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Exchange rate shocks in multicurrency interbank markets

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Abstract

We develop a framework for studying financial contagion triggered by exchange rate shocks. To this end, we simulate multicurrency interbank markets with stylized properties and study their behavior in response to sudden appreciations and depreciations of a particular currency. A key result of our analysis is that the concentration of many interbank exposures in the same currency can lead to significant systemic risk.

Keywords: Systemic risk, financial contagion, interbank markets, multilayer networks

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1 Introduction

Most, if not all, banking crises have their roots in cheap credit, overconfident investors and lax regulation. What serve as the triggers and contagion mechanisms, however, vary widely. Therefore, a sizeable literature on systemic risk in interbank markets has emerged. Researchers first modeled these markets using simple interbank lending matrices in which banks are linked through a network of bilateral exposures (see Upper 2011, and the references therein). More recently, researchers have started to model interbank markets as multiplex networks. In these networks, financial institutions are linked to one another through multiple layers of different subnetworks. These different layers can, for example, pertain to different asset classes (Poledna et al. 2015), different maturities (Gabrieli & Salakhova 2019) or both (Bargigli et al. 2014, Aldasoro & Alves 2018).[1] In this sense, banks do not engage with one another in a single market. Instead, banks are connected to one another across different markets, i.e., markets for long-term assets vs. markets for short-term assets or markets for deposits and loans vs. markets for derivatives.

In this paper, we develop a simple framework in which financial institutions are connected to each other via currency exposures. In doing so, we are able to model one of the most notorious sources of financial contagion: exchange rate shocks. In his 2011 literature review, Upper concludes that existing work suffers from "an exaggerated focus on scenarios involving the idiosyncratic failure of an individual bank rather than common shocks" (Upper 2011, p. 121). Such truly idiosyncratic failures are, however, very rare. The literature frequently points to the bankruptcies of Barings Bank and Drexel Burnham Lambert, but ironically neither of these failures triggered any significant contagion effects. Conversely, macroeconomic shocks, which affect many banks at once, have fre-

[1] Alternatively, additional network layers can connect banks through common exposures as in Montagna & Kok (2016) or shared information as in Ding et al. (2017).

quently triggered financial crises (viz., the Peso crisis of 1994, the Asian financial crisis of 1997 or the Ruble crises of 1998).

Moreover, researchers and policy makers (e.g., Georgieva 2020) have recently warned about the global dominance of the US dollar and the implications this has for economic and financial stability.[2] In particular emerging markets rely heavily on a stable exchange rate towards the dollar. Therefore, in our analysis, we will lay emphasis on the question of how asymmetries in the use of different currencies can amplify or dampen financial contagion effects. We do so by simulating stylized multicurrency interbank markets and studying how these markets behave when one of the currencies in the system suddenly gains or loses in value.[3]

Our paper makes two important contributions to the literature. First, we develop a framework for the study of financial contagion in which knock-on defaults are not triggered by an initial idiosyncratic bank failure but a currency crisis. Such exchange rate shocks have in the past been one of the most frequent sources of financial contagion.[4] Second, our paper derives important results regarding asymmetries in banks' exposures denominated in different currencies. A key result of our paper is that a strongly dominant currency, in which many banks borrow, can be a significant source of financial contagion. Moreover, a common equity fund, to which all banks are forced to contribute and which is then used to rescue failing banks, proves to be a powerful tool in preventing

[2] At least since Gopinath et al. (2010) it has been known that pass-through effects of exchange rate changes are sensitive according to whether goods are invoiced in local currencies or US dollars.

[3] At the time of writing, the world finds itself in a state of severe economic turmoil due to the ongoing coronavirus pandemic. In the wake of this crisis, many exchange rates have experienced dramatic increases in volatility with currencies gaining or losing up to 25 % in value in a matter of weeks (Collins & Gagnon 2020). IMF officials even fear that "it is very likely that this year the global economy will experience its worst recession since the Great Depression" (Gopinath 2020, p. v).

[4] Macroeconomic shocks have so far largely been ignored by the financial contagion literature. One of the very few exceptions is Elsinger et al. (2006) who consider macroeconomic shocks such as FX shocks and shocks to stock markets and interest rates.

knock-on bank defaults.

The paper is organized as follows. Section 2 relates our work to the literature. Section 3 describes a framework of multicurrency interbank markets. Section 4 then uses this framework to conduct a series of Monte Carlo simulations of stylized interbank markets. Thereafter, Section 5 studies how these simulated multicurrency interbank markets behave, when one of their currencies suddenly appreciates or depreciates. Various subsections explore how changes to the different simulation parameters affect the ensuing contagion process. The same section also conducts two policy exercises. Section 6 concludes.

2 Related literature

One of the earliest branches of the systemic risk literature deals with the question of how idiosyncratic bank failures might cause subsequent defaults of other financial institutions. To this end, financial contagion has typically been modeled using a matrix of bilateral exposures. Such a matrix records how much financial institutions stand to lose in case one of their debtors defaults. When an initial financial institution defaults, its creditors might experience losses greater than their own capital reserves. Consequently, they will default, too. These second-round bank failures might then induce a third round of bank failures and so on. Eventually, the system reaches a new equilibrium in which no further bank defaults. By applying the mechanics of an interbank market's exposure matrix to any possible initial default in this market, researchers can gauge how robust or fragile it is. Analyses of this kind have been carried out for many real-world interbank markets (e.g., Furfine (2003), Wells (2002), Upper & Worms (2004), Mistrulli (2011), Sheldon & Maurer (1998), Blåvarg & Nimander (2002), van Lelyveld & Liedorp (2006), Degryse & Nguyen (2007), Diez Canedo & Martínez Jaramillo (2009), for the interbank markets of the US, the UK, Germany, Italy, Switzerland, Sweden, the Netherlands, Belgium and Mexico, respectively) as well as simulated interbank markets (see, e.g., Iori et al. 2006, Nier et al. 2007, Roukny et al. 2013, Leventides et al. 2019).

A closely related branch of the literature has introduced additional channels of financial contagion. Cifuentes et al. (2005), Gai & Kapadia (2010) and Ding et al. (2017) introduce asset prices into their models, such that banks propagate shocks not only via their immediate bilateral linkages but also via reduced asset prices. A similar route is taken by Greenwood et al. (2015), where banks are forced to sell assets to meet target levels of leverage. Müller (2006) and Gai et al. (2011) endogenize liquidity shortages. In their models, troubled banks stop extending credit to other banks and begin hoarding liquidity, which again inflicts losses at other banks. Fink et al. (2016) introduce a "credit quality" channel. Through this channel, shocks not only spread to other banks once a default has actually occurred. Instead, a shock spreads from a debtor bank to its creditors as soon as its default becomes more likely. Lee (2013) and Teply & Klinger (2018) propose models in which banks hold two types of assets: liquid assets and illiquid assets. When in trouble, banks must sell some of their more liquid assets to cover losses on their illiquid assets. Again, these fire-sales then induce losses at other banks.

Naturally, the notion of different contagion channels and the modeling of different types of assets provides a smooth transition towards the more modern understanding of interbank markets as multiplex networks. A number of papers have empirically analyzed the similarities, differences and relationships between the different layers of such networks (e.g., Langfield et al. 2014, Bargigli et al. 2014, Aldasoro & Alves 2018, for the interbank markets of the UK, Italy, and Europe as a whole, respectively). Poledna et al. (2015) show that modeling interbank markets as networks with multiple layers has important implications for assessing systemic risk. Using very granular data on Mexican banks, the authors distinguish between four layers of different exposures in the Mexican interbank market. In this multiplex network, banks are connected via deposits and loans, security holdings, derivatives, and uncleared FX transactions. The authors then demonstrate that systemic risk, when computed for the entire multiplex network, is greater than the sum of the same systemic risk scores evaluated at the network's individual layers.

Our own work is closely related to that Montagna & Kok (2016) and Gabrieli & Salakhova (2019). Both study knock-on defaults using simulated interbank markets with multiple layers. Montagna & Kok (2016) simulate interbank markets with different maturities and correlated assets based on a probability map which they calibrate to match key characteristics of the European interbank market.[5] Gabrieli & Salakhova (2019) use a similar approach. But unlike Montagna & Kok (2016) they consider two types of initial shocks: Idiosyncratic bank failures and simultaneous equity shocks to all banks in the system. In what follows, we also simulate multiplex interbank markets. We also consider common shocks instead of idiosyncratic bank failures. However, in our network, the different layers correspond to different currencies. This enables us to study exchange rate shocks as triggers of cascading defaults. For that matter, our work is also related to Elsinger et al. (2006) who have also studied macroeconomic shocks as sources of financial contagion, albeit in interbank markets with a single currency.

3 Multicurrency interbank markets

In case of a single currency and n many banks, interbank markets can be described by an $n \times n$ matrix of exposures. The individual elements of this matrix

[5]In the context of simulating interbank marekts, this concept has been pioneered by Hałaj & Kok (2013).

resemble the loans that banks grant each other. The ij^{th} element of this matrix resembles the exposure of bank i towards bank j. As no bank lends to itself, the main diagonal of the interbank lending matrix is equal to zero.

To describe multicurrency interbank markets with m different currencies, we follow Avdjiev et al. (2019) and generalize the traditional $n \times n$ interbank lending matrix to an $n \times n \times m$ interbank lending array or tensor $\boldsymbol{X}$:

[Figure 1 about here.]

Each of this tensor's m different $n \times n$ slices or layers summarizes the interbank loans denominated in one of the m different currencies. The tensor element $x_{ij}^{(k)}$, thus, resembles the amount of money that bank i has lent to bank j in currency k. As in the two-dimensional case, the main diagonal of each layer is equal to zero. Without loss of generality, all of the array's m layers can be expressed in a single currency.

To compute the total amount of money that bank i has lent to other banks in currency k, i.e., the total amount of i's interbank assets denominated in currency k, one computes the row sum

$$\sum_{j=1}^{n} x_{ij}^{(k)} = A_i^{(k)} \ . \tag{1}$$

Similarly, computing the column sum

$$\sum_{i=1}^{n} x_{ij}^{(k)} = L_j^{(k)} \ , \tag{2}$$

yields the total amount of money that bank j has borrowed in currency k.[6] Summing both across other banks and across currencies, yields i's total inter-

[6]Summing across currencies for a fixed pair of banks $\sum_{k=1}^{m} x_{ij}^{(k)}$, yields the total exposure of bank i towards bank j across all currencies.

bank assets

$$\sum_{k=1}^{m} A_i^{(k)} = A_i \tag{3}$$

and j's total interbank liabilities

$$\sum_{k=1}^{m} L_j^{(k)} = L_j \ . \tag{4}$$

Letting $A_i^{(nb)}$, $L_i^{(nb)}$ and E_i denote banks' nonbank assets, nonbank liabilities and equity levels, respectively, the balance sheet identity requires that

$$A_i + A_i^{(nb)} \equiv L_i + L_i^{(nb)} + E_i \ . \tag{5}$$

Banks' balance sheets thus look as follows:

[Table 1 about here.]

This generalization of traditional single-currency interbank markets allows us to model two sources of financial contagion. First, like traditional interbank markets with a single currency, multicurrency interbank markets can suffer from shocks to nonbank assets. If a particular bank cannot survive such a shock and defaults, all of this bank's interbank liabilities, which are the interbank assets of other banks, are erased from the interbank market, i.e., all of these array elements are set to zero. Second, multicurrency interbank markets can suffer from exchange rate shocks. In this case, one particular layer of the interbank lending array increases or decreases by a certain percentage. Both shock scenarios directly impact a bank's balance sheet. If any bank suffers a loss in its assets or an increase in its liabilities greater than its equity, this bank will default, too, and potentially trigger an entire default cascade. In what follows we focus on this second channel of contagion.

4 Monte Carlo simulations

The previous section describes how traditional approaches to assessing contagion in single-currency interbank markets can be generalized to the case of multicurrency interbank markets. In the upcoming section, we describe how we simulate different interbank markets within this multicurrency framework. Thereafter, we submit these simulated multicurrency interbank markets to a series of stress-tests to study how prone they are to financial contagion effects triggered by exchange rate shocks. Note, however, that our framework is not limited to simulated interbank markets. Instead, one could readily use it to investigate real-world interbank markets, too.

4.1 Simulation parameters

Both the traditional interbank lending matrix and the interbank lending array used here describe a network or graph. The nodes or vertices of this network are the different banks. The network's links or edges are the banks' bilateral exposures. As these exposures resemble credit relationships between a creditor bank and borrower bank, they are weighted and directed. In our simulation framework, each bank can borrow both in its home currency and in foreign currencies. We let l_i denote the number of banks from which bank i borrows in domestic currency. Analogously, l'_i denotes the number of banks from which bank i borrows in foreign currency. To ensure heterogeneity across banks, l_i and l'_i are realizations of two random variables that are uniformly distributed on the intervals $[0, l]$ and $[0, l']$, whereby l and l' are two exogenous parameters.[7] The resulting network will thus feature a uniform degree distribution. Moreover, links can run in opposite directions between the same two banks. This is

[7]Potential real world drivers of a bank's willingness to borrow from other banks are, e.g., forecasts of future economic growth. Depending on whether such forecasts pertain to the domestic market or foreign markets, this will either affect l or l'.

consistent with typical bankruptcy regulations which do not allow the netting of individual positions.

A third parameter s is then used to control the size of banks' exposures. We model loan volumes such that banks vary significantly in terms of their so-called systemic importance. The Basel Committee on Banking Supervision (2018) determines the global systemic importance of banks based on the following criteria: cross-jurisdictional activity, size, interconnectedness, degree of substitutability, and complexity. As the latter two criteria are rather technical and refer to specific revenue-based figures and balance sheet items, we focus on the first three of these indicators. In our framework, banks' levels of cross-jurisdictional activity are governed by l, while their levels of overall interconnectedness are driven by both l and l'. To directly control the systemic importance of large banks in our simulation framework, we set each of bank i's exposures equal to $s_i = (l_i + l'_i)^s$, whereby s is again an exogenous simulation parameter. Because s enters this equation in the exponent, this procedure ensures that the loan volumes of well-connected banks are disproportionately larger the greater s. Thus, by adjusting s, we can alter the systemic importance of these banks.

Given banks' interbank assets and interbank liabilities, we then use two exogenously determined ratios r_1 and r_2 to determine their nonbank assets and nonbank liabilities. Multiplying each bank's interbank assets with r_1 yields banks' nonbank assets.[8] Similarly, banks' equity levels follow from multiplying each bank's total assets with r_2. Lastly, banks' nonbank liabilities follow from the balance sheet identity in equation (5). The two parameters r_1 and r_2, thus, determine how heavily banks rely on interbank assets in relation to nonbank assets and how large their equity is.

[8] In case a bank has a net liability position in the interbank market, we determine its nonbank assets by multiplying r_1 with its interbank liabilities. This procedure ensures that none of the balance sheet items becomes negative.

In addition to the simulation parameters explained above, our simulation framework comprises two discrete probability distributions. A first distribution (D_1) controls the number of banks located in each currency area. A second discrete probability distribution (D_2) controls the preferences that banks, when borrowing in foreign currency, have vis-à-vis the different foreign currencies. In effect, these two probability distributions control how important the different currencies are in the global banking market. Note that a currency can be dominant because of two reasons: There are either many banks located in this currency area that borrow domestically or this currency is the favorite choice for borrowing in foreign currency.

4.2 Simulation procedure

Given a set of simulation parameters n, m, l, l', s, r_1 and r_2, and the distributions D_1 and D_2, our simulation procedure consists of eight steps:

1. Depending on D_1, randomly determine each bank's home currency.
2. Depending on l and l' as well as D_1 and D_2, randomly determine each bank's domestic and foreign lending relationships.
3. Depending on the realizations of l_i and l'_i and the parameter s, determine each bank's interbank exposures.
4. Depending on the resulting interbank market and r_1, determine each bank's nonbank assets.
5. Given each bank's total amount of assets, use r_2 to determine each bank's equity level.
6. Nonbank liabilities follow from the balance sheet identity in equation (5).
7. Simulate the financial contagion effects of exchange rate shocks of varying magnitude.
8. Repeat steps 1-7 1000 times.

An example of a simulated interbank market is given in Appendix A.

4.3 Comparing simulated markets

To compare markets simulated from different parameter values, we compute three different metrics. The first of these measures is the "density" (D) of the interbank market. A network's density is defined as its share of non-zero edges. In our case, this is the number of non-zero interbank relationships, such that, D is computed as

$$D = \frac{\sum_{ijk:\, x_{ij}^{(k)} \neq 0}}{m \cdot (n^2 - n)} \,. \tag{6}$$

Notice that higher or lower density does not automatically imply greater or lower financial contagion effects. While sparse interbank networks have few routes that default shocks can travel on, they typically also feature great asymmetry in exposures. In this case, the failure of a single critical bank can cause the collapse of the entire market.

Therefore, we compute a second measure which is directly related to financial contagion. We refer to it as the "share of unilaterally critical linkages" (UCL). These are loans that exceed the creditor's equity. Consequently, a default on such a loan will automatically trigger the failure of the creditor bank:

$$UCL = \frac{\sum_{ijk:\, x_{ij}^{(k)} > E_i}}{\sum_{ijk:\, x_{ij}^{(k)} \neq 0}} \,. \tag{7}$$

UCL will be particularly high in sparse networks with large individual exposures relative to banks' total interbank exposures. In this case, large fractions of banks' exposures are concentrated on a relatively low number of linkages. The repayment of these loans is thus critical for the survival of the creditor banks. As argued by Craig & von Peter (2014), sparse interbank markets are empirically far more common than high-density interbank markets with relatively small individual exposures.[9] While D, will by design, be approximately

[9]Nonetheless, it should be noted that financial contagion can also arise in situations where UCL is low. While less likely than when UCL is high, such scenarios can still occur if there are

the same for each of the 1000 realizations per set of parameters, UCL will vary more strongly. In each crisis simulation, we, therefore, compute the average value of UCL across the 1000 simulated markets.

Finally, we analyze banks' systemic importance. To this end, we compute a version of the "global systemic importance" index developed by the Basel Committee on Banking Supervision. The BCBS's original index consists of five equally weighted sub-indexes pertaining to the five criteria of systemic importance explained above. In our version of the index, we only use the first three of these criteria, i.e., cross-jurisdictional activity, bank size, and interconnectedness. A bank's level of cross-jurisdictional activity (CJA) is measured as the average amount of assets and liabilities it holds in foreign currency, i.e.,

$$CJA_i = 1/2 \cdot \left(\sum_{jk:\ k \neq h_i} x_{ij}^{(k)} + \sum_{ik:\ k \neq h_i} x_{ij}^{(k)} \right) , \tag{8}$$

where h_i denotes bank i's home currency.

Second, a bank's size (S) is computed as the sum of its interbank assets and nonbank assets, i.e.,

$$S_i = A_i + A_i^{(nb)} . \tag{9}$$

Lastly, a bank's interconnectedness (IC) is determined by the number of loans it granted to and received from other banks.

A bank's global systemic importance (GSI) is then computed as an equally weighted average of each of these three subindexes relative to their respective market totals:

$$GSI_i = 1/3 \cdot \frac{CJA_i}{\sum_i CJA_i} + 1/3 \cdot \frac{S_i}{\sum_i S_i} + 1/3 \cdot \frac{IC_i}{\sum_i IC_i} . \tag{10}$$

numerous creditors that are, e.g., dependent on the repayment of loans from any two separate borrowing banks.

By design, when summing across banks, GSI sums up to one or 100 %. Similar to UCL, banks' systemic importance will also vary across different simulations. Hence, we report the averages across the 1000 simulated markets.

5 Currency crisis simulations

In the preceding section we outlined our framework for simulating multicurrency interbank markets. In this section, we now simulate such markets with different sets of simulation parameters. For each set of parameters, we simulate 1000 interbank markets and study how these are affected by different exchange rate shocks. We begin with a baseline case and then alter each of its simulation parameters in different alternative scenarios. In our model, an exchange rate shock of size x to currency y, changes the value of interbank exposures denominated in this currency by x percent. In case of an appreciation of y, banks that are net borrowers (lenders) in currency y, will experience a loss (gain) in equity. If a bank's losses wipe out its entire equity, the bank defaults. Throughout, we follow Gai & Kapadia (2010) and Leventides et al. (2019), who also work with simulated interbank markets, and assume that creditor banks cannot make any recoveries from defaults on their loans. In case a creditor bank now also experiences losses that are greater than its equity, domino-like knock-on defaults set in.

5.1 Baseline simulation

In the baseline scenario, we simulate a market with $n = 100$ banks and $m = 4$ different currencies. We set $l = 10$ and $l' = 10$, such that each bank borrows on average from five other banks in domestic currency and five other banks in foreign currency. We choose $s = 2$, such that loans taken out by the average bank are of size $(5 + 5)^2 = 100$. We assume, for now, that on average all currency areas are home to the same number of banks. As there are four different currencies, we set $D_1 = (0.25, 0.25, 0.25, 0.25)$. Moreover, we also assume that $D_2 = (0.25, 0.25, 0.25, 0.25)$. This means that when borrowing from abroad, banks have no particular preference over different currencies. Of course, both of these assumptions are very unrealistic. Later on, we vary these assumptions via a set of alternative calibrations. There, we will pay particular attention to the case where a large number of banks which are, e.g., located in emerging markets, have large liabilities in one particular currency, e.g., the US-dollar. Lastly, we set $r_1 = 3/2$ and $r_2 = 0.06$ such that banks hold more nonbank assets than interbank assets and maintain an equity ratio of 6 %.

As explained above, we use these specifications to simulate 1000 markets and study how each of them reacts to exchange rate shocks ranging between -50 % and +50 %.[10] Table 2 summarizes the markets' key characteristics, which have been discussed in Section 4.3. The density of the average baseline interbank network amounts to $100 \cdot (5 + 5)/(4 \cdot 100^2 - 4 \cdot 100) = 0.025$, suggesting that 2.5 % of all possible links in the network are realized. Close to 15 % of these interbank loans are unilaterally critical, i.e., they are larger than the creditors' equity such that defaults on these loans will cause subsequent bank failures. Lastly, the global systemic importance of the top five most important banks ranges between 1.8 and 2.3 percent.

[Table 2 about here.]

As we assume that all currency areas are home to the same number of banks and no currency is preferred over another when banks borrow in foreign currency, the same exchange rate shock will have the same effect for all different currencies. Thus, we only show the results for shocks to Currency 1. These are

[10] An oft-used definition of a currency crisis usually involves a depreciation of the nominal exchange rate that exceeds 25 % on an annual basis. See, for example, Frankel & Rose (1996). Hence, our chosen values comfortably exceed commonly used thresholds.

displayed in Figure 2. In this figure, the horizontal axis depicts the different exchange rate shock sizes, while the vertical axis shows the resulting losses in interbank assets averaged across the 1000 simulated markets.

[Figure 2 about here.]

Obviously, the loss in assets is the greater the larger the initial currency shock and no losses occur if the shock size is equal to zero. Thus, for all currencies, the results follow a U-shaped pattern around zero. When starting from zero and moving to the left, we observe that losses first follow a linear relationship with the size of the currency shock. For shocks more severe than -15 %, the slope of this relationship, however, suddenly increases. This is because currency shocks now not only proportionately reduce banks' assets, but also trigger defaults which in turn cause entire default cascades to the point where almost no bank survives the crisis and close to 100 % of assets are lost. This phenomenon is even more striking when looking at positive exchange rate shocks. For exchange rate shocks of up to around +20 %, bank assets actually increase. But once these shocks are too profound, some banks, that have great liabilities in the suddenly appreciated currency, fail and in turn cause the default of their creditors.

5.2 Greater nonbank assets and higher equity

We begin our analysis of alternative scenarios by increasing the parameters r_1 and r_2, i.e. the ratio of nonbank to interbank assets and the equity ratio. Naturally, higher levels of equity directly reduce the risk of financial contagion as banks have greater cushions to survive failing interbank loans. Similarly, a greater reliance on nonbank assets makes a bank less vulnerable to financial contagion in the interbank market. This holds for both single-currency and multicurrency interbank markets alike. However, as we model a multicurrency interbank market where banks are located in different currency areas, an exchange rate shock will not affect all banks in the same way. If a bank sees its home currency depreciate, all of its assets and liabilities lose in value. Its equity thus increases or decreases depending on the currencies in which most of its interbank assets and interbank liabilities are denominated. Conversely, a bank located in another currency area only sees parts of its interbank assets change in value. Therefore, we expect the equity ratio r_2 to have a greater effect on financial contagion than r_1.

[Figure 3 about here.]

Figure 3 shows the effects of increasing r_1 from 2/3 to 5/2 and raising r_2 from 0.06 to 0.08 while keeping all other parameters constant. Figure 3 (a) shows the effects of increasing r_1, while Figure 3 (b) shows the effects of increasing r_2. In both charts white bars refer to the effects of exchange rate shocks in the baseline scenario, while red bars reflect the effects of exchange rate shocks in the new alternative scenarios. We observe that in both subfigures the red bars are shorter than the white bars, suggesting that the losses of interbank assets are, as expected, less severe than in the baseline scenario. This is unsurprising, as the increase in r_1 (r_2) significantly reduces the share of unilaterally critical linkages (see Table 2) from 14.8 percent to 5.3 (6.4) percent, while having little to no effect on network density and the systemic importance of the largest banks in the market.

5.3 Greater network density and greater interbank exposures

Next, we investigate how the maximum number of loans denominated in domestic currency l and the maximum number of loans denominated in foreign currency l' affect financial contagion. Essentially, these two parameters determine the density of the interbank network. The effect of increasing network density on financial contagion is twofold. On the one hand, it increases the number of routes that shocks can travel on, such that shocks can now quickly affect many other banks before the default wave comes to a halt. This effect is particularly strong in extremely sparse networks. In fact, if the interbank market is so sparse that certain banks have no relation to other banks at all, not even through intermediary banks, their default can never affect these other banks. In this case, increasing the number of loans will merge these independent interbank markets into one large network of loans, such that financial contagion can now, at least in theory, affect all banks. On the other hand, once the interbank market has surpassed a critical level of interconnectedness, further increasing the density of the interbank market will help to spread banks' exposures more evenly across different counterparties. Banks are then less exposed to individual borrowers such that default waves are less likely to arise in the first place.

This twofold effect of network density arises in single-currency and multicurrency interbank markets alike. In addition to this, multicurrency interbank markets are also driven by the proportions of each bank's exposure denominated in domestic currency to its exposure denominated in foreign currency. If banks have increased interbank liabilities in domestic currency, they will be more robust towards depreciations of their home currency. Of course, banks located in other currency areas, who are the creditors to these interbank liabilities, will be more exposed to depreciations of this particular currency. However, depending on the number of currencies in the market, this increased risk is shared among many different banks, such that the overall risk of financial contagion decreases. Conversely, an increasing number of loans in foreign currency increases financial contagion in case of appreciations.

[Figure 4 about here.]

Figure 4 shows the effects of altering l and l'. First, we increase the number of loans in domestic currency from $l = 10$ to $l = 30$. Thus, on average, banks now borrow money from fifteen instead of only five other banks in domestic currency. Table 2 shows that this change increases the average network density to five percent. At the same time UCL plummets from around 15 % to 1 %. The effect this change has on the severity of exchange-rate-triggered banking crises is depicted in Figure 4 (a). Again, white bars refer to the baseline scenario, while red bars refer to the alternative. The results show that the effects of both positive and negative exchange rate shocks are now less pronounced than in the baseline scenario. Figure 4 (b) shows the results of increasing l' from $l' = 10$ to $l' = 30$. Here, the effects from positive exchange rate shocks are also decreased, but only slightly. Conversely, negative exchange rate shocks now prove more to be harmful than before. Lastly, we increase both l and l' from ten to thirty. Here, the interbank market's density amounts to 7.6 % on average, while the average share of unilaterally critical linkages drops to less than half a percent. The effects of this joint increase in the number of domestic and foreign loans are depicted in Figure 4 (c). The loss in assets is generally greater than when increasing only l, but smaller than when increasing only l'. Compared to the baseline scenario, the joint increase in l and l' nonetheless significantly reduces financial contagion, in particular concerning positive exchange rate shocks.

Of course, the effects of different parameter values on financial contagion can be non-linear and even non-monotonic.[11] Given their twofold effect on financial contagion, this concern is particularly pressing for the parameters l and l'. Therefore, we repeat the earlier analysis for a whole range of values for these two parameters. In particular, we study values of l and l' between 1 and 50. The results of these exercises are displayed in Figure 11 in the appendix.[12]

The results show that adding to the number of domestic loans significantly

[11] See, e.g., the simulated interbank markets of Nier et al. (2007).

[12] The appendix also includes this additional analysis for the parameters r_1 and r_2 (See Figure 10).

reduces the financial contagion effects of negative exchange rate shocks. This effect is particularly strong when $l < 20$. For values of l between 20 and 30 this effect is still there but becomes smaller, while increases of l beyond $l = 30$ have practically no effect on financial contagion. Concerning positive exchange rate shocks, we find a similar pattern. Up until $l = 10$, increases in l significantly reduce financial contagion effects. Thereafter, i.e., when $l > 10$, further increases in l are once again ineffective in reducing financial contagion effects. A completely different pattern emerges for increases in l'. First, i.e., when l' is very low, increases in l' worsen the impacts of negative exchange rate shocks, but dampen those of positive exchange rate shocks. Once l' reaches a level of around $l' = 20$, further increases have once again no impact on financial contagion. Regarding joint increases of both l and l' we observe that negative exchange rate shocks remain unaffected by increases of the parameters beyond $l = l' = 10$, where as positive exchange rate shocks can be significantly reduced by further increases in the number of loans, even if that number is already quite high. Thus, on the whole, we find that greater network density reduces the effects of financial contagion.

Next, we consider changes to the parameter s. Recall that s controls the size of loans but also banks' so-called global systemic importance. In the baseline-scenario we set this value to $s = 2$. Now, we increase it to $s = 8$. Obviously, this change has no effect on network density. However, as can be seen from Table 2, it greatly increases the share of unilaterally critical linkages and the systemic importance of the most important banks. Initially, close to 15 percent of all loans were critical to the survival of creditor banks. Now, this value increases to almost 19 percent. Similarly, the global systemic importance of the top five banks ranged between 1.8 to 2.3 percent. Now, these banks' systemic importance ranges between 2.7 to 5.9 percent. The effects these changes have on financial contagion are displayed in Figure 5. Here, we see that in particular the effects of large exchange rate shocks are now significantly dampened. This is because, unless there is a default cascade triggered by one of the now very large borrowers, domino effects only occur across small banks. Default waves can, therefore, more easily come to a halt, as the larger institutions have sufficient assets to survive defaults on loans extended to smaller institutions.

[Figure 5 about here.]

Similar to l and l', we now also study how financial contagion develops across a range of values for s. Figure 12 in the appendix shows the losses of interbank assets when s ranges between $s = 1$ and $s = 10$. In the case of negative exchange rate shocks more severe than -20 %, higher values of s only appear to reduce the amount of assets lost, but not the fact that some banks will default. Conversely, greater values of s appear to reduce the effects of positive exchange rate shocks regardless of their severity.

5.4 Alternative currency distributions

Lastly, we turn to one of the most important questions regarding the connection between financial contagion and exchange rates. This is the question of whether and how financial stability is affected by the relative dominance of one or a few reserve currencies. To this end, we now vary the two distributions D_1 and D_2. While D_1 controls how many banks are located in one currency area, D_2 controls which currencies banks use when borrowing from abroad. We first change D_1 from $(0.25, 0.25, 0.25, 0.25)$ to $(0.7, 0.1, 0.1, 0.1)$. Then we do the same for D_2. In both cases there will be a clearly dominant currency and three equally small minor currencies. In the first case the asymmetry arises from banks' locations. In the second case the dominance of Currency 1 is due to banks' preference for using this particular currency when borrowing from abroad.

Figure 6 (a) shows the effects of exchange rate shocks to Currency 1 in the case of locational asymmetry. Figure 6 (b) does so for shocks to one of the minor currencies. The results show that positive exchange rate shocks to the major currency now have a smaller impact on financial contagion. Conversely, depreciations now trigger greater losses in interbank assets. The opposite can be observed for the minor currencies. Depreciations now show small financial contagion effects, whereas little to no change can be observed for appreciations. Again, we also study these patterns across a variety of values. Therefore, we repeat the earlier analyses for further locational distributions D_1. In these, the dominance of Currency 1 varies between 25 and 99 %. The results of these additional simulations are depicted in Figure 13 in the appendix.

[Figure 6 about here.]

Finally, Figures 7 (a) and (b) repeat the analysis for asymmetry in foreign borrowing instead of asymmetry in bank location. Concerning exchange rate shocks to the minor currencies, the results are largely unchanged to the baseline scenario. However, exchange rate shocks to the dominant currency, now trigger greater losses regardless of whether the preceding shocks are positive or negative. Figure 14 in the appendix shows that this finding persists across different values in D_2. In fact, the greater the dominance of one particular currency in the system, the greater are the resulting losses in interbank assets following exchange rate shocks to this currency. This key result suggests that asymmetries in interbank lending can lead to increased levels of financial contagion.

[Figure 7 about here.]

5.5 Policy interventions

The previous sections illustrate how the results of our simulations react to changes to the key simulation parameters. The results show that greater nonbank assets, higher equity levels and greater interbank network density can significantly reduce financial contagion effects. Apart from the equity ratio, however, policy makers cannot directly alter these market characteristics. Nonetheless, policy makers can resort to different tools to mitigate financial contagion effects triggered by exchange rate shocks. In what follows, we analyze the effects of two such policies. First, we consider the case of bank breakups. Then, we investigate the effect of a common equity pool among banks. Similar policy exercises have, e.g., been carried out by Greenwood et al. (2015) or Ramadiah et al. (2020).

When splitting a bank in two, the easiest approach would be to split every asset and liability in half. One half would remain in the old bank, the other half would form a new bank. This procedure, however, would not reduce financial contagion. Both banks would be exposed to the exact same loans. In the event of a defaulting borrower, they would simultaneously fail and propagate the initial default shock to other banks just like the original bank would have done before the breakup. Therefore, we assume that policy makers attempt to create two roughly equally-sized smaller banks without splitting up individual exposures. This procedure ensures that the two smaller banks are not exposed to the same risks in the interbank market. Moreover, they have no loans between them. The failure of a third bank, which would have caused the original large bank to fail, will now only cause the failure of one of the two newly created smaller banks. Consequently, the default wave will now not immediately spread to all of the original bank's creditors. Intuitively, bank breakups, therefore, significantly reduce financial contagion. However, there is a second channel through which bank breakups affect financial contagion. The smaller banks will now have some loans on their balance sheets, whose failure the original large bank would have survived, but the smaller banks could not. This second channel works in the opposite direction of the first channel creating an ambiguous total effect.

Figure 8 (a) shows the effects of exchange rate shocks in a scenario where, in terms of interbank liabilities, the top ten largest banks are broken up. We observe, that this policy intervention clearly fails to reduce financial contagion effects. Regardless of whether exchange rate shocks are positive or negative, the loss in interbank assets is unchanged or even greater than in the baseline scenario.

[Figure 8 about here.]

The second policy intervention, which is the common equity pool, forces banks to surrender a certain share of their equity to a government-controlled emergency equity fund. If a bank faces default, this fund is used to supply this bank with fresh funding. In what follows, we consider a very basic version of this fund. In the beginning, i.e., before any exchange rate shock has occurred, banks commit five percent of their equity to this fund. Throughout a crisis, banks that are on the brink of default are supplied with new equity from the common equity pool, as long as the fund has not been depleted yet. Moreover, we assume that during the crisis the common pool is not replenished with new funds. Of course, this policy reduces banks' equity. However, in the event of a crisis, it redirects this equity to "where it is needed the most" and thus "nips financial crises in the bud".[13]

The results of implementing this policy are depicted in Figure 8 (b). We find that this second type of policy proves very successful in mitigating financial contagion effects caused by exchange rate shocks. Both the effects of appreciations and depreciations are now significantly reduced. Figure 15 in the appendix studies how effective these policies are for a range of different values,

[13]In a way, the common equity pool works like a fire department. Without it, home owners try to put out the fire in their house using only the water of their private swimming pool. With the equity fund in place, home owners give some of their fire water to the fire department. Firefighters can then use this water to put out fires anywhere in the city, before flames start spreading from one house to the next.

i.e., either the number of banks to be broken up or the share of equity banks must commit the common equity pool. We observe that the effectiveness of bank breakups is largely independent from the number of banks that are broken up. In fact, positive exchange rate shocks cause greater asset losses the more banks are broken up. Conversely, the effectiveness of the common equity pool strongly increases if more capital is added to it.

6 Conclusion

This paper has developed a framework for studying financial contagion triggered by exchange rate shocks. To this end, we adapted the existing concept of multiplex interbank markets and simulated interbank markets with multiple currencies. Our results have shown that the contagion effects of exchange rate shocks are reduced if banks are well linked to other banks in their domestic currency. Increased exposures in foreign currency, however, have increased the potential for cascading defaults in response to sudden depreciations. Moreover, asymmetric currency distributions in the interbank market have also proven to increase systemic risk concerning both positive and negative exchange rate shocks. Lastly, the results of two policy exercises show that bank breakups do not lead to smaller systemic risk. To the contrary, bank breakups increase the likelihood of knock-on defaults. Conversely, the introduction of a common equity pool greatly reduces the risk of financial contagion effects. This result is of particular importance for financial regulators in emerging market economies, where banks tend to be heavily exposed to foreign currencies, in particular the US dollar.

There are ample opportunities for future research. As we had to make many stylized assumptions, a critical extension of our paper would be an application of our concept of multicurrency interbank markets to real world data. Of course, a major obstacle for this kind of research would be the lack of data on bilateral exposures denominated in different currencies. A promising solution to this problem could be the use of calibrated probability maps à la Hałaj & Kok (2013), which have, in the context of multiplex interbank markets, e.g., been used by Montagna & Kok (2016) and Gabrieli & Salakhova (2019). Another important avenue could be the introduction of additional channels of contagion. For that matter, one would have to add further layers to the interbank network pertaining, e.g., to different maturities and asset classes. Algebraically, this would be no different than moving from the traditional two-dimensional exposure matrix to the three-dimensional exposure array used in this study.

With a focus on simulated interbank networks, researchers could explore the implications of different degree distributions in multicurrency interbank networks. In this paper, we employed a uniform distribution. Alternatives to this approach are random interbank networks as in Nier et al. (2007) or entire sets of different degree distributions as in Gai & Kapadia (2010). Yet another way in which one could extend our research is to model situations where banks, in the event of mass-spread financial contagion, flee to a particular currency, even if the original shock did not affect that currency. This kind of modeling would allow for endogenous responses in the FX market. Then, instead of hoarding liquidity (see, e.g., Gai et al. 2011, Gabrieli & Salakhova 2019), banks would start hoarding currency.

Beyond extensions for future research, there are also potential policy implications from our analysis. As Maggiori et al. (2019) point out, for the case of debt securities, currency denomination is an important component that shapes portfolios. If, as we suspect, this spills over into the banking system (via bonds held as assets), exchange rate shocks are also critical. Hence, concerns about the ability of stress-tests as an early warning system might want to pay more attention to the role of exchange rate shocks and the resulting contagion effects.

The ongoing pandemic's impact on the volatility of exchange rates only serves to further highlight this concern despite the broadening of central bank swap lines though these have clearly helped (Collins & Gagnon 2020). Moreover, since the dominance of the US dollar in debt markets is unlikely to be reversed anytime soon, this also means that the potential for contagion effects from large exchange rate shocks remains undiminished. Despite progress made by emerging markets in recent years to reduce their propensity to be exposed to the 'original sin' of borrowing in foreign currencies (Eichengreen & Hausmann 1999), risks still remain because investors have increasingly left themselves open to exchange rate risks (Carstens & Shin 2019).

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A Example of a multicurrency interbank market

For illustrative purposes, we use our framework to simulate a market with $n = 20$ different banks and $m = 3$ different currencies. The parameters l, l' and s are set to 5, 2 and 2, respectively. The currency distributions D_1 and D_2 are both equal to (0.65, 0.25, 0.1). Thus, most banks are located in the first currency area, while the fewest number of banks are located in the third. The resulting interbank market is shown in Figure (9). The different subfigures pertain to the interbank market's different currency layers.

[Figure 9 about here.]

B Simulations across different parameter values

[Figure 10 about here.]

[Figure 11 about here.]

[Figure 12 about here.]

[Figure 13 about here.]

[Figure 14 about here.]

[Figure 15 about here.]

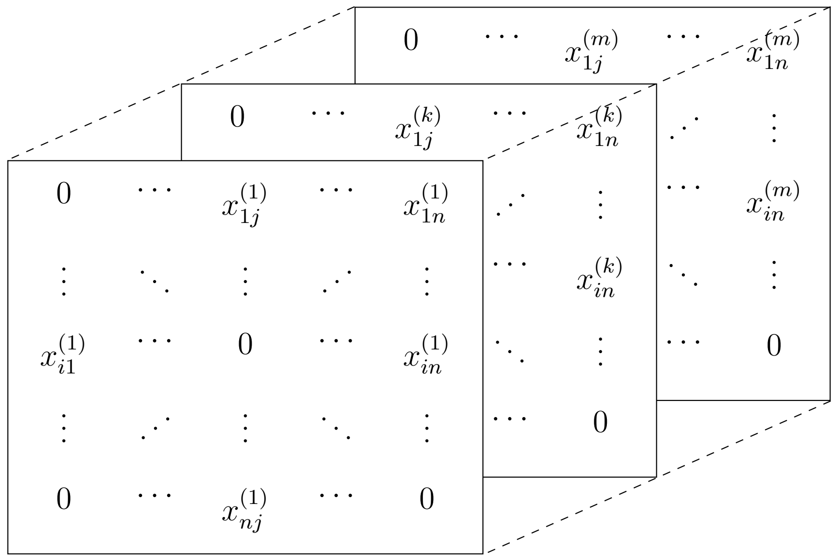


Figure 1: Interbank lending array

Table 1: Bank balance sheet

Assets		Liabilities	
Interbank assets	A_i	Interbank liabilities	L_i
nonbank assets	$A_i^{(nb)}$	nonbank liabilities	$L_i^{(nb)}$
		Equity	E_i

Table 2: Market characteristics in different scenarios

Scenario	Change to baseline	D (in %)	UCL (in %)	GSI_5 (in %)	GSI_1 (in %)
Baseline	-	2.5	14.8	1.8	2.3
Greater nonbank assets	$r_1 = 5/2$	2.5	**5.3**	1.9	2.4
Greater equity	$r_2 = 0.08$	2.5	**6.4**	1.9	2.3
More domestic loans	$l = 30$	**5.1**	**1.0**	1.8	2.3
More foreign loans	$l' = 30$	**5.0**	**1.8**	1.8	2.2
More loans overall	$l = l' = 30$	**7.6**	**0.4**	1.8	2.2
Greater loan sizes	$s = 8$	2.5	**18.7**	**2.7**	**5.9**
Dom. in bank location	$D_1 = (0.70, 0.10, 0.10, 0.10)$	2.5	14.9	1.9	2.3
Dom. currency preference	$D_2 = (0.70, 0.10, 0.10, 0.10)$	2.5	14.7	1.9	2.3
Bank breakups	Breakup of ten largest banks	**2.1**	**16.0**	1.5	1.9
Common equity pool	5 % common equity pool	2.5	14.9	1.9	2.3

Note: The table summarizes which parameters have been changed in the different scenarios relative to the baseline scenario and how these changes affect the key characteristics of the simulated interbank market. D refers to the market's density, while UCL to the market's share of unilaterally critical linkages. GSI_5 denotes the systemic importance of the fifth most important bank. GSI_1 refers to the systemic importance of the bank with the greatest systemic importance. For each scenario, the reported values are the mean values across all 1000 simulated markets. The greatest differences to the baseline scenario are typeset in bold.

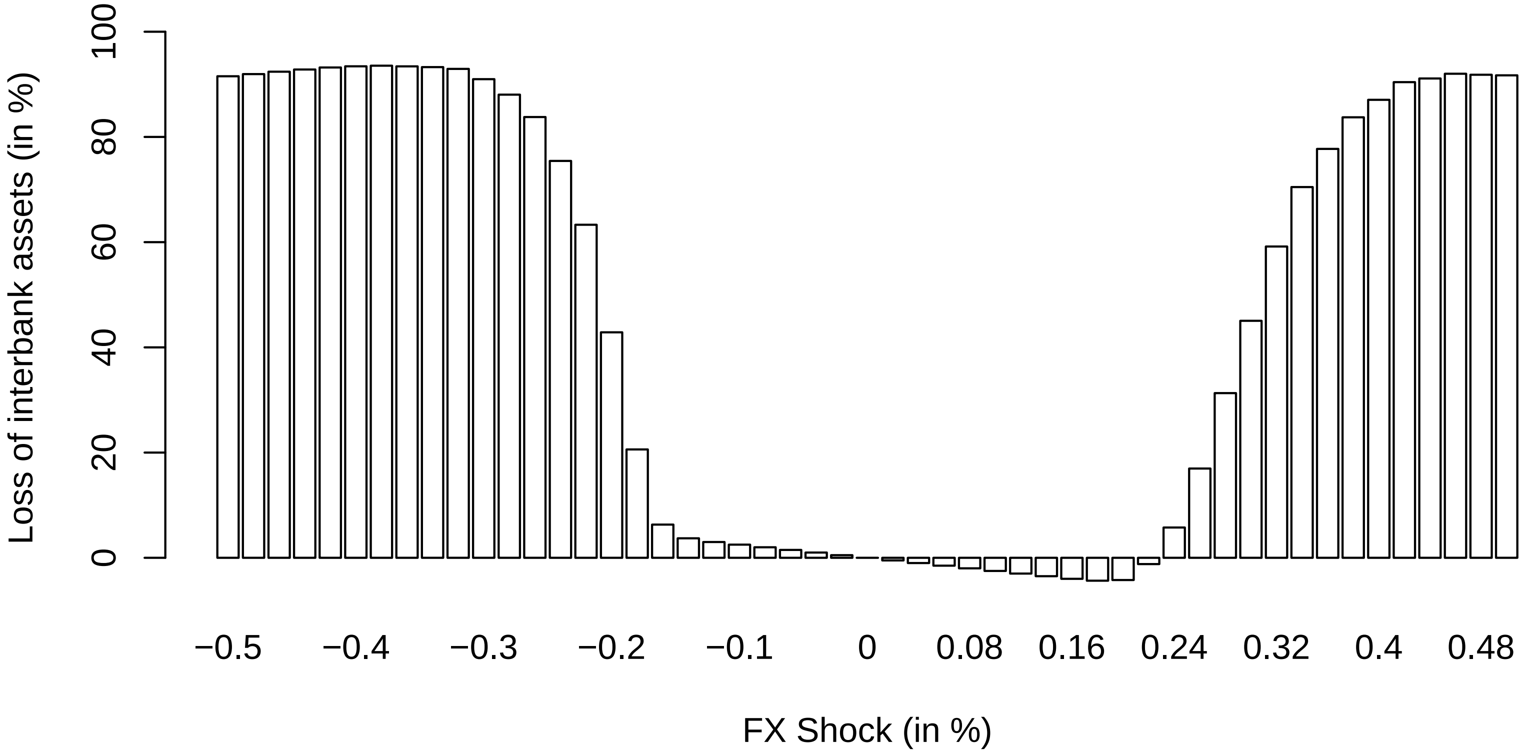
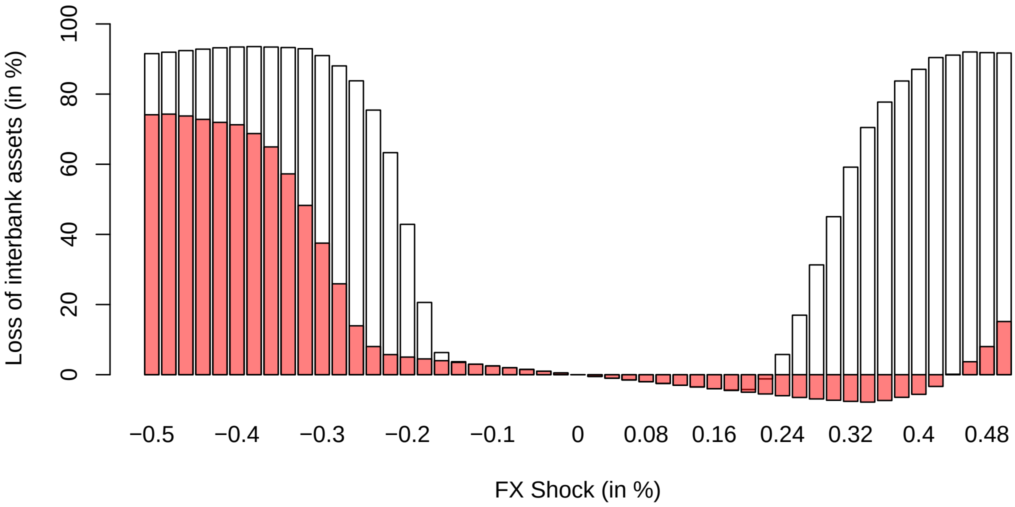


Figure 2: Baseline simulations

(a) Greater nonbank assets



(b) Higher equity

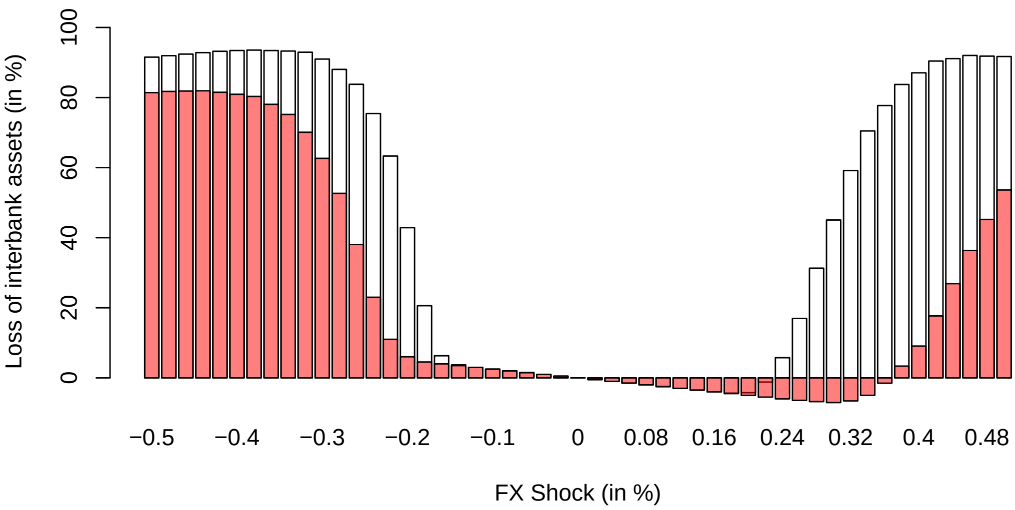
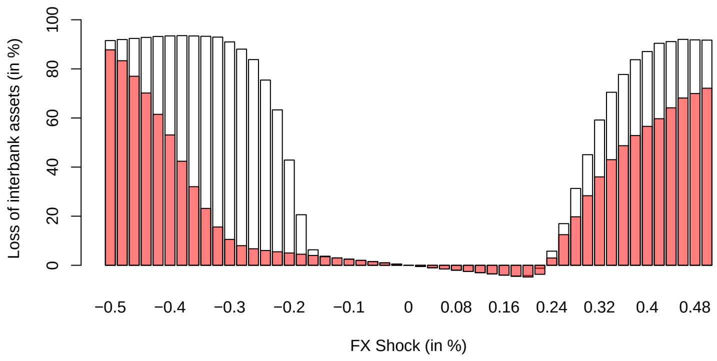


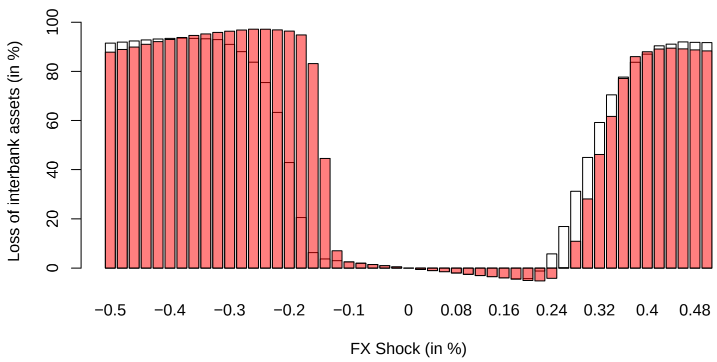
Figure 3: Greater nonbank assets and higher equity

Note: Subfigure (a) depicts interbank losses in the baseline scenario (white) where $r_1 = 3/2$ and in an alternative scenario (red) where $r_1 = 5/2$. Subfigure (b) depicts interbank losses in the baseline scenario (white) where $r_2 = 0.06$ and in an alternative scenario (red) where $r_2 = 0.08$.

(a) More domestic loans



(b) More foreign loans



(c) More domestic and more foreign loans

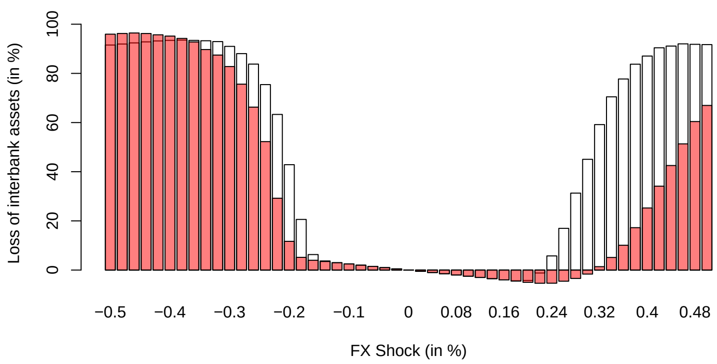


Figure 4: More interbank loans

Note: Subfigure (a) depicts interbank losses in the baseline scenario (white) where $l = 10$ and in an alternative scenario (red) where $l = 30$. Subfigure (b) depicts interbank losses in the baseline scenario (white) where $l' = 10$ and in an alternative scenario (red) where $l' = 30$. Subfigure (c) depicts interbank losses in the baseline scenario (white) where $l = l' = 10$ and in an alternative scenario (red) where $l = l' = 30$.

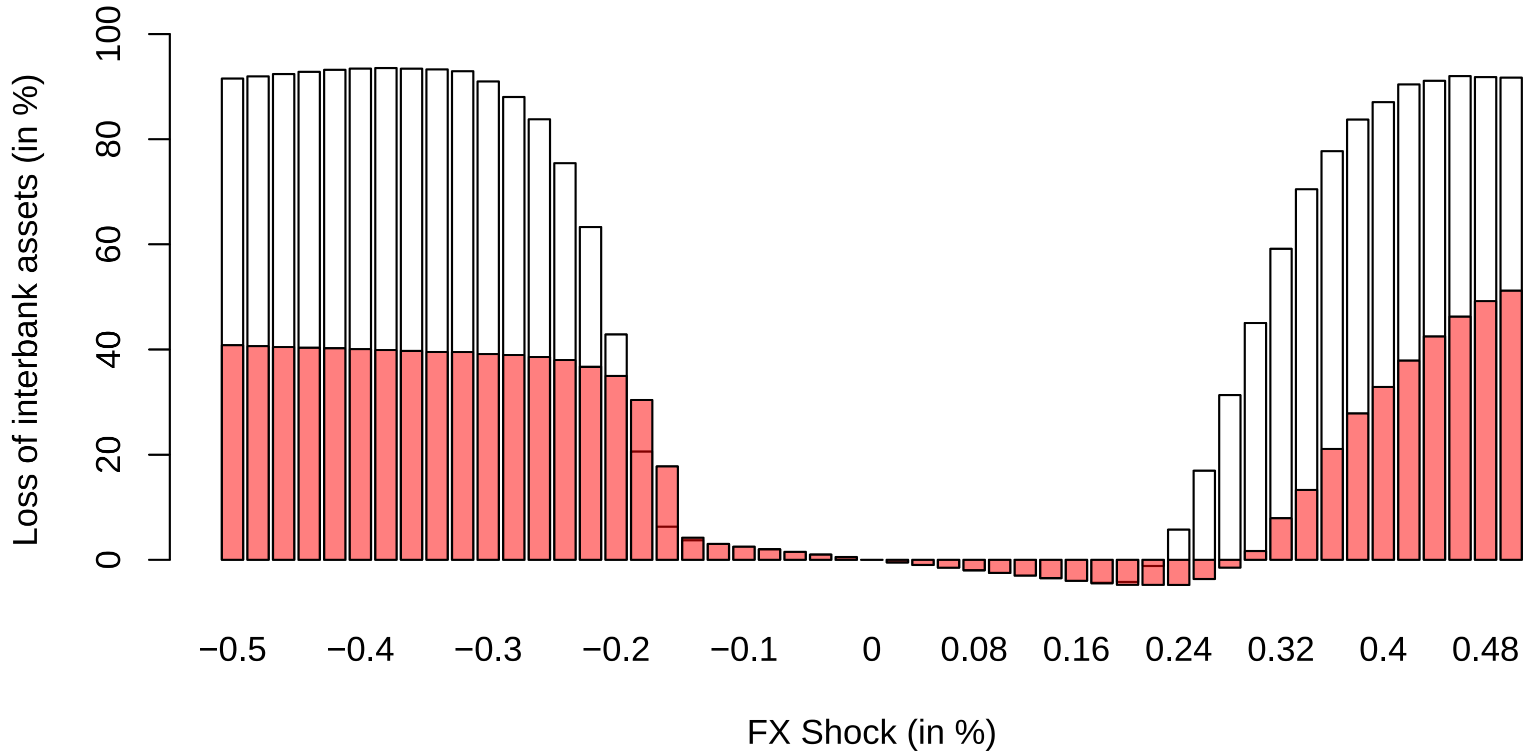
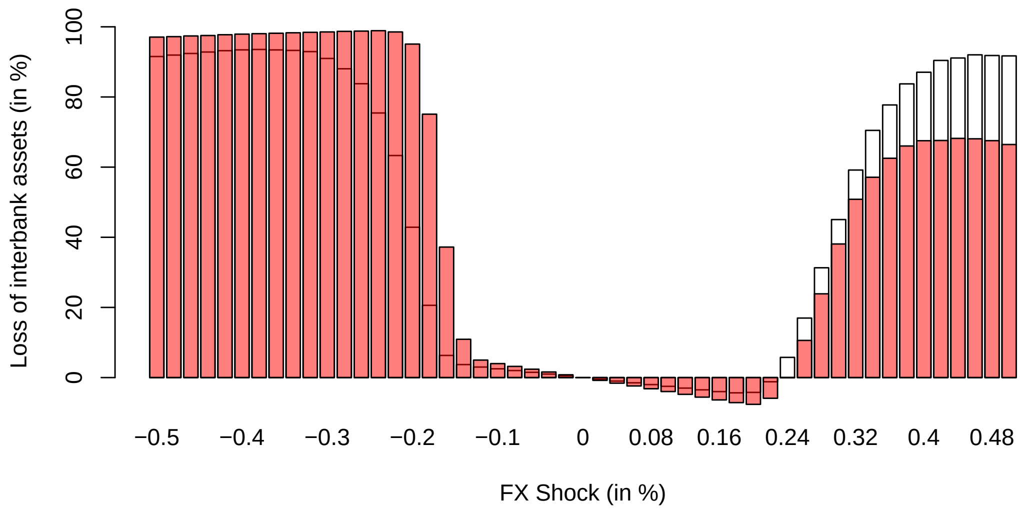


Figure 5: Greater interbank exposures

Note: The figure depicts interbank losses in the baseline scenario (white) where $s = 2$ and in an alternative scenario (red) where $s = 8$.

(a) Shocks to dominant currency



(b) Shocks to other currencies

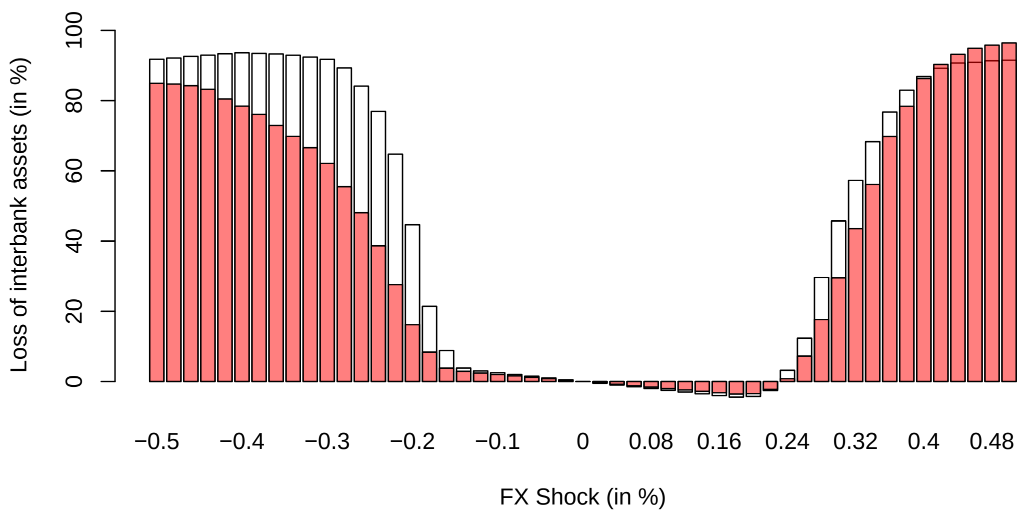
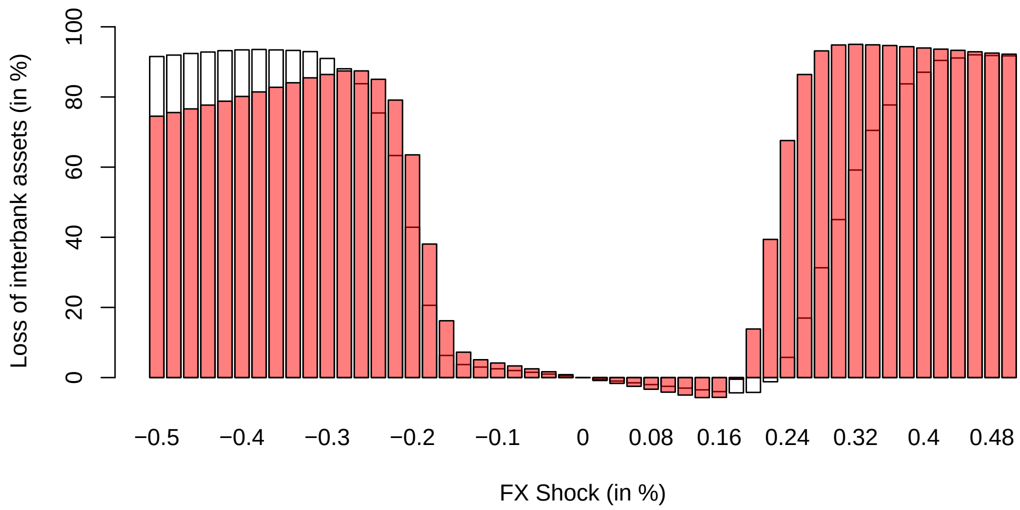


Figure 6: Asymmetry in bank location

Note: The two subfigures depict losses in the baseline scenario (white) where $D_1 = (0.25, 0.25, 0.25, 0.25)$ and in an alternative scenario (red) where $D_1 = (0.7, 0.10, 0.10, 0.10)$. Subfigure (a) shows the effects of exchange rate shocks to the dominant currency, while subfigure (b) depicts the effects of exchange rate shocks to any of the smaller currencies.

(a) Shocks to dominant currency



(b) Shocks to other currencies

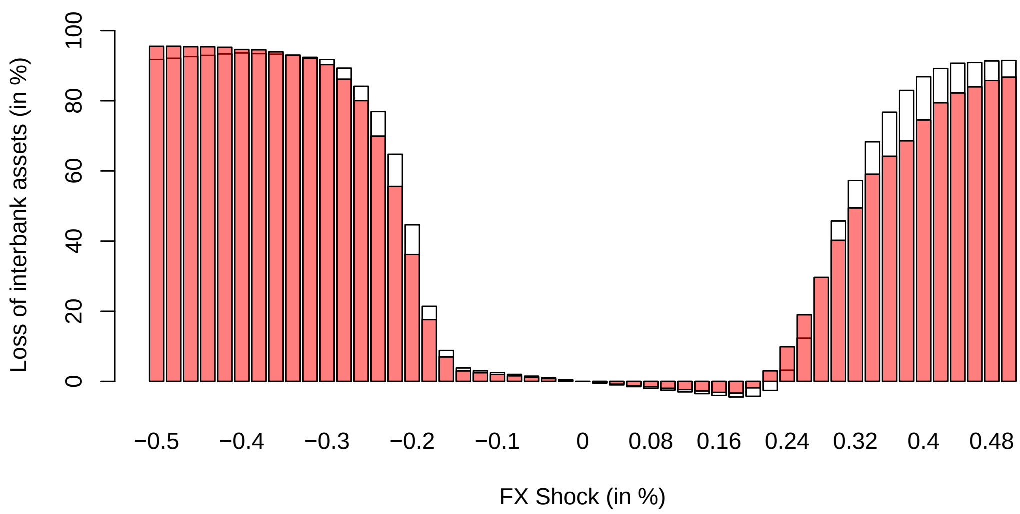
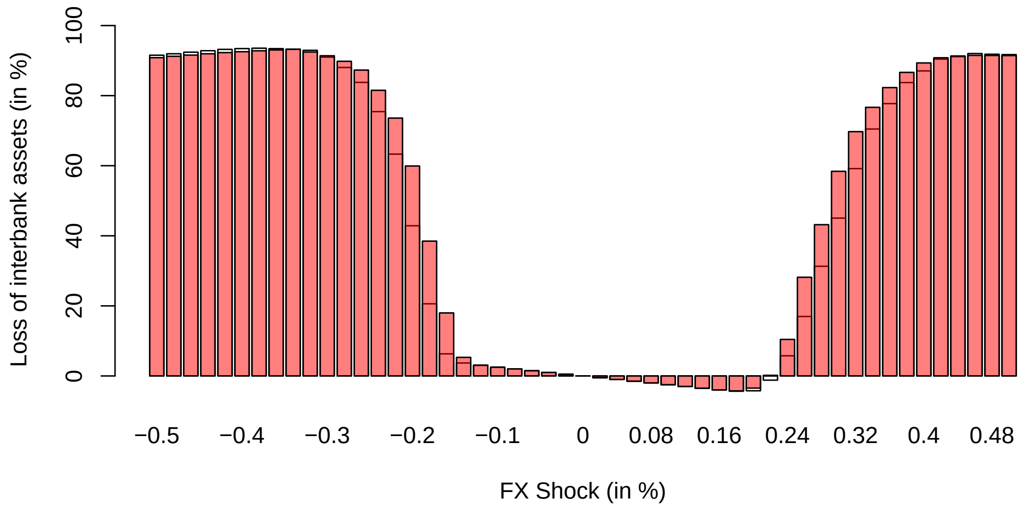


Figure 7: Asymmetry in interbank borrowing

Note: The two subfigures depict losses in the baseline scenario (white) where $D_2 = (0.25, 0.25, 0.25, 0.25)$ and in an alternative scenario (red) where $D_2 = (0.70, 0.10, 0.10, 0.10)$. Subfigure (a) shows the effects of exchange rate shocks to the dominant currency, while subfigure (b) depicts the effects of exchange rate shocks to any of the smaller currencies.

(a) Bank breakups



(b) Common equity pool

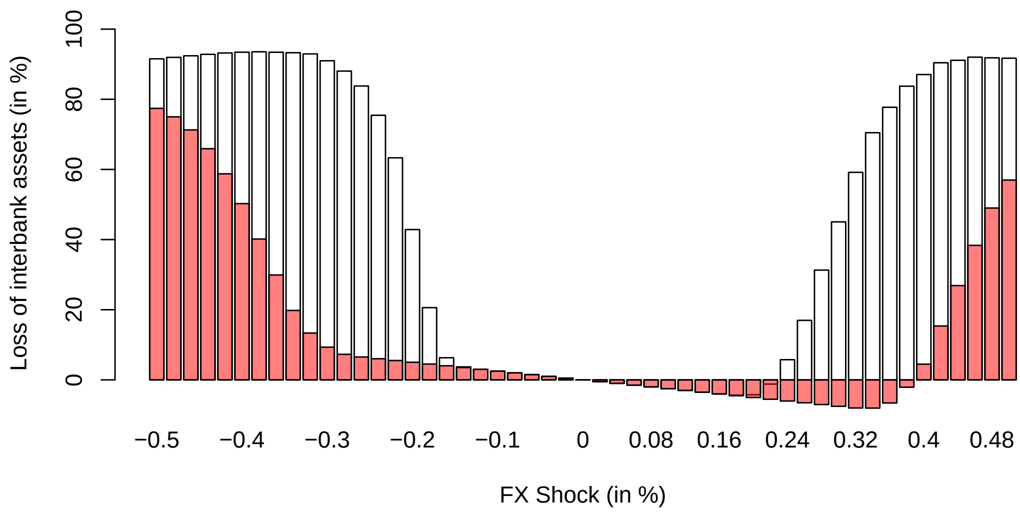
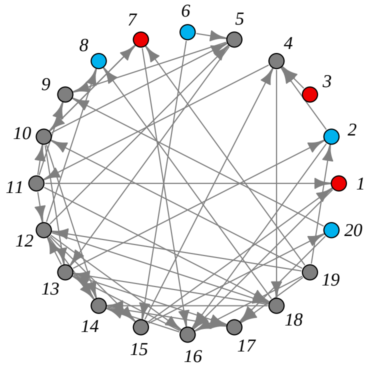
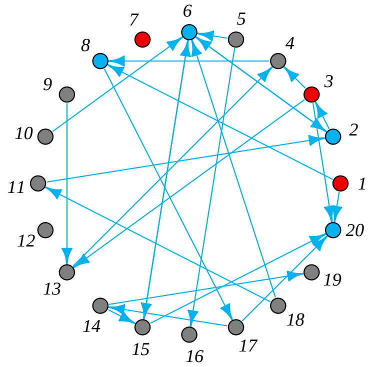


Figure 8: Policy interventions

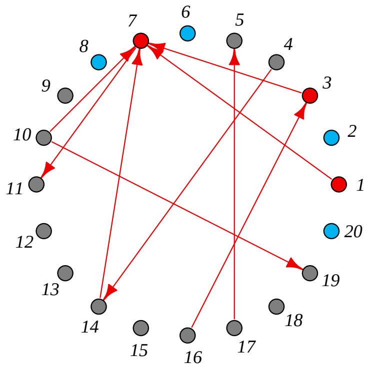
Note: The two subfigures depict losses in the baseline scenario (white) and when conducting one of the policy interventions. Subfigure (a) shows the effects of exchange rate shocks when the 10 banks with the largest interbank liabilities are broken up into 20 smaller banks. Subfigure (b) shows the results when banks commit five percent of their equity to a common equity pool.



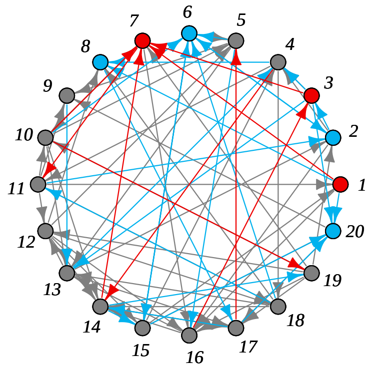
(a) Currency 1



(b) Currency 2



(c) Currency 3

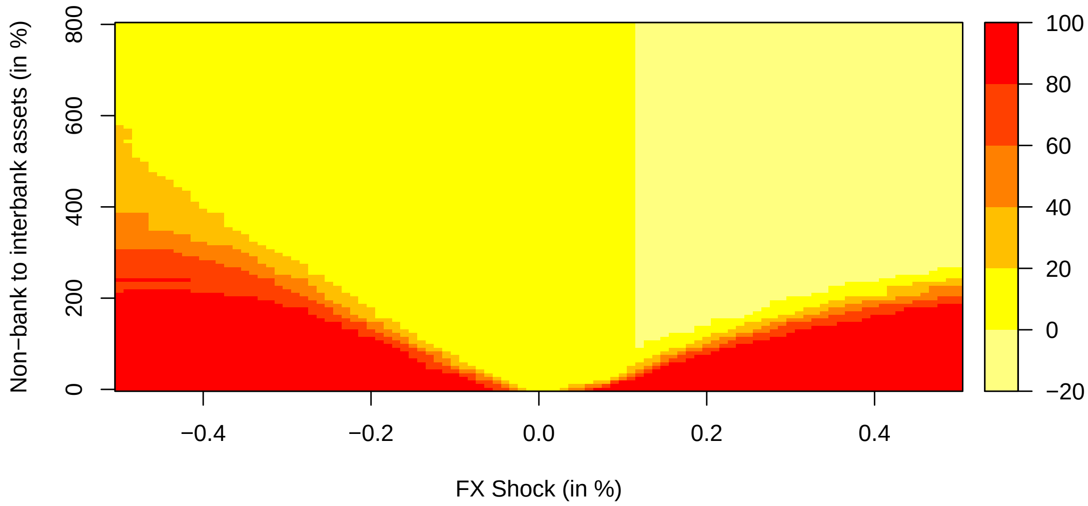


(d) All currencies

Figure 9: A multicurrency interbank market

Note: Nodes correspond to banks, edges to exposures. The different colors of the nodes resemble banks' different home currencies. Currency 1 is depicted in gray, Currency 2 in blue, and Currency 3 in red. Edges are colored the same way depending on the currency of the corresponding exposure. Arrows point from creditors towards debtors.

(a) Greater nonbank assets



(b) Higher equity

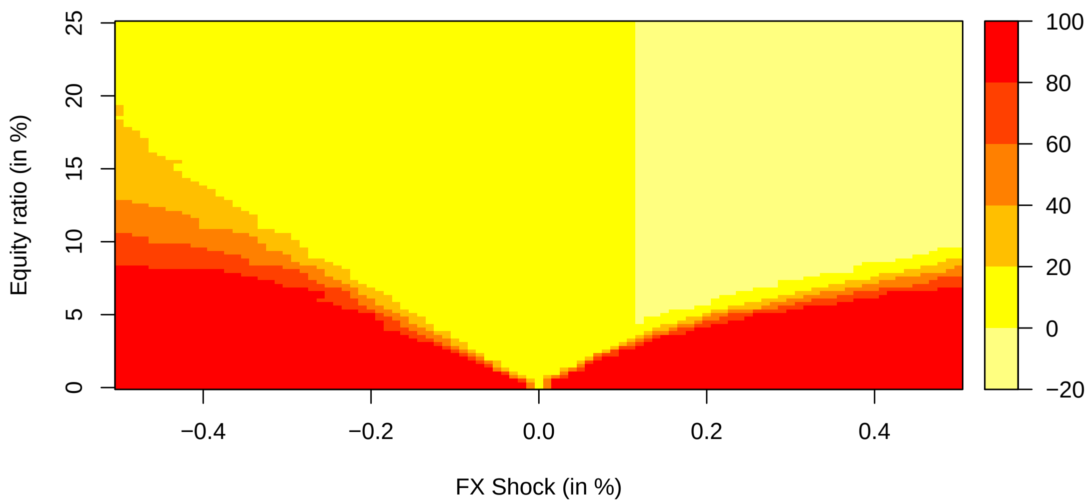
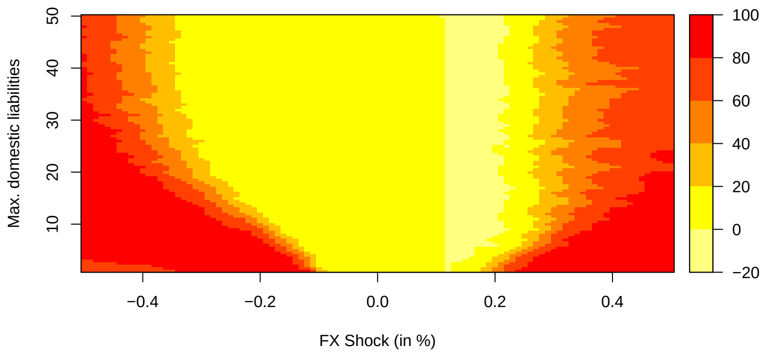


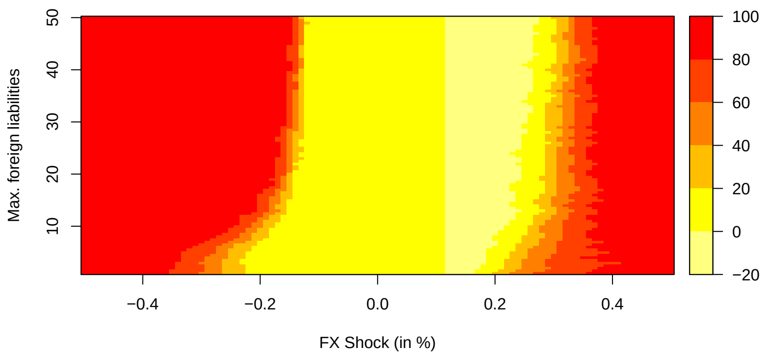
Figure 10: Greater nonbank assets and higher equity

Note: Subfigures (a) and (b) depicts interbank losses as a function of the currency shock and r_1 and r_2, respectively. Bright colors indicate small losses, dark colors reflect large losses.

(a) More domestic loans



(b) More foreign loans



(c) More domestic and more foreign loans

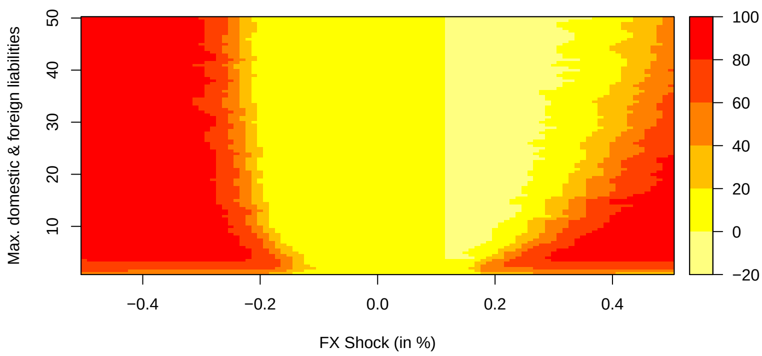


Figure 11: More interbank loans

Note: Subfigures (a) through (c) depict interbank losses as a function of the currency shock and l, l' and both of them, respectively. Bright colors indicate small losses, dark colors reflect large losses.

(a) Greater domestic exposures

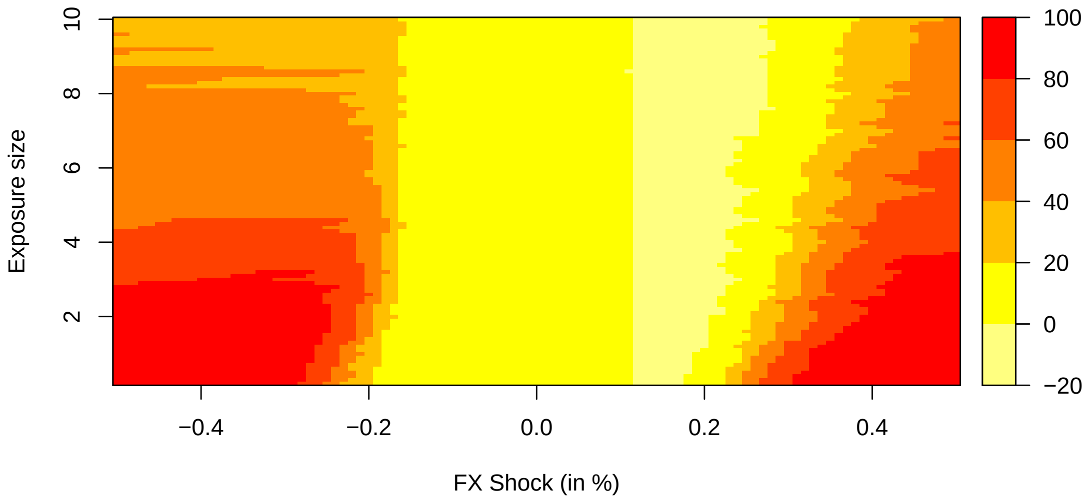
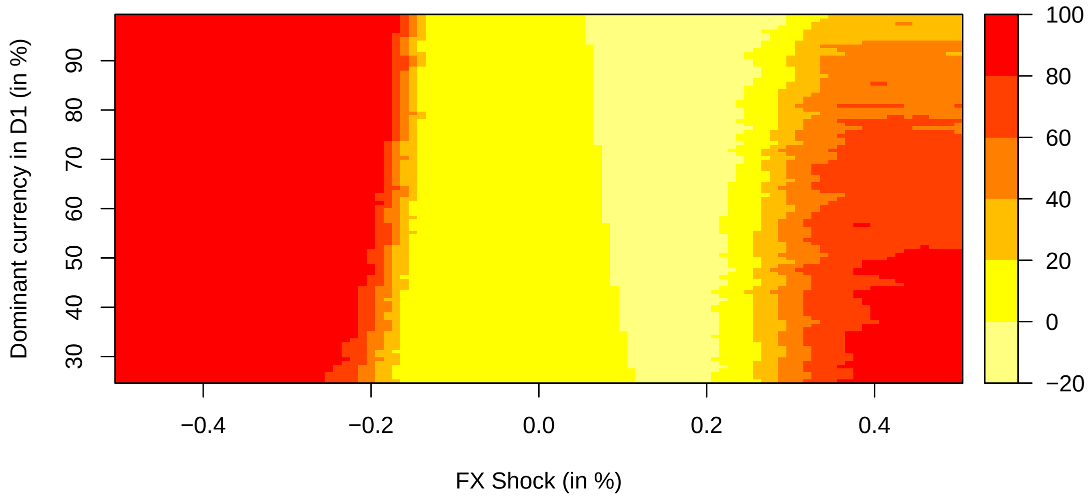


Figure 12: Greater interbank exposures

Note: The figure depicts interbank losses as a function of the currency shock and s. Bright colors indicate small losses, dark colors reflect large losses.

(a) Shocks to dominant currency



(b) Shocks to other currencies

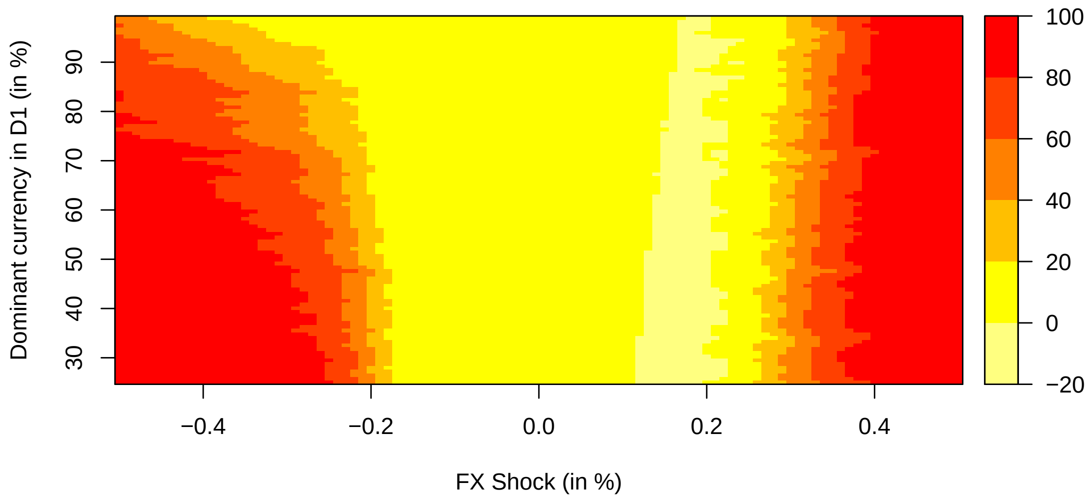
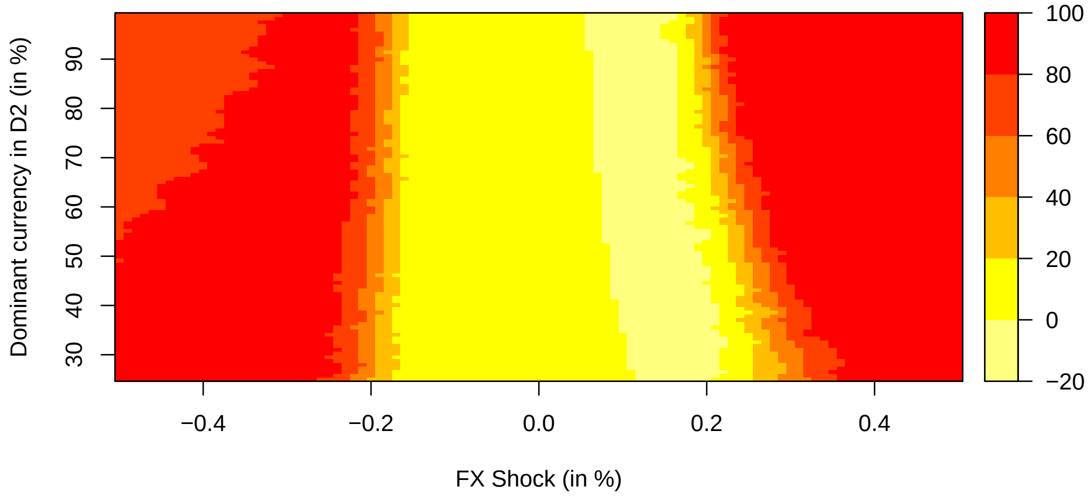


Figure 13: Asymmetry in bank location

Note: The two subfigures depict interbank losses as a function of the probability associated with the dominant currency in D_1. The probabilities associated with the other currencies are set to equal values. E.g., if the dominant currency is home to 40 % of all banks in the market, then $D_1 = (0.4, 0.2, 0.2, 0.2)$. Subfigure (a) shows the effects of exchange rate shocks to the dominant currency, while subfigure (b) depicts the effects of exchange rate shocks to any of the smaller currencies. Bright colors indicate small losses, dark colors reflect large losses.

(a) Shocks to dominant currency



(b) Shocks to other currencies

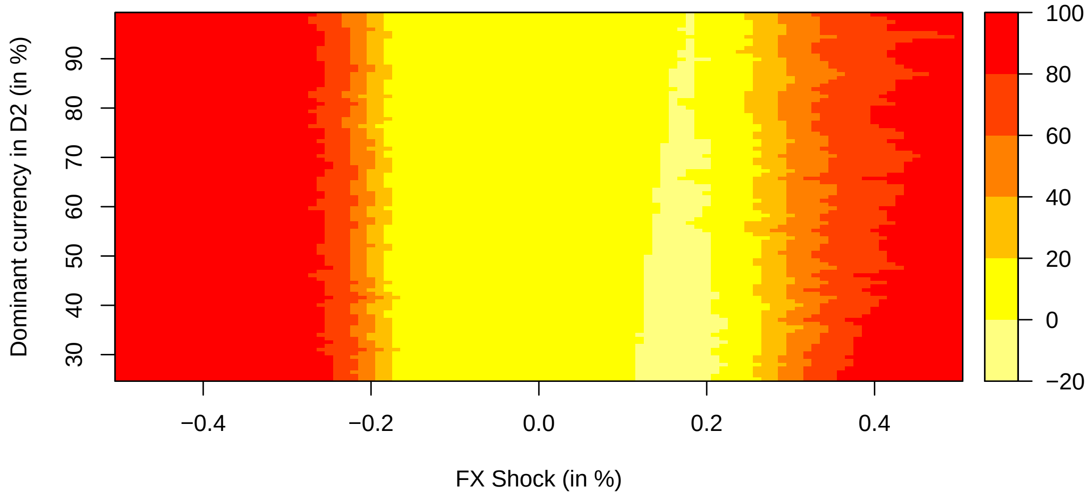
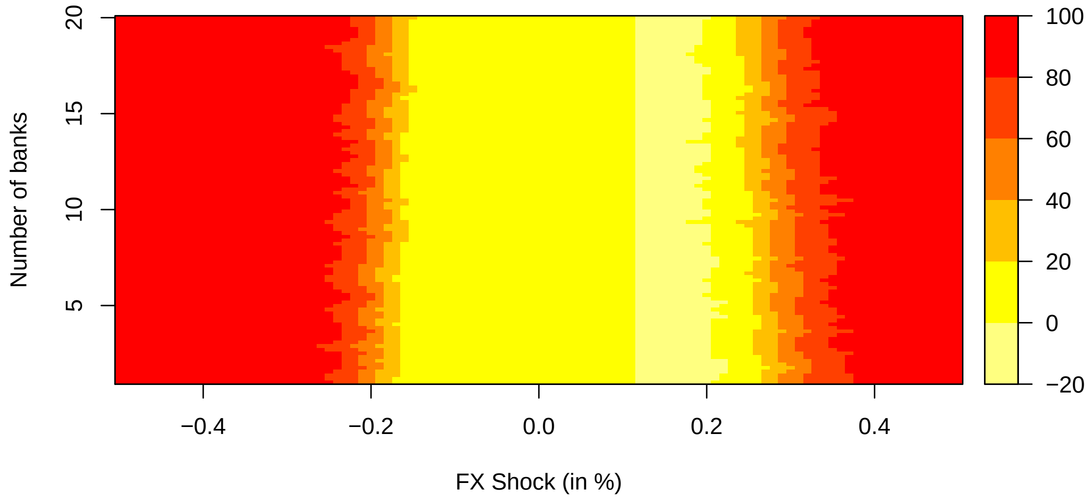


Figure 14: Asymmetry in interbank borrowing

Note: The two subfigures depict interbank losses as a function of the probability associated with the dominant currency in D_2. The probabilities associated with the other currencies are set to equal values. E.g., if the dominant currency originates 40 % of all loans in foreign currency, then $D_2 = (0.4, 0.2, 0.2, 0.2)$. Subfigure (a) shows the effects of exchange rate shocks to the dominant currency, while ubfigure (b) depicts the effects of exchange rate shocks to any of the smaller currencies. Bright colors indicate small losses, dark colors reflect large losses.

(a) Bank breakup



(b) Common equity pool

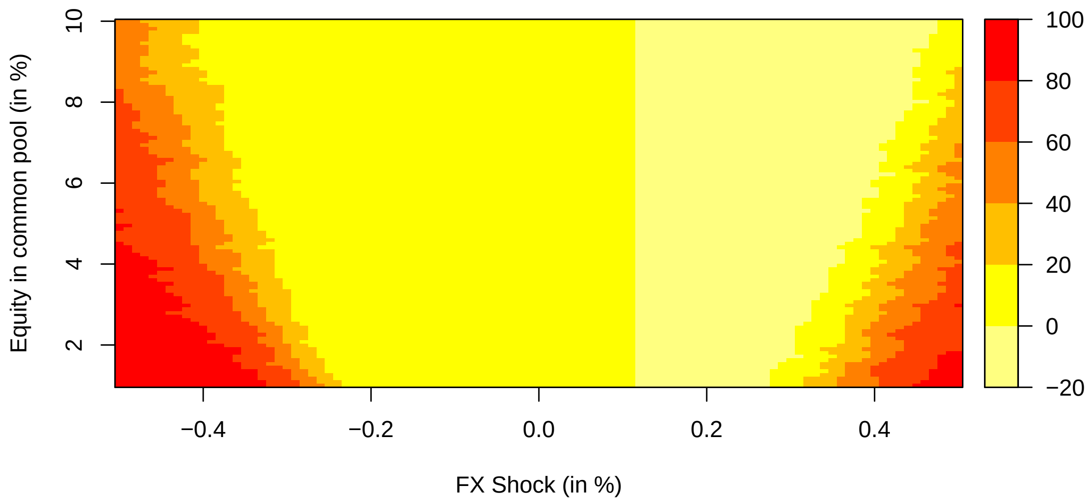


Figure 15: Policy interventions

Note: Subfigures (a) and (b) depicts interbank losses as a function of the number of banks to be split up and the amount of equity committed to the common equity pool, respectively. Bright colors indicate small losses, dark colors reflect large losses.