Chapter 5

Do Safe Havens Make Asset Markets Safer?

5.1 Introduction

Over the past half-decade, since the onset of the global financial crisis, asset prices and capital flows have gyrated and their movements have differed strongly across different groups of countries. In particular, some countries (let us call them “safe havens”) experienced strong inflows into sovereign bond markets while others found their most liquid markets drying up. Has the presence of these safe haven flows changed the resilience of the global financial network that was buffeted by repeated shocks since 2007? In this chapter we present some stylized facts on the role of safe havens in spreading or containing contagion.

A rapidly expanding literature has documented contagion across asset prices and, in particular, between sovereign and bank debt. Several authors have provided evidence of cross-country contagion in long-term sovereign bond yields (Basurto et al., 2010; Gilmore et al., 2010) or sovereign Credit Default Swap (CDS) spreads (Caporin et al., 2012) for euro area countries or a broader sample of European countries, the US, and Japan. While there is some concern that strong sovereign-sovereign correlations simply reflect correlations in fundamental finan-
cial factors, especially short-term interest rates (Manganelli and Wolswijk, 2007), Mody (2009) has shown that 2007 was a turning point in sovereign-sovereign correlations with increasing differentiation according to credit risk. In addition to sovereign-sovereign correlations, several authors have also documented sovereign-bank contagion. After bank bailout episodes and financial rescue packages in the euro area, the correlation between bank and sovereign CDS spreads increased significantly (Acharya et al., 2011), and bank and sovereign CDS spreads’ sensitivity to a global risk factor became more similar (Ejsing and Lemke, 2011). Also outside these financial rescue episodes, Merton et al. (2013) show rising correlations between sovereign and bank CDS spreads. By estimating correlations, this literature has essentially mapped the shape of the network of asset prices, whether around periods of stress or over longer time spans. To our knowledge, the literature has not yet analyzed how this network’s shape affects contagion once a shock enters this network.

Several authors have shown network measures to be significant correlates of banking system and general financial system stress. Minoiu et al. (2013) found rising interconnectedness (measured as clustering coefficients and degree centrality) in the global network of cross-border banking exposures from the BIS locational statistics to be significant predictors of systemic banking crises. So were degree and betweenness centrality in a bank-level network of syndicated loans (Caballero, 2012). At the same time, increased connectivity in the same network fostered trade (Hale et al., 2013). While the previous papers related mainly to the pre-crisis period, Chinazzi et al. (2013) found that degree centrality in a network of cross-country debt and equity exposures was a significant predictor of the drop growth and stock market volatility during the crisis. The measures these authors used were country-level measures of a country’s position in the network. While these are useful to predict crises or trade in any particular country, they do not explain the dynamics of contagion from a crisis. In contrast, here we do not attempt to predict a crisis or any other shock but, contingent on a shock occurring somewhere, we trace how contagion travels through global asset prices.

Blending elements of the literatures on asset price contagion and exposure networks, we
examine how the shape of the global network of asset price co-movements has been conducive (or not) to the spread of contagion. We hone in on a particular group of countries with unique characteristics, the safe haven countries, and their role in amplifying or slowing the spread of contagion across borders and asset classes. In particular, we find important differences in sovereign-bank feedback loops between safe haven and non-safe haven countries. This distinction comes out more clearly in our sample than in those of previous authors because we deliberately expand it to include many emerging markets (50 sovereigns) and individual banks (331 banks). To achieve this larger sample, we rely on sovereign bond yields and bank equity prices, which in many countries are more liquid than CDS spreads. By using individual bank data, we are able to distinguish sovereign-bank correlations between more and less systemic banks which are too big to fail to different degrees.

The existing literature on safe havens has defined safe haven assets as hedges of returns on reference portfolios during times of financial stress or rising risk aversion. This literature has examined exchange rates (Beck and Rahbari, 2008; Habib and Stracca, 2012; Ranaldo and Söderlind, 2010), gold (Baur and McDermott, 2010), or sovereign bonds (Hartmann et al., 2004) as hedges against stock market risk. To our knowledge, the literature has not defined safe haven status based on the potential for sovereign bonds to serve as hedges against individual banking risk. Since ours is a network of sovereign bond yields and individual bank equity returns, we prefer a definition of safe havens relevant to our data instead of one that is exogenous to our data set. However, our definition, as we show below, does not deviate more from common usage than other definitions in the literature or definitions used by financial market participants.

Our definition of a safe haven country explicitly treats sovereign bonds as possible safe haven assets when banks (not the stock market more generally) are under stress: safe havens are those countries where bank equity prices and sovereign bond yields move strongly in tandem. If bank equity prices and sovereign bond yields were purely driven by country-level credit risk, one would have expected the opposite: if credit risk rises, sovereign bond yields increase and bank equity prices fall. In contrast, where credit risk is of negligible concern, i.e. in safe
havens, expectations about future growth and monetary policy become predominant: an improving growth outlook raises bank equity prices and the expectation of tightening monetary policy which, in turn, puts pressure on sovereign bond yields.

Hence, by definition, safe havens are countries without sovereign-bank feedback loops that amplify shocks to both banks and sovereigns. For example, contagion from a global shock that simultaneously raises bond yields and reduces bank equity prices in a safe haven could trigger the expectation of a monetary policy response in the safe haven that would raise bank equity prices and reduce sovereign bond yields. In contrast, outside safe havens, a similar shock could trigger concerns about credit risk and set in motion self-fulfilling bank-sovereign feedback loops. It turns out, however, that in our network, this benign property of safe havens is offset by a less benign one. In particular, safe havens tend to have stronger sovereign-sovereign and stronger bank-bank correlations than non-safe havens. As a result, if a shock arrives in safe havens, they can propagate shocks to other countries faster than non-safe havens. Which of the two effects dominates depends on the nature of the shock and the nature of the broader network. In our sample, we find that, on balance, safe havens amplify shocks (although to varying degrees depending on the shock).

In the next section, we describe our data, followed by our definition of safe havens and their properties in Section 5.3. Section 5.4 describes the global network structure of sovereign bond yields and bank equity returns. In Sections 5.5 and 5.6, we document some stylized facts of feedback loops in shock propagation. In Section 5.7, we examine the role of the two characteristics of safe havens in amplifying or dampening shock propagation. Several of these facts raise intriguing questions, summarized in Section 5.8, that are left for further research.

5.2 Data

We use daily changes in 5-year bond yields of 50 sovereigns and daily log changes in bank equity prices of 331 individual banks using Bloomberg data.1 Because of limited data availability

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1The results are broadly robust to including the smaller sample using 10-year bond yields.
in the 1990s, the time span for our network of global bank equity prices and sovereign bond yields comprises 2000-2013. The full sample is divided into four subsamples: years 2000-2006 (Great Moderation), 2007-2009 (Subprime Crisis), 2010-2012 (Sovereign Debt Crisis), 2013 (Emerging Markets (EM) Stress). We adjust the daily data for time zones and exchange rate changes.

For each bank-bank, sovereign-sovereign, and bank-sovereign pair, we calculate bilateral Pearson correlation coefficients between bank equity price log changes and sovereign bond yield changes over each of our four subperiods. Ideally, we would have used measures that explicitly incorporate causality, e.g. Granger (1969) causality or spillover coefficients as in Diebold and Yilmaz (2011), but the estimations necessary to derive these measures would typically have constrained our sample size. Therefore, here we begin by focusing on simple correlations. To eliminate spurious correlations, we set the correlations between sovereigns and banks outside their countries to zero.

We call our network $G(V, E)$ a representation of a set of nodes $V = \{v_1, v_2, \ldots, v_n\}$, connected by a set of edges $E \subset V \times V$. For now, the strength of the edge between two adjacent nodes is determined by our Pearson correlation coefficient. Formally, we may represent a network $G$ in a matrix form, denote it by $A_{n \times n}$, where all diagonal elements are equal to zero, i.e. the relation between the same assets is irrelevant, and elements $a_{ij}$ represent the correlation between assets $i$ and $j$. Since we use time adjusted data, matrix $A$ is not symmetric, making the network directed, i.e. $a_{ij} \neq a_{ji}$ for some $i$ and $j$. Formally, if we denote the number of sovereigns by $n_s$ and number of banking sectors by $n_b$, one may rewrite the complete network as a block matrix $B_{(n_s+n_b) \times (n_s+n_b)}$, where two diagonal blocks represent the individual networks

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2 The majority of the euro zone countries provide sovereign bond yields ranging back to 1994. Therefore, we consider this as a special case and we devote Box 1 to analyze the situation in the Economic and Monetary Union (EMU) individually over the years 1994-2012.

3 In principle, shocks can of course also jump from equity and bank stock prices to interbank money markets or foreign exchange markets. We will consider these asset classes in future research.

4 While this does mean that, e.g. the correlation between the Greek sovereign bond yield and a French bank’s equity price is eliminated by assumption, it also avoids many spurious correlations, e.g. between the Finnish sovereign and Argentinian banks. Here, to avoid the many spurious correlations at the cost of eliminating some valid ones, we remove all sovereign-bank correlations except those within each country.
and the remaining blocks are zeros except for the case when the sovereign and banks refer to the same country.

Fig. 5.1 shows the distribution of correlations over our four subperiods. The bulk of them are inside the 95% confidence interval $[-0.2, +0.2]$ for Pearson correlation coefficients and, hence, statistically insignificant. This is especially the case for bank-sovereign correlations where less than one-fifth of the correlations are statistically significantly negative or positive. Sovereign-sovereign correlations are stronger than bank-bank and, even more so, bank-sovereign correlations (the distribution of sovereign correlations is further to the right and has fatter tails than that of bank-bank or bank-sovereign correlations). In addition, even if not visible in Fig. 5.1, within-country bank-bank correlations are stronger than cross-country bank-bank correlations.

Negative correlations between sovereigns and other sovereigns or banks and other banks are rare. Negative correlations among sovereigns are confined to a few country pairs.\(^5\)

In aggregate, correlations strengthened in 2007-09 but by 2013 had fallen back to pre-crisis levels (the right tail of all three distributions moved sharply out in 2007-09 but has since moved back inwards). The number of strong bank-sovereign correlations has shrunk even below pre-crisis levels.

The global financial crisis and the subsequent euro area crisis triggered increasing clustering of sovereign and bank asset prices. Fig. 5.2 shows the distribution of clustering coefficients (loosely speaking, the share of “friends” that are also “friends” with each other) for bank equity prices (Fagiolo, 2007). The distribution shifted sharply to the right as banks equity prices became strongly correlated globally in 2007-09 and regionally in 2010-12. Since then, there has been some reversion towards 2000-06 norms. Similarly, clustering of sovereign bond yields increased sharply in 2007-09 and even more so in 2010-12. The rightward shift of the distribu-

\(^5\)In 2000-06, they include the US against 14 EU countries and Switzerland. In 2007-09, they include Japan against several advance and emerging market commodity producers (Australia, New Zealand, Canada, Mexico, Brazil, South Africa, Turkey), the US against Switzerland, and Colombia against several Asian and European emerging markets (China, Singapore, Malaysia, Indonesia, Slovakia, Ukraine). In 2010-12, there is only one negative correlation, between Japan and the US. In 2013, negative correlations are between the US and large emerging markets (Brazil, Turkey, Hungary, Mexico, Thailand, Malaysia, Philippines, South Africa) and/or commodity producers (Australia, New Zealand, Norway) and global financial centers (Japan, Switzerland, UK).
Figure 5.1: Distribution of correlations at the sovereign, bank and sovereign-bank levels.

(a) 5-year sovereign bond yields

(b) Daily bank equity returns

(c) Daily bank equity returns and 5-year sovereign bond yields
tion 2007-09 reflects a stronger clustering especially in Asia whereas the rightward shift of the distribution in 2010-12 reflects especially a stronger clustering in Europe.

5.3 Defining safe havens

We distinguish between “safe havens” and “non-safe havens” on the basis of their correlation between sovereign bond yields and bank equity prices. For advanced countries, including the US, the positive correlation between sovereign bond yields and prices of riskier assets has been documented by Bauer and Rudebusch (2013) and Pandl (2013). In contrast, for emerging markets, Drainville et al. (2011) show a negative correlation between bond yields and bank equity prices and speculate that this reflects strongly correlated risk premia of EM assets.

Here, we also base our definition on the correlation between sovereign bond yields as potentially the safe assets, and individual bank equity returns as the riskier assets. Specifically, we define countries as “safe havens” if daily changes of sovereign bond yields and bank equity prices are significantly positively correlated (correlation $> 0.2$). The rationale is as follows.

Long term sovereign bond yields can be broadly decomposed into two components: (i) expectations of average future short-term interest rates and (ii) a premium that investors require for bearing the (e.g., credit, liquidity) risk of a long-term bond investment. The expectations component (i) is driven by inflation expectations and expectations of future real rates of return, which depend on future economic growth. The risk premium component (ii) is determined by the degree of uncertainty about these future developments and by the degree of investors’ risk aversion. Similarly, bank equity prices can be decomposed into a component that reflects expectations of future profitability and a risk premium.

During a downturn, a pessimistic economic outlook drives down bank equity prices; the expectation of a loosening monetary policy response drives down sovereign bond yields. This is our expectations component (i). Separately, rising risk aversion during a downturn induces investors to turn away from riskier assets to safer ones. This reduces yields on safe assets and
Figure 5.2: Distribution of clustering coefficients for bank equity price correlations and sovereign bond yield correlations. Source: Fagiolo (2007).

5.3. DEFINING SAFE HAVENS
raises yields (i.e. reduces prices) of riskier assets. This is our risk premium component (ii).

In safe haven countries, sovereign bonds are considered safe assets. Hence, both effects generate a positive correlation between bank equity prices and sovereign bond yields.

In contrast, in non-safe haven countries, sovereign bonds are not considered a “safe asset” to which investors will turn when risk aversion rises. As global risk aversion rises, therefore, investors will move out of both sovereign bonds and bank equity, sovereign bond yields will rise while bank equity prices fall, and, for a given economic outlook, a negative correlation between sovereign bond yields and bank equity prices will emerge. Since expectations about economic outlook and risk aversion drive the correlation between sovereign bond yields and bank equity prices into opposite directions, the sign of overall correlation is ambiguous.

Safe havens thus defined vary over time (Table 5.1). Japan, Germany, Finland and the United States have been considered safe havens throughout our sample period. But some euro area countries such as Austria, Belgium, France, Italy, Portugal, and Spain lost their safe haven status during the European crisis. Other countries gained safe haven status as the global financial crisis unfolded, including some commodity exporting countries such as Canada and Australia. As European economies are crawling out of recession against the backdrop of public and private deleveraging and as emerging markets are slowing down, many European economies and oil producers with close trade and financial links to emerging markets lost their safe haven status, including Australia, Canada, the UK, and Switzerland. How does our definition compare with other definitions of safe havens? Fig. 5.3 shows our list of safe havens against two other definitions:

- countries with AAA ratings from S&P, Fitch, and Moody’s (similar to definition used in the International Monetary Fund (2012));

- “negative-beta” countries whose sovereign bond yields are negatively correlated with global (here, S&P500) equity prices, a commonly used definition among financial market analysts.

In particular, Luxembourg, Singapore, and some Northern European countries are not identified
5.4 Mapping the network of sovereign bond yields and bank equity

Table 5.1: “Safe havens”: positive co-movement between sovereign yields and bank equity.

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as safe havens by our definition even though they are either AAA-rated or can be considered “negative beta” countries. Note that all these countries have fixed exchange rate regimes. Our expectations channel that distinguishes safe havens from others, and which works through expected monetary policy changes, would therefore be not expected to be strong.

For visual clarity, we can only show a subset of all the pairwise links. As discussed above, sovereign-sovereign correlations tend to be much higher than bank-bank correlations and bank-sovereign correlations tend to be the weakest. To make sure that at least some links in each data set are represented, we select the strongest 10 percent of sovereign-sovereign, bank-bank, and
Figure 5.3: Safe havens by three definitions.
bank-sovereign links.\textsuperscript{6}

Fig. 5.A.1 shows the characteristics of sovereign-sovereign interconnectedness. Pre-crisis (2000-06), Singapore and, less directly, Korea were the main “bridges” between Emerging Asian and European sovereign bond yields. Since the crisis, sovereign bond yields in Emerging Asia have been drawn into the group of advanced country sovereign bond yield correlations. European sovereign bond yields remain the most closely intertwined, despite some recent weakening of links with some of the periphery. In contrast, correlations with North American sovereign bond yields have weakened since the pre-crisis period.

Fig. 5.A.2 shows the characteristics of bank-bank interconnectedness. Pre-crisis (2000-06), there were few strong bank-bank correlations and they were confined to individual regions, Europe in particular, or individual countries. The global financial crisis (2007-09) tightened these disparate pre-crisis groups into one knot of cross-border correlations between bank equity returns. One Singaporean bank tied this tight global cluster to Asian-Pacific banks. Since then (2010-12) only the European cluster remains tightly intertwined (see also Box 1 for euro area countries) whereas other countries’ bank equity prices have drifted out of the dense global cluster.

In our sample, bank links across countries are significantly smaller than bank links within a country. There are only a few strong cross-border correlations outside Europe: in Asia-Pacific (Singapore and Australia) and North America (Canada and the US).

During the European crisis (2010-12), Asian and Latin American banks decoupled from banks in other advanced economies. In Asia, two cross-country bank clusters remained strong: one including individual Australian, Singaporean, Korean, and Malaysian banks and another including banks in Hong Kong and China. In Europe, banks in Greece and Cyprus separated from the main European cluster.

In Figs 5.A.3-5.A.5, for individual country groups, we parse the network for cross-country chains of correlations between banks and sovereigns.

\textsuperscript{6}Due to space constraints, we only show the networks up to 2010-12. However, networks for 2013 do not materially differ from those for 2010-12.
Emerging Asia: Significant (negative) correlations between sovereign bond yields and bank equity prices were present within each country. In contrast to these within-country correlations, cross-country correlations between sovereign bond markets and banking sector were relatively weak prior to the global financial crisis. This suggests that sovereign-bank feedback loops have played an important role in propagating shocks in emerging Asian economies domestically (despite the size and relative impact compare to the European countries) whereas cross-country contagion through either sovereign or banking channels was more muted. At the height of the global financial crisis (2007-09), sovereign-bank linkages strengthened in almost all the emerging Asian economies: shocks from European banks were transmitted through Singapore to other Asian banks which further propagated them to Asian sovereigns. During the subsequent euro area crisis (2010-12), sovereign-bank links weakened again whereas bank-bank links tightened, especially with European banks. Singaporean banks have continued to be the cross-continental “bridge”, affecting directly Thailand, China, Malaysia, and indirectly India and Indonesia. In contrast, Philippine and (some) Korean banks decoupled from the rest.

Emerging Europe: Like emerging Asian countries, Turkey, Poland and Hungary (less in magnitude than the other two) bank equity prices were highly correlated with their own countries’ sovereign bond yields. During the global financial crisis (2007-09), both sovereign-bank links and cross-country banking sector linkages strengthened, contributing to stronger contagion. Stress in Turkey’s tightly-linked banking sector could potentially affect both sovereigns and banks in Poland and Hungary through the banking channel. During the subsequent European crisis (2010-12), Turkey decoupled from Poland and Hungary which remain together in a tightly interconnected cluster. Turkey and Romania developed into two highly correlated within-country groups.

GIIPS and Cyprus: Unlike in emerging Asian and European countries, sovereign-bank interconnections were weak prior to the global financial crisis. During the global financial crisis
5.4. MAPPING THE NETWORK OF SOVEREIGN BOND YIELDS AND BANK EQUITY

crisis (2007-09), Spanish and Italian banks began to be highly correlated with core European banks whereas the Greek and Cypriot banks formed a separate group of strong bank-bank correlation. Sovereign-bank linkages remained quite weak, however. As the European crisis deepened (2010-12), aside from higher interconnectedness of global banks, sovereign-bank inter-linkages also strengthened. Take Spain for example. Stress in bank 6 would have first affected Spain’s sovereign which then could have propagated it most strongly to banks 2, 4 and 7 which, in turn, are highly correlated with Austrian and Italian banks, etc. Similar contagion chains can be drawn for Belgium, Portugal, Italy and Austria. Greece and Cyprus remained decoupled from the other European banks and sovereigns during this period.

Box 1. Clustering and declustering of the euro zone community in sovereign bond yields.

Since data is available from 1994, we construct a time line of the evolution of the network of the Economic Monetary Union (EMU) sovereign bond yields in 12 EMU and later euro area countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Slovakia and Spain). We can detect a changing core community in Europe over time. By a community, we understand a part of the global network where the interconnectedness is relatively higher than to the rest of the network. In order to distinguish communities we apply the random-walk algorithm developed by Rosvall and Bergstrom (2007).

In 1994-1996 the core of the EMU: Austria, Belgium, France, Germany and the Netherlands, built a separate cluster, visibly distinct from all remaining countries. In 1997-1999, Italy and Spain joined the core EMU cluster, and Greece, Ireland, Portugal, Finland joined it in 2000-2006. As might be expected from its late membership in the euro area in 2009, Slovakia did not join the community.

In 2010-2012 the core cluster partly dissolved. Belgium, Greece, Ireland and Portugal separated completely, whereas Italy and Spain joined a common cluster.
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Box Figure 1: The evolution of the clustering structure in the sovereign bond yields within the euro zone network. Source: Graph prepared by the software delivered by the courtesy of Rosvall and Bergstrom (2007).
Note: GIIPS countries are shown in red. Lines refer to clusters. For instance in 2000-2006 all the countries except for Slovakia joined one big cluster of sovereigns.

5.5 Modeling shock propagation

To investigate how shocks are propagated in this network we adapt a standard model from the disease spreading literature, developed by Jammazi and Aloui (2012). Every period each node propagates the cumulative shock it has received to all adjacent nodes. The impact of the shock is weighted by the strength of the link between the nodes. To keep it simple, we make two simplifying assumptions in our use of Jammazi and Aloui (2012). Firstly, we assume that nodes are neutral, i.e. our nodes cannot stop shock propagation, so that the propagation depends on the network structure only. Secondly, we do not put any boundaries on nodes’ absorptive capacity, i.e. our nodes cannot slow down shock propagation, as it could hamper the actual cascade effect observed in financial markets. The details of the shock propagation mechanism are described in Appendix 5.B.

Our shock propagation exercise inherently assumes some degree of causality: a shock is “triggered” in one country and “passed on” to others. While the correlations themselves are agnostic on the direction of causality, we posit that causality is unlikely to run from small
5.5. MODELING SHOCK PROPAGATION

entities to large entities. For example, the 93 percent correlation between changes of the 5-year sovereign bond yields of Ireland and Germany in 2010-12 is more likely to reflect the Irish sovereign bond market responding to shocks in Germany than *vice versa*. To capture this discrepancy when the source market is much smaller than the destination market, we scale the correlation between the two entities down proportionately to the relative size: We weight each correlation by the relative size of the source’s and destination’s total assets (for banks) or government debt (for sovereigns), capping the weight at one. (In future research, we aim to determine the direction of causality of the correlation in a less *ad hoc* manner, e.g. by using Diebold and Yilmaz (2011) spillover coefficients or including Granger (1969) causality measures.)

We simulate two types of shocks, one in each of our markets: a sovereign bond yield shock and a bank equity price shock. The initial shock is assumed to be a 1 percent increase in either sovereign bond yields or in daily bank equity prices. For example, in the first step, the source country’s sovereign bond yield is increased by 1 percent. All the adjacent countries’ (destinations’) sovereign bond yields are then impacted by their (weighted) correlations with the source country sovereign bond yield. Also, the local banks’ equity prices are affected by their correlation with their home sovereign bond yield. In the second step, the destination countries themselves become the countries of origins of the next round of shocks: each of them propagates the shock they received in the previous round to all their partner countries. The mechanism repeats step after step and in each step we calculate the cumulative effects of shock propagation in all the countries. We simulate shocks in three subsets of countries: a random shock in any country of the network, a simultaneous shock in all the GIIPS countries (Greece, Ireland, Italy, Portugal, and Spain), or a simultaneous shock in all the Fragile Five countries (Indonesia, India, Brazil, Turkey, South Africa).

Two more caveats are in order. Firstly, by assumption, there is nothing in our experiment that stops shock propagation; in practice, of course, policy steps would (and did) contain shock propagation. Of course, these policy interventions are also implicit in our estimated correla-
tions. Nevertheless, for now we interpret our results as counterfactuals that may have occurred, had modest additional shocks happened and/or had there been no additional policy measures. Secondly, our experiment does not say anything about the speed of contagion from shocks. Since almost all sovereigns bond yields and all bank equity prices have at least some correlation (even if small) and we do not exclude any by assumption. Therefore, the network is complete, i.e. a shock in any one part of the network will immediately travel to all other parts of the network. Instead of speed of contagion, our results are indicative of the size of the impact and the amplification over time of an initial shock on each country and on average. Although the steps have no time dimension, they show the path along which a shock travels around the network. Therefore, in our results below, we retain the notion of distinct steps for illustrative purposes.

5.6 Feedback loops in shock propagation

Feedback loops, even along the relatively weak sovereign-bank correlations in our data set, spread a shock from one asset class into another, where it can then proliferate and return to the initial asset class. We test the effect of feedback loops in sovereign bond contagion by comparing shock propagation under two scenarios: the actual network of sovereign-sovereign and bank-sovereign correlations and a counterfactual network where we assume all bank-sovereign links are zero, i.e. a counterfactual network in which feedback loops are not possible. In our counterfactual network without bank-sovereign links, a sovereign bond yield shock would not travel into the banking system at all and vice versa.

5.6.1 Sovereign bond yield shock

Fig. 5.4 shows the results of a sovereign bond shock in the GIIPS, the Fragile Five, or any country. Each line displays the average impact on sovereign bond yields of a 1 percent bond yield shock in any country (bottom panel), the GIIPS (top right panel), or the Fragile Five (top
left panel). We measure the impact relative to the impact under a baseline scenario: the baseline scenario is one where we assume all bank-sovereign feedback loops are zero. On average, feedback loops have amplified the impact of sovereign bond yield shocks (all curves are above 1). However, the strength of feedback loops varies across countries and over time depending on the source of the shock.\footnote{The statistical significance of the differences in shock propagation between various settings and years depend on the size of the initial shock and the number of steps the shock has traveled across the network. Therefore, for presentational clarity, we do not report them in the main body of the text. The exercise aims to illustrate the general patterns of shock propagation in different years with different network structures.}

On average, the amplification of feedback loops in 2013 is broadly similar for sovereign bond yield shocks in the Fragile Five and in the GIIPS (the curves in the top left chart are about level with those in the top right chart). We speculate that a sovereign bond shock propagates strongly in the highly interconnected sovereign bond yield network. It thus reaches countries with strong bank-sovereign feedback loops quickly and strongly, independent of the source of shocks. (This contrasts with a bank shock, see Section 5.6.2.) Not surprisingly, shocks in an average single country propagate less fast than shocks originating in all of the GIIPS or Fragile Five (the curve in the bottom chart is below those in the top right and top left charts).

For both Fragile Five and GIIPS sovereign shocks, the amplification by feedback loops has strengthened in 2013 compared with 2010-12 (the curve for 2013 is above that for 2010-12). This reflects a strengthening of bank-sovereign correlations in both sets of countries over these two periods. In the case of the GIIPS, for which earlier data are available, feedback loops are now only little stronger than pre-crisis.\footnote{Data is not available for India and Turkey from mid-/late-2001, for Indonesia from 2003, and for Brazil from 2007.}

The weak impact of feedback loops in the case of a GIIPS shock in 2010-12 raises the possibility of an interesting interpretation. Shock propagation among asset prices may have been short-circuited by policy interventions, of which there were many in Europe during 2010-12. In 2013, when there were fewer policy actions targeted at dampening GIIPS shocks, a similar GIIPS shock would have propagated more strongly.

This contrasts with a shock in any single country which triggers broadly unchanged feed-
Figure 5.4: Average impact of bond market shock on global sovereign bond yields, with feedback loops (in multiples of average impact of same shock on sovereign bond yields without feedback loops).

(a) Shock propagation to Fragile Five

(b) Shock propagation to GIIPS

(c) Shock propagation to any country
back loops. The correlation of the Fragile Five and GIIPS sovereign bond yields with their banks’ equity prices (already well above the sample average) increased more than for the average country between 2010-12 and 2013. As a result, these correlations intensified feedback loops from shocks originating from the GIIPS and Fragile Five.

Table 5.2 traces how feedback loops amplified sovereign bond yield shocks in the GIIPS or the Fragile Five in 2010-12. A redder tone indicates greater amplification by feedback loops. For example, feedback loops would have intensified the impact of a sovereign bond yield shock in the GIIPS initially (Step 1) more strongly (light orange) to the euro area core than the Nordics. Over time, feedback loops would have also amplified contagion to the Nordics (light orange in Step 2). In contrast, feedback loops would have strongly amplified contagion to the Nordics from a sovereign bond yield shock in the Fragile Five, mainly because strong bank-bank correlations with banks in the Fragile Five would have transmitted the shock to the Nordic sovereigns. In the euro area periphery, where bank-bank correlations with Fragile Five were less strong, feedback loops from a Fragile Five sovereign shock would have built more slowly over time.
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Table 5.2: Average strength of feedback loops after sovereign bond yield shock by region in years 2010-12.

<table>
<thead>
<tr>
<th>Sovereign bond yield shock in GIIPS</th>
<th>Sovereign bond yield shock in Fragile Five</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emerging Markets</td>
<td>Emerging markets</td>
</tr>
<tr>
<td>Euro area core</td>
<td>Euro area core</td>
</tr>
<tr>
<td>Euro area periphery</td>
<td>Euro area periphery</td>
</tr>
<tr>
<td>Nordics</td>
<td>Nordics</td>
</tr>
<tr>
<td>Financial centers</td>
<td>Financial centers</td>
</tr>
</tbody>
</table>

Note: Red = increase in sovereign bond yield in the highest quintile of each step; decline in bank equity price in the lowest quintile of each step. Orange = increase in sovereign bond yield in the second highest quintile of each step; decline in bank equity price in the second lowest quintile of each step. Yellow = increase in sovereign bond yield in the third highest quintile of each step; decline in bank equity price in the third lowest quintile of each step. Light blue = increase in sovereign bond yield in the second lowest quintile of each step; decline in bank equity price in the second highest quintile of each step. Dark blue = increase in sovereign bond yield in the lowest quintile of each step; decline in bank equity price in the highest quintile of each step.

5.6.2 Bank equity price shock

We repeat the exercise but this time for a shock to bank equity prices in the GIIPS, the Fragile Five, or any country (Fig. 5.5). In general, feedback loops matter less for the propagation of bank shocks than for sovereign bond yield shocks (the scale of the vertical axis of Fig. 5.5 below is smaller than that of Fig. 5.4). This presumably reflects the fact that bank-sovereign correlations are generally weaker than sovereign-sovereign correlations and hence dampen the transmission of shocks from loosely interconnected bank equity prices to highly interconnected sovereign bond yields.

There are some notable differences to the propagation of bond shocks that deserve highlighting. In 2013, feedback loops amplify bank shocks in the GIIPS more than Fragile Five.
Figure 5.5: Average impact of bank equity shock on bank equity prices, with feedback loops (in multiples of average impact of same shock on bank equity prices without feedback loops).

(a) Shock propagation to Fragile Five

(b) Shock propagation to GIIPS

(c) Shock propagation to any country
shocks. In contrast to the sovereign bond yield shock, the greatest shock propagation occurs when the shock reaches the highly interconnected sovereign bond yield network. The entry point for a bank shock into the sovereign bond network is through bank-sovereign correlations. On average, bank-sovereign correlations in the GIIPS are twice as strong as those in the Fragile Five. As a result, bank shocks originating in the GIIPS are transmitted more strongly than bank shocks in the Fragile Five into the highly interconnected sovereign bond network. From there, shocks spread rapidly.

Also in contrast to sovereign bond shocks, feedback loops amplify bank shocks in the GIIPS or in any country more strongly now (2013) than they did at the height of the global financial crisis (2007-09). The reason for strengthening feedback loops after bank shocks is the shrinking number of safe havens. At the height of the financial crisis, bank equity price shocks in Italy and Spain triggered a decline in yields (probably as a result of a monetary policy response to financial system disruptions) that generated benign spillovers in the sovereign-sovereign network. In the next section, we explore the role of safe havens in more detail.

5.7 The role of safe havens in shock propagation

Our next exercise is focused on safe havens as defined above. In our sample, safe havens have two characteristics, one by definition and one by coincidence. Firstly, by our definition, safe havens display strong positive correlations between sovereign bond yields and bank equity prices. Secondly, by coincidence, they also display strong sovereign-sovereign and bank-bank correlations. This is the case not only for strongly correlated European sovereign bonds but also for non-European safe haven bonds. Even sovereign bond yields for non-European safe havens are, on average, correlated 50 percent more strongly with other sovereign bond yields than non-safe havens. In principle, the first characteristic is stabilizing to the network, whereas the second characteristic is destabilizing. A positive correlation between domestic banks and

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10This difference is due both to stronger unweighted correlations and to higher weights (i.e. higher bank assets relative to sovereign debt) in the GIIPS than in the Fragile Five.
their sovereign (the first characteristic) dampens the impact of a foreign shock that, by itself, would spill over into a spike in sovereign bond yields and a drop in bank equity prices. A strong positive correlation with other sovereigns and banks, however (the second characteristic) generates strong transmission of any shock that arrives in a safe haven. Fig. 5.6 shows the different distributions of sovereign-sovereign, bank-bank and bank-sovereign correlations for safe havens and non-safe havens.

5.7.1 Sovereign bond yield shock

To distill the unique role of safe havens, we need to construct a “no-safe havens” counterfactual network that we can compare against our actual network. For our “no-safe havens” counterfactual network, we replace all the safe havens’ correlations with average correlations of non-safe haven countries (for bank-sovereign links alone, or in a separate experiment for sovereign-sovereign, bank-bank, and bank-sovereign links) as if they were the average non-safe haven country. Then we repeat the shock propagation exercises and compare with the results for the actual network.

Figs 5.7 and 5.8 show the role of safe havens in the propagation of sovereign bond shocks in the Fragile Five and the GIIPS. We measure the impact of a shock in a network without safe havens (one in which all safe haven correlations have been replaced with non-safe haven average correlations (continuous line)) against a baseline of the actual network of correlations. A line below 1 indicates that shocks propagate more strongly in a network with safe havens than in one without safe havens: the destabilizing effect of safe havens’ first characteristic predominates.

To distil separately the stabilizing effect of safe havens, we compare the same baseline of actual correlations against another counterfactual (dotted line) in which only bank-sovereign correlations of safe havens have been replaced with average non-safe haven correlations but all sovereign-sovereign and bank-bank correlations remain actual correlations. A dotted line above 1 indicates that the bank-sovereign links of safe havens dampen the propagation of shocks. In all our scenarios, shocks eventually propagate faster in networks with safe havens than without.
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Figure 5.6: Distribution of bilateral correlations for safe havens and non-safe havens.

Between sovereigns

Between banks

Between sovereigns and banks

(a) Years 2000-2006

(b) Years 2007-2009

(c) Years 2010-2012

(d) Year 2013
5.7. THE ROLE OF SAFE HAVENS IN SHOCK PROPAGATION

Figure 5.7: Average impact of Fragile Five sovereign bond shock without safe havens (in multiples of average impact of Fragile File bond market shock in the actual network of correlations).

Note: The upper limit of the band indicates the impact when only bank-sovereign correlations are replaced for safe havens by sample averages; the lower limit indicates the impact when all correlations for safe havens are replaced by sample averages.
Figure 5.8: Average impact of GIIPS sovereign bond shock without safe havens (in multiples of average impact of GIIPS market shock in the actual network of correlations).

Note: The upper limit of the band indicates the impact when only bank-sovereign correlations are replaced for safe havens by sample averages; the lower limit indicates the impact when all correlations for safe havens are replaced by sample averages.
safe havens (the continuous lines are eventually below 1). Not surprisingly, the larger group of safe havens in 2010-12 than in 2013 results in stronger effects in 2010-12 than in 2013.

The stabilizing effects of safe havens take time to gather momentum after a sovereign bond shock. A sovereign bond shock spreads rapidly and strongly across the highly interconnected sovereign bond network. In contrast, the stabilizing bank-sovereign effect in safe havens only operates once a shock hits either a safe haven banking system or a safe haven sovereign.

The stabilizing effect of safe havens depends on the origin of the shock. For example, in 2010-12, the stabilizing effect emerged more strongly and faster if the shock originated in the GIIPS than in the Fragile Five. Because GIIPS sovereign bond yields were on average one-third more strongly correlated with safe haven sovereign bond yields than Fragile Five sovereign bond yields, a sovereign shock originating in the GIIPS reached safe havens more strongly. This also triggered stronger stabilizing bank-sovereign links in safe havens.

5.7.2 Bank equity price shock

In Fig. 5.9, we conduct the same experiment for a bank equity shock in the Fragile Five countries. Again, a continuous line below 1 indicates that the presence of safe havens amplifies the propagation of shocks. The stabilizing effect of safe havens is too small to be noticeable in the chart because the origin of the shock (the Fragile Five) is weakly correlated with safe haven banks or sovereigns. However, as the shock reaches into the sovereign bond yield network, it is strongly amplified by the presence of safe havens.

In 2013, bank-bank correlations between Fragile Five banks and safe havens, on average, doubled compared with 2010-12 whereas sovereign-sovereign correlation between Fragile Five and safe havens halved. As a result, the stabilizing effects of safe havens were triggered more strongly in the initial phases of shock propagation but were later superseded by the destabilizing effects.
Figure 5.9: Average impact of Fragile Five bank equity shock on bank equity prices without safe havens (in multiples of average impact of Fragile Five bank equity shock on bank equity prices in the actual network of correlations).

(a) Fragile Five bank equity shock in 2010-12

(b) Fragile Five bank equity shock in 2013

The upper limit of the band indicates the impact when only bank-sovereign correlations are replaced for safe havens by sample averages; the lower limit indicates the impact when all correlations for safe havens are replaced by sample averages.
5.8 Conclusions and issues for further research

Our results thus far highlight a few stylized facts. We show how competing features of safe havens (highly interconnected sovereign bond yields versus stabilizing bank-sovereign links) combine to accelerate shock propagation in global bond and bank equity prices. We also show how feedback loops amplify especially shocks in the highly interconnected sovereign bond yield network. We speculate that these feedback loops may have been short-circuited by policy measures to contain contagion from GIIPS sovereign bond stress during the euro area crisis of 2010-12.

Our results raise some intriguing follow-on questions for further research. Firstly, the role of safe havens probably changes depending on their “neighborhood” in the network. Safe havens in deeply interconnected Europe may well play a different role than safe havens in Asia. Secondly, although we speculate in some instances about policies, their role is not directly addressed in this chapter. It is likely that announced policies altered the shape of the correlation network and drastically change shock propagation.
Appendix 5.A  Network graphs

Figure 5.A.1: Sovereign interconnectedness.

(a) Years 2000-2006

(b) Years 2007-2009

(c) Years 2010-2012
Figure 5.A.2: Bank interconnectedness.

(a) Years 2000-2006

(b) Years 2007-2009

(c) Years 2010-2012
Figure 5.A.3: Sovereign-bank correlations in Emerging Asia.

(a) Years 2000-2006

(b) Years 2007-2009

(c) Years 2010-2012

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Figure 5.A.4: Sovereign-bank correlations in Emerging Europe.

(a) Years 2000-2006

(b) Years 2007-2009

(c) Years 2010-2012
Figure 5.A.5: Sovereign-bank correlations in GIIPS and Cyprus.

(a) Years 2000-2006

(b) Years 2007-2009

(c) Years 2010-2012
Appendix 5.B  Shock propagation mechanism

For illustration purposes, imagine a very simple network structure, consisting of 4 nodes connected by links of weights -0.25 and 0.25 in the following way

Before the shock, none of the nodes is affected so that all of them are 0. Imagine now, that in step 1 node A is hit by a shock of magnitude one.

The node is now a source of the shock to the adjacent nodes B and C, propagating 25% of its initial magnitude with an appropriate sign.
Figure 5.B.8: Shock propagation (step 1).

In the second step, there are three sources of the shock, i.e. nodes A, B and C each, propagating 25% of the initial shock accumulated. Node A would therefore propagate 0.25 to the adjacent nodes B and C again. Node B would which would propagate 0.0625 to adjacent node D, and node C would propagate 0.0625 to node A. At the end of the second step, the network looks the following:

Figure 5.B.9: Shock propagation (step 2).

The process repeats itself for 10 steps. In each of them we calculate the cumulative shock in each of the nodes.