frac{1}{2}\rho\theta^2 x_{s,t}^2\sigma^2} \tag{1.11}$$

Bank

Consider an international bank with domestic assets A^*, dollar assets A, domestic deposits D^*, and bank equity K. The bank has some access to direct dollar funding B, but has to swap some of it's domestic currency $x_\$^B$ into dollars. Asset returns stochastic with $\tilde{y}_{A^*} \sim N\left(y_{A^*}, \sigma_{A^*}^2\right)$ and $\tilde{y}_A \sim N\left(y_A, \sigma_A^2\right)$. There is a fixed borrowing cost on deposits denoted by c_d. The bank's optimization problem is given by:

$\max_{A_t, A_t^*, x_\$^B, B_{s,t}, D_{d,t}} V_{t+1} = \tilde{y}_A A_t + \tilde{y}_{A^*} A_t^* - (\ell_\$ + R_t)\,B$

-$(\ell_d + R_t^* + f_t - s_t + \gamma)x_{\$}^B - c_d D_{d,t} - F\left(x_{\$}^B\right)$

Where $\ell_{\$/d}$ is the dollar/domestic credit spread. $F\left(x_{\$,t}\right.$ is the hedging cost of an FX swap, and $F'() > 0, F'' > 0$ as in Abbassi and Brauning (2020). I use a similar banking set up as in Avdjiev et al. (2020). The bank is subject the following constraints:

$$K = A_t + A_t^* - D_{d,t} - B_{\$,t} - x_{\$}^B \tag{1.12}$$

$$A_t = x_{\$}^B + B_t \tag{1.13}$$

$$B_t \leq \omega K \tag{1.14}$$

Taking FOCs, we arrive at the following condition:

$$\underbrace{\ell_{d,t} + R_t + f_t - s_t + F'(x_{\$}^B) + \gamma_t}_{\text{synthetic dollar cost}} = \underbrace{\ell_{\$,t} + R_t^* + \lambda_t}_{\text{direct dollar cost}} \tag{1.15}$$

where λ_t is the Lagrangian for constraint 7.

In equilibrium, the arbitrageur will supply $x_{\$,t}^*$ dollars, optimizing mean-variance preferences. A representative bank demands $x_{\$,t}^B$, optimizing the value of their portfolio such that:

$$x_{\$,t}^B = F'^{-1}\left(\ell_{\$} - (\ell_d + \Delta)\right) \tag{1.16}$$

In summary, as the key liquidity risk parameter γ increases, bank will demand less dollar funding and leave some domestic currency unhedged.

Figures

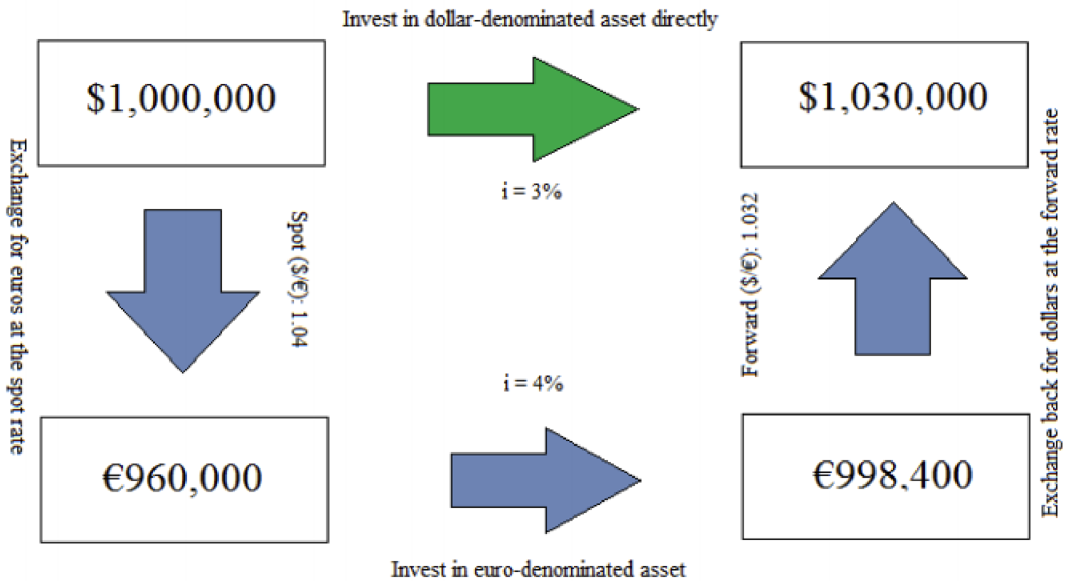

Figure 1.1: CIP Trade Diagram

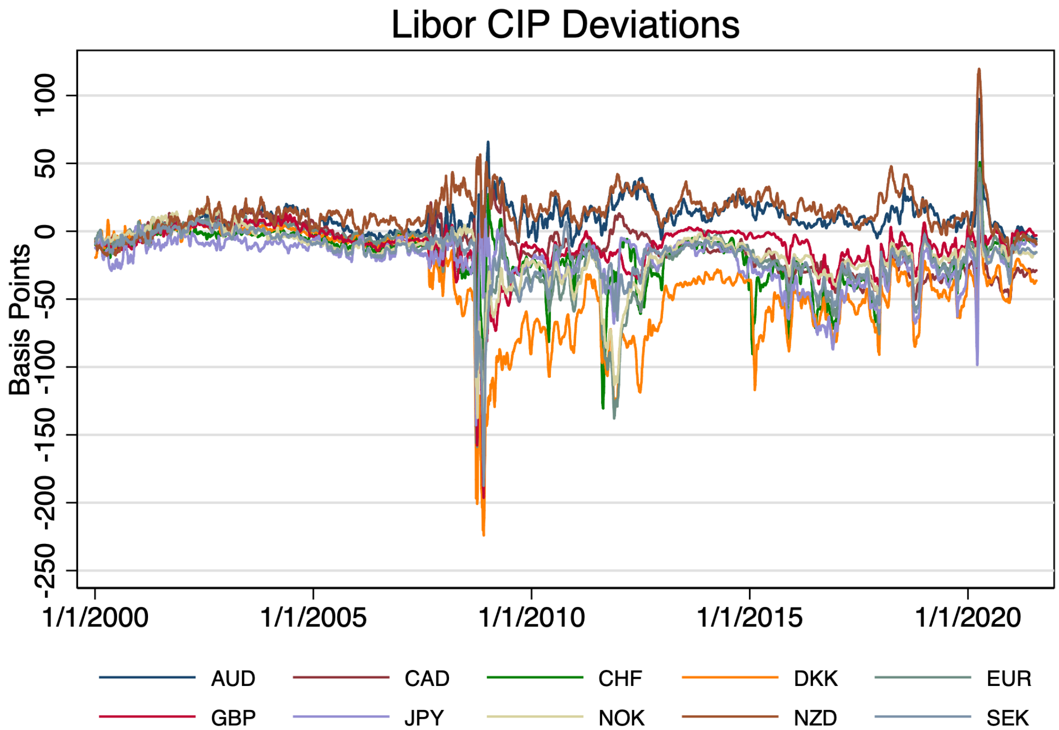

Figure 1.2: Libor CIP Deviations

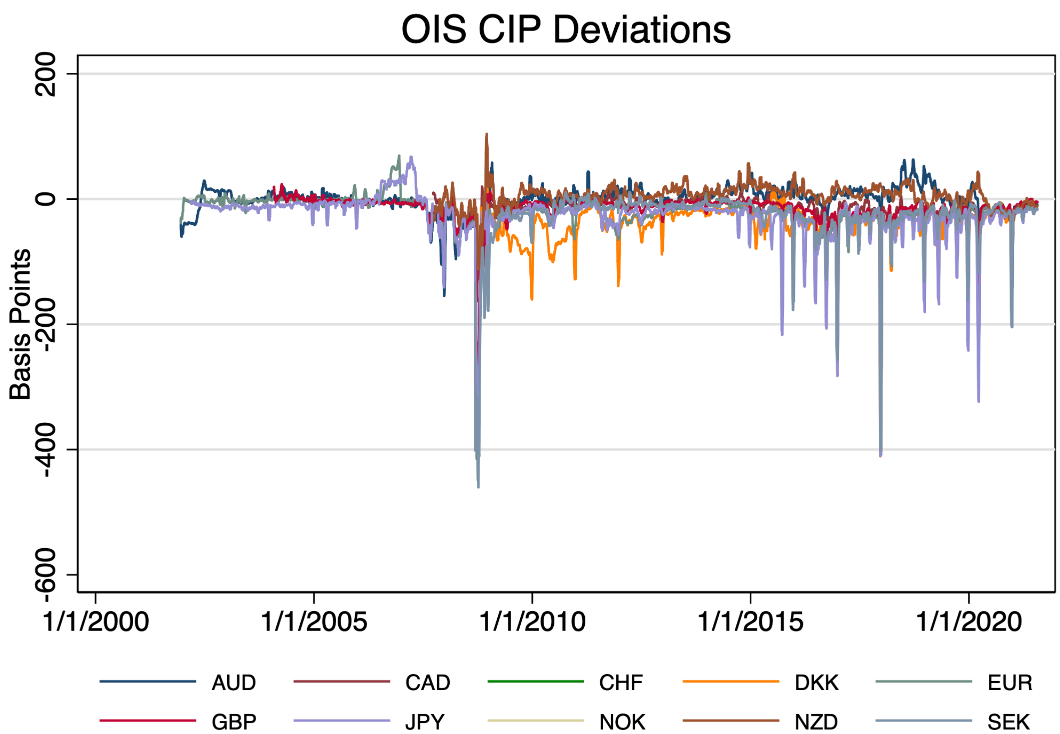

Figure 1.3: OIS CIP Deviations

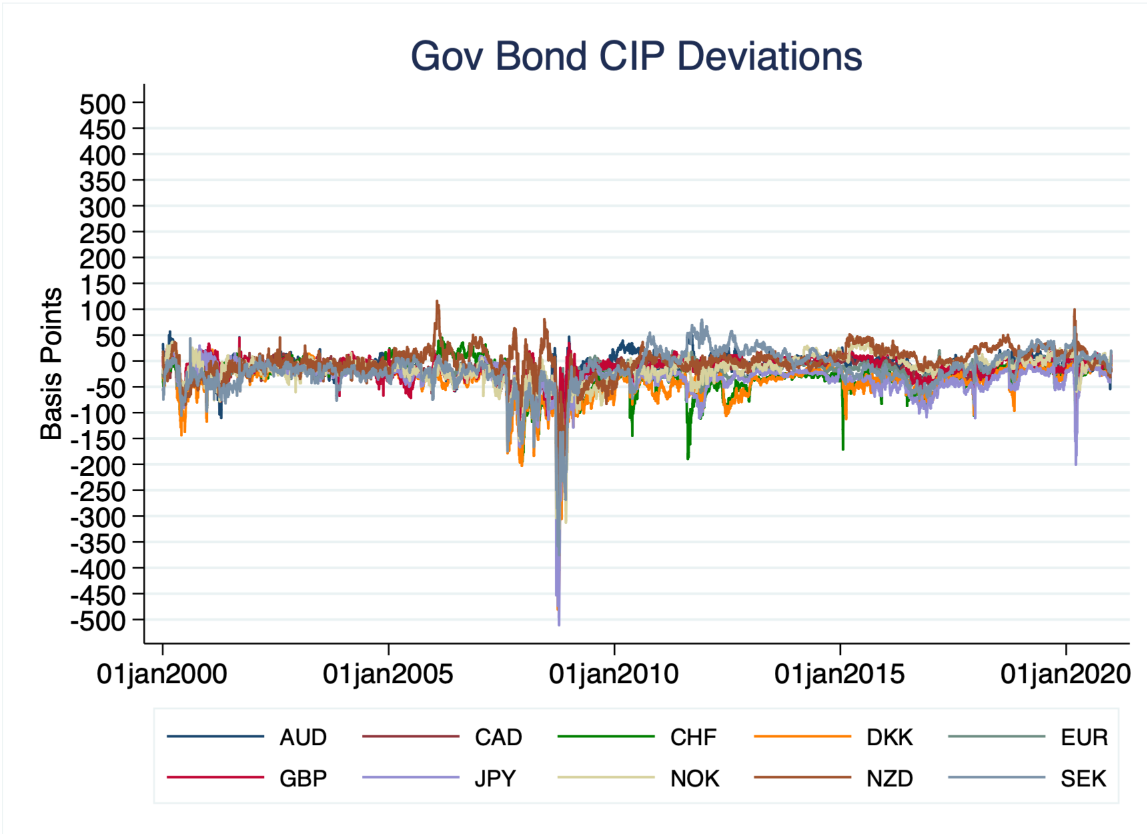

Figure 1.4: Government Bond CIP Deviations

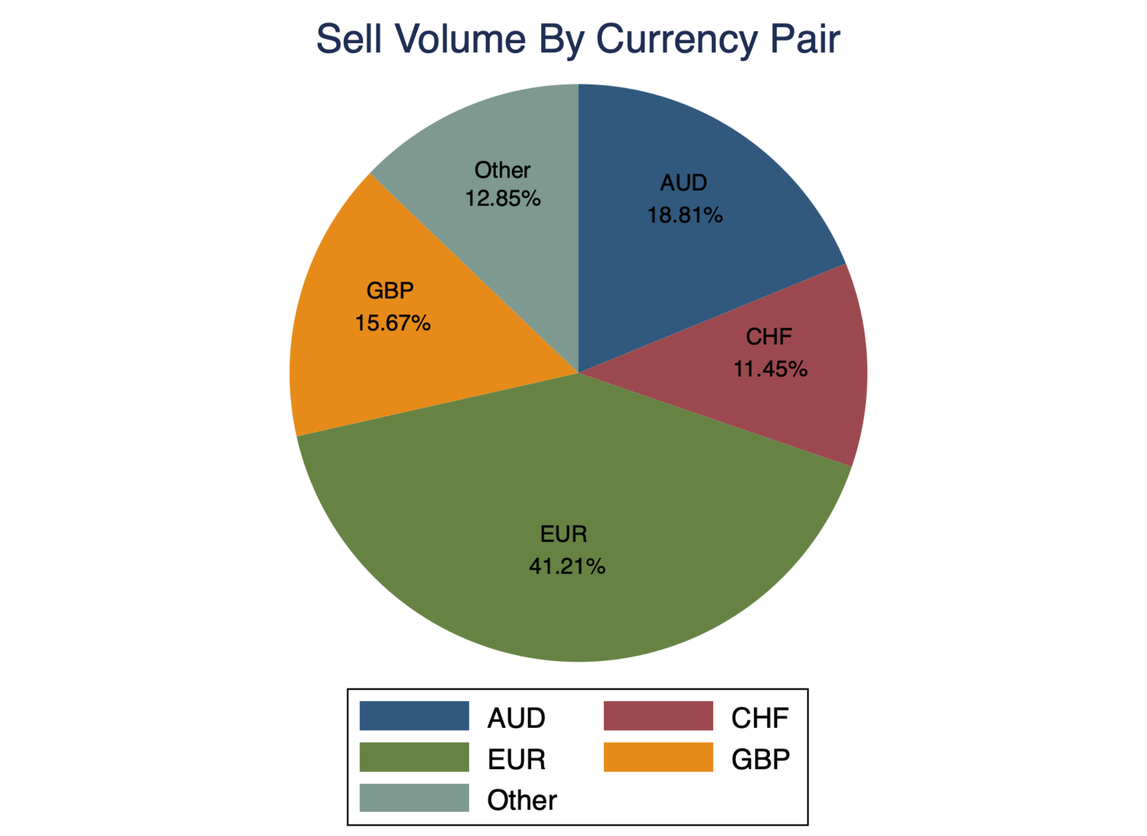

Figure 1.5: CLS FX Swap Volume By Currency Against USD

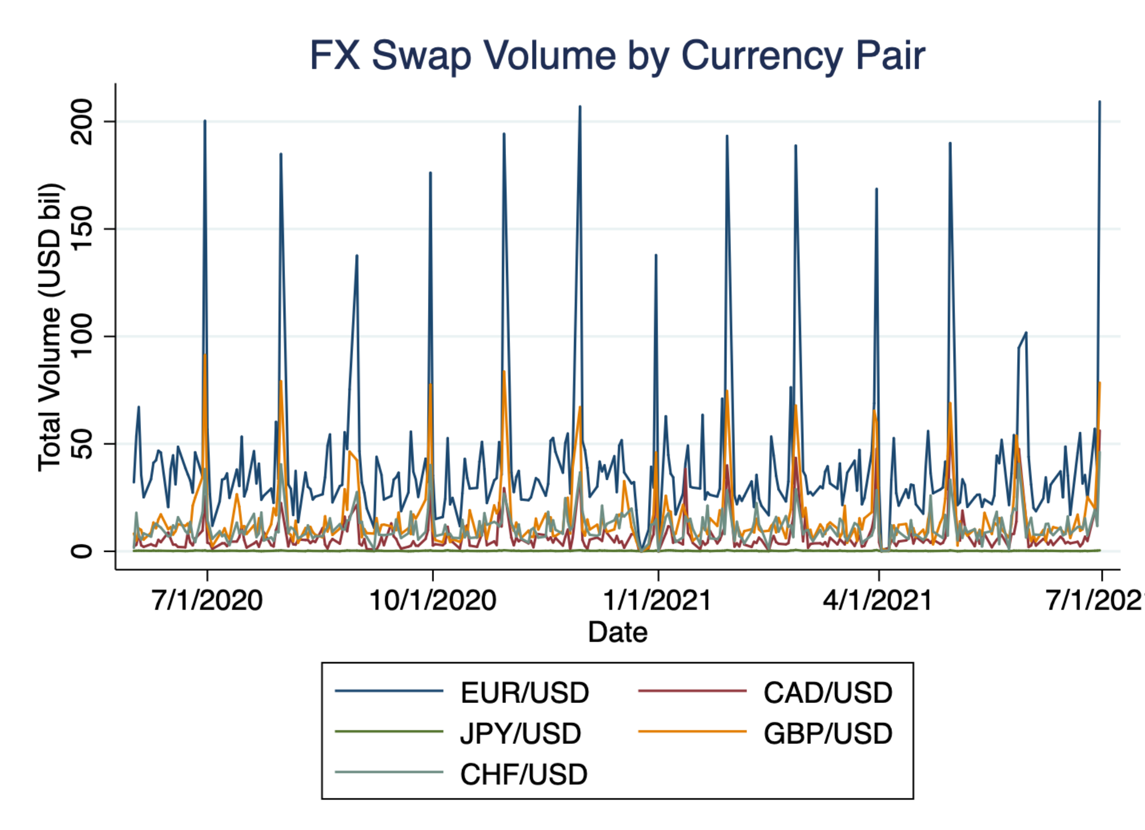

Figure 1.6: CLS FX Swap Volume By Currency Pair

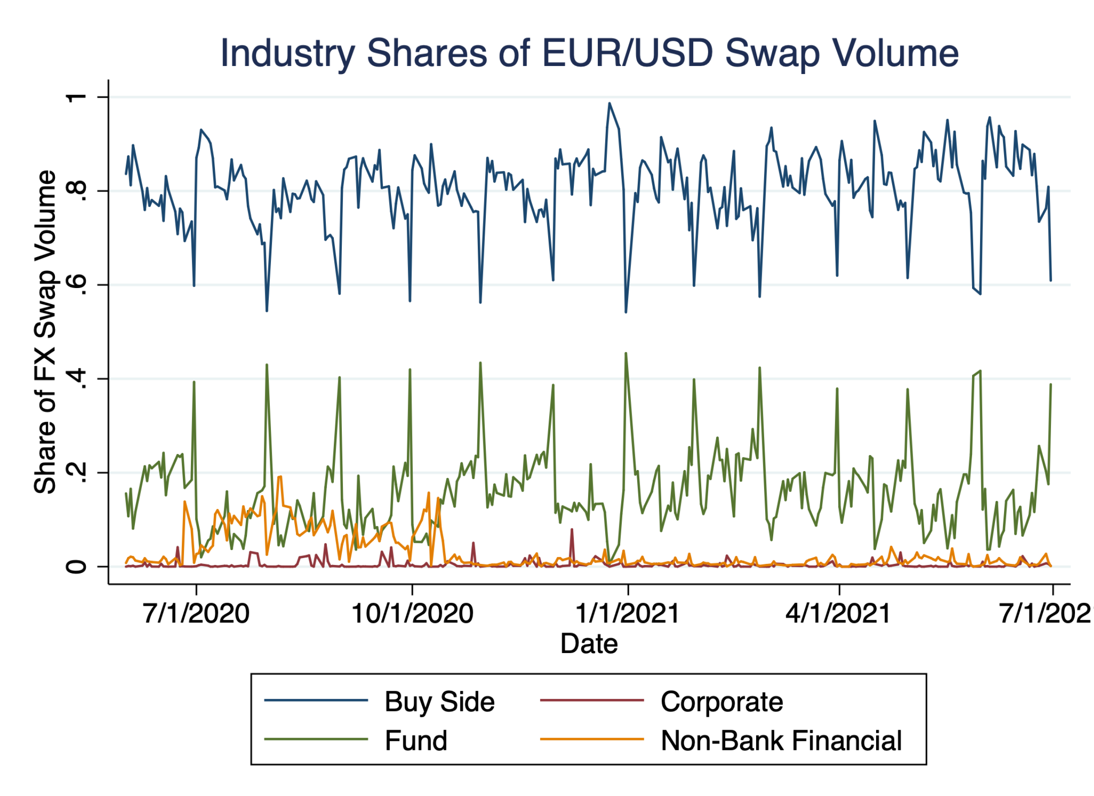

Figure 1.7: Industry Shares of EUR/USD Swap Volume

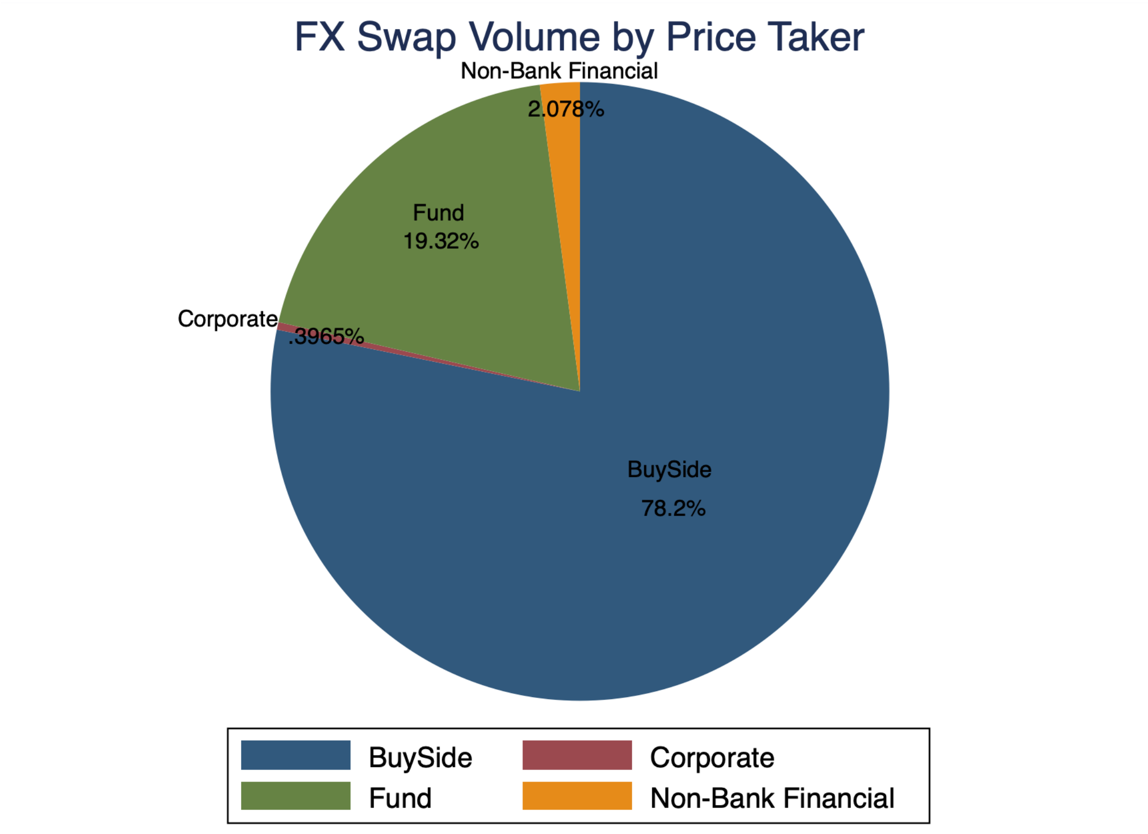

Figure 1.8: Industry Shares of Total Swap Volume

Tables

CLS FX Swap Volume (USD Billions)

AUD/USD	N	Mean	Std Dev	Min	Max
Buy volume	843	4.144	4.219	0	35.065
Sell volume	843	6.176	9.642	0	69.148
CAD/USD					
Buy volume	843	1.867	2.635	0	29.296
Sell volume	843	2.361	4.798	0	53.931
CHF/USD					
Buy volume	843	2.28	1.946	0	14.065
Sell volume	843	3.759	4.39	0	40.372
DKK/USD					
Buy volume	843	.035	.062	0	.564
Sell volume	843	.059	.072	0	.435
EUR/USD					
Buy volume	843	11.958	19.414	0	188.734
Sell volume	843	13.529	20.581	0	187.214
GBP/USD					
Buy volume	843	4	5.031	0	52.51
Sell volume	843	5.144	9.156	0	86.132
JPY/USD					
Buy volume	843	.07	.071	0	.652
Sell volume	843	.073	.072	0	.472
NOK/USD					
Buy volume	843	.044	.051	0	.296
Sell volume	843	.076	.078	0	.495
NZD/USD					
Buy volume	843	1.189	1.531	0	13.938
Sell volume	843	1.561	2.465	0	22.964
SEK/USD					
Buy volume	843	.073	.08	0	.612
Sell volume	843	.088	.101	0	.647

Table 1.1: CLS Summary Statistics by Currency Pair

CLS FX Swap Volume (USD Billions)					
1 Month	N	Mean	Std Dev	Min	Max
Foreign ccy	2810	4.611	11.993	0	188.734
USD	2810	5.831	14.174	0	187.214
1 Week					
Foreign ccy	2810	1.023	1.871	0	24.365
USD	2810	.806	1.44	0	20.098
3 Months					
Foreign ccy	2810	2.064	3.438	0	46.541
USD	2810	3.211	5.242	0	64.298

Table 1.2: CLS Summary Statistics by Maturity

CLS FX Swap Volume Trade Counts					
AUD/USD	N	Mean	Std Dev	Min	Max
Trade Count	843	104.605	94.332	0	585
CAD/USD					
Trade Count	843	69.47	81.962	0	880
CHF/USD					
Trade Count	843	65.218	60.669	0	357
DKK/USD					
Trade Count	843	8.335	11.656	0	119
EUR/USD					
Trade Count	843	363.107	341.859	0	1963
GBP/USD					
Trade Count	843	162.102	139.449	0	840
JPY/USD					
Trade Count	843	108.161	110.785	0	1014
NOK/USD					
Trade Count	843	23.899	29.308	0	244
NZD/USD					
Trade Count	843	31.094	30.324	0	224
SEK/USD					
Trade Count	843	28	28.93	0	254

Table 1.3: CLS Trade Counts by Currency Pair

VARIABLES	(1) Δ Log CIP Dev	(2) Δ Log CIP Dev	(3) Δ Log CIP Dev	(4) Δ Log CIP Dev
Δ Log Swap Vol	0.0110*	0.0174**	0.0189**	0.0197***
	(0.00625)	(0.00739)	(0.00739)	(0.00740)
Δ Broad Dollar		0.0193	0.0401	0.0392
		(0.0253)	(0.0259)	(0.0259)
Δ Log VIX			-0.375***	-0.370***
			(0.110)	(0.110)
Δ Fwd Bid-Ask Spread				-0.0114
				(0.00794)
Constant	-0.0198***	-0.0192**	-0.0207**	-0.0210**
	(0.00726)	(0.00862)	(0.00860)	(0.00860)
Observations	2,197	1,702	1,702	1,702
R-squared	0.003	0.005	0.012	0.013

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.4: 1 Month Tenor Panel Regression - Libor CIP Deviations

VARIABLES	(1) Δ Log CIP Dev	(2) Δ Log CIP Dev	(3) Δ Log CIP Dev	(4) Δ Log CIP Dev
Δ Log Swap Vol	-0.0360***	-0.0188*	-0.0184*	-0.0183*
	(0.0114)	(0.0109)	(0.0109)	(0.0109)
Δ Broad Dollar		0.214***	0.238***	0.240***
		(0.0583)	(0.0603)	(0.0604)
Δ Log VIX			-0.390	-0.400
			(0.248)	(0.248)
Δ Fwd Bid-Ask Spread				0.0113
				(0.0135)
Constant	-0.000802	0.0116	0.0110	0.0115
	(0.0205)	(0.0197)	(0.0197)	(0.0197)
Observations	1,296	1,012	1,012	1,012
R-squared	0.011	0.020	0.023	0.023

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.5: 1 Week Tenor Panel Regression - Libor CIP Deviations

VARIABLES	(1) Δ Log CIP Dev	(2) Δ Log CIP Dev	(3) Δ Log CIP Dev	(4) Δ Log CIP Dev
Δ Log Swap Vol	0.00321	0.00493	0.00501	0.00528
	(0.00731)	(0.00866)	(0.00868)	(0.00868)
Δ Broad Dollar		0.0205	0.0214	0.0221
		(0.0305)	(0.0313)	(0.0313)
Δ Log VIX			-0.0163	-0.0175
			(0.134)	(0.134)
Δ Fwd Bid-Ask Spread				-0.0106
				(0.00736)
Constant	-0.00827	-0.0100	-0.0101	-0.0107
	(0.00883)	(0.0104)	(0.0104)	(0.0105)
Observations	2,188	1,693	1,693	1,693
R-squared	0.001	0.002	0.002	0.003

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.6: 3 Month Tenor Panel Regression - Libor CIP Deviations

VARIABLES	(1) CIP LIBOR Post 2000	(2) CIP LIBOR Post 2000	(3) CIP LIBOR Post 2007	(4) CIP LIBOR Post 2007	(5) CIP LIBOR Post June 2020	(6) CIP LIBOR Post June 2020
Quarter End	3.631***		3.216**		-1.121	
	(1.007)		(1.400)		(1.013)	
Month End		0.151		0.213		-0.803
		(0.424)		(0.616)		(0.932)
Constant	23.62***	23.66***	29.55***	29.58***	19.02***	19.03***
	(0.0752)	(0.0765)	(0.108)	(0.110)	(0.248)	(0.251)
Observations	156,187	156,187	99,148	99,148	8,456	8,456
R-squared	0.000	0.000	0.000	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.7: Quarter and Month End Effects on Level of CIP Deviations

VARIABLES	(1) Log(CIP LIBOR) Post 2000	(2) Log(CIP LIBOR) Post 2000	(3) Log(CIP LIBOR) Post 2007	(4) Log(CIP LIBOR) Post 2007	(5) Log(CIP LIBOR) Post June 2020	(6) Log(CIP LIBOR) Post June 2020
Quarter End	0.102***		0.0357		0.102	
	(0.0316)		(0.0341)		(0.0765)	
Month End		-0.00452		-0.00312		0.0356
		(0.0180)		(0.0201)		(0.0604)
Constant	2.577***	2.578***	2.924***	2.924***	2.496***	2.496***
	(0.00319)	(0.00323)	(0.00350)	(0.00354)	(0.0119)	(0.0120)
Observations	156,187	156,187	99,148	99,148	8,456	8,456
R-squared	0.000	0.000	0.000	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.8: Quarter and Month End Effects on Log of CIP Deviations

VARIABLES	(1) Δ Log CIP Dev OIS	(2) Δ Log CIP Dev OIS	(3) Δ Log CIP Dev OIS	(4) Δ Log CIP Dev OIS
Δ Log Swap Vol	0.0135*	0.00992	0.0106*	0.0108*
	(0.00687)	(0.00636)	(0.00635)	(0.00636)
Δ Broad Dollar		0.0996***	0.124***	0.124***
		(0.0348)	(0.0361)	(0.0361)
Δ Log VIX			-0.366**	-0.368**
			(0.150)	(0.150)
Δ Fwd Bid-Ask Spread				0.00562
				(0.0120)
Constant	-0.0127	-0.000597	-0.00114	-0.000954
	(0.0124)	(0.0118)	(0.0117)	(0.0118)
Observations	1,300	1,021	1,021	1,021
R-squared	0.007	0.016	0.022	0.022

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 1.9: 1 Week Tenor Panel Regression - OIS CIP Deviations

VARIABLES	(1) Δ Log CIP Dev OIS	(2) Δ Log CIP Dev OIS	(3) Δ Log CIP Dev OIS	(4) Δ Log CIP Dev OIS
Δ Log Swap Vol	0.00741	0.00510	0.00681	0.00777*
	(0.00551)	(0.00442)	(0.00439)	(0.00439)
Δ Broad Dollar		0.0260*	0.0435***	0.0426***
		(0.0151)	(0.0155)	(0.0154)
Δ Log VIX			-0.316***	-0.309***
			(0.0658)	(0.0656)
Δ Fwd Bid-Ask Spread				-0.0147***
				(0.00506)
Constant	-0.0130**	-0.0113**	-0.0125**	-0.0129**
	(0.00640)	(0.00516)	(0.00512)	(0.00511)
Observations	1,753	1,358	1,358	1,358
R-squared	0.002	0.007	0.023	0.029

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.10: 1 Month Tenor Panel Regression - OIS CIP Deviations

VARIABLES	(1) Δ Log CIP Dev OIS	(2) Δ Log CIP Dev OIS	(3) Δ Log CIP Dev OIS	(4) Δ Log CIP Dev OIS
Δ Log Swap Vol	-0.00251	-0.00253	-0.00189	-0.00193
	(0.00296)	(0.00247)	(0.00246)	(0.00246)
Δ Broad Dollar		0.0280***	0.0359***	0.0360***
		(0.00859)	(0.00878)	(0.00877)
Δ Log VIX			-0.146***	-0.146***
			(0.0376)	(0.0376)
Δ Fwd Bid-Ask Spread				-0.00523**
				(0.00251)
Constant	-0.00602*	-0.00278	-0.00336	-0.00363
	(0.00354)	(0.00294)	(0.00292)	(0.00292)
Observations	1,746	1,351	1,351	1,351
R-squared	0.002	0.009	0.020	0.023

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.11: 3 Month Tenor Panel Regression - OIS CIP Deviations

Chapter 2

THE EFFECTS OF ORDER FLOW AND CENTRAL BANK SWAP LINES ON THE FOREIGN EXCHANGE SWAP MARKET

2.1 Introduction

In this chapter, I extend the analysis from the first chapter by analyzing how prices are set in the FX swap market. While most of the literature focuses on excess demand for USD in the swap market and its reflection in the Covered Interest Parity (CIP) basis, few studies have focused on order flow and the recent effects of swap lines on FX forward rates. I construct a measure of order flow using the CLS database referenced in chapter 1, the net of buyer and seller-initiated transactions. I focus on the 1-month tenor due to high market volume and use the 1-month CIP deviation and 1-month FX swap and forward flow for the empirical analysis.

I first examine the price impact of order flow during the COVID period, when price heterogeneity in USD was high and dollar funding was in high demand across the world. Regulatory reporting at quarter-ends often resulted in higher demand as market participants would often roll forward their FX contracts or rebalance their portfolios in line with the Basel III accords. Regulatory requirements also make it more difficult for arbitrageurs to use their capital. Prior to 2008, money markets in general featured low variance in funding costs across banks and tighter risk premiums. The London Interbank Offered Rate (Libor) was the primary measure of banks' marginal cost across currencies. Dealers in FX markets simply set the FX forward rate according to CIP and banks could easily capitalize on arbitrage opportunities as their balance sheets were not constrained. Post 2008, there is a considerable amount of heterogeneity in dollar funding costs and higher regulatory constraints for banks. As a result, the FX forward rate is harder to price from the dealer's perspective and policymakers are often in the dark about the size of the USD funding gap.

I then test whether or not the Federal Reserve swap lines reduced order flow and volume into USD during the COVID period. Historically, swap lines between central banks can ease dollar liquidity stresses globally and can improve financial stability. The Federal Reserve simply exchanges dollars for a domicile currency at a foreign central bank, set at a premium over the interbank dollar rate. This paper focuses on swap lines between the Federal Reserve, Bank of England (BOE), Bank of Canada (BOC), European Central Bank (ECB), Bank of Japan (BOJ) and Swiss National Bank (SNB).

2.2 Literature Review

The recent literature on CIP has focused on explanations of persistent violations since 2008 (Du et. al (2018), Liao (2020), Brauning and Puria (2017)). Evans and Lyons (2006), Rime et al. (2010), Ranaldo and Somogyi (2021) examine the price impact of order flow in the spot FX markets. Krohn and Sushko (2022) analyze the impacts of market liquidity and bid/ask spreads during the quarter-end periods. Rime et al. (2022) find that order flow has an impact on FX forward prices during the post-2008 period. My paper relates to this literature by using novel CLS data to estimate the price impact of order flow and Federal Reserve swap lines during the COVID stress period.

A large literature exists on the effects of swap lines on prices (Bahaj and Reis (2018), Aizenman et al. (2022), Goldberg and Ravazzolo (2021)). These papers document positive price effects, ceilings on CIP deviations, and a reduction in forward premia over a variety of swap line provision periods. More recently, Abbassi and Brauning (2021) show that dollar forward sales by non-U.S. banks that are initiated at quarter-ends trade at higher prices and higher volumes. Syrstad and Viswanath-

Natraj (2020) find that central bank swap lines reduced order flow in the post-2008 period. Similarly, Ferrara et al. (2022) discover that dealers that draw on Fed swap lines reduce their demand for dollars in the FX swap market. My paper contributes to the literature by analyzing how volume and order flow from the CLS Group, which represents a majority of FX forward volume, is affected by swap line usage during the COVID period.

2.3 Data Description

Due to market depth, I use FX swaps and forwards and CIP deviations at the 1 month maturity as mentioned in Chapter 1:

$$1 + i_{USD} = \frac{F}{S}(1 + i_{EUR}) \tag{2.1}$$

where i_{USD} is the interest rate in dollars, i_{USD} is the interest rate in euros, S is the spot exchange rate of USD in terms of EUR, and F is the forward exchange rate of USD in terms of EUR. Note that both interest rates and the forward exchange rate have the same maturity. Moreover, both of these interest-bearing monetary assets should, except for their currency denomination, also be similar in other dimensions, such as the credit risk profile and liquidity. After a logarithmic approximation, the CIP condition implies that the forward premium— the relative difference between the forward and spot exchange rate—is given by:

$$f := log(F/S) = i_{USD} - i_{EUR} \tag{2.2}$$

Which states that the cost of the FX swap equals the interest rate differential under the covered interest parity condition. Note that the forward premium f is a rate, such that that $f * 100$ measures the percentage cost of the notional value of the swap. Furthermore, the forward premium does not have to be greater than zero; a negative forward premium is also referred to as a forward discount.I define order flow as the net of transactions initiated by the price taker. In this case, this would represent a counterparty swapping a foreign currency into USD. I use the order flow data from the CLS Group which includes data by counterparty, tenor, and currency position from 6/1/2020-6/30/2021. The CLS data provides counterparty level aggregation (Buy Side, Corporate, Fund, or Non-Bank Financial) on a daily basis. The measure of order flow represents a net of buyer-initiated transactions over a trading day, where I denote buyer-initiated transactions as +1 and seller-intiated transactions as -1. I exclude days when no inter-dealer trades are recorded. As in Syrstad and Viswanath-Natraj (2020), I define order flow as:

$$OF_t^{count} = \sum_{k=t}^{k=t+1} 1\left[T_k = B\right] - 1\left[T_k = S\right] \tag{2.3}$$

Where B denotes transactions initiated by a buyer and S denotes transactions initiated by a seller. Summary statistics of order flow by currency are provided in Table 2.1. The EUR/USD pair has the highest range or order flow, ranging from [-1658,1089] followed by the GBP/USD pair with a range of [-1436,869]. Order flow summary statistics by tenor are shown in Table 2.2. The 1 month tenor has the largest range of order flow at [-1658,1089]. Plots of daily order flow by maturity are provided in Figures 2.1-2.3.

The BOC, BOE, BOJ, ECB and the SNB set up a network of bilateral central bank swap lines with the Federal Reserve, which have been in place on a standing basis since 2013. These swap lines allow foreign central banks to provide liquidity to their domestic markets. As a first step, the Federal Reserve swaps USD for the counterparty central bank's currency at a given exchange rate. The foreign central bank then distributes the USD, typically through repo auctions. At the maturity of the contract, the currencies are re-exchanged at the same exchange rate. The counterparty central bank pays a penalty rate for this operation, typically OIS+25bp to OIS+50bp for the 1 week through 3 month maturities. Data on the Federal Reserve swap lines available from the New York Federal Reserve contain details on the amount, currency, tenor and receiving central bank of each swap line auction. I construct a measure of outstanding swap line amounts lent to each of the respective foreign central banks using this data provided.

2.4 Price Impact of FX Order Flow

I now analyze the price impact of FX order flow. A higher order flow often results in an increase in the forward premium and a widening of the CIP deviation. We test this hypothesis using the following baseline specification:

$$\Delta Log(CIP_t) = \alpha + \beta_1 OF_t + \beta_j x_{j,t} + \epsilon_t \tag{2.4}$$

The dependent variable is the CIP deviation at a specified maturity level and $beta_1$ represents the price impact of Order Flow (OF). X is a vector of control variables including the change in the Bid-Ask spreads, the VIX index, and the USD trade-weighted exchange rate. We run this specification for all currency pairs and maturities as a panel and for the pairs EUR/USD, JPY/USD, and GBP/USD separately as they are the most in-demand for FX swaps and forwards. Since the sample period of 6/1/2020-6/1/2021 is during the COVID period, I hypothesize that higher demand for USD borrowing through FX swaps (positive order flow) leads to an increase in the synthetic USD rate implied from the FX swap market relative to the direct USD rate. Thus, dealers need to adjust the forward rate aggressively to attract opposite flows.

I present the results from the baseline specification in Table 2.3, using CIP calculated with OIS rates. Column (1) depicts the Price impact of Order Flow using the panel of currencies and includes currency pair fixed effects. Columns (2) through (4) show the effects for the top 3 most traded currencies against the dollar. I find that order flow has significant price impact at the 5% level for the EUR/USD pair, which is the most traded pair in the dataset. Specifically, a 100 trade increase in order flow results in a decrease in the CIP deviation by 0.3%. I now test benchmark Libor rates instead of OIS rates for the CIP calculation, shown in Table 2.4. The key coefficient on order flow is insignificant aside from the GBP/USD pair. For this GBP/USD pair, I find that a 100 trade increase in order flow results in a decrease in the CIP deviation by 1.4%. This result is driven by the swap line program being heavily utilized during the first 2 quarters of 2020 by foreign central banks.

2.5 Dollar Funding Costs at Quarter-Ends

I now modify the framework above and measure the effect of regulatory constraints at quarter-end periods, as mentioned by Du et al. (2018). During quarter-ends, many mutual and hedge funds rebalance their portfolios and roll forward their FX swap contracts. Banks look to ensure that they are compliant with balance sheet and leverage regulatory requirements, and price makers often face large heterogeneity in USD funding costs. As a result, the price impact of order flow is expected to increase during these periods of adjustment. I test this hypothesis by running the following specification:

$$\Delta Log(CIP_t) = \alpha + \beta_1 OF_t * QEnd + \beta_j x_{j,t} + \epsilon_t \tag{2.5}$$

where $QEnd$ is a dummy variable for the quarter-end period. The key interaction term captures the price impact of an increase in funding costs when an FX swap contract crosses the end of a given quarter in the sample 6/1/2020-6/1/2021.

The results are presented in Table 2.5. Similar to the baseline specification, column (1) displays the panel of currencies and all maturities, while columns (2) through (4) show the individual currency pairs with the highest demand. Consistent with the findings above, I estimate a 1.93% decrease in the OIS CIP basis during high funding heterogeneity at quarter-ends given a 100 trade increase in order flow for the EUR/USD pair (significant at the 1% level). Table 2.6 tells a similar story, where I estimate a 3.18% decrease in the Libor CIP basis given a 100 trade increase in order flow for the EUR/USD pair (significant at the 1% level).

2.6 Swap Line Allotment During COVID

I now examine the effect of swap lines on FX dollar funding markets during the COVID period. Figures 2.4-2.6 plot the outstanding swap lines to counterparty central banks during this period. The majority of these lines were drawn in the first quarter of 2020 and the Bank of Japan utilized swap lines heavily during the second quarter of 2020 as well. I run a simple regression of order flow on a dummy where swap lines were drawn from a counterparty central bank. The sample runs from 6/1/2020-6/1/2021. Table 2.7 shows that order flow is substantially lower for the panel of currencies on the days when USD liquidity is provided by the Federal Reserve. Column (1) includes all currencies in the sample and includes currency fixed effects, while columns (2)-(4) show the effects for the top individual currency pairs.

I now test the effects of swap line allotment on CIP deviations using a similar specification:

$$\Delta Log(CIP_t) = \alpha + \beta_1 Allotment_i + \beta_j x_{j,t} + \epsilon_{i,t} + \gamma_i \tag{2.6}$$

where *Allotment* measures the change in outstanding swap lines for currency i in billions of USD. γ_i denotes currency fixed effects in order to control for currency differences in OIS CIP deviations. x represents a vector of control variables as in the specifications above. The sample period is 1/8/2020-7/21/2020 corresponding with the COVID wave of swap line agreements. The results are shown in Table 2.8: a 1 billion dollar increase in swap line allotment results in a 0.25% decrease in the absolute value of the CIP deviation. This finding supports the view that swap lines are beneficial for USD funding markets in times of financial stress.

2.7 Conclusion

In this chapter, I identify FX order flow as a key driver of FX swap pricing. During the COVID period and at quarter-ends, USD funding costs increased and adjustments were made in the FX swap and forward markets. Based on counterparty level data from the CLS group, I estimate a 1.93% decrease in the OIS CIP basis during high funding heterogeneity at quarter-ends given a 100 trade increase in order flow for the EUR/USD pair during 2020. Furthermore, order flow is substantially lower for the panel of currencies on the days when USD liquidity is provided by the Federal Reserve. These findings support the Federal Reserve's swap line program and identifies heterogeneity in USD funding costs at quarter-ends.

Figures

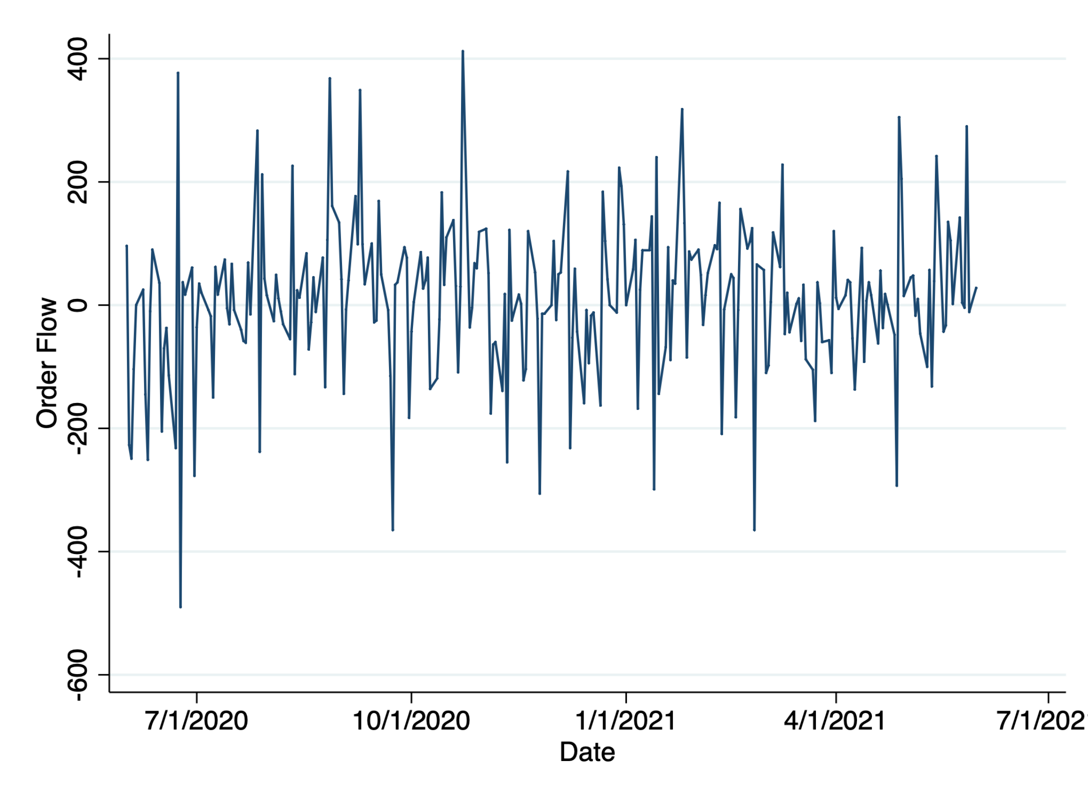

Figure 2.1: 1 Week Tenor Daily Order Flow

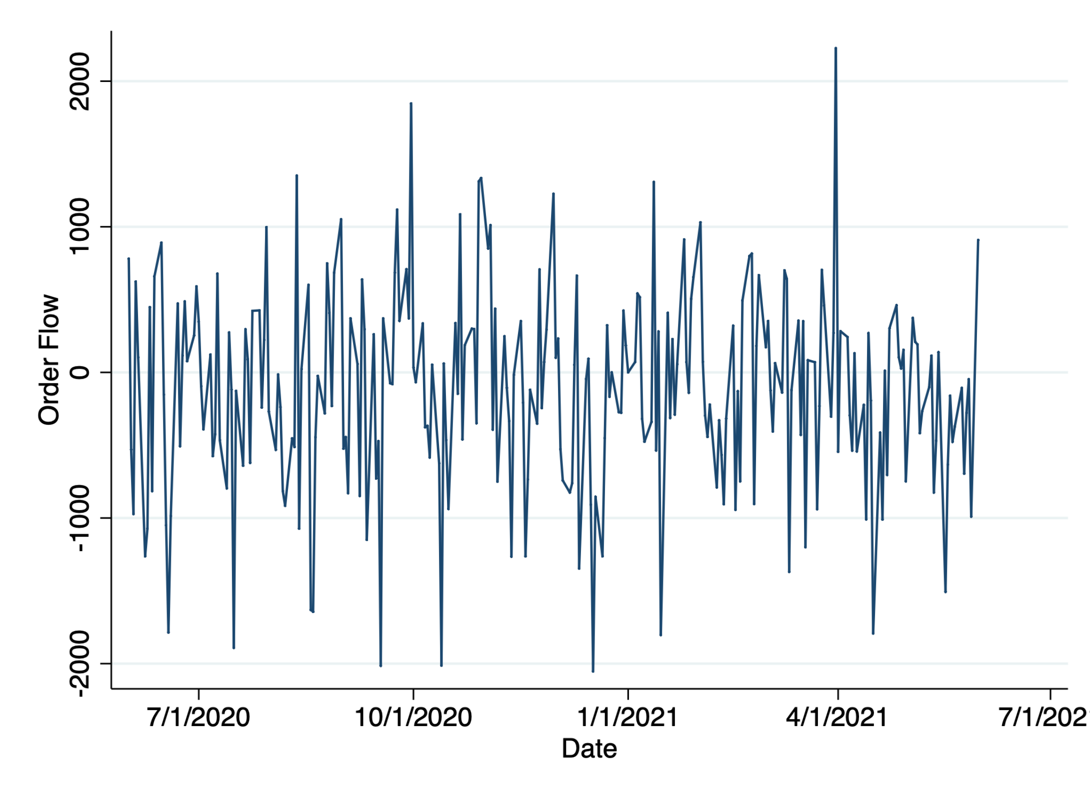

Figure 2.2: 1 Month Tenor Daily Order Flow

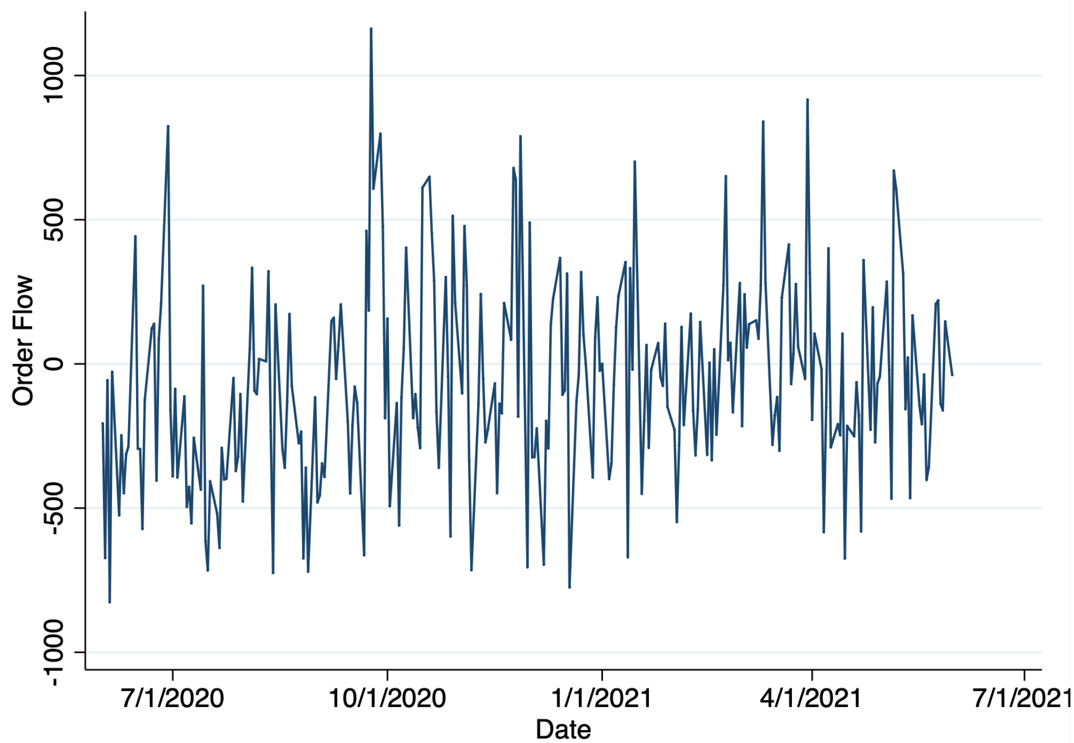

Figure 2.3: 3 Month Tenor Daily Order Flow

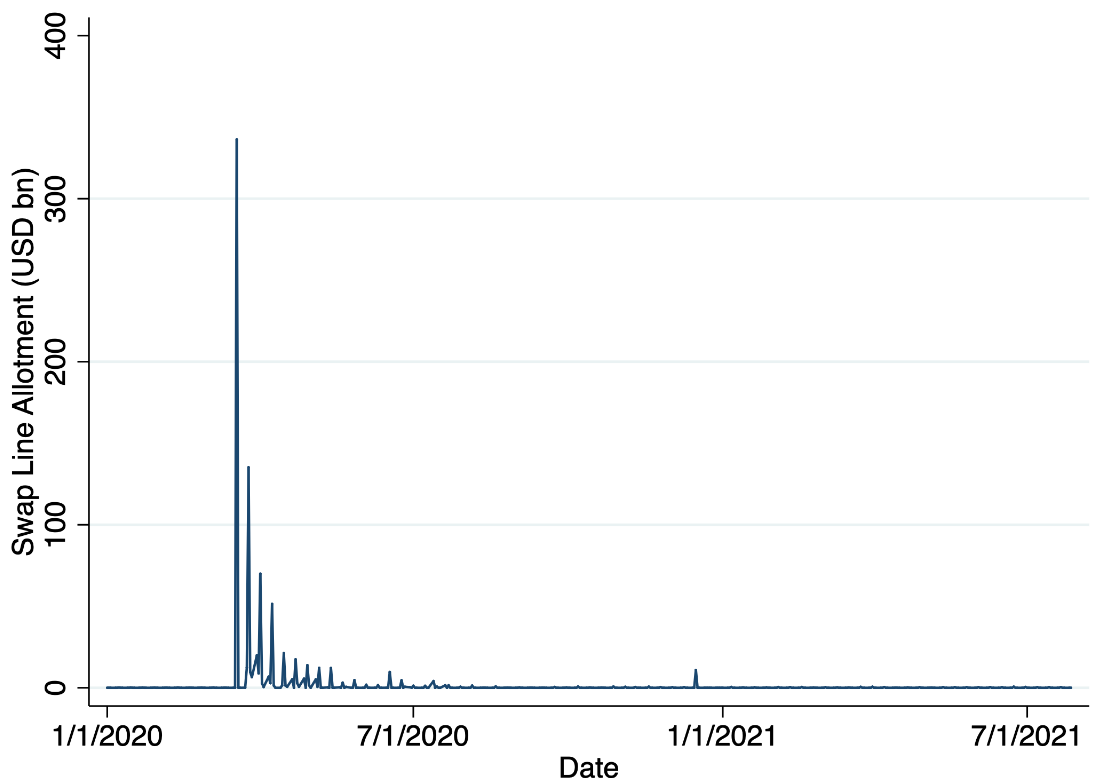

Figure 2.4: 2020 Swap Line Allotment with the European Central Bank

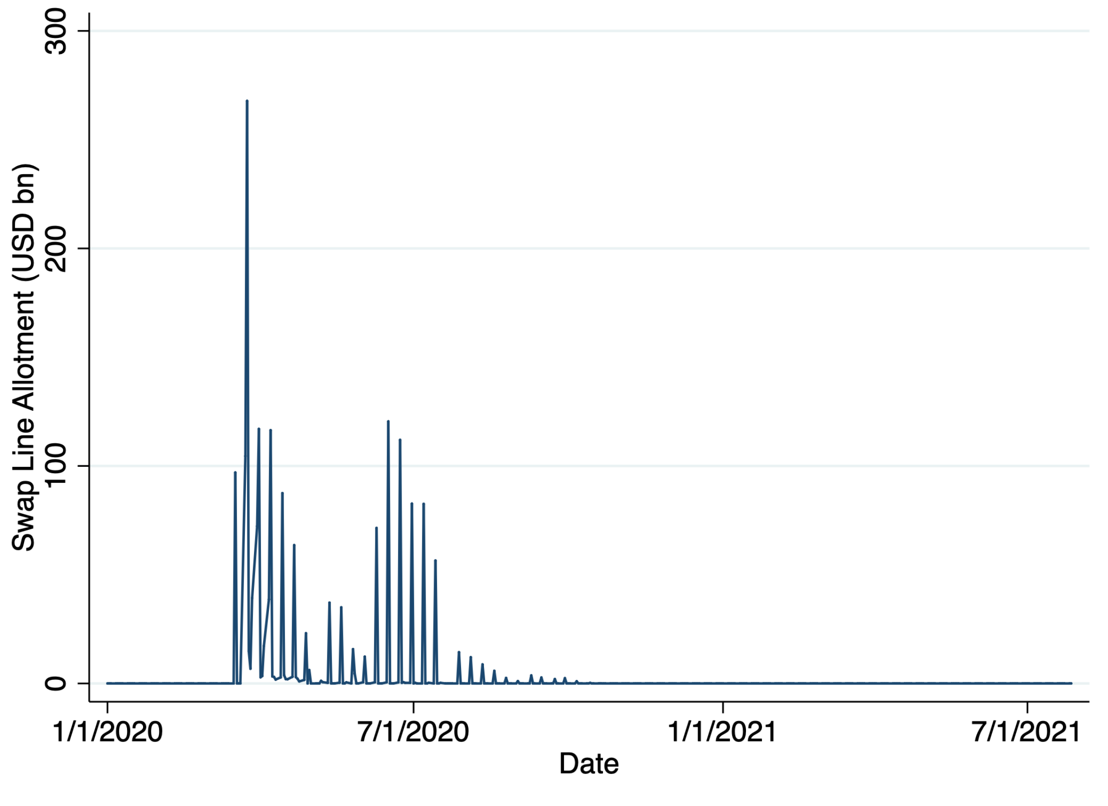

Figure 2.5: 2020 Swap Line Allotment with the Bank of Japan

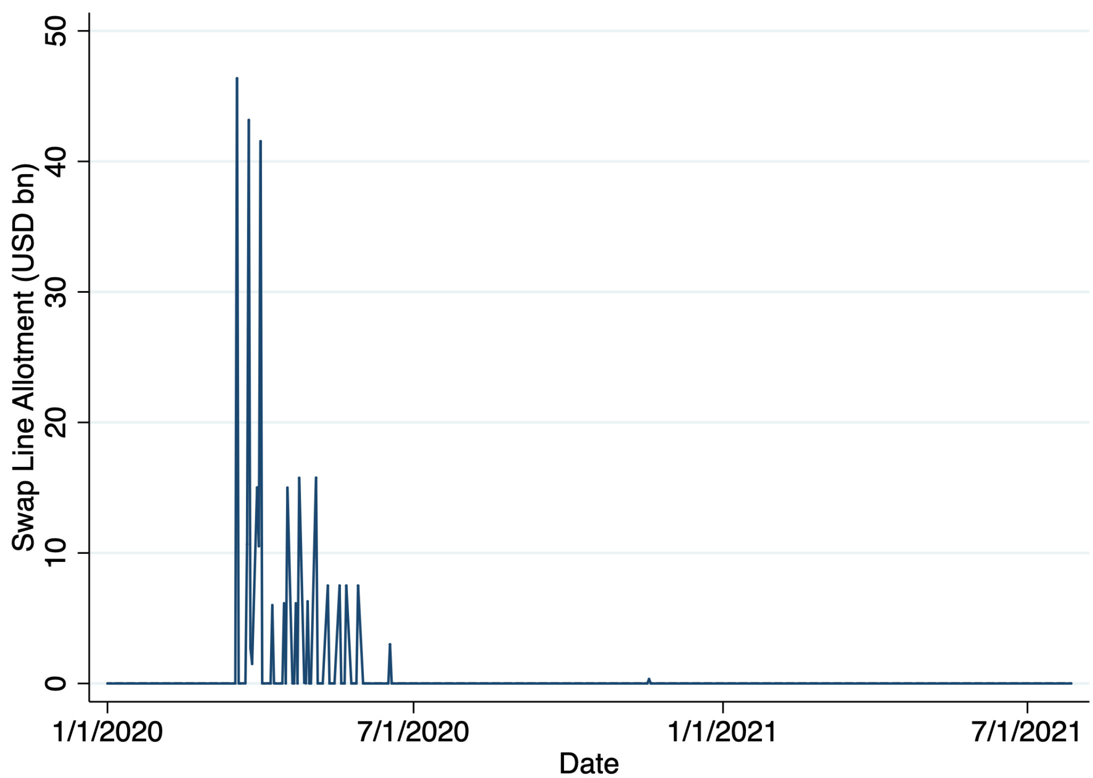

Figure 2.6: 2020 Swap Line Allotment with the Bank of England

Tables

Summary Statistics: Order Flow by Currency Pair

Currency Pair With USD	N	Mean	SD	Min	Max
AUD	843	-4.588	145.776	-974	913
CAD	843	19.679	132.59	-735	884
CHF	843	-14.881	120.692	-834	563
DKK	843	7.751	36.909	-158	305
EUR	843	-51.106	257.402	-1658	1089
GBP	843	-36.903	185.942	-1436	869
JPY	843	10.569	153.837	-628	991
NOK	843	.083	105.915	-576	767
NZD	843	10.619	116.606	-1150	721
SEK	843	.563	93.985	-622	511

Table 2.1: Order Flow by Currency Pair

Summary Statistics: Order Flow by Tenor

Tenor	N	Mean	SD	Min	Max
1 Month	2810	-11.857	222.359	-1658	1089
1 Week	2810	.413	55.987	-749	721
3 Months	2810	-6.021	111.939	-974	671

Table 2.2: Order Flow by Tenor

VARIABLES	(1) CIP Panel	(2) CIP EUR	(3) CIP JPY	(4) CIP GBP
Δ Order Flow	-1.16e-05	-3.28e-05**	1.95e-05	-1.40e-05
	(1.38e-05)	(1.36e-05)	(1.92e-05)	(2.08e-05)
Δ Broad Dollar	0.0672***	0.0691***	0.0648***	0.0672***
	(0.0108)	(0.0221)	(0.0242)	(0.0219)
Δ Log(VIX)	-0.299***	-0.107	-0.224**	-0.0965
	(0.0593)	(0.0748)	(0.0869)	(0.103)
Δ Forward Bid-Ask	-0.0159*	-0.757*	-0.106*	-0.579**
	(0.00864)	(0.449)	(0.0590)	(0.251)
Constant	-0.00838*	-0.0126	-0.00258	-0.00940
	(0.00428)	(0.00822)	(0.00829)	(0.00958)
Observations	4,176	522	522	522
R-squared	0.016	0.076	0.027	0.090

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3: Price impact of order flow using OIS Rates

VARIABLES	(1) CIP Panel	(2) CIP EUR	(3) CIP JPY	(4) CIP GBP
Δ Order Flow	-4.80e-05	-3.58e-05	3.70e-05	-0.000142**
	(3.60e-05)	(2.76e-05)	(2.86e-05)	(5.54e-05)
Δ Broad Dollar	0.0818***	0.176***	0.0794***	0.0466
	(0.0190)	(0.0475)	(0.0303)	(0.0588)
Δ Log(VIX)	-0.192***	-0.240	-0.290***	0.234
	(0.0737)	(0.184)	(0.109)	(0.266)
Δ Forward Bid-Ask	-0.0121**	-1.159**	-0.135*	-1.119***
	(0.00614)	(0.571)	(0.0748)	(0.300)
Constant	-0.0146**	-0.0150	-0.00539	-0.0289
	(0.00673)	(0.0192)	(0.0106)	(0.0225)
Observations	4,872	522	522	522
R-squared	0.006	0.043	0.027	0.064

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Price impact of order flow using Libor Rates

VARIABLES	(1) CIP Panel	(2) CIP EUR	(3) CIP JPY	(4) CIP GBP
Δ Order Flow	-7.99e-06	-2.63e-05*	2.06e-05	-1.73e-05
	(1.40e-05)	(1.34e-05)	(1.98e-05)	(2.16e-05)
Δ Order Flow*End of Quarter	-0.000103	-0.000193***	-4.58e-05	5.22e-05
	(7.63e-05)	(3.46e-05)	(6.34e-05)	(5.49e-05)
Δ Broad Dollar	0.0670***	0.0679***	0.0648***	0.0674***
	(0.0108)	(0.0220)	(0.0242)	(0.0219)
Δ Log(VIX)	-0.299***	-0.105	-0.224**	-0.0960
	(0.0593)	(0.0749)	(0.0870)	(0.104)
Δ Forward Bid-Ask	-0.0159*	-0.763*	-0.106*	-0.578**
	(0.00864)	(0.449)	(0.0591)	(0.251)
Constant	-0.00840**	-0.0124	-0.00269	-0.00946
	(0.00428)	(0.00821)	(0.00835)	(0.00959)
Observations	4,176	522	522	522
R-squared	0.017	0.080	0.027	0.090

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Price impact at Quarter-Ends of order flow using OIS Rates

VARIABLES	(1) CIP Panel	(2) CIP EUR	(3) CIP JPY	(4) CIP GBP
Δ Order Flow	-4.82e-05	-2.49e-05	3.85e-05	-0.000157***
	(3.71e-05)	(2.77e-05)	(2.93e-05)	(5.70e-05)
Δ Order Flow*End of Quarter	4.88e-06	-0.000319***	-6.15e-05	0.000218*
	(0.000114)	(6.75e-05)	(9.80e-05)	(0.000113)
Δ Broad Dollar	0.0818***	0.174***	0.0794***	0.0471
	(0.0190)	(0.0475)	(0.0303)	(0.0588)
Δ Log(VIX)	-0.192***	-0.236	-0.289***	0.236
	(0.0737)	(0.184)	(0.109)	(0.267)
Δ Forward Bid-Ask	-0.0121**	-1.170**	-0.135*	-1.118***
	(0.00614)	(0.570)	(0.0749)	(0.300)
Constant	-0.0146**	-0.0146	-0.00555	-0.0292
	(0.00673)	(0.0192)	(0.0107)	(0.0225)
Observations	4,872	522	522	522
R-squared	0.006	0.046	0.027	0.064

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Price impact at Quarter-Ends of order flow using Libor Rates.

VARIABLES	(1) OF Panel	(2) OF EUR	(3) OF JPY	(4) OF GBP
$D_{\text{Swap Line Allotment}}$	-25.34**	-15.74	-7.130	18.92
	(10.44)	(21.81)	(14.58)	(63.15)
Constant	-4.559***	-47.46***	11.51**	-37.17***
	(1.599)	(9.949)	(5.757)	(6.436)
Observations	8,430	843	843	843
R-squared	0.001	0.001	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Order Flow on Swap Line Allotment Days

VARIABLES	(1) Δ Log(CIP)	(2) Δ Log(CIP)
Δ Allotment	-0.00241***	-0.00247***
	(0.000595)	(0.000626)
Δ Broad Dollar		-0.0143
		(0.0166)
Δ Log(VIX)		0.323**
		(0.137)
Δ Forward Bid-Ask		-0.0306
		(0.0245)
Constant	-0.0698***	-0.0690***
	(0.0133)	(0.0143)
Observations	207	207
R-squared	0.062	0.083

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Effect of Swap Line Agreements on OIS CIP Deviations

Chapter 3

BALANCE SHEET RATIOS, CREDIT GROWTH, AND FINANCIAL CRISIS PREDICTION

3.1 Introduction

Macroprudential policies have become an important part of the policymakers' toolkit since the 2008 crisis. While policies are being commonly used by advanced and emerging economies, such as caps on loan-to-value ratios, loan-to-deposit ratios, capital ratios, and others, their effectiveness is still widely unknown. The literature has widely documented the use of these policies but has not yet narrowed down which one might be more beneficial for a country facing financial risk. Furthermore, there are few papers that study their impacts on financial crisis probabilities and how macroprudential targets can help predict crises using machine learning methods.

This paper aims to fill this gap in the literature. I will first describe the usage of 17 macroprudential policies for a panel of 135 countries, provided by the IMF Integrated Macroprudential Policy (iMaPP) Database from 1990-2022. The survey includes details on timing and scope of macroprudential policies and is the largest of its kind in terms of documenting the historical implementation. Second, I will turn to the Jorda-Schularick-Taylor Macrohistory Database to predict crises for 18 countries since 1870. By examining non-linear relationships among the loan-to-deposit and loan-to-value ratios, a random forest model can outperform the literature's predictions for a longer panel from 1870-2021 compared to the benchmark logistic model results.

While most of the literature has studied the impacts of macroprudential policy on levels of credit, I focus on the binary outcome variable indicating a future looming crisis within 1 and 2 years. I compare the linear probability model, logistic and probit models, and compare their effectiveness to a variety of modern machine learning models. I find that limits on LTV ratios, loan restrictions, and sector-specific capital requirements are most effective in preventing future crises. Furthermore, I confirm the literature's suspicion that general capital requirements alone will fail to prevent future financial risk. When we turn to the longer sample using the Macrohistory database from 1870 onwards, the loan to deposit ratio is highly significant across the linear probability model, logit, or probit specifications. This result could support the idea that adding in these historical macroprudential ratios to a machine learning model would give us a richer set of variables for predicting a crisis 2 years out. Additionally, I find that a random forest model has higher predictive power compared to the literature's benchmark logit or probit specifications. Using a Shapley value approach, we are able to decompose crisis probabilities so that they are more easily interpretable and comparable with other plain vanilla models.

3.2 Literature Review

Sufi and Taylor (2021) provide an excellent summary of the macroprudential policy literature, stressing that more research is needed on sector-specific and time-varying macroprudential tools. Svensson (2017) concludes that learning via the interest rate channel alone may not be optimal. In systemic risk models, time-varying and/or sectorally-targeted tools could be important in addition to Basel minimum standards as seen in Jeanne and Korinek (2020). Nakatani (2020) utilizes a probit model to analyze the effect of changes in the loan-to-value (LTV) ratio on crisis probability, finding that macroprudential policy is effective in changing the probability of a banking crisis via the credit channel. Cerutti et al. (2017) find that macroprudential tools are generally associated with lower growth in household credit and work better in booms opposed to busts. Jorda et al. (202) find that higher capital ratios are unlikely to prevent a financial crisis and has no value as a crisis predictor. Naceur et al. (2020) conclude that that macroprudential policies have a positive net effect on financial stability using an aggregate index measure. In a recent panel study, Akinci and Olmstead-Rumsey (2018) find that macroprudential tightening is associated with lower bank credit growth, housing credit growth, and house price appreciation.

In the wider literature on predicting financial crises, Bluwstein et al. (2020) use a similar Shapley value approach and note that the most important predictors of crises are credit growth and the slope of the yield curve. Using the linear probability model, Greenwood et al. (2021) show that the combination of rapid credit and asset price growth is associated with increased crisis risk. Fouliard et al. (2020) utilize online machine learning methods to predict out-of-sample crises up to 12 quarters ahead for the Euro area. I contribute to this literature by comparing all the various models used in these papers and selecting the best model for prediction. I confirm that financial crises are not random events and can be mitigated with proper macroprudential policy.

The findings of this analysis are meaningful for policymakers, as it is one of the first studies to compare the effectiveness of specific macroprudential tools. While mostly effective in lowering crisis probabilities, modern tools are highly dependent on other macroeconomic factors such as debt levels, capital controls, and exchange rate regimes. Thus, it is important for policymakers to coordinate among governmental organizations in order to ensure that macroprudential tools are used accordingly.

3.3 Motivation

The iMaPP dataset

The IMF's Integrated Macroprudential Policy (iMaPP) database is taken from Alam et al. (2019), who compile quarterly dummy-type indicators of tightening and loosening actions of various macroprudential policy instruments since 1990. The authors also provide a unique numerical indicator of regulatory limits on the loan-to-value ratio, combining information from five existing databases and the IMF's Macroprudential Policy Survey. The database is compiled exclusively from information provided by IMF member countries and is self-reported. The dataset includes 17 indices for various macropruduential tools from 1990-2021 for 135 countries globally. I use the Baron et al. (2020) collection of historical data to contruct the indicator variable for a financial crisis. BVX use hand-collected historical data on bank stock returns to improve on the literature's definition of a crisis and capture more crisis periods compared to previous efforts.

The iMaPP dataset contains quarterly medians and means of LTV limits for each country-year for real estate mortgage loans, where the default value is 100. A value of 100 denotes that one can borrow the full maount against the collateral value. Countercyclical capital buffers, leverage limits, loan-to-value, loan-to-deposits, and other constraints are coded as quarterly dummy-type indices where the value 1 denotes a tightening, -1 denotes a loosening, and 0 represents no change in the index. I take the yearly sum of each of these indicators as our financial crisis indicator is at the yearly level. The IMF authors also include an aggregate macroprudential measure of all instruments, which is the sum of all tools for a given country and quarter.

In order to predict crises ahead of time, I set the binary outcome variable equal to 1 for one and two years prior to the start of the crisis. I exclude the actual year of the crisis and 4 years post-crisis in order to remove post-crisis bias and better identify the early warning signals of financial turmoil. In the appendix, I also remove the 2008 and 2020 crises in order to determine the effects in the post-GFC period. I also exclude any observations with missing values of the predictors.

Jordà-Schularick-Taylor Macrohistory Database

The Jordà-Schularick-Taylor Macrohistory Database (see Jorda et al. 2020) contains annual macroeconomic and financial measures from 17 developed countries between 1870 and 2016. This is the longest cross-country dataset available for predicting financial crises and has been used in other studies mentioned in the literature review section. The dataset contains common macroeconomic variables including: yield curve slope, credit (loans to the non-financial private sector, loans to households, loans to businesses), stock prices, the debt service ratio (credit × long-term interest rate over GDP), consumption, investment, the current account, public debt, broad money, and CPI. The dataset also includes the most comprehensive data on capital ratios and loan-to-deposit ratios for a country-year pair which will be key variables used for this paper.

In addition to these variables, we define dummy variable that indicate if total loans, household loans, business loans, house prices, and stock prices are in their highest quartile. This is similar to the approach by Greenwood et al. (2021) that will allow us to explore non-linearities with respect to credit and asset price growth. Variable selection is subject to data availability. Aside from ratio and dummy variables: credit, money, public debt, debt servicing, investment, and the current account, are differences of GDP-ratios. Variable transformations address potential issues of non-stationarity and comparitability.

Variable Selection

Credit growth has been a key predictor of financial crises, especially at the highest quartile (Greenwood et al. (2021), Schularick and Taylor (2012)). Both at the household and business level, rapid credit growth demonstrates excessive risk taking which can lead to an overleveraged financial system. In a seminal paper, Bernanke and Blinder (1992) show that financial accelerator effects can cause credit growth to spiral after an initial shock. Both at the domestic and global level, Fouliard, Howell, and Rey (2020) remind us that these cycles can be driven both by cross-country spillovers as well as at the domestic level.

Rising asset prices in tandem with high credit growth are highly indicative of a crisis. Greenwood et al. (2021) shows that house prices in their highest quartile along with high credit growth leads to an increased probability of a crisis. Additionally, the slope of the yield curve and current account (both included in the dataset) are key predictors identified in Bluwstein et al. (2020). I also include controls for macroeconomic conditions, namely real consumption per capita, investment, and the consumer price index (CPI).

3.4 Results

Preliminary Analysis

Table 1 reports the summary statistics for the iMaPP indices and LTV ratios. Many tools were adopted post-2008, when macroprudential policies started to become more common in response to financial instability. Figure 1 plots the histogram of mean LTV ratios under 100, and Figure 2 plots the median LTV ratios under 100. There is a large amount of variance among the LTV ratios, with the average LTV at 94.131 and a median of 94.212. Table 2 reports the counts of policy actions by advanced economies from 1990-2020. These policy actions can represent a loosening or tightening of a given macroprudential tool listed in the table. The most highly used tool for advanced economies was liquidity requirements, followed by reserve requirements, LTV ratios, and capital conservation buffers. For emerging economies, reserve requirements were highly used, followed by liquidity requirements, and capital conservation buffers.

Figure 3 reports the number of macroprudential actions (tightening or loosening) for the top 5 tools in the iMaPP dataset. Liquidity and Conservation Capital requirements increased in usage sharply in the mid 2010s, in accordance with the Basel III implementation starting in 2013. Reserve requirements dropped in usage compared to capital and leverage requirements, while loan restriction and LTV ratio requirements have been slowly increasing in usage since 2000.

Table 4 reports a linear probability model using the iMaPP policy indices and LTV ratios to predict the probability of a a crisis 1 and 2 years ahead. All specifications include country and year fixed effects. Using a linear probability model allows us to used a fixed effects specification while improving the interpretability of the coefficients.

I add macroeconomic controls in specifications 3 and 4, controlling for debt-to-GDP, CPI, current account, and changes in monetary policy. Contrary to other studies such as Nakatani (2020), I find only a small weak association between the median LTV ratio and the probability of a crisis within 1 year. Corporate capital requirements are negatively associated with the probability of a crisis for all specifications. Other similar papers on this topic typically use a standard logit specificiation and do not include country or time fixed effects, which lead to biased point estimates.

Full Panel Results

Use of the iMaPP dataset to predict financial crises is limited by the small sample and limited quantitative information (only the LTV ratio is a non-index variable). In order to determine which macroeconomic conditions lead to financial crises more broadly, we turn to the Jordà-Schularick-Taylor Macrohistory Database for a longer panel for 17 developed countries between 1870 and 2017. In order to gain a sense of the importance of the key economic variables in the Macrohistory database, I compare the mean values up to 2 years before the crisis with non-crisis values (4 years post-crises are removed from the dataset). This removes any potential post-crisis bias and allows us to compare the economy on a country pre-crisis with the post-crisis period. I also exclude all observations between 1933 and 1939 (later years of the Great Depression), the two world wars (1914-1918, 1939-1945) and Germany between 1920-1925 due to extreme outliers in the dataset. These exclusions are standard practice in the financial crisis prediction literature (see Bluwstein et al. (2020) for a summary of other papers that employ this practice). A t-test confirms that there are significant differences ($p < 0.05$) in almost all of the variables mentioned in the Variable Selection section. Notably, the capital ratio, loan-to-deposit ratio, and noncore funding ratios have a p value of approximately 0 for this difference in means test. Below are the definitions of these balance sheet ratios used in this analysis. The first is the capital/leverage ratio defined in the Basel III accords:

$$\text{Capital ratio} = \frac{\text{Capital}}{\text{Total Assets}} \tag{3.1}$$

The next tool is the ratio of loans to deposits, often considered a measure of banking sector illiquidity or vulnerability:

$$\text{LTD Ratio} = \frac{\text{Loans}}{\text{Deposits}} \tag{3.2}$$

Finally, I include the share of other liabilities in total debt liabilities (excluding capital):

$$\text{Noncore funding ratio} = \frac{\text{Other Liabilities}}{\text{Deposits+Other Liabilities}} \tag{3.3}$$

Figure 4 plots the mean loan to deposit and noncore funding ratios from 1870-2017. Both series trended upwards following the Bretton Woods era, with sharp dips during recessionary periods. Capital ratios on the other hand have decreased since the 1800s, remaining relatively flat since Bretton Woods. In the postwar period, banks grew their loans relative to GDP (Figures 6 and 7). See Schularick and Taylor (2012) for a more detailed analysis of credit growth and crisis predictability.

The literature has stressed the importance of credit growth, asset price growth, and the yield curve as the primary predictors of financial crises within two to three years. However, there have been few studies that examine whether or not macroprudential have predictive power. To test for this link, I propose a basic forecasting framework to ask: does a country's capital ratio, loan-to-deposit ratio, or noncore funding ratio help predict a financial crisis? I use a simple linear probability model and logistic model to test this question. Table 6 presents simple variations of these models without any additional control variables. In line with the literature, I find that the 2-year growth rate has the best predictive power for these macroprudential ratios (also tested 1 and 3 year growth rates).

Model specification 1 presents an OLS Linear Probability Model with simple pooled data. Model specification 2 adds Country fixed effects. Model specification 3 includes Country and Year fixed effects, taking into account a global time component driving financial crises. Unfortunately, we cannot implement a Logit model with year effects: these can only be estimated using years in the panel where there is actual variation in the outcome variable. The key finding in Table 6 is an increase in the growth rate of the Loan to Deposit ratio and the Noncore funding ratio, to a lesser extent, is indicative of a heightened financial crisis. Surprisingly, the growth rate of the capital ratio has limited predictive ability, a finding confirmed by Schularick and Taylor (2012). There are some issues regarding the Linear Probability Model (LPM), notably that the domain of its fitted values is not constrained to the unit interval relevant for a probability outcome. However, the LPM model is easier to interpret over Logit or Probit specifications and allows us to include multiple fixed effects. In Models 4 and 5 I switch to a Logit model and include Country fixed effects in model 5.

Next, we fit the linear probability model with Country and Year fixed effects to the dataset, including all variables in Table 5 as controls. This model shows that the 2-year growth rate of the loan-to-deposit ratio is an important predictor for financial crises even after controlling for all covariates used in other papers on predicting financial crises. This result suggests that including underlying macroprudential ratios may be important to include in machine learning classification models, as stressed by Bluwstein et al. (2020). In contrast to Schularick and Taylor (2012), I find that the loan-to-deposit ratio is a much better predictor compared to Non-Financial Loans/GDP which has been primarily used in the literature. I find that once we include time fixed effects and include the other covariates used in Bluwstein et al. (2020), the significance of the Non-Financial Loans/GDP diminishes. This result points to bank illiquidity as a more robust measure of a looming financial crisis compared to the total amount of loans.

3.5 Machine Learning Methodology

Although the linear probability model in Section 2 allows us to use a fixed effects specification and interpret coefficients, it does not account for various non-linearities and interactions as noted by Greenwood et al. (2021). As the literature has shown, there is an increased probability of a crisis when credit growth and asset price growth are in their highest tercile. Furthermore, classification accuracy overall is typically higher using a random forest or boosting models. Using a LPM or a logistic model with non-linear terms can be challenging, either the modeler uses dummy variables for high growth situations or adds polynomial terms to the regression. It can be difficult to know how many of these terms to include in a model and including polynomial terms often reduces the power of an effects. Thus, in this section, I utilize machine learning methods that are capable of learning non-linearities and interactions while including the macroprudential ratio variables described above (see James et al. (2013) for more information these methods).

Let f be a prediction model $\hat{y} = f(X)$, where $X_{n \times k}$ is the predictor matrix containing n observations on k variables. $\hat{y} \in [0, 1]$ is the predicted probability of a crisis. The label for each observation is given by $\hat{y} \in (0, 1)$, where 1 is the pre-crisis target 1 and 2 years before the start of the crisis (positive class). All other observations are denoted 0 (negative class) and 4 years post-crisis are dropped for each country instance. In the section following, I compare a range of machine learning classification algorithms and review the literature's findings on accuracy and prediction power.

Decision Trees

A decision tree splits the data by testing one feature at each node. At the root node, all observations are divided into 2 child nodes and this process is repeated recursively. For each test, choice is determined by iterating through all predictors and possible split points choosing the one that best separates the observations of the positive and negative class. The recursion is completed when the subset at a node has all the same values of the target variable, or when splitting no longer adds value to the predictions. Decision trees are flexible, easy to interpret, and typically perform well on large datasets. However, any small change in the training data can result in a large change in the tree and can reduce robustness. This model also suffers from overfitting, where highly complex trees do not generalize well from the training data.

Random Forests

A random forest is a large collection of decision trees. A random forest averages the predictions of many, often hundreds, of trees leading to less overfitting overall. As a result, there is small increase in the bias, some loss of interpretability, but overall greater performance of the model. The training algorithm for random forests applies the general technique of *bagging* to tree learners. Given a training set $X = x_1, \ldots, x_n$ with responses $Y = y_1, \ldots, y_n$, bagging repeatedly (B times) selects a random sample with replacement of the training set and fits trees to these samples: For $b = 1, \ldots, B$ 1. Sample, with replacement, n training examples from X, Y; call these X_b, Y_b. 2. Train a classification or regression tree f_b on X_b, Y_b. After training, predictions for unseen samples x' can be made by averaging the predictions from all the individual regression trees on x' :

$$\hat{f} = \frac{1}{B} \sum_{b=1}^{B} f_b\left(x'\right)$$

Random forests also employ "feature bagging", in which at each candidate split a random subset of the features are selected. This algorithm often performs much better than individual decision trees and is one of the most used machine learning methods.

Extremely Randomized Trees

Extremely randomized trees, or ExtraTrees, is a variation of a random forest. Each tree is trained using the whole learning sample instead of the bootstrapped sample. Futhermore, the top-down splitting in the tree learner is randomized. A random cut-point is established for each feature, selected from a uniform distribution within the feature's empirical range. The split that gives the highest model score is chosen to be the cut point. These extra steps make the ExtraTrees classifier even more effective compared to the random forest model and produces the highest AUC score in our comparisons.

Furthermore, I use cross-validation to evaluate the out-of-sample performance of a given model. This process involves dividing the data into k groups, or $folds$, which are equal in size. A given model is split into $k-1$ groups as the training set and run on the remaining data as the test set. The process is repeated k times, with each group representing the test set. In this analysis, we use a 5-fold cross validation procedure where each training set comprises 80% of the observations and 20% represents the corresponding test set. I then repeat this procedure 100 times in order to achieve stability.

Model Evaluation

I now evaluate the performance of each model in the cross-validation to the logistic models and performance of other machine learning models in the literature. I use the Receiver Operating Space (ROC) which evaluates performance by comparing the trade off between Type I and Type II error. The horizontal axis shows the false positive rate, also known as the false alarm rate, which is defined as the proportion of negative instances (non-crises) incorrectly identified as positive (crisis). The perfect model would obtain a hit rate of 1 and a false alarm rate of 0. In practice, a higher hit rate comes at the cost of a higher false alarm rate. The Area under the Curve (AUC) best summarizes the overall performance of the model in the ROC space. Figure 8 shows how a variety of machine learning methods compare in out-of-sample prediction in the ROC space. As confirmed in the literature, machine learning approaches are much more valuable compared to their logistic regression counterparts.

I use the Shapley additive explanations approach formulated in Shapley (1952) in order to determine the feature importance of the model. Shapley values are a widely used approach from cooperative game theory and provide a principled way to explain the predictions of nonlinear models. In a cooperative game framework, the individual contribution within a coalition of players is directly observable but the payoff generated by the group as a whole is. In order to determine the contribution of player j, coalitions can be formed sequentially and j's contribution can be measured by her marginal contribution when entering a coalition, which also depends on the other players in the group. Let's say player j joins a coalition in which player k has similar skills. In this case, j's contribution is smaller than if she had joined the group when k was absent. Therefore, all possible coalitions of players need to be evaluated to make a precise statement of j's contribution to the payoff.

Let N be the set of all players in the game, and $f(S)$ be the payoff of a coalition S. Then the Shapley value for player j is computed by:

$$\phi_j = \sum_{S \subseteq N \setminus j} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{j\}) - f(S)] \tag{3.4}$$

The set of N here are the predictors of the model. In order to calculate the Shapley value for variable j and observation i, we calculate the magnitude that j adds to the predictive value $(f_i(S \cup \{j\}) - f_i(S))$ in all the possible subsets of the other predictors $(S \subseteq N \setminus j)$. Figure 9 shows the mean absolute Shapley values for all the predictors in the extreme trees model. The loan-to-deposit ratio, the first bar, has the highest contribution to the model relative to all other variables proposed in the literature.

3.6 Conclusion

There have been few studies that link balance sheet ratios with financial crisis probabilities. In this paper, I study these effects using the updated iMaPP panel dataset provided by the IMF. Using a linear probability model, I find a weaker effect of LTV ratio tightening on financial crises compared to the existing literature. Based on the results, policymakers may find it useful to monitor the loan-to-deposit rate and other macroprudential ratios closely in order to monitor a financial crisis, as it is a more robust measure compared to the change in outstanding debt. Higher capital ratios alone will fail to prevent future crises, thus, stronger and more sectorally-targeted measures may be required in addition to the Basel III minimum standards. For future research, it would be interesting to see general equilibrium models with appropriate friction and information assumptions in order to frame these policy directions more specifically.

Figures

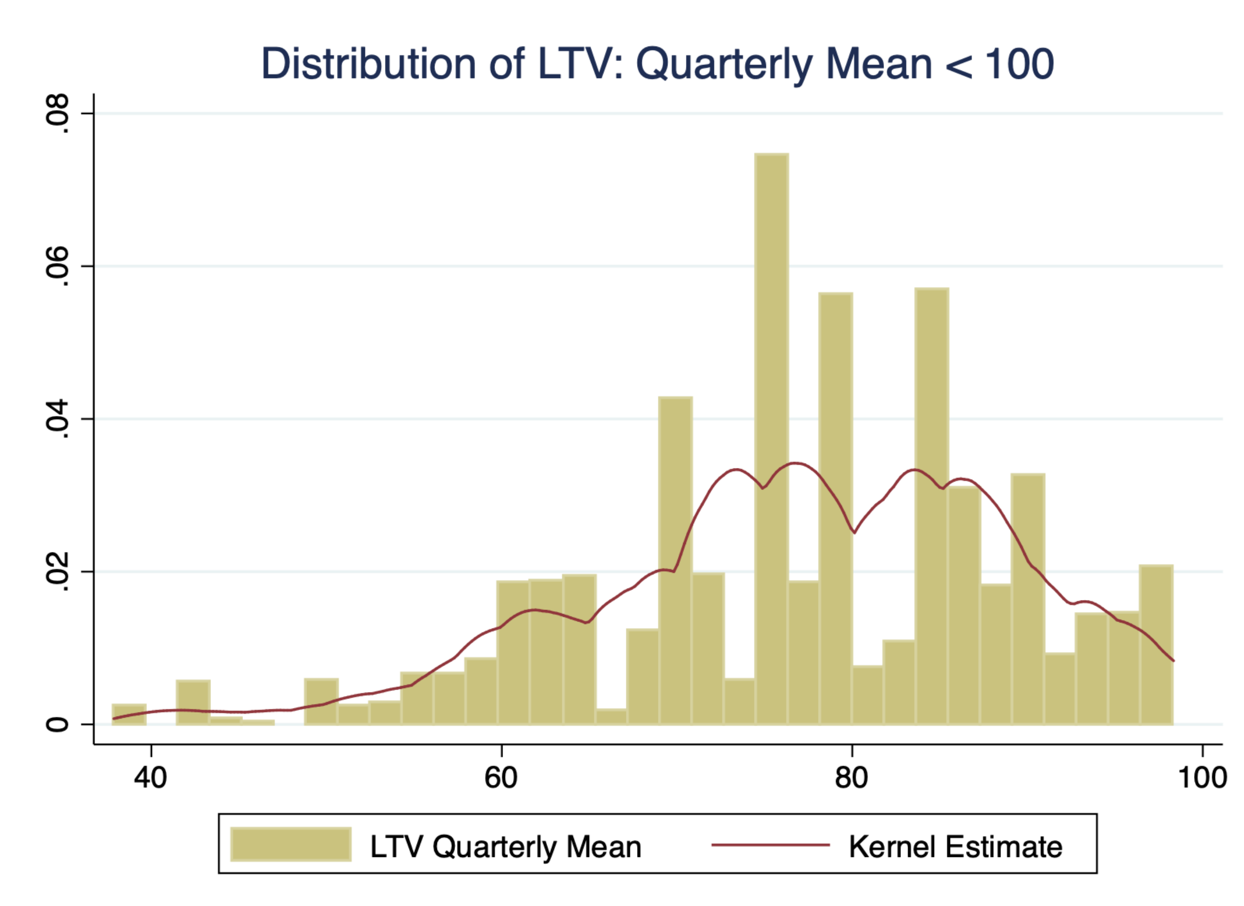

Figure 3.1: Histogram of Mean Loan-To-Value Ratio

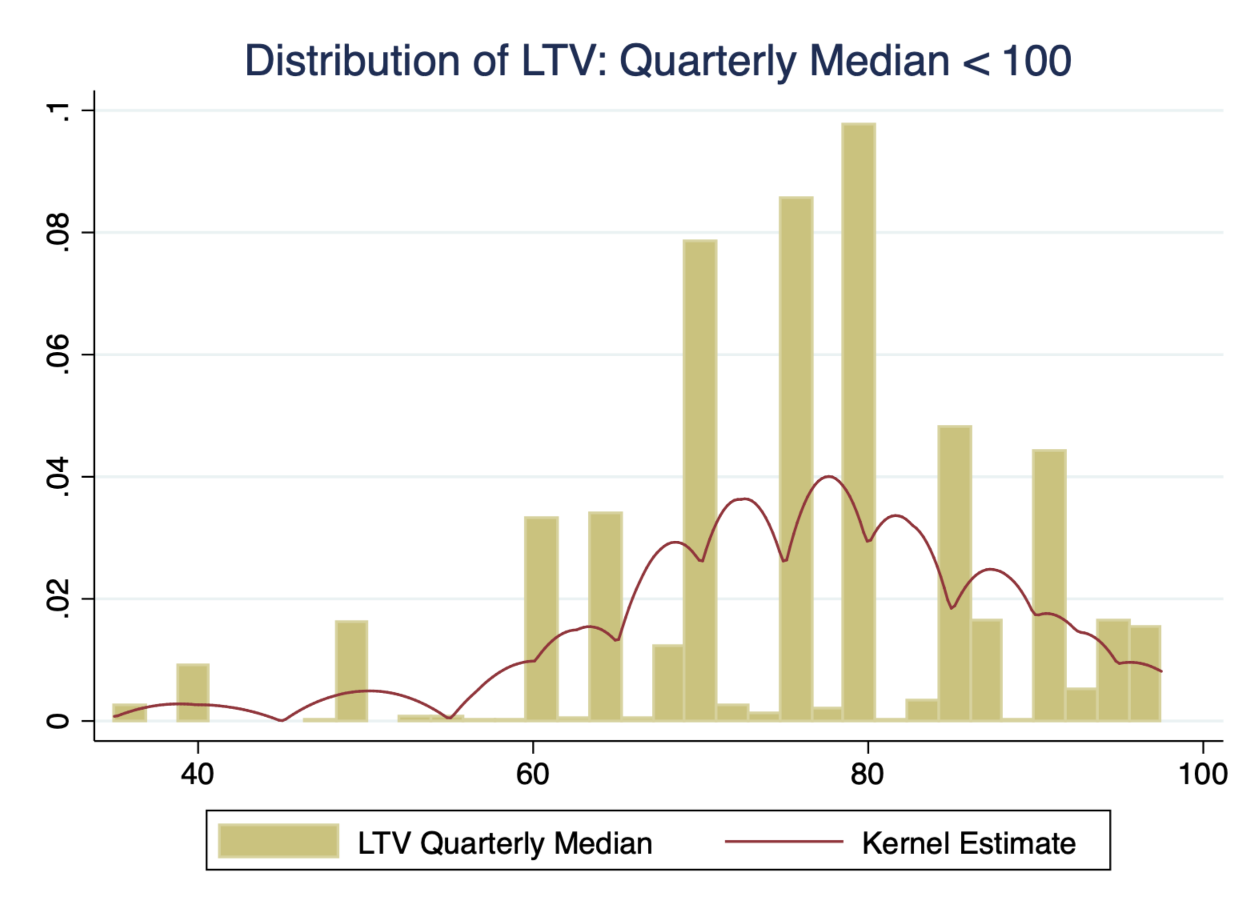

Figure 3.2: Histogram of Median Loan-To-Value Ratio

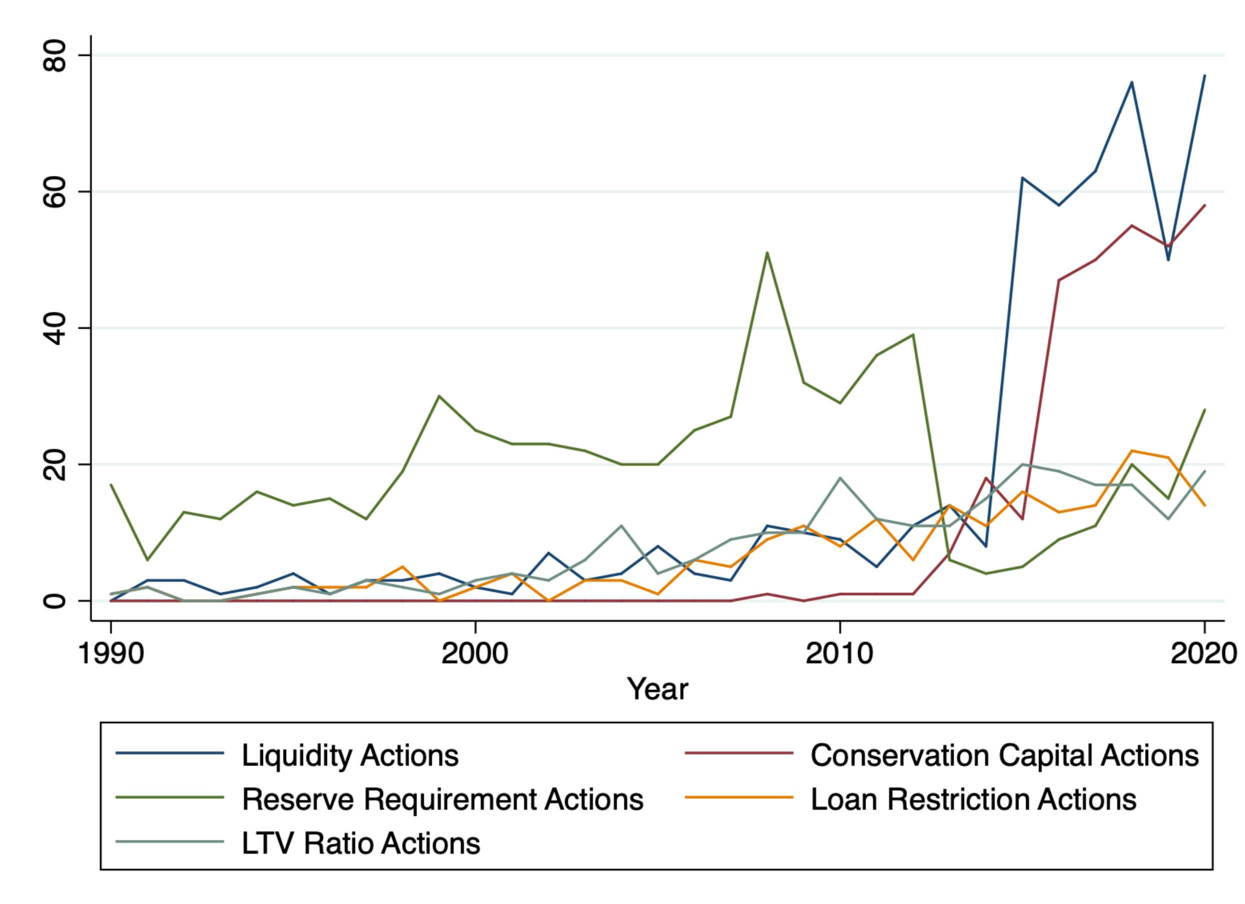

Figure 3.3: Macroprudential Actions Over Time

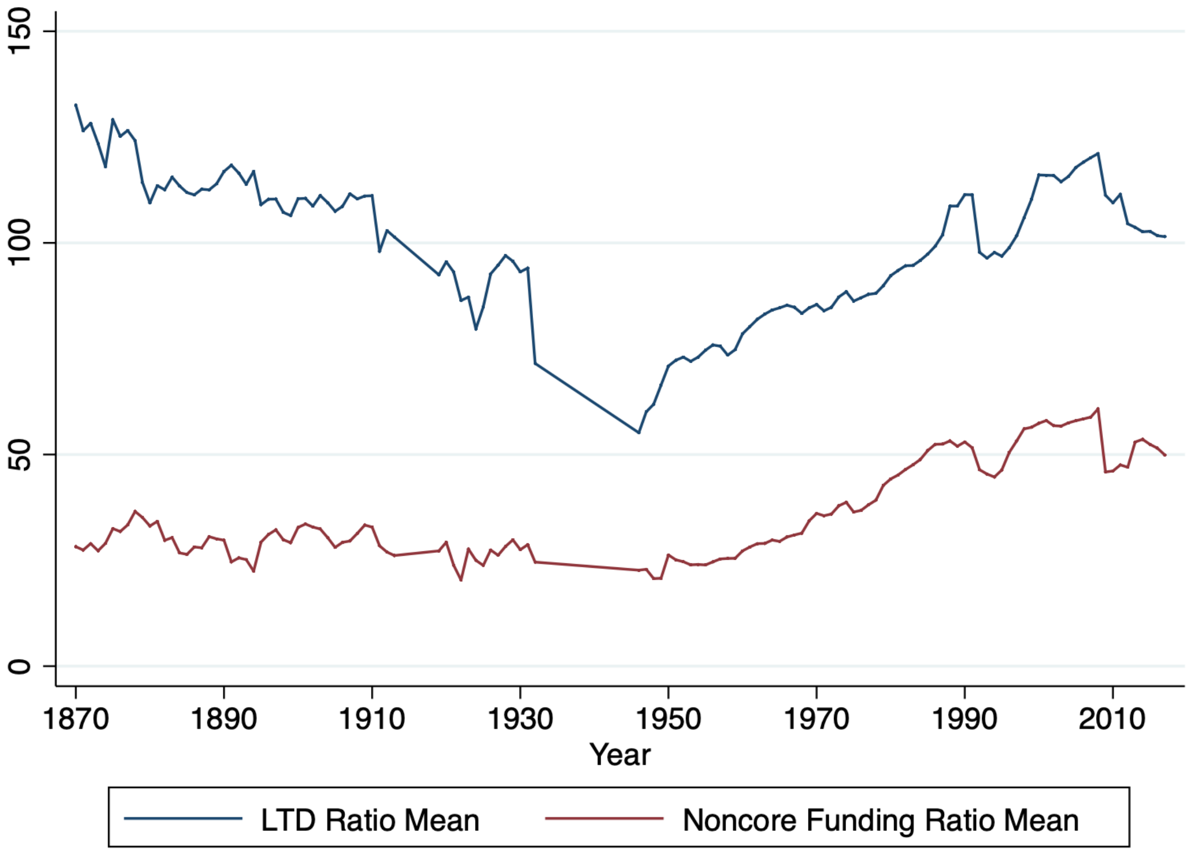

Figure 3.4: Loan-To-Deposit and Noncore Funding Ratio Means Over Time

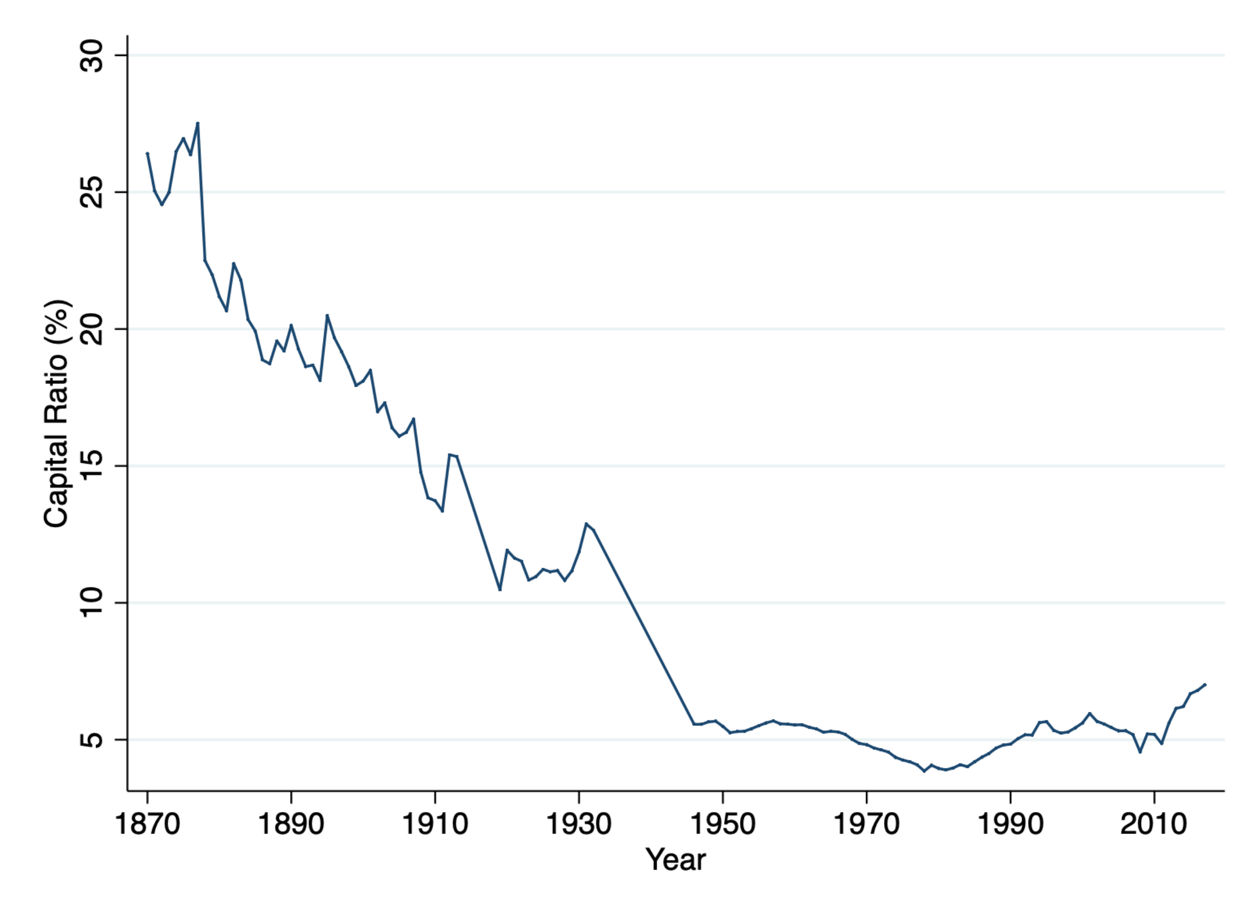

Figure 3.5: Capital Ratio Means Over Time

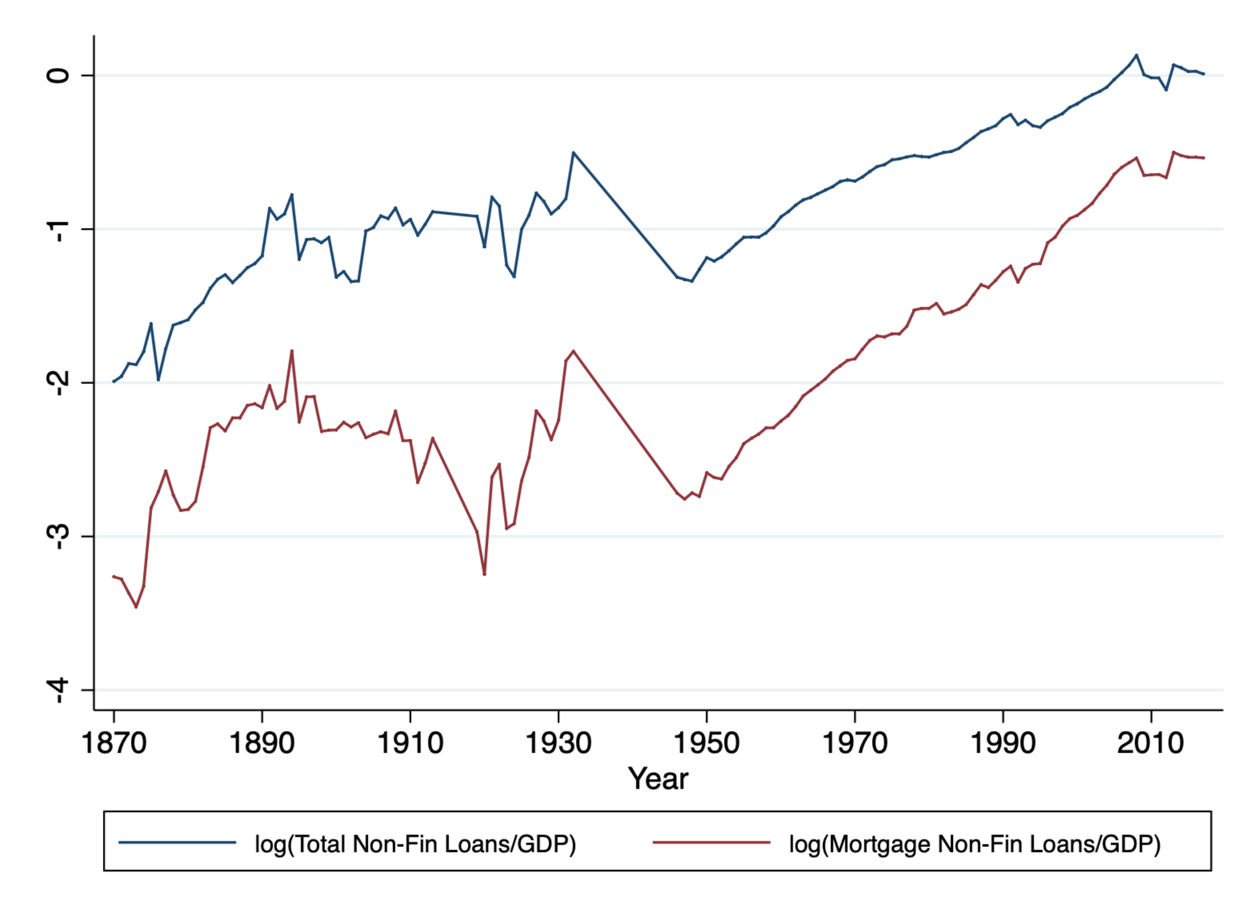

Figure 3.6: Nonfinancial Loans Over Time Relative to GDP

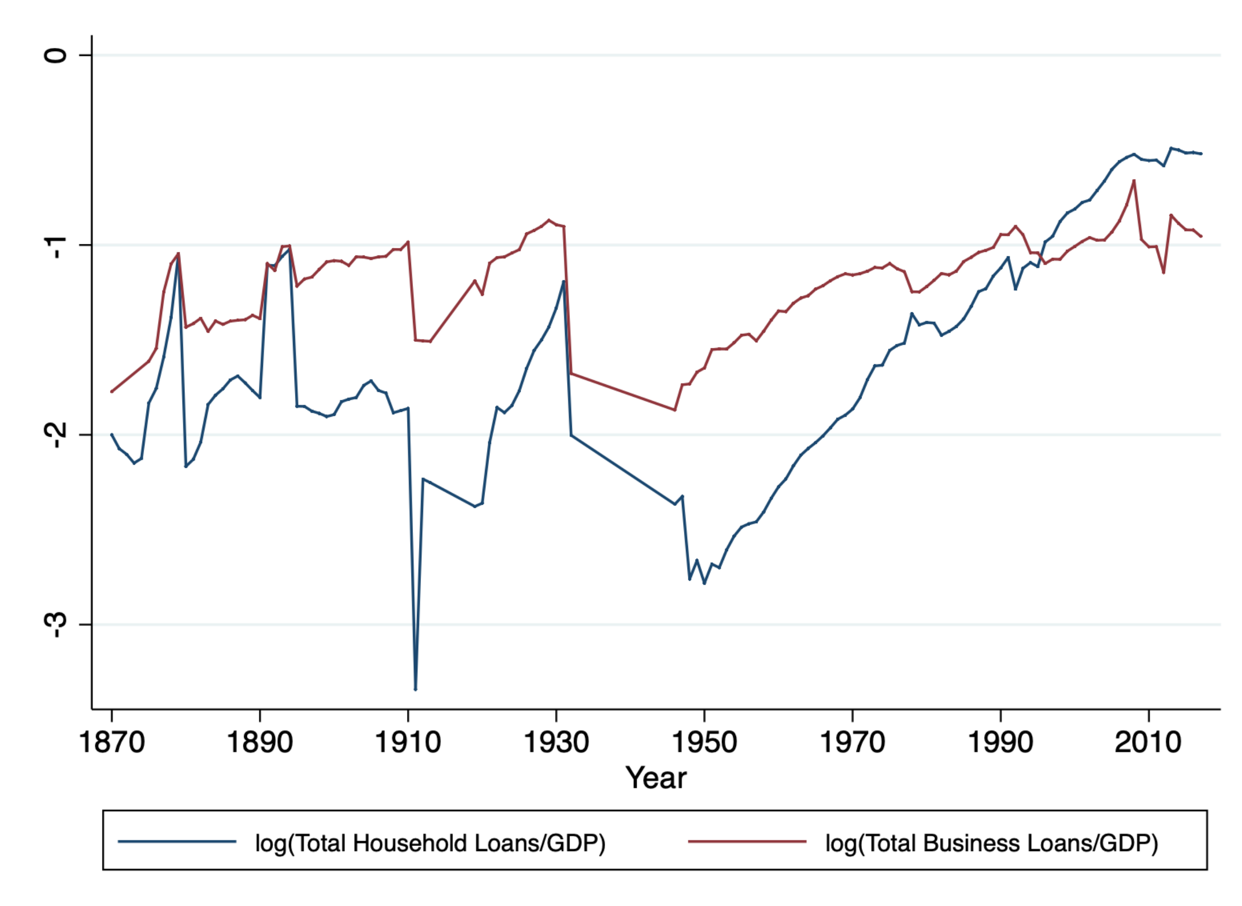

Figure 3.7: Household and Business Loans Over Time Relative to GDP

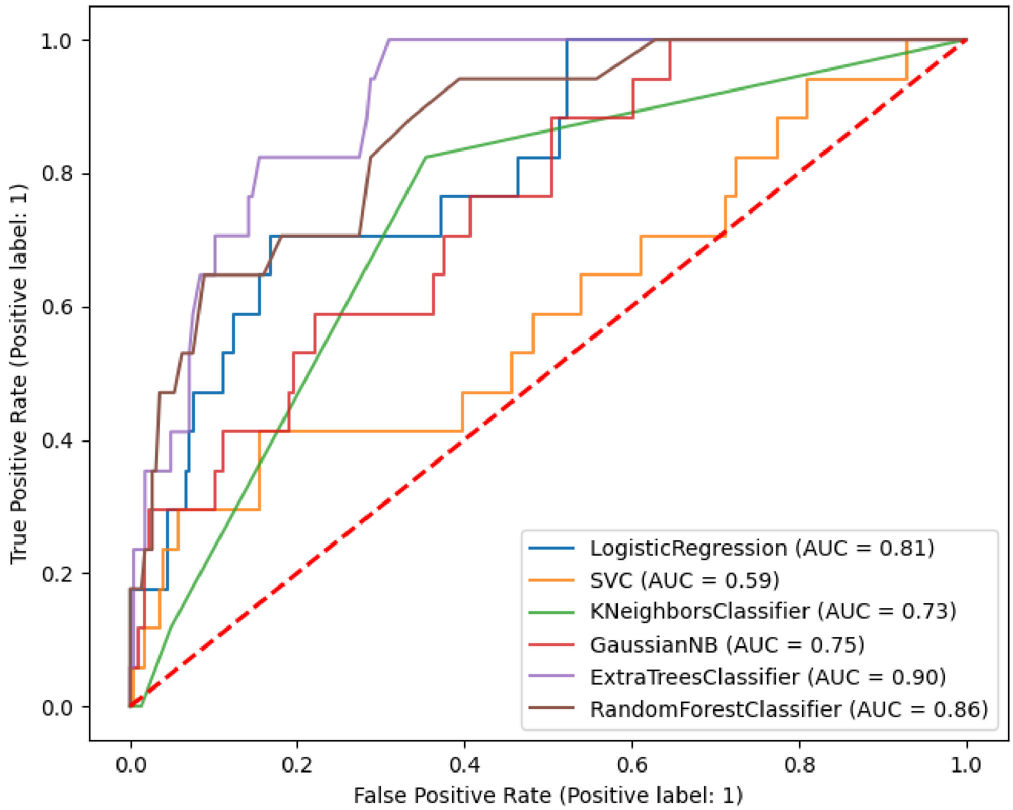

Figure 3.8: ROC Curves for Various ML Methods

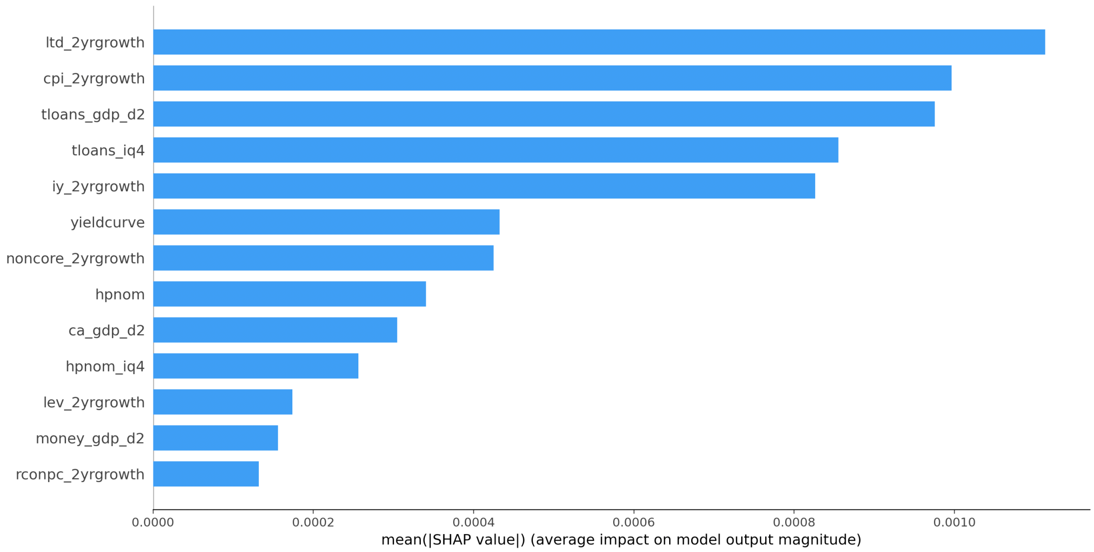

Figure 3.9: Mean Absolute Shapley Values: Extreme Trees Model

Tables

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Countercyclical buffers	16740	.001	.063	-1	1
Capital conservation buffers	16740	.011	.134	-1	1
Capital requirements	16740	.009	.14	-2	3
Capital requirements: General	16740	.003	.088	-1	2
Capital requirements: Household	16740	.005	.101	-2	2
Capital requirements: Corporate	16740	.002	.059	-1	1
Capital requirements: FX loans	16740	.001	.048	-1	2
Leverage limits	16740	.004	.072	-2	1
Loan loss provisions	16740	.004	.111	-2	1
Limits on credit growth	16740	.001	.046	-1	2
Limits on credit growth: General	16740	0	.035	-1	1
Limits on credit growth: HH	16740	.001	.035	-1	2
Limits on credit growth: Corpora	16740	0	.015	-1	1
Loan restrictions	16740	.008	.116	-2	2
Loan restrictions: Household sec	16740	.006	.105	-2	2
Loan restrictions: Corporate sec	16740	.002	.064	-2	1
Restrictions on foreign currency	16740	.002	.054	-1	1
Limits on the loan-to-value ratio	16740	.006	.124	-1	2
Limits on the DSTI ratio	16740	.004	.093	-1	2
Tax measures for macroprudential	16740	.002	.067	-1	2
Liquidity requirements	16740	.016	.176	-2	2
Limits on the loan-to-deposit ratio	16740	.001	.049	-1	1
Limits on the foreign exchange p	16740	.007	.105	-1	2
Reserve requirements	16740	0	.244	-3	3
Reserve requirements: foreign cu	16740	0	.121	-3	3
SIFI Measures	16740	.009	.111	-2	1
Other macroprudential measures	16740	.009	.118	-2	3
iMaPP Aggregate Score	16740	.094	.607	-7	8
Average LTV limit	8018	94.131	12.149	37.857	110
Median LTV	8018	94.212	12.361	35	110
Average LTV limit: end-quarter	8018	94.097	12.192	37.857	110
Median LTV limit: end-quarter	8018	94.18	12.41	35	110
LTV Quarter Max	8018	94.199	12.109	37.857	110

Table 3.1: iMaPP Summary Statistics

Macroprudential Policy Actions 1990-2020: Advanced Economies

	Count
Countercyclical buffers	53
Capital conservation buffers	125
Capital requirements	117
Leverage limits	21
Loan loss provisions	73
Limits on credit growth	6
Loan restrictions	76
Restrictions on foreign currency	10
Limits on the loan-to-value ratio	125
Limits on the debt-service-to-income	71
Tax measures for macroprudential	33
Liquidity requirements	180
Limits on the loan-to-deposit ratio	4
Limits on foreign exchange	9
Reserve requirements	133
Measures for the systemically important institutions	119
Other macroprudential measures	104

Table 3.2: iMaPP Action Counts, Advanced Economies

Macroprudential Policy Actions 1990-2020: Emerging Economies

	Count
Countercyclical buffers	13
Capital conservation buffers	178
Capital requirements	177
Leverage limits	62
Loan loss provisions	123
Limits on credit growth	27
Loan restrictions	134
Restrictions on foreign currency	38
Limits on the loan-to-value ratio	124
Limits on the debt-service-to-income	68
Tax measures for macroprudential	34
Liquidity requirements	330
Limits on the loan-to-deposit ratio	35
Limits on foreign exchange	171
Reserve requirements	490
Measures for the systemically important institutions	81
Other macroprudential measures	98

Table 3.3: iMaPP Action Counts, Emerging Economies

	(1) Crisis Within 1 Year	(2) Crisis Within 2 Years	(3) Crisis Within 1 Year	(4) Crisis Within 2 Years
LTV Median Change	.006*	.006	.007**	.008
	(.003)	(.005)	(.003)	(.005)
Countercyclical Capital Buffer	.057	.102*	.064	.117*
	(.046)	(.054)	(.047)	(.057)
Capital Requirements HH Sector	.026	-.013	.014	-.033
	(.055)	(.049)	(.052)	(.047)
Capital Requirements: Corporate	-.268**	-.313**	-.291**	-.352**
	(.126)	(.125)	(.125)	(.123)
Leverage Ratio Limits	.004	-.007	.008	.001
	(.037)	(.043)	(.041)	(.048)
Loan Restrictions: Households	-.064	-.069	-.08	-.103
	(.077)	(.068)	(.078)	(.067)
Loan Restrictions: Corporate	.1	.111	.182**	.28*
	(.061)	(.07)	(.084)	(.16)
Debt-Service-To-Income Limits	.063*	.052	.06*	.047
	(.036)	(.04)	(.033)	(.037)
Taxes on Capital Gains	.095	.205	.082	.179
	(.078)	(.151)	(.077)	(.15)
Liquidity and Funding Limits	.002	.009	.001	.007
	(.02)	(.028)	(.019)	(.024)
Loan Loss Provisions	-.027	-.051	-.01	-.015
	(.025)	(.077)	(.021)	(.073)
Reserve Requirements	.036**	.012	.038**	.018
	(.015)	(.028)	(.015)	(.024)
SIFI Surcharges	-.024	-.033	-.028	-.038
	(.023)	(.035)	(.022)	(.037)
Other Tools	-.017	.031	-.011	.043
	(.045)	(.045)	(.047)	(.047)
Public debt-to-GDP ratio			-.05	-.114*
			(.035)	(.062)
Consumer prices (index, 1990=100)			.002***	.005***
			(.001)	(.001)
Current account (nominal, local currency)			0***	0***
			(0)	(0)
Monetary Policy Change			.002	.001
			(.007)	(.009)
Constant	.061***	.105***	-.231*	-.477**
	(.004)	(.005)	(.118)	(.202)
Observations	476	476	475	475
R-squared	.399	.486	.413	.515

Standard errors are in parentheses
****** p<.01, ** p<.05, * p<.1*

Table 3.4: iMaPP Linear Probability Model

	Post-Crisis	Crisis Build	Mean Post	Mean Build	Differenc e	Std Err	t value	p value
Yield Curve Slope (level)	1715	153	-.804	.109	-.913	.169	-5.4	0
Capital Ratio (level)	1599	144	9.184	12.819	-3.636	.635	-5.7	0
Loan-to-Deposit Ratio (level)	1571	142	96.243	111.302	-15.059	2.752	-5.45	0
Noncore Funding Ratio (level)	1526	140	36.804	40.279	-3.474	1.754	-2	.048
Capital Ratio (2-year Growth Rate)	1570	141	.659	.605	.054	1.203	.05	.964
Loan-to-Deposit Ratio (2-year Growth Rate)	1540	139	2.668	6.885	-4.216	1.033	-4.1	0
Noncore Funding Ratio (2-year Growth Rate)	1495	137	3.072	8.367	-5.295	1.385	-3.8	0
CPI (2-year Growth Rate)	1796	155	8.675	7.739	.936	3.968	.25	.814
Investment-to-GDP (2-year Growth Rate)	1669	141	3.942	8.511	-4.569	1.842	-2.5	.013
Consumption per Capita (2-year Growth Rate)	1724	150	5.011	4.19	.821	.615	1.35	.182
Equity Total Return (level)	1511	142	.107	.067	.04	.02	2	.046
Housing Price Index (level)	1441	117	62.912	94.219	-31.308	9.364	-3.35	.001
Total Loans to Non-Fin Businesses/GDP (2-year difference)	1665	140	2.127	5.846	-3.72	.545	-6.85	0
Total Mortgage Non-Fin Loans/GDP (2-year difference)	1568	131	1.258	2.369	-1.111	.313	-3.55	.001
Total Business Loans/GDP (2-year difference)	1001	61	.667	4.841	-4.174	.593	-7.05	0
Total Household Loans/GDP (2-year difference)	1040	69	1.569	3.846	-2.277	.468	-4.85	0
Broad Money/GDP (2-year difference)	1699	147	.523	2.511	-1.988	.618	-3.2	.002
Current Account/GDP (2-year difference)	1708	144	-.005	-.547	.543	.268	2.05	.043

Table 3.5: Macro History Descriptive Statistics

	(1) OLS	(2) OLS	(3) OLS	(4) Logit	(5) Logit
Total Loans/GDP 2 Year Difference	.003***	.003***	.001	.048***	.049***
	(.001)	(.001)	(.001)	(.01)	(.011)
LTD 2 Year Growth Rate	.003***	.002**	.004***	.035**	.024
	(.001)	(.001)	(.001)	(.015)	(.016)
Capital Ratio 2 Year Growth Rate	0	0	-.001	-.004	-.002
	(.001)	(.001)	(.001)	(.012)	(.013)
Noncore Ratio 2 Year Growth Rate	-.001	-.001	0	-.011	-.005
	(.001)	(.001)	(.001)	(.014)	(.015)
Constant	.039***	.039***	.047***	-3.35***	
	(.009)	(.009)	(.006)	(.202)	
Observations	954	954	904	954	899
R^2	.05	.06	.38	.099	.101
Country FE	No	Yes	Yes	No	Yes
Year FE	No	No	Yes	No	No

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 3.6: Financial Crisis Prediction Using Macroprudential Ratios

	(1) Crisis Within 2 Years	(2) Crisis Within 2 Years	(3) Crisis Within 2 Years	(4) Crisis Within 2 Years	(5) Crisis Within 2 Years	(6) Crisis Within 2 Years	(7) Crisis Within 2 Years	(8) Crisis Within 2 Years	(9) Crisis Within 2 Years	(10) Crisis Within 2 Years	(11) Crisis Within 2 Years
Total Loans/GDP 2 Year Difference	.001	.001	.001	0	.001	.001	.001	0	0	-.001	-.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
LTD 2 Year Growth Rate	.004**	.004**	.004***	.004***	.004***	.004***	.004***	.005***	.005***	.005***	.005***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Capital Ratio 2 Year Growth Rate		-.001	-.001	-.001	-.001	-.001	-.001	-.001	-.001	-.001	-.001
		(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Noncore Ratio 2 Year Growth Rate			0	0	0	0	0	.001	.001	0	0
			(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Yield Curve Slope				.003	.002	.002	.002	.002	.002	.003	.003
				(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.007)	(.007)
CPI 2 Year Growth Rate					.002	.002	.002	.003	.003	.003*	.003
					(.002)	(.002)	(.001)	(.002)	(.002)	(.002)	(.002)
Investment/GDP 2 Year Growth Rate						-.001	0	-.001	-.001	0	-.001
						(.001)	(.001)	(.001)	(.001)	(.001)	(.002)
Consumption 2 Year Growth Rate							-.002	-.002	-.002	-.003	-.004
							(.002)	(.002)	(.002)	(.002)	(.002)
Housing Price Index								0	0	.001*	.001*
								(0)	(0)	(0)	(0)
Broad Money/GDP 2 Year Difference										.004	.004
										(.003)	(.003)
Current Account/GDP 2 Year Difference											-.009**
											(.004)
Constant	.046***	.048***	.047***	.05***	.027	.027	.035*	-.013	-.013	-.023	-.013
	(.004)	(.004)	(.006)	(.01)	(.019)	(.019)	(.019)	(.036)	(.036)	(.04)	(.041)
Observations	983	983	904	897	897	893	893	835	835	805	805
R-squared	.387	.388	.381	.382	.383	.384	.385	.391	.391	.394	.398

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 3.7: Macro History Linear Probability Model

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