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Rise of NBFIs and the Global Structural Change in the Transmission of Market Shocks

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Abstract

The March 2020 market turmoil raised concerns over vulnerabilities associated with the increasing market interconnectedness with Non-Bank Financial Intermediaries (NBFIs), most notably investment funds, in the global financial system (GFS). Studies on the measurement of fire sale vulnerabilities in part those associated with NBFIs in a financial system are often conducted at the jurisdiction level using fire-sale (FS) models. While existing studies use granular data to analyze details of fire sale dynamics; in most of these cases, the scope of analysis is focused on a certain jurisdiction or asset class, leaving the cross-jurisdiction or cross-asset spillover dimension out of the scope. To address these points, this paper measures cross-border and cross-asset spillovers of market shocks ("interlinkage effect") in the GFS using a standard FS model, specifically focusing on the role of NBFIs. With the help of existing FS models, we construct measures of the interlinkage effect across different types of financial institutions, including banks and various types of NBFIs, in Japan's financial system as well as those for the foreign financial system (the U.S. and Euro area) using flow of funds data of these jurisdictions. We find that the interlinkage effect has increased substantially, not only for Japan's financial system, but also for the overseas financial system since the Global Financial Crisis (GFC). These increasing interlinkages of NBFIs with various types of entities suggest there has been a global structural change in the transmission of market shocks.

Keywords: Interconnectedness; NBFI; cross-border spillovers; fire sales; systemic risk

JEL classifications: G10; G11; G21; G23

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1. Introduction

Since the global financial crisis (GFC), the presence of non-bank financial intermediaries (NBFIs) in global financial intermediation has been growing substantially. This has been driven mainly by inflows to investment funds - mutual funds including money market funds (MMFs) - from various entities around the globe against the backdrop of accommodative financial conditions after the GFC and search-for-yield by investors in a prolonged low interest rate environment up to end-2021, when U.S. interest rates started to rise (chart 1, FSB (2021a), IMF (2014, 2016)).[1] As a consequence, vulnerabilities such as those with respect to market interconnectedness of the global financial system (GFS) have deepened, which could amplify the effects of shocks to NBFIs in times of stress (FSB (2020), Morris, Shim and Shin (2017)).[2] In this context, the Japanese financial system can be considered as a leading example, as Japanese banks have been facing downward pressure on profitability due to structural factors such as the fall in the potential growth rate, reflecting the declining population and the resultant secular decline in loan demand. In fact, Japanese banks' deposit-lending margins started to shrink from around 2000, when the corporate sector turned to persistent "excess savings" (chart 2). Against this background, Japanese banks have been actively investing in overseas financial assets to secure profits. Meanwhile, overseas entities including overseas investment funds have increased investment in Japanese stocks and bonds in recent years (chart 3).

Such vulnerabilities associated with the activities of NBFIs were uncovered during the March market turmoil of 2020. Large-scale redemptions took place at prime MMFs and open-end funds, leading to selloffs of not only risky assets but also highly liquid assets to meet redemption obligations (chart 4). This so-called "dash for cash" of

[1] Other potential driving forces of expansion of NBFIs include increases in savings due to long-term demographic trends and rises in the relative cost of financing from the banking sector due to regulatory reforms after the GFC (FSB (2020)).

[2] Market interconnectedness in this paper refers mainly to common asset holdings focusing on the system-wide market interconnectedness of the GFS. Other vulnerabilities of NBFIs include effects of leverage or margin calls (Aramonte, Schrimpf and Shin (2022)).

investment funds dried up liquidity in various financial markets and destabilized global financial markets, as indicated by sharp rises in the U.S. dollar funding premium and sharp price declines in various asset markets (FSB (2020)). Under these circumstances, many financial institutions in Japan experienced price declines in their securities holdings and saw breaches in the various risk management limits, such as loss limits (chart 5, Bank of Japan (2021)). Market functioning was restored soon after the introduction of central bank's policy measures, such as large-scale bond purchases, expanding the liquidity facilities, or the adoption of U.S. dollar swap lines among major central banks. This March 2020 market turmoil raised financial stability concerns in particular those regarding the vulnerabilities of NBFIs at the FSB and various standard-setting bodies, and this initiated the post-March 2020 market turmoil discussion on how to enhance the resilience of MMFs and open-end funds in the GFS.[3]

In light of these developments, this paper aims to better understand the systemic risks that are potentially inherent in the GFS, which has been one of the focal points of the ongoing discussion (FSB (2020)), by constructing some measures of the interlinkage effect across different types of financial institutions, including banks and various types of NBFIs. We measure the interlinkage effect for Japan's financial system and compare developments of those with the foreign financial system (the U.S. and Euro area). On the measurement of interconnectedness in the GFS, existing studies have often looked into the degree of portfolio overlap between institutions of the same type, such as U.S. mutual funds (Delpini et al. (2020), Fricke (2019)), insurance companies (Girardi et al. (2021)), or across multiple types of NBFIs in the U.S. (Gualdi et al. (2016)). Some of these studies indicate an increasing portfolio overlap since the GFC, which could lead to a larger propagation of market shocks to NBFIs (Fricke (2019), Gualdi et al. (2016)). Others have considered a broader scope of entity types and looked into the interlinkage between banks and NBFIs. Barucca, Mahmood, and Sivestri (2021) applies the measurement method of

[3] Regulatory reforms of NBFIs after the GFC include, for example, the U.S. MMF reform in October 2016 and strengthening the solvency ratio regulation for insurance companies. Post-March 2020 market turmoil discussion focuses on further enhancing the resilience of MMFs and open-end funds (FSB (2021b), FSB (2021c)).

Delpini et al (2020) to multiple types of financial institutions, namely U.K. banks, U.K. insurers, and European open-end investment funds as of the first quarter of 2016. Abad et al. (2022) uses data collected by the EBA that cover exposures of banks and investment firms in the E.U. as of March 2015. Although these studies provide implications of the deepening interconnectedness with NBFIs, they focus on certain entity types, jurisdiction or a specific time period, and do not necessarily address the dynamic evolution of cross-border spillovers of global market shocks to NBFIs across different types of entities. This may be due to the large data gap reflecting the lack of a long historical track record of security-level holdings of various types on a global scale, which has made the measurement of portfolio overlap and analysis of cross-border spillovers of NBFI activities a challenging task.

The rising presence of NBFIs in the GFS could indicate rising vulnerabilities spanning multiple jurisdictions. In this regard, one of the lessons learned from the March 2020 market turmoil is to have a better understanding of how the interconnectedness with NBFIs across different types of entities has evolved on a global scale. Indeed, the FSB (2020) views gauging the interactions among banks, NBFIs and cross-border spillovers as one of the primary subjects for enhancing the understanding of systemic risks inherent in the GFS as a whole.

This paper attempts to fill the gap by estimating cross-border spillover of market shocks to NBFIs to other types of financial institutions in the GFS and changes of the spillover effects over time. First, we formulate a system estimation that models the GFS that consists of advanced economies using flow of funds data. We consider two –sub-financial systems of the GFS - domestic (Japan) and foreign (U.S. and Euro area) - which consists of three types of entities for each region: banks, ICPFs (i.e. insurance corporations and pension funds), and investment funds. The long historical track record based on a common methodology makes flow of funds an attractable source for measuring how cross-border spillovers of market shocks to NBFIs to other financial institutions have taken place and how the spillovers have changed over time. Next, we use the information from the estimated GFS to measure what we call the "interlinkage effect", which captures how a price shock to an entity's asset portfolio is amplified in a standard fire-sale (FS) model (Greenwood, Landier and Thesmar (2015), Duarte and Eisenbach (2021), Fricke and Fricke (2021)). A fire sale generally refers to a situation where assets are sold at heavily discounted prices. As these models illustrate, fire sale spillovers are considered to be an important channel for the propagation of financial stress that may lead to systemic risk. That is, when assets prices are falling, losses by financial institutions could trigger further simultaneous sell orders, leading to downward spirals for asset prices. From this point of view, distinguishing the role of transactions and prices is necessary to understand the precise nature of these fire sale dynamics. In this regard, these standard FS models distinguish transactions and asset returns to calculate fire sale spillovers generated from sequences of asset sales induced by an initial negative price shock. With the help of these FS models, the interlinkage effect in this paper is defined as a sum of first- and second-round spillover effects. The first-round spillover is a product of three parameters: portfolio overlap across different types of entities, portfolio adjustment rate, and price impact. The second round of asset sales is induced by, for example, funding constraints due to the initial fire sales. We measure the case for Japan's financial system and compare development of those with the foreign financial system.

There are three features of our paper that make our analysis distinct from existing studies. First, the estimated GFS of our paper is designed to measure cross-border spillovers of market shocks; therefore, our universe of entities in the GFS is broad and includes banks and NBFIs (i.e., investment funds and ICPFs) for domestic and foreign financial institutions. Second, due to the lack of security-level asset holdings of various entities on a global scale, we calculate contributions of changes in transactions and those of asset returns to changes in market values of financial assets using an alternative data, i.e., the flow of funds data. This enables us, under some assumptions, to shed light on how securities transactions of the three types of entities or changes in asset returns of securities held by a specific type of entity spill over to market values of other types of entities' financial assets. Third, we use a time-varying parameter to analyze how the propagation has evolved over time.

Our main finding is that the interlinkage effect across jurisdictions and different types of entities is present in the GFS and has increased since the GFC. It should be noted that the pace of increase in the interlinkage effect faced by Japan's financial system since the GFC is significantly higher compared to that in the U.S. and Europe. This observation suggests that, with the degree of portfolio overlap having risen globally, a market shock in one part of the world may be amplified and spread globally including the effect on Japan's financial system.

The remainder of the paper proceeds as follows. Section 2 provides the related literature and describes how our analysis compares to existing studies. Section 3 gives a detailed explanation of the data and methodology for estimating the GFS, which forms the basis for analyzing the interlinkage effect. Section 4 gives a detailed description of the interlinkage effect and how this is calculated in line with standard FS models. Section 5 describes estimation results of the interlinkage effect for the domestic (Japanese) and foreign financial systems. Section 6 is our conclusion.

2. Related Literature

Our paper contributes to several strands of the literature. First, it contributes to the literature on the measurement of interconnectedness in the GFS. In this literature, it is typical to use granular security-level data to measure the common asset holdings of firms and analyze vulnerabilities associated with fire sales through the common exposure. Girardi et al. (2021) measures common asset holdings of U.S. insurance companies with the cosine similarity[4], using security-level holdings data, and finds that sales of commonly held risky assets became pronounced in periods of stress. Barucca, Mahmood and Sivestri (2021) examines fire sale vulnerabilities across multiple entities, namely U.K. banks, U.K.

[4] Cosine similarity (S_{mn}) is technically the angle between the vectors of portfolio weights between institution m and n, which is defined as $S_{mn} \equiv \sum_k w_{mk} w_{nk} / (\sqrt{\sum_k w_{mk}^2} \sqrt{\sum_k w_{nk}^2})$, where w_{mk} is the share of asset k held by institution m.

insurers, and European open-end investment funds, and finds that portfolio similarity (cosine similarity) can be a useful indicator for quantifying the propagation effects of market shocks. Delpini et al. (2020) investigates portfolio similarity of U.S. mutual funds and points out that commonality of asset holdings emerges as a result of similar diversification strategies of mutual funds that could amplify market shocks in stress periods. Others have shown high interconnectedness between banks and NBFIs using entity-level data (Abad et al. (2022)) and flow of funds data (Castrén and Kavonius (2009)). Fricke (2019) shows that the pairwise portfolio overlap, defined as cosine similarity among the U.S. investment funds calculated from security-level data, is positively correlated with pairwise asset return correlation. This paper measures the portfolio overlap by the correlation of asset returns measured from the flow of funds data following Fricke (2019).

Second, more broadly, we add to the literature on the market impact of large redemptions observed at MMFs and open-end funds in times of stress. Conceptually, the interlinkage effect of this paper includes the overall market impact of these large redemptions and associated asset sales and how they spill over to other entities' financial asset value fluctuations. In terms of MMFs, large redemptions are typically observed in prime MMFs, which invest in non-government assets, in stress periods such as during the GFC and the March 2020 market turmoil (Schmidt, Timmermann and Wermers (2016), Haddad, Moreira and Muir (2021)). These MMFs provide short-term liquidity not only to U.S. entities but also to international entities; prime MMFs are large holders of CDs and CP issued by various foreign entities. When large redemptions take place at prime MMFs, financial entities that rely on funding by CDs and CP held by these MMFs need to substitute their funding sources to other instruments; as a result, market strains occur in, for example, FX and currency swap markets due to sharp rises in these substitution demands (Eren, Schrimpf and Sushko (2020)). These liquidity supply constraints from MMFs could induce large-scale asset sales of highly liquid assets of other entities in order to secure liquidity. Open-end funds also tend to face large redemptions in stress periods and they often liquidate assets under these circumstances, which in turn affects market prices. The underlying mechanism for such fund-run type behavior is often attributed to the first-mover advantage for shareholders to redeem their shares as early as possible, since liquidation costs are often borne by remaining fund investors. In a theoretical model, Chen, Goldstein and Jiang (2010) shows that information on fund returns can allow fund investors to learn about redemption decisions of others and as a corollary negative returns can serve as a signal for asset liquidations. Another motive for a first-mover advantage could be due to stale pricing (Qian (2011), Choi, Kronlund and Oh (2021)). The existence of a positive correlation between asset portfolio returns and transaction flows has become a stylized fact in the mutual fund literature (Sirri and Tufano (1998), Berk and Green (2004), Fricke and Fricke (2021), Baranova, Coen and Lowe (2017), Goldstein, Jian and Ng (2017)). This mechanism can be stronger when mutual funds hold more illiquid assets, which could ultimately lead to disorderly fire sales of assets for securing liquidity (Chen, Goldstein, and Jiang (2010), Fricke and Fricke (2021)). In light of the March 2020 market turmoil, Falato, Goldstein and Hortaçsu (2021) reports that sharp increases in redemption requests to mutual funds triggered significant asset sales, especially for funds investing in illiquid assets and those investing heavily in industries where the impact of the COVID-19 was pronounced. Haddad, Moreira and Muir (2021) points out that, in order to secure liquidity, investors sold massive amounts of investment grade bonds and the U.S. treasury bonds, which eventually spread to sales of illiquid assets. Another driving force for acceleration of investors' dash for cash behavior is increases in margin calls for additional collateral (FSB (2020), Aramonte, Schrimpf and Shin (2022)).

Third, this paper adds to the literature on the application of the time-series based estimation method of networks pioneered by Diebold and Yilmaz (2009, 2014). This method has been widely used in the estimation of connectedness in various financial markets (e.g. Diebold and Yilmaz (2009)), financial institutions (Demirer et al. (2018)), and analysis on contagion in financial networks (Elliott, Golub and Jackson (2014)). To the best of our knowledge, this is the first paper to apply this method to the estimation of the network of GFS where transactions and asset returns of various entities' asset holdings are isolated on a global scale.

Fourth, this paper also contributes to the literature of FS models, which has been increasingly used by central banks and international organizations as a toolkit to assess the financial vulnerabilities in recent years. The key idea of this paper is to isolate contributions of transactions and various entities' asset returns using flow of funds data, which enables us to calculate global spillovers stemming from a certain entity in line with standard FS models. The literature on fire sales is vast and the related theoretical models go back to the seminal work by Schleifer and Vishney (1992).[5] More recently, the FS model of Greenwood, Landier and Thesmar (2015) has become a workhorse for modelling fire sales where they focus on the European banking sector, taking into account the role of regulatory requirements in fire sales. In their model, the FS mechanism starts with an initial exogenous negative price shock to an entity's asset holdings, which leads to their "first-round" asset sales. This then leads to a further decline in sold assets through the price impact, which triggers an array of "second-round" asset sales by other entities. In these standard FS models, the overall loss through this process - such as the total loss metrics - is often calculated as a function of four components: the initial price shock, portfolio overlap, portfolio adjustment rate, and price impact. Duarte and Eisenbach (2021) finds that fire sales vulnerability of U.S. banks has been declining since the GFC, which implies that the banking sector has become more resilient as a consequence of the progress of the regulatory reforms. Given the seemingly rising resilience in the US banking sector, the focus in the literature has gradually shifted toward fire sales spillovers of NBFIs. Fricke and Fricke (2021) models the FS mechanism of U.S. investment funds taking into account redemption risks. They show that investment funds with more illiquid assets tend to face higher amounts of redemption in response to negative asset returns.

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[5] As for the empirical evidence about the existence of fire sales, see Pulvino (1998) for real assets, Coval and Stafford (2007), Ben-Rephael, Kandel and Wohl (2011), and Lou (2012) for equities and Ellul, Jotikasthira and Lundblad (2011) and Manconi, Massa and Yasuda (2012) for corporate bonds. Also, Jotikasthira, Lundblad and Ramadorai (2012) measure the transmission of shocks among international markets by investment funds domiciled in advanced economies that liquidate their holdings of emerging markets equities. Manconi, Massa and Yasuda (2012) study the contagion of the crisis from the securitized bonds to corporate bonds in August 2007 triggered by portfolio rebalancing of mutual funds following investors' redemptions.

Cetorelli, Duarte and Eisenbach (2016) finds that spillover from large-scale redemptions in mutual funds has risen from 2005 to 2015. More recently, these FS mechanisms of various entities have been integrated into a more general model. Caccioli, Ferrara and Ramadiah (2020) construct models for banks, investment funds, and insurance companies in the U.K. and Mirza et al. (2020) for the E.U. financial system. These studies mainly focus on spillovers within a single country or jurisdiction rather than the cross-border contagion of market shocks. Conceptually, the interlinkage effect in this paper is analogous to these fire sale spillover metrics.

There are some notable features of our paper that make our analysis distinct from existing studies. First, the estimated GFS in our paper is designed to measure cross-border spillovers of market shocks; therefore, our universe of entities in the GFS is broad and includes banks and NBFIs, investment funds, and insurance companies and pension funds (ICPFs) for home and abroad. Second, due to the lack of security-level asset holdings of various entities on a global scale, we measure cross-border spillovers of market shocks using flow of funds data, decomposing the contributions of asset prices and transactions.[6] Although we consider security holdings data as the first-best approach for measuring portfolio overlap and analyzing transmission of market shocks, we believe the flow of funds data can serve as a second-best alternative to overcoming this data gap. Third, we use a time-varying parameter to analyze how the propagation has evolved over time. In doing so, rather than modeling changes in regulatory requirements explicitly in the underlying analytical model, as in previous studies (Duarte and Eisenbach (2021), Caccioli, Ferrara and Ramadiah (2020)), we address changes in the way that entities respond to shocks by using time-varying model parameters. We believe this is a reasonable simplification since the effects of non-linearities arising from binding capital requirements will be more or less reflected in the observed data.

[6] Asset returns are contribution of price changes (ΔP_t) in asset value fluctuation ($\Delta P_t + \Delta Q_t$).

3. Estimation of the GFS

This section provides details of the data and the estimation methodology of the interconnectedness of GFS, which we use to analyze the interlinkage effects in section 4.

3.1. Data

We formulate a system estimation that models the GFS that consists of advanced economies using flow of funds data. We consider two regional financial systems - domestic (Japan) and foreign (U.S. and Euro area) - which consist of three types of entities for each region: banks, insurance corporations and pension funds (ICPFs), and investment funds. The investment funds include MMFs, mutual funds, and ETFs. In constructing the GFS, it is ideal to use granular security-level data across entities, since this is the most precise way of measuring the size of common asset holdings or asset-liability linkages (Girardi et al. (2021), Barucca and Sivestri (2021), Caccioli, Ferrara and Ramadiah (2020), Fricke (2019)). However, this level of granularity is only available for certain jurisdictions and even when such data exists, their long historical records are not available. This large data gap has made analysis of cross-border spillovers of fire sales - i.e. how market shocks to an entity's asset holdings transmit to asset values of entities in other jurisdictions - a challenging task. This paper attempts to overcome this difficulty by using flow of funds statistics from selected large jurisdictions.[7] Flow of funds have long historical data regarding financial transactions and outstanding amounts of financial assets and liabilities, which are evaluated at market prices based on a common methodology that makes them comparable across jurisdictions.[8] In our FS model in section 4, we use total financial assets held by each type of entity.[9] Data for total financial assets and transactions for

[7] We consider three jurisdictions; Japan the U.S. and the Euro area, which amounts to a total of approximately 60% of world total financial assets as of 2020 (source: FSB).

[8] Flow of funds statistics are compiled based on the international guidelines and the common terminology defined by the System of National Accounts.

[9] Caccioli, Ferrara and Ramadiah (2020) considers different varieties of assets such as bonds and stocks. For the sake of simplicity, this paper focuses on fluctuations of aggregate financial assets of each entity.

entities in Japan are taken from the Flow of Funds Accounts published by the Bank of Japan. Likewise, for overseas entities, Financial Accounts of the United States published by the Federal Reserve and the Euro area Accounts published jointly by the ECB and Eurostat are used. Figures denominated in U.S. dollars and Euros for overseas entities are converted to being aggregated in Japanese Yen using end-of-quarter cross-currency rates.

One of the challenges in measuring the interlinkage effect in line with standard FS models is to pin down the contributions of transactions and asset returns in fluctuations of financial asset values. In this regard, we isolate changes in the total value of financial assets held by entity i into contributions by changes in transactions ($\Delta Q_{t,i}$) and asset returns ($\Delta P_{t,i}$) using the flow of funds data as follows: $\Delta Q_{t,i}$ is pinned down by the transaction table and $\Delta P_{t,i}$ is defined as changes in the value of financial assets less contributions from the transactions. These changes in the numbers for the transactions $\Delta Q_{t,i}$ capture acquisitions and sales of financial assets executed by the entity, and changes in asset returns $\Delta P_{t,i}$ reflect changes in the financial balance sheet due to other factors, which based on our interpretation are considered to be caused by market price fluctuations.[10] We normalize $\Delta Q_{t,i}$ and $\Delta P_{t,i}$ by the outstanding amount of total financial assets at the end of the previous quarter.

3.2. Estimation of the GFS

Our estimation method closely follows Diebold and Yilmaz (2009, 2014), which provides the milestone for measuring the connectedness in networks using the time series method. We consider the following vector auto-regression VAR(1) of asset returns ($\Delta P_{t,i}$) and

[10] The calculation of contributions of asset returns is consistent with the construction of the "Reconciliation Table," which is published as a part of the Flow of Funds Accounts in Japan. This table is compiled to resolve the discrepancies between the accumulated sum of flow data and stock data that emerge especially in bonds and stock shares, since they are evaluated at market value. In other words, when a price change occurs during a period, the difference between the amounts outstanding at the beginning of the period and those at the end does not match the amount of transactions for the corresponding period. The table therefore makes it possible to capture the asset returns due to market price fluctuations. We apply this approach to overseas flow of funds data to back out the contributions from asset returns.

intra-quarter asset portfolio transactions ($\Delta Q_{t,i}$) of entity i:

$$Y_t = \nu_t + A_t Y_{t-1} + u_t, \tag{1}$$

where

$$Y_t := \begin{bmatrix} \Delta P_{t,bank} \\ \vdots \\ \Delta P^*_{t,inv.fund} \\ \Delta Q_{t,bank} \\ \vdots \\ \Delta Q^*_{t,inv.fund} \end{bmatrix}, \ \nu_t := \begin{bmatrix} \nu_{t,\Delta P,bank} \\ \vdots \\ \nu_{t,\Delta P^*,inv.fund} \\ \nu_{t,\Delta Q,bank} \\ \vdots \\ \nu_{t,\Delta Q^*,inv.fund} \end{bmatrix},$$

$$A_t := \begin{bmatrix} a_{\Delta P,bank,\Delta P,bank,t} & \cdots & a_{\Delta P,bank,\Delta Q^*,inv.fund,t} \\ \vdots & \ddots & \vdots \\ a_{\Delta Q^*,inv.fund,\Delta P,bank,t} & \cdots & a_{\Delta Q^*,inv.fund,\Delta Q^*,inv.fund,t} \end{bmatrix},$$

$$u_t := \begin{bmatrix} e_{t,\Delta P,bank} \\ \vdots \\ e_{t,\Delta P^*,inv.fund} \\ e_{t,\Delta Q,bank} \\ \vdots \\ e_{t,\Delta Q^*,inv.fund} \end{bmatrix}, \text{ with } u_t \sim \mathrm{N}(0, \Sigma_t) \text{ and}$$

$$\Sigma_t := \begin{bmatrix} \sigma_{\Delta P,bank,\Delta P,bank,t} & \cdots & \sigma_{\Delta P,bank,\Delta Q^*,inv.fund,t} \\ \vdots & \ddots & \vdots \\ \sigma_{\Delta Q^*,inv.fund,\Delta P,bank,t} & \cdots & \sigma_{\Delta Q^*,inv.fund,\Delta Q^*,inv.fund,t} \end{bmatrix}.$$

ν_t is a vector of deterministic constant terms, A_t is the one period lag coefficient matrix, and u_t is a vector of mean zero Gaussian error terms with variance covariance matrix Σ_t. We take into account a one-quarter lag to capture any persistence in changes in transactions and asset returns.[11] Variables with superscript * indicate that the variables are those for foreign entities. The estimation is done using the Least Absolute Shrinkage and Selection Operator method (LASSO) and the estimation period is from the July-September quarter of 1999 to the October-December quarter of 2019.[12] In addition, we allow model parameters to vary overtime by conducting a rolling estimation with a

[11] Alternatively, we also assumed a white noise process in (1), but this did not change the qualitative results.

[12] We follow Tibshirani (1996), where the regularization parameter λ is chosen to minimize RMSE (Root Mean Square Error) by using 10-fold cross validation.

window of eight years.

The core concept of Diebold and Yilmaz (2009, 2014) is that the variance decomposition calculated from generalized impulse response functions (GIRFs) can be interpreted as a measure of connectedness discussed in the network literature. For illustration, denoting two arbitrary variables of Y_t as $y_{t,k}$ and $y_{t,i}$, one-step ahead GIRF of $y_{t,k}$ to an exogenous shock to $y_{t,i}$ can be written as:

$$
\begin{aligned}
GIRF_{t,y_{t,i}\rightarrow y_{t,k}} &= E\left(y_{t,k} \middle| u_{t,y_{t,i}} = \delta_{t,i},\ I_{t-1}\right) - E\left(y_{t,k} \middle| I_{t-1}\right) \\
&= \sigma_{t,ii}^{-1} s_k' \Sigma_t s_i \delta_{t,i} \\
&= \sigma_{t,ki} / \sqrt{\sigma_{t,ii}} \\
&= \rho_{t,ki} \sqrt{\sigma_{t,kk}},
\end{aligned}
$$

where $\delta_{t,i}$ is the exogenous shock to $y_{t,i}$, I_{t-1} is the information set in a period before the exogenous shock occurs, s_j is a selection vector (i.e. unity at the *j*-th element and zeros elsewhere), $\sigma_{t,ki}$ and $\rho_{t,ki}$ represents the (*k*, *i*) elements in the variance covariance matrix of Σ_t and correlation of variable *k* and *i*, respectively. In the second equality, the exogenous shock $\delta_{t,i}$ is normalized to one standard deviation shock ($\sqrt{\sigma_{t,ii}}$) to $y_{t,i}$ (Koop, Pesaran and Potter (1996), Pesaran and Shin (1998)).[13] Using this expression, the one-step ahead forecast error variance of $y_{t,i}$'s contribution to $y_{t,k}$ ($\theta_{t,y_{t,i}\rightarrow y_{t,k}}$) can be written as:

$$
\begin{aligned}
\theta_{t,y_{t,i}\rightarrow y_{t,k}} &= \frac{(\sigma_{t,ii}^{-1} s_k' \Sigma_t s_i \delta_{t,i})^2}{\sum_{j=1}^{N} (\sigma_{t,jj}^{-1} s_k' \Sigma_t s_j \delta_{t,j})^2} \\
&= \frac{(\sigma_{t,ki} / \sqrt{\sigma_{t,ii}})^2}{\sum_{j=1}^{N} (\sigma_{t,kj} / \sqrt{\sigma_{t,jj}})^2} \qquad (2) \\
&= \frac{(\rho_{t,ki})^2}{\sum_{j=1}^{N} (\rho_{t,kj})^2}.
\end{aligned}
$$

As shown in Diebold and Yilmaz (2015), this variance decomposition can be

[13] Cholesky variance decompositions require assumption on the ordering of variables. In practice, the rationality of a certain ordering is sometimes hard to justify, so we use the generalized impulse response as the second-best approach.

constructed into a connectedness table, where each element represents pairwise directional connectedness in the sense of how much of the forecast error variations in variables are driven by shocks arising by their own and other variables. Rows in this table correspond to variables affected by the shock (to) and columns represent origins of shocks (from). In the estimated GFS using flow of funds, changes in prices and transactions are decomposed, and we formulate a connectedness table in the same spirit as Diebold and Yilmaz (2015) in chart 6. For example, the upper-left block of this table represents pairwise directional connectedness (correlations) of asset returns held by three types of entities at domestic and foreign financial systems. As (2) shows, the fundamental information of each connectedness is given by the correlations of shocks across types of entities and across financial systems. In section 4.2, we use the information in this connectedness table to calibrate parameters of our FS model.

In terms of the variance decomposition calculated from GIRFs, there is an issue that rows do not generally sum to one, unlike the case with orthogonalized Cholesky decompositions. In order to deal with this issue, Diebold and Yilmaz (2014) renormalize the rows of the variance decomposition matrix to meet this property. There are other proposed methods, such as the one in Lanne and Nyberg (2016), where they consider the non-linearity of the variance decomposition (2) and use a bootstrap method to obtain variance decomposition with the desirable property. We follow Lanne and Nyberg (2016) to calculate the variance decomposition matrix: the estimator of each element of the matrix is the average $\hat{\theta}_{t,y_{t,i}\rightarrow y_{t,k}}$ calculated from 5,000 draws of u_t from the estimated forecast-error variance covariance matrix $\hat{\Sigma}_t$. Through this procedure, we obtained a 12 $\times$ 12 matrix representing pairwise directional connectedness of asset returns and transactions across entities.

4. Interlinkage Effect

In this section, we define the FS model to measure the interlinkage effect and the calibration procedures using the information on the estimated connectedness of the GFS.

FS models, such as Greenwood, Landier and Thesmar (2015), Duarte and Eisenbach (2021), and Fricke and Fricke (2021), consider the case where asset returns of securities portfolios held by entity i are determined by mainly two components. One is changes due to initial negative price shocks that occur possibly in securities portfolios including those held by other entities, and the other is contributions of the endogenous amplification effects that arise through changes in transactions among different entities induced by the initial shock. The latter effect is referred to as the "interlinkage effect". In this mechanism, the portfolio overlap is considered to have a pivotal role in the transmission of market shocks (Girardi et al. (2021), Barucca, Mahmood and Sivestri (2021)). For example, consider a case where an initial negative price shock takes place in securities portfolios held by investment funds. This leads to large redemptions and asset sales in parts of investment funds, which puts downward pressure on prices of sold assets. This portfolio adjustment of investment funds spills over to other entities' value of assets through the portfolio overlap. This shows that, even when the asset positions of other entities are unchanged or not strictly equivalent to those of investment funds, their asset values can be affected by asset sales of investment funds. In a situation where portfolio overlap across financial entities has deepened, this increasing interconnectedness can serve as a contagion factor, leading to higher propagations of market shocks to specific entities in the global financial market.

Another notable feature of a standard FS model is that it distinguishes how transactions and asset returns can separately lead to amplification of the initial negative price shock.

4.1. A Standard Fire-Sale (FS) Model

The estimation of the interlinkage effect is based on a simplified version of the FS model of Greenwood, Landier and Thesmar (2015). The model is a 2-period model with N entities that hold total financial assets $A_{0,i}$. Each entity's asset holding is distinct, and for each pair of entities, asset return correlations are not perfectly collinear but assume to take values from negative one to positive one. In existing studies, it is often considered that banks adjust their portfolio to a desired level of leverage (Duarte and Eisenbach (2021)); however, we assume that parameters vary over time in our estimation, so that the model is able to capture secular changes of structural factors such as changes in the distance between the capital holding and regulatory capital requirements or changes in the asset portfolio composition etc., and thus refrain from considering this adjustment process for simplicity. The main steps are shown in chart 7 and contain four steps:

1. An initial price shock materializes for a certain entity, which faces direct losses,
2. Institutions liquidate their assets,
3. Asset liquidations generate price impacts,
4. Asset returns spill over to other entities through portfolio overlap.

In step 1, a negative price shock $\eta_{0,i}$ materializes in entity i's financial asset portfolio.

In step 2, we assume a policy function of entity j's asset portfolio management, which states a positive linear relationship between entities' asset returns and transactions (e.g. Sirri and Tufano (1998), Berk and Green (2004)). Hence, a negative price shock leads to contemporaneous asset sales of entity i. Caccioli, Ferrara and Ramadiah (2020) points out that portfolio adjustment patterns differ by regulatory requirements faced by different types of entities. Furthermore, in practice, risk management practices may depend on each entity type in a jurisdiction. Given these insights, we allow for heterogeneous responses of portfolio adjustment in response to price changes for different types of entities for different regions. Hence, we denote "first-round" asset sales as FR_i and assume that $FR_i = \gamma_i \eta_{0,i}$ where γ_i captures the response of each type of entity to the initial shock. In addition, we assume that the first-round asset sales trigger an array of "second-round" asset sales, which leads to amplifications of the initial negative price shock. These second-round asset sales could be due to similarities in their investment strategies or effects from forced sales due to liquidity effects. That is, in the latter case, when an entity i sells assets - or refrains from rolling-over certain assets - this could lead to liquidity strains of other entities inducing more asset sales, such as the case observed with the stress in prime MMFs during the March turmoil of 2020. We introduce these concepts as sales inducements and denote the effects as $\varphi_{t,i \to j}$. Similarities of investment strategies or liquidity effects is a bilateral relation, so we assume that this parameter depends on both entity i and j. We denote the degree of "second-round" asset sales of entity j induced by entity i as SR_j: $SR_j = \varphi_{i \to j} FR_i = \varphi_{i \to j} \gamma_i \eta_{0,i}$, where the magnitude of second-round asset sales is proportionate to the sales inducement parameter and first-round asset sales of entity i. Using the expression for the first-round asset sales, second-round asset sales can be expressed as a product of three parameters: the initial price shock, portfolio adjustment rate and sales inducement.

In step 3, these asset sales incur additional price declines through heterogeneous price impact θ_i. Each type of entity holds distinct assets, so the impact on market prices could differ depending on its liquidity. Hence, the resulting asset return of portfolios incurred by the first-round and second-round asset sales by entity i and j are expressed as $\theta_i \gamma_i \eta_{0,i}$ and $\theta_j \varphi_{i \to j} \gamma_i \eta_{0,i}$, respectively.

In step 4, these negative asset returns spill over to other entities via a degree of portfolio overlap. Writing the portfolio overlap between i and k as $\omega_{0,i \to k}$, we can write the first-round spillover of entity k as $FR_{i \to k} = \omega_{0,i \to k} \theta_i \gamma_i \eta_{0,i}$ and the second-round effects from j to k as $SR_{j \to k} = \omega_{0,j \to k} \theta_j \varphi_{i \to j} \gamma_i \eta_{0,i}$.

In modelling the interlinkage effect, it is crucial to account for heterogeneity among entities across jurisdictions, such as how they respond to market shocks. For example, how much a bank sells assets in response to a negative price shock could be influenced by how close the bank's capital ratio is to the regulatory requirements at the impact period. In existing studies, it is often considered that banks adjust their portfolio gradually to a desired level of leverage (Duarte and Eisenbach (2021), Caccioli, Ferrara and Ramadiah (2020)); however, for simplicity, we assume financial asset holdings are adjusted immediately after market shocks and use time-varying parameters to capture this profile. There could be other non-linearities such as how an entity's asset sales affect prices, which could depend on the composition of the asset portfolio or liquidity conditions. We believe that assuming time varying parameters is a reasonable simplification since the effects of persistent changes in structural factors will be somewhat reflected in the observed data.

Aggregate fire sale spillover metrics, which measure how negative market shocks transmit to the financial system through transactions of entities, are often calculated assuming each entity faces a negative price shock simultaneously. Normalizing the initial negative price shock $\eta_{0,i}$ to one standard deviation for all entities, we define the interlinkage effect faced by entity k triggered by a negative price shock to entity i's portfolio as:

$$Link_{t,i\to k} = \gamma_{t,i}\theta_{t,i}\omega_{t,i\to k} + \gamma_{t,i}\left(\sum\nolimits_{j} \varphi_{t,i\to j}\theta_{t,j}\omega_{t,j\to k}\right), \tag{3}$$

where the first and second term of the right-hand side correspond to "first-round" effects and "second-round" effects, respectively. The aggregate interlinkage effect faced by entity k is defined as the sum of spillovers from all other entities.

$$Link_{t,k} = \sum\nolimits_{i\neq k} Link_{t,i\to k}. \tag{4}$$

4.2. Calibrating Parameters of the FS model using the Estimated GFS

From equation (3), the interlinkage effect is determined by four parameters: portfolio overlap ω, portfolio adjustment rate γ, price impact θ and sales inducement φ. In existing studies of FS models, most of which focus on a certain jurisdiction or time period but in an often data-rich environment within the scope, it is common to calibrate these parameters using estimates from granular security holdings or fund-level data. Portfolio overlap is often measured using granular security holdings data (Fricke and Fricke (2021), Caccioli, Ferrara and Ramadiah (2020)). The portfolio adjustment rate is often calibrated to the observed response of capital flows to changes in asset portfolio returns and capital flows, which has become a stylized fact in the mutual fund literature (Baranova, Coen and Lowe (2017), Sirri and Tufano (1998), Berk and Green (2004), Fricke and Fricke

(2021), Goldstein, Jian and Ng (2017)).[14] The price impact is often assumed to be a function of the Amihud liquidity ratio (Fricke and Fricke (2021), Baranova, Coen and Lowe (2017)) which is typically calculated by asset classes from security-level data.[15]

However, when the scope of entities is expanded to include those from many jurisdictions, this level of granular data is not available, so it is difficult to conduct the same type of calibration as in existing studies. In this paper, we do not let this data gap be the enemy of the greater good and make the measurement of the interlinkage effect operational by calibrating the FS model parameters from the estimated GFS, with some additional assumptions for pinning down $\gamma_{t,i}$ and $\theta_{t,i}$. Details of the calibration of the FS model parameters in this paper are described as follows.

First, degree of portfolio overlap $\omega_{t,i\to k}$ and sales inducement $\varphi_{t,i\to k}$ are calibrated to the correlation from the corresponding block of chart 6. For example, Fricke (2019) shows that the pairwise portfolio overlap calculated from security-level data is positively correlated with pairwise asset return correlations, so our calibration can serve as a reasonable approximation.

Second, as for the portfolio adjustment rate $\gamma_{t,i}$, conceptually this parameter governs how a type of entity adjusts its portfolio in response to an asset price shock. In practice, internal risk management practices differ across different types of entities. Therefore, we use entity i-specific information contained in the lower-left block of the connectedness table, which measures directional connectedness (correlations) from asset prices to transactions of entity i. More specifically, we calibrate the value of this parameter $\gamma_{t,i} = \sum_j \rho_{t,ij}/N$ to the average response (correlation) of entity i's transactions to various asset return shocks. This means entities respond in the same way to different price shocks and

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[14] For example, Baranova , Coen and Lowe (2017) uses a panel regression on Morningstar European fund-level monthly data on changes in total net assets and estimated net flows to pin down the fund-flow sensitivity parameters.

[15] Amihud ratio of asset k at time t is calculated as follows: $\text{Amihud}_{k,t} = \left|Return_{k,t}\right| / \text{DVolume}_{k,t}$, where $\left|Return_{k,t}\right|$ is absolute return and $\text{DVolume}_{k,t}$ is the total traded volume.

this degree of response also depends on the type of financial institution and jurisdiction. In practice, each type of entity in a jurisdiction can be considered to be different depending on the degree of leverage, the amount of capital, or risk management practices.

Third, although each entity holds distinct assets, the market response to asset sales should not depend on which entity actually sold the asset. Therefore, we assume that the impact of transactions to prices is a macro phenomenon, and take a sum of the total directional connectedness contained in this submatrix and allocate this according to the size of the observed volatility of asset price of each entity. In determining the allocation rule, we look into the findings of Chordia, Sarkar and Subrahmanyam (2005), which points out that the observed volatility of asset returns is positively correlated with illiquidity of assets. Given this insight, we assume that price impact $\theta_{t,i}$ is proportional to the observed asset return volatilities; we distribute total connectedness to each entity by the ratio of the observed volatilities of total asset prices -- more specifically, for the calibration of the price impact $\theta_{t,i} = \sum_i \sum_j \rho_{t,ij} \times \sqrt{\sigma_{t,ii}} / \sum_j \sqrt{\sigma_{t,jj}} \times 1/N$. As mentioned earlier, the impact of liquidity on prices by asset classes is often characterized in existing studies. In this paper, characteristics of an entity's asset holdings differ in terms of the composition of the asset portfolio, so this assumption can serve as an approximation. However, we do acknowledge that this assumption may be too strong, and thus perform a robustness check in the Appendix with minimal restrictions on the assumption regarding the calibration of the price impact. The qualitative features of the benchmark specification are unchanged under an alternative specification of the price impact.

5. Measurement of the Interlinkage Effect

This section goes over estimates of the interlinkage effect and relevant parameters for the domestic (Japanese) and foreign financial systems.

5.1. Portfolio Overlap

Our portfolio overlap $\omega_{t,i \to k}$ is a measure of common asset holdings that represents how similar asset portfolios are in terms of the market value of asset returns. The estimated results are summarized in chart 8, which makes a comparison with those before the GFC and before the March market turmoil of 2020. The thickness of a line shows the degree of portfolio overlap between two entities. Before the GFC, the degree of overlap was generally low except for the overlap between domestic (Japanese) and foreign investment funds. Since then, however, the portfolio overlap of all three types of entities in Japan with the other types has increased. The portfolio overlap of Japanese banks with foreign investment funds has increased in addition to domestic ICPFs. As a result of this global increase in portfolio overlaps, the impact of price changes resulting from the sale of assets of an entity is likely to be more widespread globally.

Developments in the degree of overlap concerning Japanese financial institutions (banks) show several characteristics (chart 9). First, the overlap with domestic ICPFs has clearly increased since 2013. This timing coincides with the period in which both Japanese banks and domestic ICPFs reduced the weight of JGB holdings and rebalanced their portfolios toward more risky assets. Second, the degree of overlap with foreign investment funds has also increased, where this is further decomposed into trend and cyclical factors. The trend factor can be attributed to the secular increase in Japanese banks' investment in foreign securities, and the cyclical factor reflects fluctuations in foreign investment funds' investment in Japan in response to market conditions. The latter suggests that, for example, changes in foreign investment funds' investment in Japanese equities may be a factor leading to increases or decreases in the degree of portfolio overlap with Japanese banks, which hold large amounts of strategic stock investments.

5.2. Portfolio Adjustment Rate

The portfolio adjustment rate $\gamma_{t,i}$ measures the flow-performance relationship of an entity i's asset portfolio. Estimation results of $\gamma_{t,i}$ show that they are the highest for foreign investment funds, followed by domestic investment funds, and they are low for ICPFs (chart 10). The rate for foreign investment funds has been rising since the mid-

2000s, which is consistent with the findings of Cetorelli, Duarte and Eisenbach (2016). This rise in foreign investment funds can also be interpreted as being in line with the findings of Fricke and Fricke (2021), which points out that investors are more responsive to fund performance in index funds and funds investing in illiquid assets. That is, the rise in the portfolio adjustment rate may reflect investors' increasing preference toward index funds, albeit at low transaction costs, or holding of illiquid assets by such funds (FSB (2020), ESRB (2020)).

In contrast, the portfolio adjustment rate for domestic investment funds has been on a downward trend, which is consistent with the data on investment trust redemption rates in Japan (chart 11). This likely reflects factors such as the increasing value of privately placed investment trusts, which tend to have lower redemption rates. An increase in the number of individual investors who prefer investing for the long term due to the implementation of various retail investment promotion policies, including the Japanese individual savings account (NISA, Japan's tax exemption scheme for investment by individuals) arrangement, could also have contributed to the secular downward trend in the redemption rate.

5.3. Price Impact

Price impact $\theta_{t,i}$ measures how much the amount of asset sales of an entity affects market prices and is estimated in the upper-right block of chart 6. In recent years, the degree of price impact has been on an upward trend for all entities and is the highest for foreign investment funds, while it is low for all three types of domestic entities (chart 9). The macro upward trend may reflect the increasing holdings of relatively illiquid assets under the accommodative financial conditions worldwide after the GFC (FSB (2020)).

5.4. Interlinkage Effect

Chart 12 shows the estimation results of the interlinkage effect. Conceptually, this corresponds to fire sale vulnerability metrics proposed in standard FS models. The benefit of measuring the interlinkage effect is to see how the overall tendency of this vulnerability has evolved in the financial system.

Comparing the estimated interlinkage effect for Japan and overseas financial institutions (banks), that for Japan is relatively low due to lower degrees of portfolio overlap. This may reflect differences in the structure of the financial system. That is, bank loans play a central role in credit intermediation in Japan, which is less susceptible to market shocks. The aggregate interlinkage effect faced by Japanese banks has increased significantly since 2018 due to larger contributions from foreign investment funds. The reasons for this are that (1) under the prolonged low interest rate environment, Japanese entities are actively investing in overseas risk assets and are increasing the degree of overlap of their portfolios with foreign investment funds, and (2) foreign investment funds, which are likely to be increasing their holdings of relatively illiquid assets, are now also actively investing in Japan. This implies that Japanese banks could face more spillovers from large redemptions at foreign funds triggered by market shocks. Decomposing the interlinkage effect faced by Japanese banks into their epicenter shows that the importance of foreign investment funds has been increasing.

Putting all these findings together, the results of how the interlinkage effect in the domestic and foreign financial systems overall have evolved is shown in chart 13. This indicates that interlinkage effects have risen substantially since the early 2010s both for domestic and foreign financial systems. It should be noted that the rate of increase in the interlinkage effect faced by Japan's financial system since the GFC is significantly higher compared to that in the U.S. and Europe. This suggests that, with increased holdings of illiquid assets, especially by NBFIs, the degree of portfolio overlap has risen globally, resulting in structural changes whereby a market shock in one part of the world may be amplified and spread globally, and thus Japan's financial system has deepened its interlinkage to the GFS.

5 Concluding Remarks

In recent years, a lot of work at central banks and academia has been devoted to measuring fire sale spillover of market shocks in a financial system at the jurisdiction level using FS models. Existing studies use granular data to analyze details of fire sale dynamics - the relationship between quantities and prices -; however, in most of these cases, the scope of analysis is focused on a certain jurisdiction or asset class where this type of data is available, and thus tends to leave cross-jurisdiction or cross-asset spillover dimension out of the scope.

With these difficulties in mind, in order to gauge the overall tendency of fire sale vulnerabilities at the global scale, this paper attempts to measure the "interlinkage effect" on how a negative asset price shock propagates in the GFS through transactions of various entities. We make the measurement of the interlinkage effect operational by calibrating the FS model parameters from the estimated GFS from flow of funds data with some additional assumptions.

We find that the interlinkage effect from investment funds has increased substantially, not only for Japan's financial system but also for various overseas financial system since the GFC. These increasing interlinkages of NBFIs with various types of entities suggest a global structural change in the transmission of market shocks.

The method developed in this paper can be used as a convenient tool to gauge the overall tendency of potential cross-border spillovers of market shocks in the GFS. To this end, the model can be extended in several dimensions. First, the universe of flow of funds data can be extended to include emerging economies. This will shed light on the interconnectedness of NBFIs and emerging economies. Second, the standard FS model in this paper is comprehensive and can be integrated into a macro economic model to explore the effects of policy interventions such as ex-post central bank interventions or ex-ante regulatory measures. Third, more work needs to be done on how the actual impact of market shocks in times of stress is related to the interlinkage effect.

From a macroprudential perspective, the FSB and various standard-setting bodies across jurisdictions have recognized that fundamental measures need to be taken and have started discussions to address the vulnerabilities related to investment funds and other entities. We hope our method contributes to a better understanding of the interconnectedness and propagation of market shocks and can serve as a step forward in overcoming difficulties associated with large data gaps.

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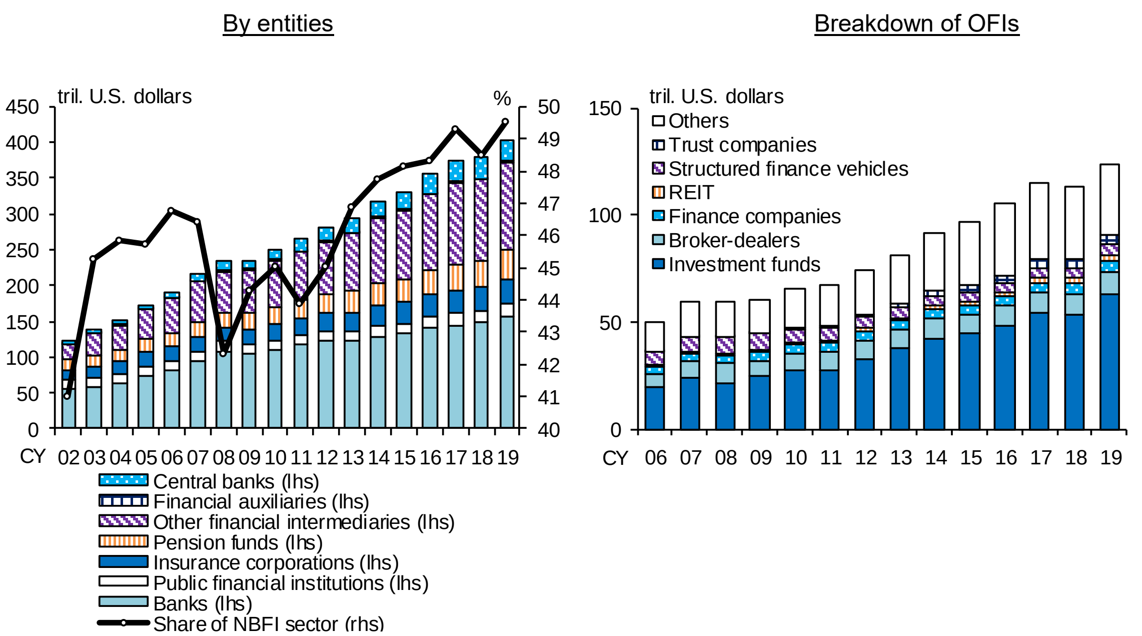
Chart 1: Global financial assets

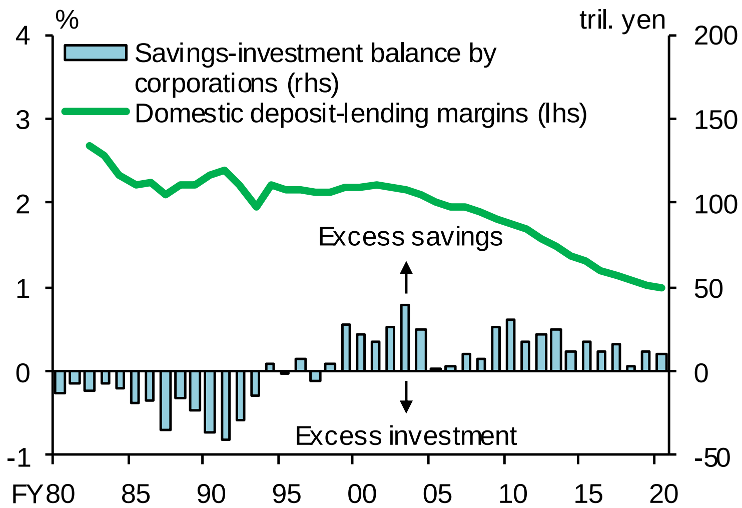


Note: 1. In the left-side panel, NBFI sector includes insurance corporations, pension funds, other financial intermediaries, and financial auxiliaries.

2. In the right-side panel, "OFIs" is other financial intermediaries. "Investment funds" includes hedge funds, money market funds, and other investment funds.

Source: FSB.

Chart 2: Deposit-lending margins among domestically licensed banks and excess savings by corporations

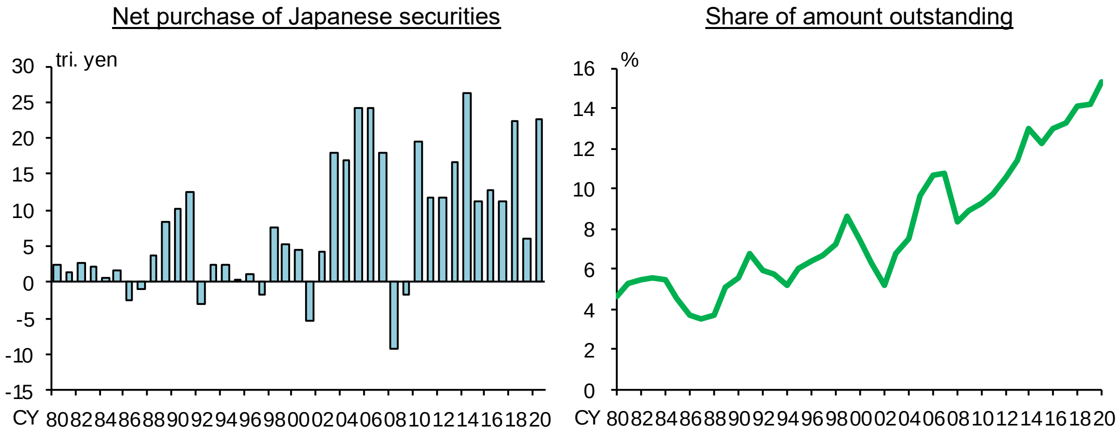


Note: 1. "Savings-investment balance by corporations" covers private nonfinancial corporations. "Domestic deposit-lending margins" covers regional banks.

2. Latest data as at fiscal 2020.

Source: BOJ.

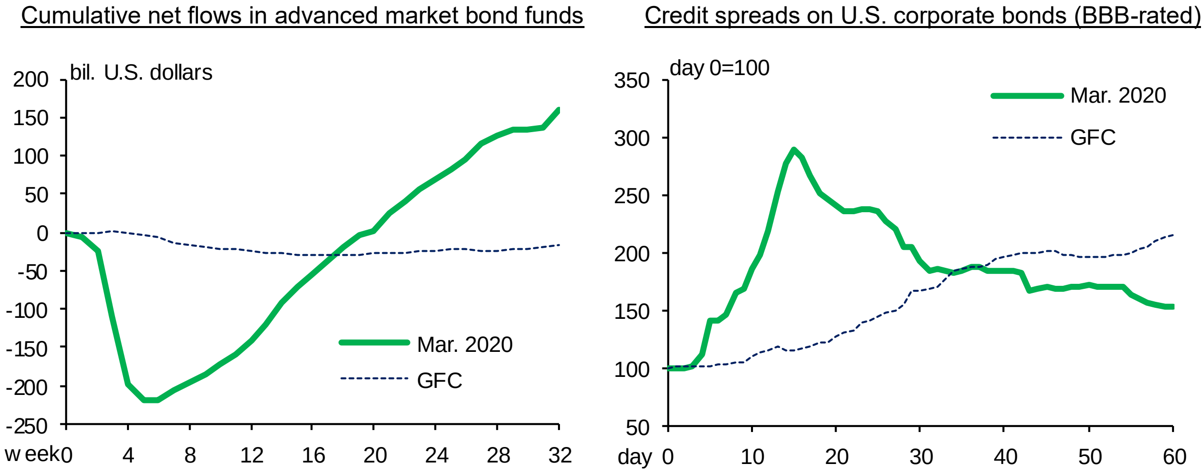
Chart 3: Japanese securities holdings by foreign investors



Note: Securities include equities, investment fund shares, and bonds issued by Japanese entities.

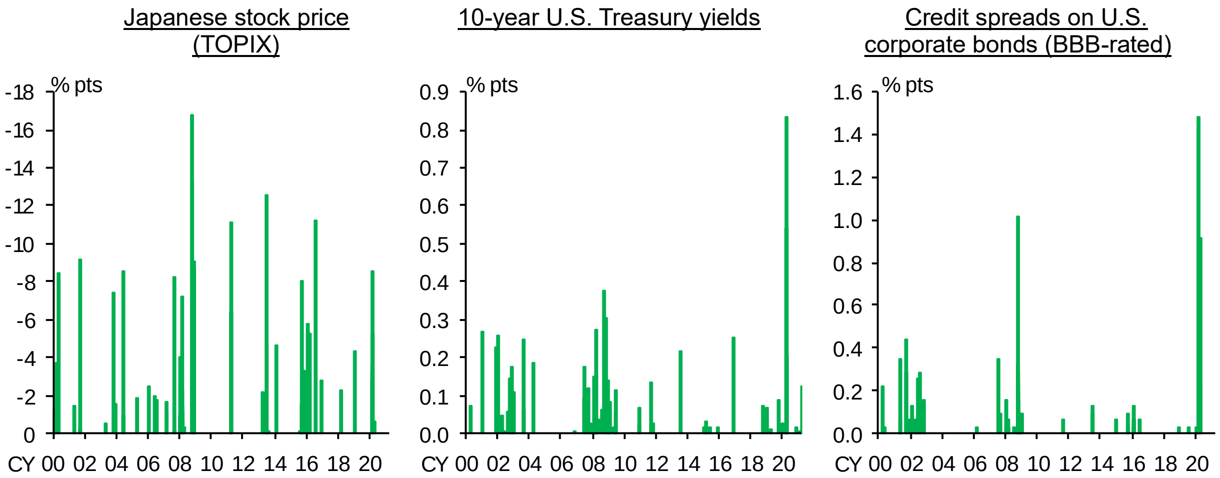
Source: BOJ.

Chart 4: Net flows in bond funds and credit spreads during March 2020 market turmoil



Note: Week 0 and day 0 of "Mar. 2020" and "GFC" are the beginning of March 2020 and September 2008, respectively.
Source: Bloomberg; EPFR Global; Haver Analytics.

Chart 5: Deviation from the historical Value at Risk (VaR)



Note: The graph shows the deviation of each index from the historical VaR with a 99 percent confidence level, 10-day holding period, and past 3-year observation period. Latest data as at March 31, 2021.
Source: Bloomberg.

Chart 6: Connectedness table of the estimated GFS

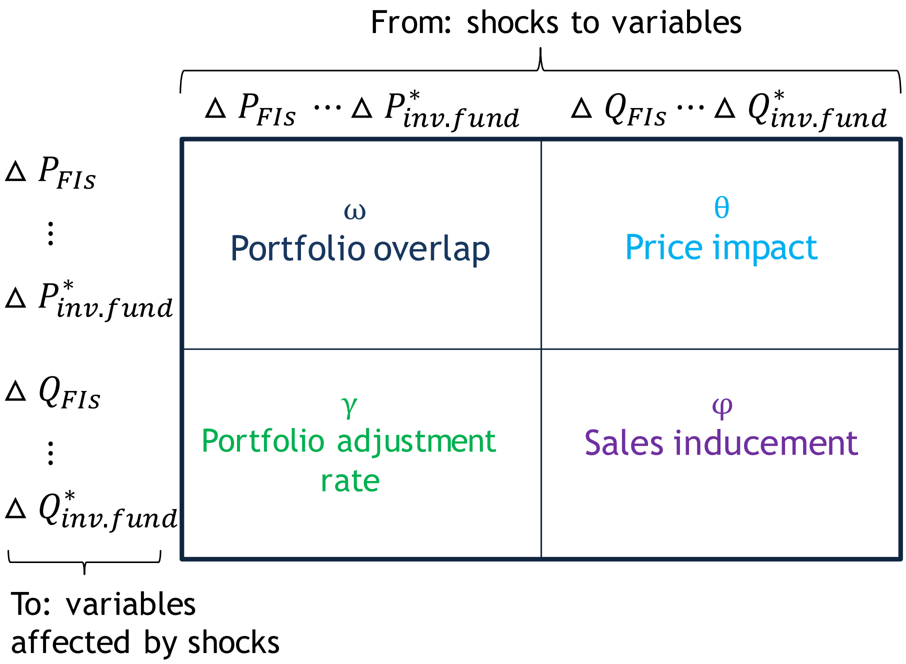


Chart 7: Fire-sale mechanism

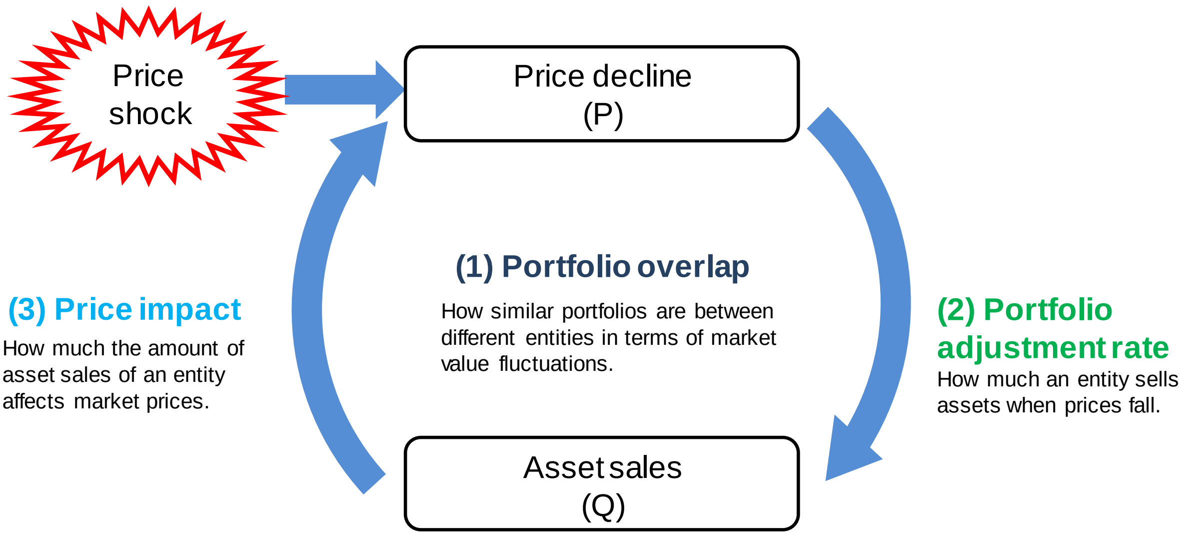
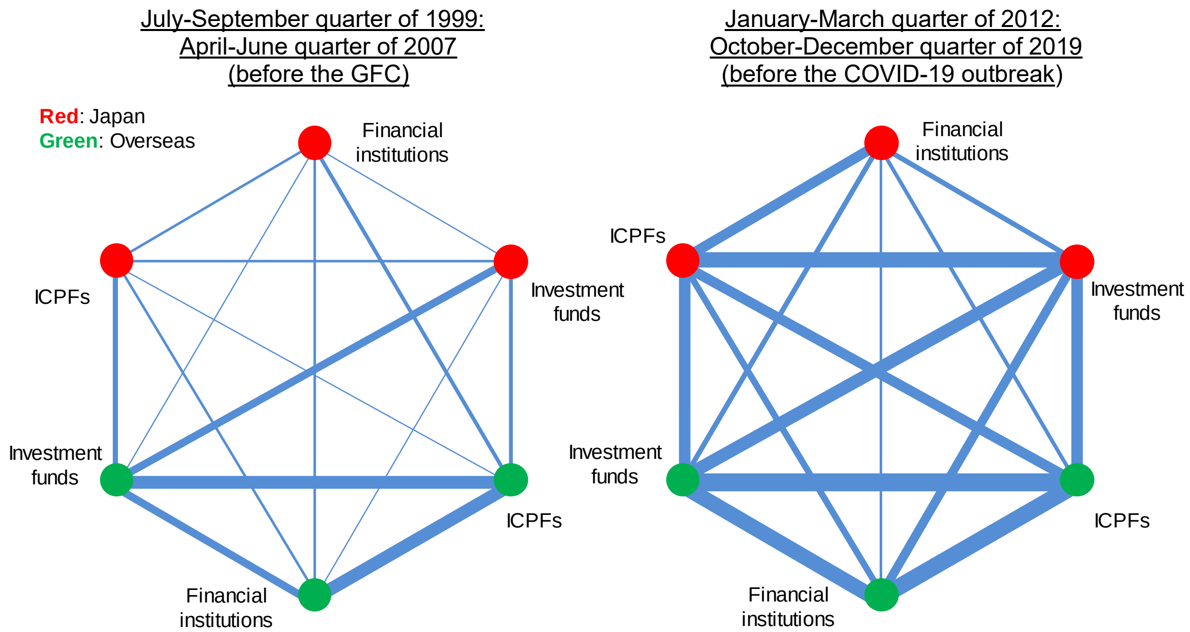


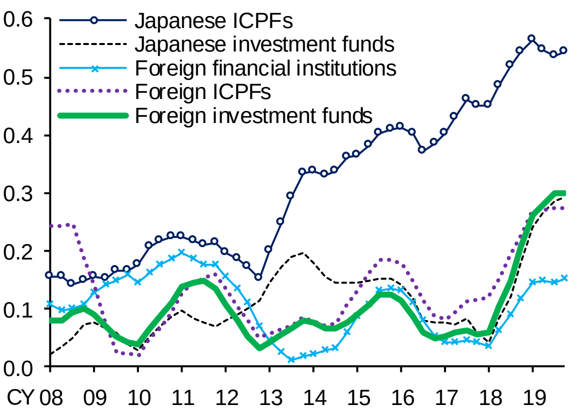
Chart 8: Portfolio overlap



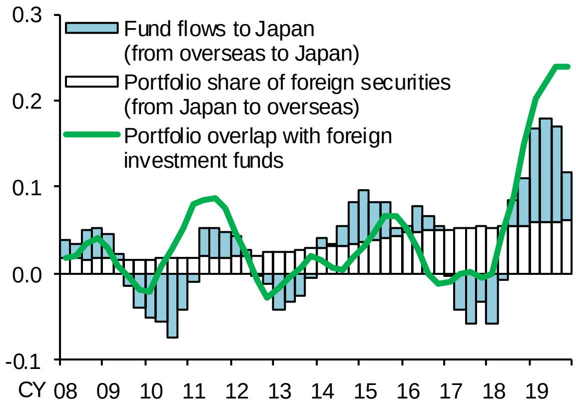
Note: The thickness of a line shows the degree of portfolio overlap between two entities.

Chart 9: Portfolio overlap between Japanese financial institutions and other entities

Linkage between Japanese financial institutions and other entities



Decomposition of linkage with foreign investment funds

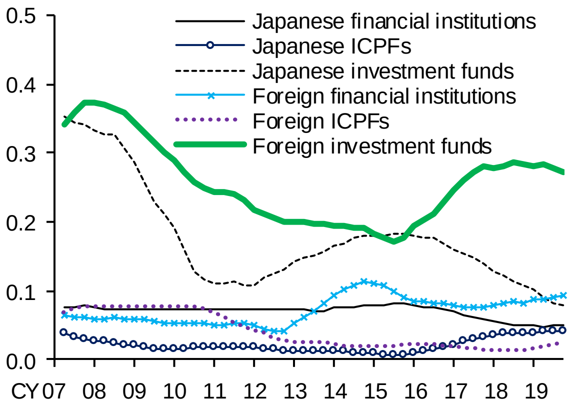


Note: 1. Portfolio overlap is 4-quarter backward moving averages. Latest data as at the October-December quarter of 2019.
2. The right-hand chart shows the decomposition of portfolio overlap between Japanese financial institutions and foreign investment funds into domestic and overseas factors by linear regression. As independent variables, the portfolio share of foreign securities of Japanese financial institutions and net fund flows to Japan are used. The chart excludes the contribution of the intercept.

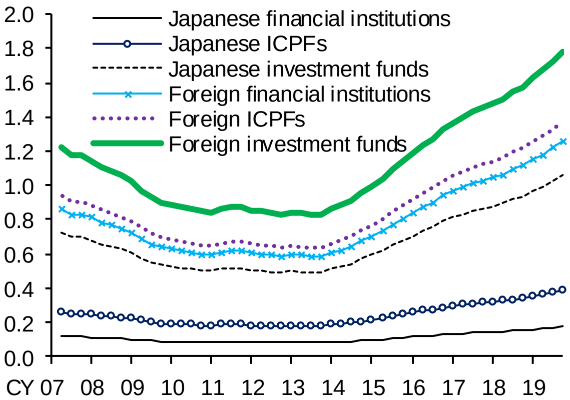
Source: EPFR Global; Haver Analytics; BOJ.

Chart 10: Portfolio adjustment rate and price impact

Portfolio adjustment rate



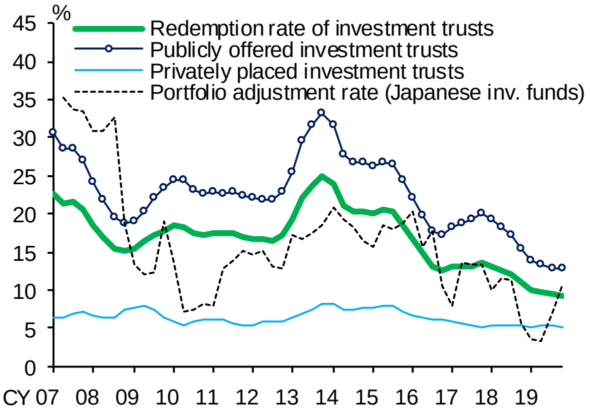
Price impact



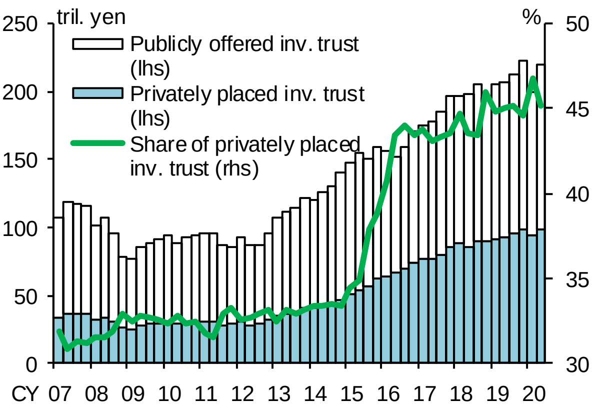
Note: The figures indicate elasticities. 8-quarter backward moving averages.

Chart 11: Portfolio adjustment rate and redemption rate of investment trusts in Japan

Comparison between the portfolio adjustment rate and redemption rate of investment trusts



Share of privately placed and publicly offered investment trusts

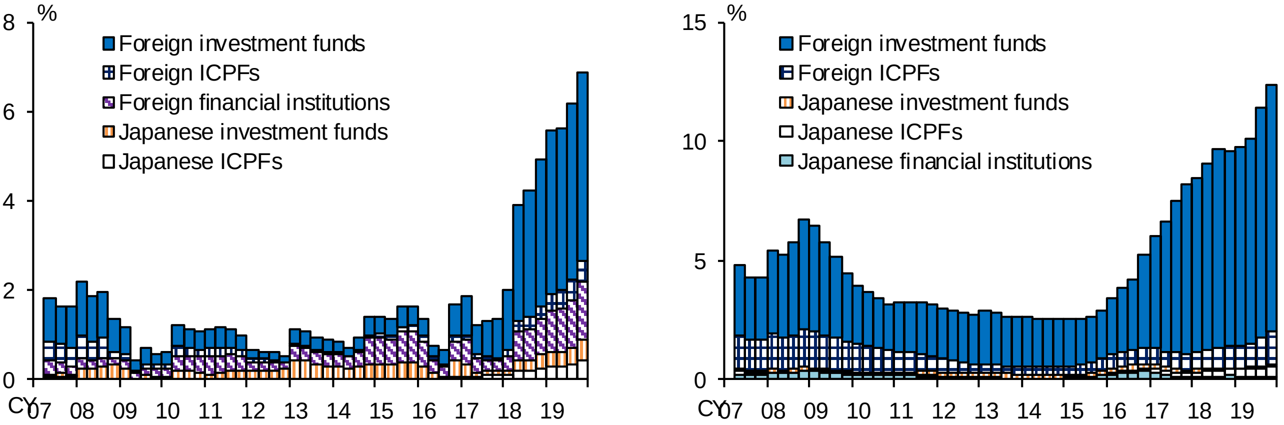


Note: The redemption rate in the left-hand chart is quarterly aggregate redemptions divided by total net assets at the beginning of the period. 12-month backward moving averages.
Source: The Investment Trusts Association, Japan.

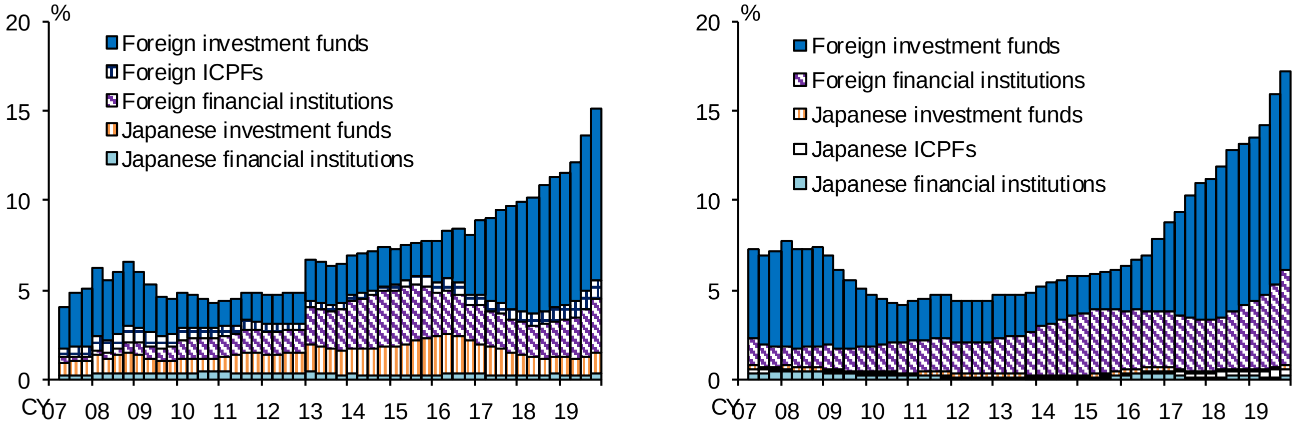
Chart 12: Interlinkage effect faced by each entity

Japan | Overseas

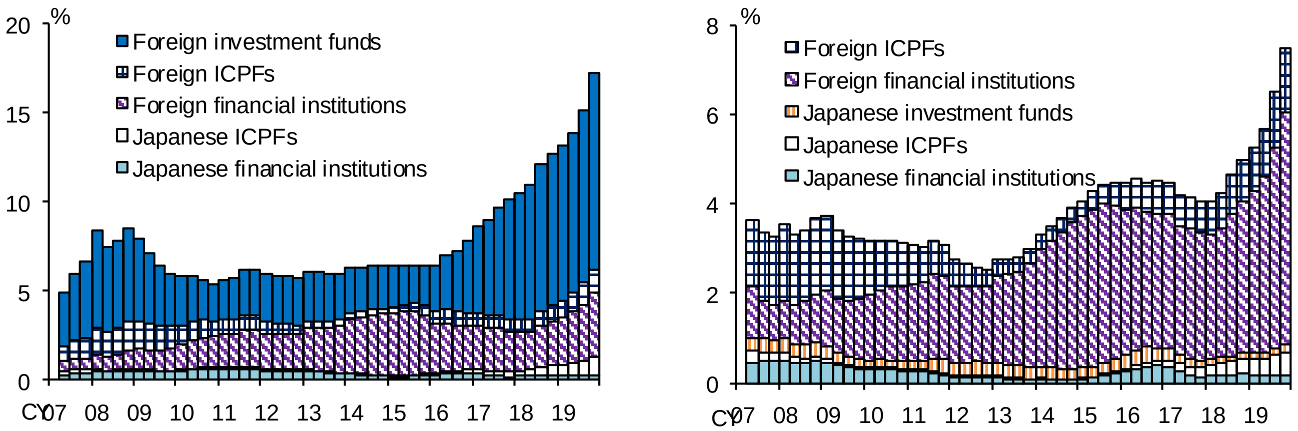
Financial institutions (banks)



ICPFs

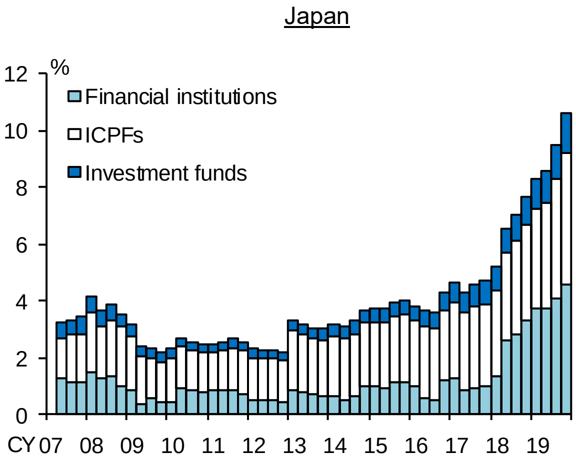


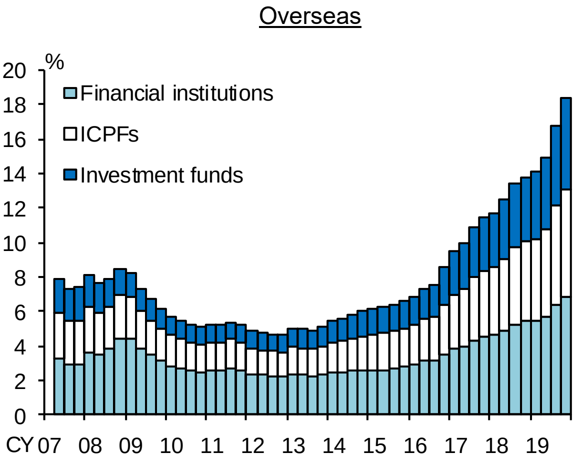
Investment funds



Note: 1. The interlinkage effect is the amplification mechanism of a price shock through transactions between entities, which shows how much one standard deviation price shock is amplified in terms of percentage.
2. Each panel shows the interlinkage effect faced by each entity described in equation (3).

Chart 13: Interlinkage effect faced by the aggregate financial system





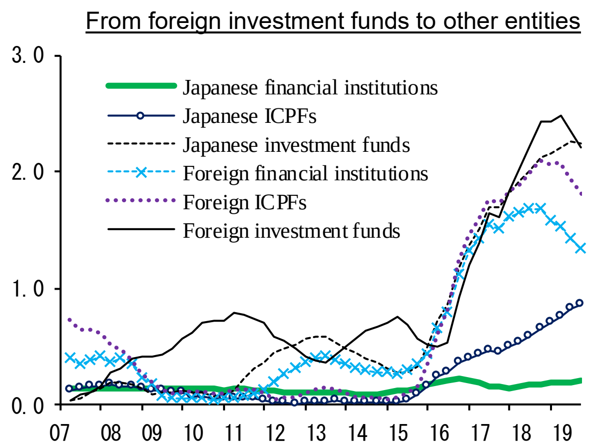
Note: The interlinkage effect faced by the aggregate financial system is calculated by taking the weighted average of interlinkage effects faced by each entity. The weight for each entity is based on the amount of total financial assets.

Appendix: Robustness Check

In this appendix, we check the robustness of our baseline results assuming that each pairwise directional connectedness in the upper-right block of the connectedness table in chart 6 represents the price impact itself. In the baseline specification, we focused on the insights of Chordia, Sarkar and Subrahmanyam (2005) and many other works in the literature that document the positive correlation between volatility of asset returns and liquidity of assets. Drawing on these findings, we assumed that price impact is proportionate to the observed volatility. Ideally, calibrating the price impact parameters with security-level data gives a precise measure of the impact; however, this level of granularity is not available on a global basis (Caccioli, Ferrara and Ramadiah (2020)).

One observation to note is that the price impact of foreign investment funds on other entities has risen in recent years (chart A-1). This could indicate that investment funds are holding more illiquid assets and have a bigger impact on other entities' portfolios when they sell assets. This, along with the rising portfolio adjustment rate (chart 10) and portfolio overlap, are the main drivers of the increasing interlinkage effect. Chart A-2 through A-4 compare the baseline results with the baseline specifications. It can be seen that the overall tendency is unaffected by the relaxation of our assumptions on the price impact, and therefore is robust.

Chart A-1: Price impact of foreign investment funds

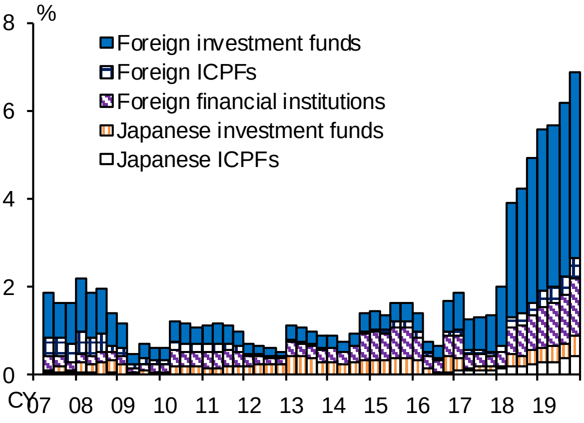


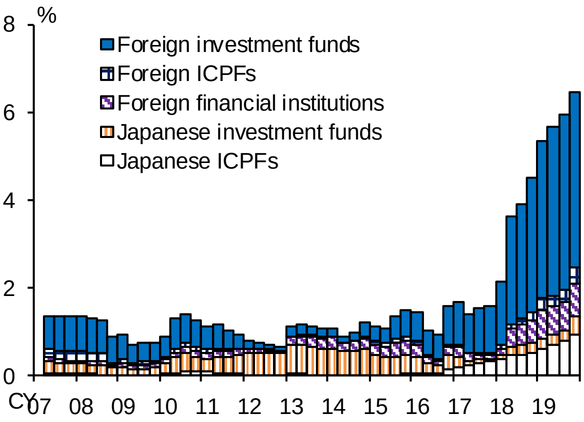
Note: The figures indicate elasticities. 8-quarter backward moving averages.

Chart A-2: Interlinkage effect faced by entities (Japan)

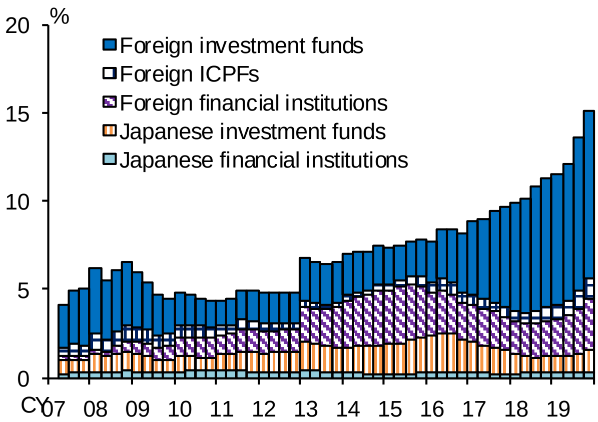
Baseline | Robustness check

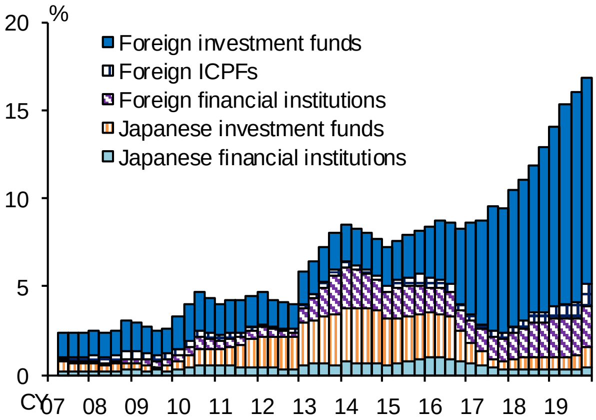
Financial institutions



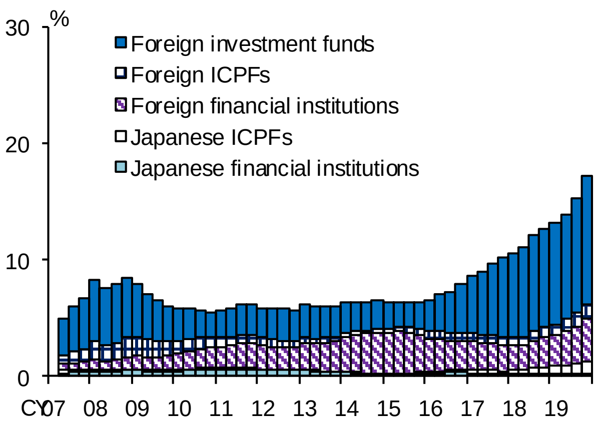


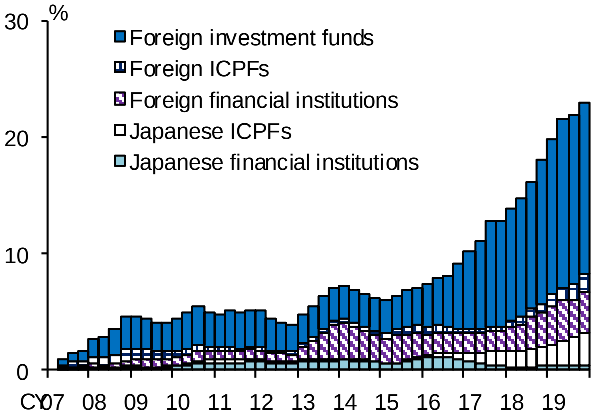
ICPFs





Investment funds



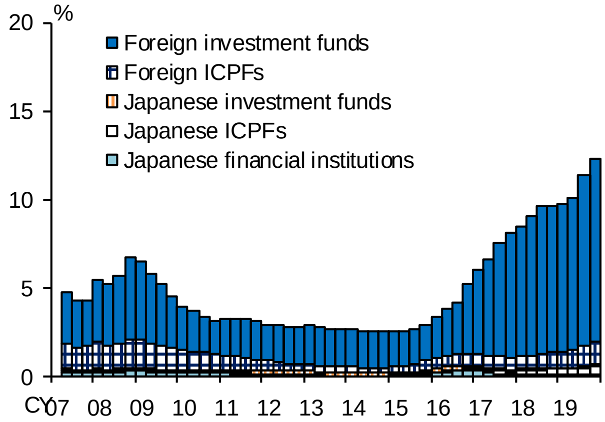


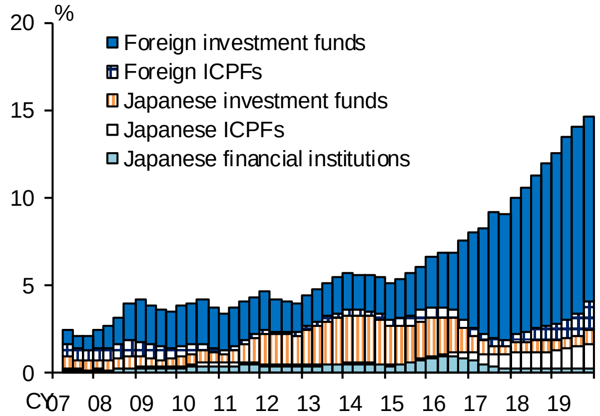
Note: 1. The interlinkage effect is the amplification mechanism of a price shock through transactions between entities, which shows how much one standard deviation price shock is amplified in terms of percentage.
2. Each panel shows the interlinkage effect faced by each entity described in equation (3).

Chart A-3: Interlinkage effect faced by entities (Overseas)

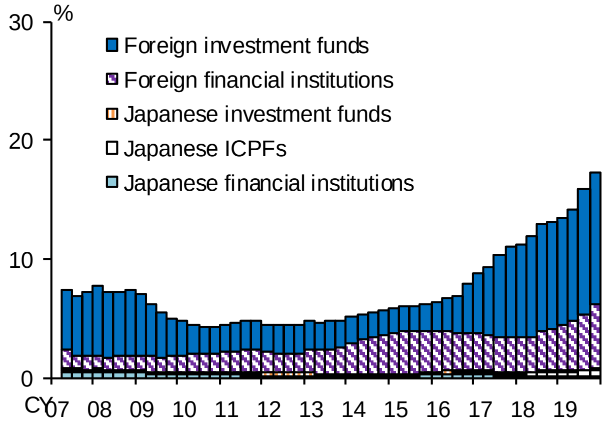
Baseline | Robustness check

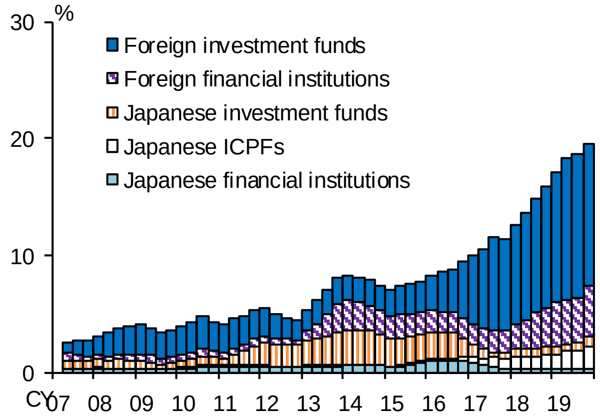
Financial institutions



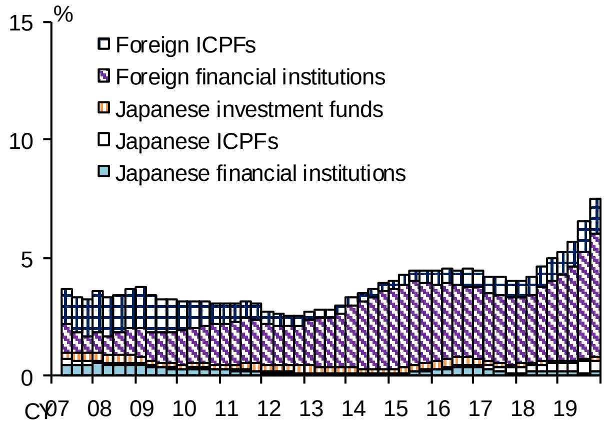


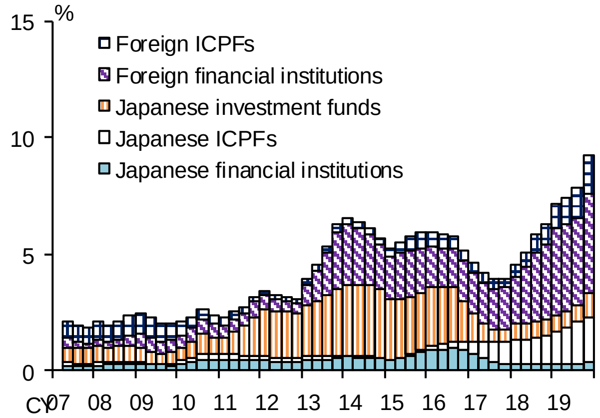
ICPFs





Investment funds



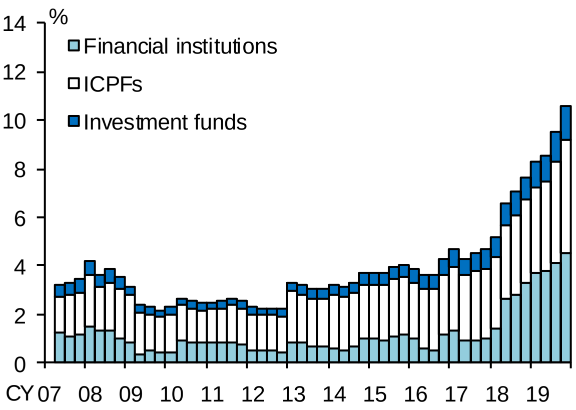


Note: 1. The interlinkage effect is the amplification mechanism of a price shock through transactions between entities, which shows how much one standard deviation price shock is amplified in terms of percentage.
2. Each panel shows the interlinkage effect faced by each entity described in equation (3).

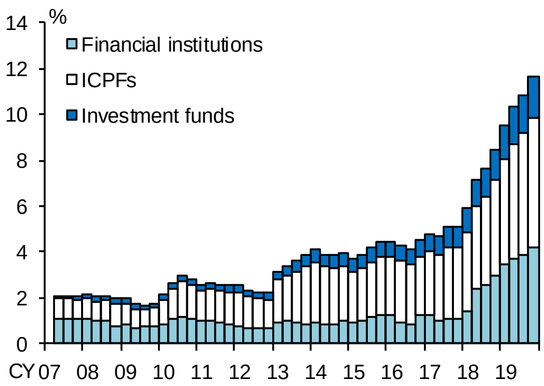
Chart A-4: Interlinkage effect faced by the aggregate financial system

<Japan>

Baseline

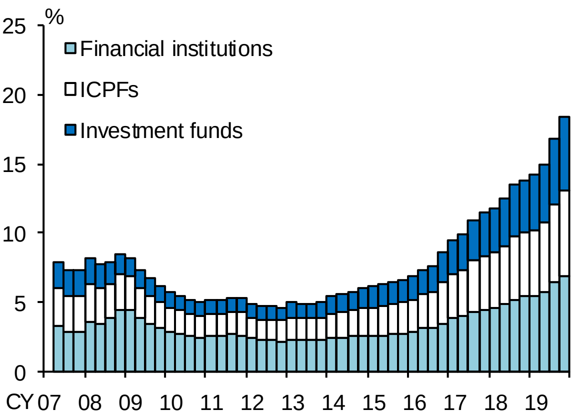


Robustness check

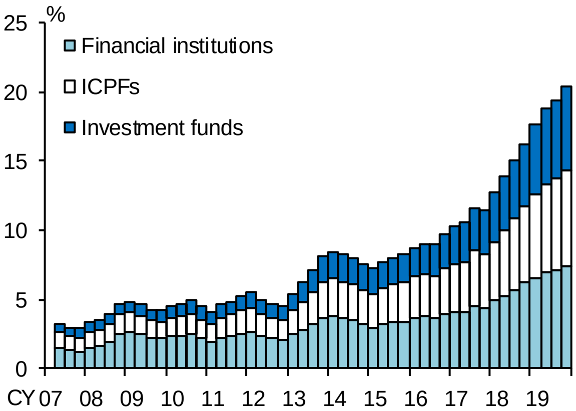


<Overseas>

Baseline



Robustness check



Note: The interlinkage effect faced by the aggregate financial system is calculated by taking the weighted average of interlinkage effects faced by each entity. The weight for each entity is based on the amount of total financial assets.