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Abstract

This paper investigates the interconnectedness among cross-border shadow banking systems using a broad measure of shadow banking defined by the Financial Stability Board. We find these interconnections are tenuous during tranquil periods, but the systems are significantly linked in times of tightening global liquidity conditions. The interconnectedness can be mostly explained by investors' search-for-yield behaviour, financial linkages between banks, capital stringency and demand from institutional investors. After controlling for effects of these driving factors, the interconnections are generally insignificant, except the shadow banking system in North America remains influential worldwide. The results reflect that the shadow banking system in North America cannot be explained by conventional risk factors as it is far more complicated than those in other economies. Our finding highlights that the spillover risk of shadow banking is not limited by national boundaries, which requires policymakers and regulators to co-ordinate closely with their foreign counterparts. It also draws a possible policy implication for introducing necessary macro-prudential policies, such as monitoring banks' exposures to shadow banking risk and ensuring adequate supply of alternative safe assets, to mitigate the risk of shadow banking being materialised.

Keywords: shadow banking, financial intermediation, interconnectedness, spillovers, Financial Stability Board.
JEL classification: C22, C23, G01, G23

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1. Introduction

The shadow banking system has brought benefits, such as expanding access to credit, supporting market liquidity and enhancing the efficiency of the financial sector, by enabling risk sharing and healthy competition for banks. These non-bank credit intermediaries, however, have also brought vulnerabilities and could become a source of systemic risk when they are involved in maturity or liquidity transformation, or a build-up of leverage. As demonstrated in 2008 during the global financial crisis, some shadow banking institutions, which were highly leveraged or had large holdings of illiquid assets during the crisis, were vulnerable to runs when investors withdrew large quantities of funds at short notice. This led to asset fire sales and helped spread the stress to other financial institutions and international financial markets. This rapid transcendence reflects a high degree of interconnectedness among these institutions and financial markets.[1]

This paper investigates the interconnectedness among shadow banking systems across the border. The interconnectedness can arise directly from financial linkages between systems across the border,[2] or indirectly from conventional banking activities where banks are globally interconnected, real sector linkages, or common risk factors. These increasingly complex linkages across markets and borders could make the transmission of shocks in the international financial markets and the pattern of risk dispersion more opaque, which creates uncertainty for governments and policymakers about where the ultimate risks lie. This paper aims to untangle this complicated network by measuring bilateral linkages between systems, or, more specifically, measuring the response of the asset growth in one system to the asset growth in another system. We use a broad measure of shadow banking defined by the Financial Stability Board (FSB), which covers major and emerging market economies. We also estimate the responsiveness given a hypothetical scenario of tightening global financial market liquidity to assess

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[1] Reportedly, global banks, insurers and asset managers had written down more than US$200 billion in losses by early 2009 from holdings of CDOs of asset-backed securities (ABS). According to IMF data, this amount shared 42% of their crisis-related losses. The CDO was one of these entities contributing to the subprime mortgage crisis, and thereafter the financial crisis, during which marked-to-market and later-realised losses raised solvency and liquidity concerns across the financial system. Briefly speaking, CDOs is a structural product that pools together cash flow-generating assets and repackages this asset pool into discrete tranches that can be sold to investors. Details of the discussion can be seen in the FSB document SCAV/2017/09.

[2] Financial institutions can be interconnected through: (i) exposure to common assets; (ii) marked-to-market losses triggered by fire sales; (iii) margin calls and haircuts; or (iv) crisis of confidence.

the risk of spillover during adverse liquidity conditions in global financial markets.[3] In addition, we identify major economy-specific and global factors as determinants of spillover risk among shadow banking. Through the assessment, we attempt to answer "how are shadow banking systems interconnected across borders?" and "what are the major factors behind these linkages?". This is with a view to providing policy insights for relevant regulators and policymakers.

There are several major findings in this study. First, we find that the interconnectedness between shadow banking systems is tenuous across the border during tranquil periods. However, the systems are significantly linked in time of tightening global liquidity conditions, which suggests a sharp increase in the risk of spillovers during adverse liquidity conditions. Second, the interconnectedness can be largely explained by several global and economy-specific factors, among which investors' search-for-yield behaviour, funding support from the banking sector, capital stringency and growth in institutional investors are the most important. After controlling for effects of these driving factors, the interconnections are generally insignificant, except the shadow banking system in North America remains influential worldwide. The results show the shadow banking system in that economy is far more complicated than those in other economies and so the system needs closer scrutiny.

The contributions of this study are threefold. First, this study is one of a few to examine interconnectedness of shadow banking in economies. Many studies focus on the effect of interest rate normalisation in advanced economies on the banking system and sovereign bond markets (e.g., Pozsar et al., 2013; Cetorelli, 2014; Fischer, 2015; Abad et al., 2017). However, only a few of them discuss the effect on non-bank financial intermediaries that are not subject to adequate regulations.[4] How these sectors would respond to tightening liquidity conditions, and how to oversee and regulate these sectors to improve transparency in the post-crisis era remains unclear in literature. Second, we use a representative dataset of shadow banking officially collected by the shadow banking experts group

[3] We use the stock volatility index of the US (VIX) to proxy the global liquidity conditions. The VIX is commonly regarded by market participants as a measure of global market liquidity and risk appetite of global investors. Forbes and Warnock (2012) argue VIX goes a long way in explaining the direction and movement of capital flows globally. Studies such as Bruno and Shin (2015) and Rey (2015) further argue VIX can be used to proxy for global liquidity conditions, with a declining VIX representing abundant global liquidity, and vice versa.

[4] There are many studies on shadow banking risk in the empirical literature. Major studies include Acharya et al. (2013), Fischer (2015), Lysandrou and Nesvetailova (2015), Pozsar et al. (2011, 2013), Schwarcz (2012), and Watkins (2011).

(SBEG), which is a working group co-ordinated by the FSB[5], that aims to improve data coverage for monitoring shadow banking developments and cross-economy consistency.[6] The data covers 28 reporting jurisdictions, unlike any single definition or measure of shadow banking to suffice for a particular risk dimension. Finally, we apply an empirically sound econometric method, which is the dynamic panel data regression estimated by generalised method of moment, to address concerns about the endogeneity among explanatory variables under a regression framework when identifying driving factors behind spillovers among shadow banking systems. Unlike the main stream of the empirical literature, our paper allows a separate set of driving factors for advanced and emerging market economies. The expectation is that policy implications for governments and regulators of the advanced and emerging market economies are different.

The paper is organised as follows. Section 2 gives an overview of global shadow banking. Sections 3 and 4 describe our data and methodology, and empirical findings respectively. The last section concludes.

2. Overview of global shadow banking

Some recent studies commonly define this intermediation by the nature of the market entity that carries it out (e.g., Acharya et al., 2013; Pozsar et al., 2013), in which the non-bank financial institutions behave similar to banks but are less regulated when conducting maturity, credit and liquidity transformation. Some examples of these entities include hedge funds, investment companies and brokers/dealers. By the nature of market activity, some studies define shadow banking as a chain of activities between financial institutions and other institutional sectors using a variety of financial instruments (e.g., Claessens and Ratnovski, 2014; Harutyunyan et al., 2015). These activities include securitisation, collateral services, banks' wholesale funding arrangements and deposit-taking and lending by non-

[5] A working group co-ordinated by the FSB has been engaged to monitor the development of the shadow banking sector since 2011. In this working group, there are 28 participating jurisdictions representing more than 80% of global GDP, of which 11 are EMEs and the rest are AEs.

[6] In this working group, group members have set up a framework to facilitate market surveillance of several types of shadow banking entities, including investment banks, money-market funds and securities markets.

banks. Other studies consider the nature of the entity and its activity as an alternative approach to define shadow banking, regardless of the fact that the definition could provide a more comprehensive consideration of shadow banking (Schwarcz, 2012; Gorton and Metrick, 2012; FSB, 2013).

Shadow banking is broadly defined as credit intermediation outside the conventional banking system. A specific measure for non-bank financial intermediation defined by the SBEG is called “MUNFI”, which is an abbreviation for monitoring universe of non-bank financial intermediation in the monitoring exercise of the SBEG. These non-bank financial intermediaries cover pension funds, insurance companies and other financial intermediaries (OFIs).[7] In particular, the assets of OFIs, which constituted about one-fourth of the total financial intermediation worldwide in 2015, are considered by the SBEG as the major sector in the shadow banking system (Figure 1). The sector has grown significantly (Figure 2), despite the higher level of scrutiny of shadow banking institutions following the financial crisis, with more than US$70 trillion in funds flowing through the system in 2015. These assets shared more than 150% of GDP in 2015 (Figure 3), during which OFI assets of advanced economies as a share of GDP were more than 250%. Among all entities of the OFI sector, investment funds, which are comprised of equity funds, fixed income funds and mixed/other funds (other than money market funds and hedge funds), have grown notably over the past decade (Figure 4). In 2015, this entity type shared the most in 2015, representing almost 40% of the total OFIs of all economies concerned. Broker-dealers were the second largest identified sector in 2015, but their share was largely steady in the past decade. In comparison, other entities’ share was smaller in 2015 and mostly varied within a narrow range.

Comparing individual economies, the asset size of OFIs in advanced economies is mostly larger than that in emerging market economies. Among all the economies, the OFI sector in the US is the largest (Figure 5), which was more than US$25 trillion in 2015. This economy, together with the United Kingdom and China, constitutes more than 50% of OFIs worldwide. In comparison, emerging market economies (highlighted in red bar) shared only 14% of OFIs, of which EMEs, excluding China, constituted only 3%. Despite this small share, their OFI assets have grown continuously since the global

[7] Other financial institutions related to shadow banking activities include money market funds, hedge funds, other investment funds (equity funds, fixed income funds, other funds), real estate investment trust and real estate funds, finance companies (or money lenders), broker-dealers and central counterparties.

financial crisis in 2008 (Figure 6). This higher pace of growth is also observed in small advanced economies such as Hong Kong (see the box study: “Shadow banking in Hong Kong and its growth determinants”).

The size of OFIs can provide a conservative proxy for the shadow banking system and its evolution over time to governments and regulators. From regulators’ perspectives, this specific measure is regarded as a broad measure of the shadow banking risk since it covers all areas where risks to the financial system might arise. The SBEG’s monitoring exercise also adopts a narrow-down approach to focus on subsets of these non-bank credit intermediations that are directly involved in significant maturity/liquidity transformation or leverage and are typically part of a credit intermediation chain. Under the narrow measure, assets of OFIs that are prudentially consolidated into banking groups or without any economic functions (EFs)[8] are removed. This EF-based approach allows for a more accurate refinement of the shadow banking measure, compared with the broad-based approach.

Based on this EF approach, the resulting asset size of shadow banking amounted to US$34.2 trillion at the end of 2015 in these economies (Figure 7), which was almost 50% down from the size of total OFI assets. Among all economies, the US has the largest shadow banking assets, which constituted more than 40.4% of the global shadow banking system at the end of 2015.

[8] These functions include: (i) management of collective investment vehicles with features that make them susceptible to runs; (ii) loan provision that is dependent on short-term funding; (iii) intermediation of market activities that is dependent on short-term funding or on secured funding of client assets; (iv) facilitation of credit creation; and (v) securitisation-based credit intermediation and funding of financial entities.

3. Data and empirical methods

3.1 Using the OFI asset sizes as a measure of shadow banking

To cast a wider net on shadow banking and to avoid data scarcity in estimation, we use OFI asset sizes as our measure of shadow banking in this study.[9] The sample consists of 27 economies, with Cayman Islands being excluded due to limited data availability in several major explanatory variables and unusual fluctuations in some available data, representing 80.6% of world GDP.[10] Eleven economies are EMEs and the remaining 16 economies are AEs (Table 1). The sample period of the annual data covers 2002 to 2015. During the period, the average OFI asset size is US$2.9 trillion (Table 2). This sector is smaller than the banking sector but is generally larger than other sectors of non-bank financial intermediaries. All the data is based on national authorities' submission to the FSB.

Table 4 summarises the results of the Augmented Dickey-Fuller (ADF) test for the time series of OFIs, GDP and bank size for each economy.[11] As can be seen, most of the OFI series is integrated of order 1 (i.e., I(1)), meaning that most of them are non-stationary in level but stationary in first difference, regardless of whether a time trend is added in the test or not. Some OFI series are I(2), which means their time series are not stationary, even though the order of differencing is 2 or higher. Focusing on the time series of GDP and bank size, results are quite similar, except that the time series of the bank size tends to be I(2) or higher.

Table 5 reports the results of the panel unit root test. Unlike the ADF test, the panel unit root test checks whether all the panels contain unit roots. As shown in the table, except for the institutional investors, all the variables are I(0), meaning these variables are stationary.

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[9] The narrow measure constructed by the SBEG provides a more accurate measure on credit and maturity transformation of entities in the sector. However, the data has two major limitations, including (i) the time series is only publicly available since 2010; and (ii) further refinement to the EF definitions remains under way.

[10] According to World Bank data, the world GDP amounted to US$74.758 trillion in 2015.

[11] Details of these empirical results are not reported in this paper but will be available upon request.

For the sake of consistency, we consider that all the OFI series and explanatory variables are I(1). This consideration would not be too restrictive since these time series commonly exhibit an increasing trend. Higher-order differencing is not suggested because it further reduces the information available in estimation and the non-stationarity cannot be removed when the series is heteroscedastic over time. In this study, we mainly focus on: (i) the growth rate defined by the first log differencing of the time series, in equation (1); and (ii) the time series level of OFI in equation (4).

Figure 8 presents a pairwise correlation matrix of OFI asset growths by economic region. Each bar represents the average correlations between two economic regions. For example, the average correlation between Asian developed and North American economies is 0.60, the average correlation between Asian emerging and North American economies is 0.52. Taking all regions into account, the average correlation between the North American and each of the regions is 0.60 (as reported in the parenthesis in the axis). As the correlation matrix is symmetric, we present the upper triangular part of the matrix for simplicity.

Considering all region pairs, the correlation is 0.45 on average, suggesting that OFI growths among these economic regions are substantially correlated. In particular, OFI growths in North American economies are strongly correlated, compared to other region pairs, with the correlation being 0.77. The North American economies have a stronger correlation with other regions in general, with the correlations ranging from 0.52 to 0.63. For Asia, the correlations are generally lower, with the average correlations being around 0.40. These results suggest that OFI growths in most economies are substantially correlated with those in North America.

3.2 Measuring cross-border linkages of shadow banking

Empirically speaking, we first assess the strength of financial links between economies during periods of normal and tightening liquidity conditions. This assessment aims to evaluate to what extent the stress in one shadow banking system could spill over to another shadow banking system during market turbulence. When the spillover effect is strong, the resulting effect would impose a global systemic risk to shadow banking, which would lead to widespread financial instability.

Specifically, we regress the time series of the OFI growth of the *i*-th economy (denoted by $\Delta OFI_{i,t}$) on the OFI growth of the *j*-th economy (denoted by $\Delta OFI_{j,t}$) and other variables:

$$\Delta OFI_{i,t} = \alpha_{i,j} + \beta_{i,j}\Delta OFI_{j,t} + (\delta_{i,j} + \gamma_{i,j}\Delta OFI_{j,t}) \times V_t + \theta_i \Delta OFI_{i,t-1} + u_{i,j,t} \qquad (1)$$

where $u_{i,j,t}$ is an error term, and the lagged term of $\Delta OFI_{i,t}$ is added to control for the second round effect of the OFI asset growth in the previous year. V_t is a dummy variable defined as 1 (0) when the global liquidity condition proxied by the level of the stock volatility index (or VIX) exceeds (lower than) a level of *k*, or specifically,

$$V_t = \begin{cases} 1, & if\ VIX_t \geq k \\ 0, & \text{otherwise} \end{cases}.$$

Based on this specification, the time series regression can measure to what extent the OFI growth of the *i*-th economy responds to that of the *j*-th economy during normal market conditions when the VIX level is smaller than *k*, and during adverse market periods with liquidity shocks when the VIX level is larger than *k*. More specifically, when the VIX level is smaller than *k*, Equation (1) can be simplified as

$$\Delta OFI_{i,t} = \alpha_{i,j} + \beta_{i,j}\Delta OFI_{j,t} + \theta_i \Delta OFI_{i,t-1} + u_{i,j,t} \qquad (2)$$

which models the bilateral relationship between $\Delta OFI_{i,t}$ and $\Delta OFI_{j,t}$ during periods of normal liquidity conditions. The constant term $\alpha_{i,j}$ and the slope $\beta_{i,j}$ measure the average $\Delta OFI_{i,t}$ and average responsiveness of $\Delta OFI_{i,t}$ respectively given $\Delta OFI_{j,t}$ during periods of normal market liquidity.

When the VIX level is larger than or equal to *k*, Equation (1) can be re-written as

$$\Delta OFI_{i,t} = \left(\alpha_{i,j} + \delta_{i,j}\right) + (\beta_{i,j} + \gamma_{i,j})\Delta OFI_{j,t} + \theta_i \Delta OFI_{i,t-1} + u_{i,j,t} \qquad (3)$$

which models the bilateral relationship during periods of liquidity shocks. The constant term $\alpha_{i,j} + \delta_{i,j}$ and the slope $\beta_{i,j} + \gamma_{i,j}$ measure the net growth and net responsiveness of $\Delta OFI_{i,t}$ respectively, other things being equal. The significance of $\alpha_{i,j}$ and $\beta_{i,j}$ are verified directly by t-test, while that of $\alpha_{i,j} + \delta_{i,j}$ and $\beta_{i,j} + \gamma_{i,j}$ are accessed by the Wald test in this assessment.

3.3 Potential determinants of asset growth in shadow banking

A determinant of asset growth in shadow banking, which is strongly linked across economies, could contribute to stronger cross-border linkages of shadow banking. The conventional banking sector is one of the examples since the sector is the major one to provide financial support to the shadow banking sector. Therefore, we identify potential determinants of asset growth in shadow banking in this analysis to help understand the potential determinants of spillovers among shadow banking systems.

Econometrically, we apply a linear dynamic panel data regression to an individual economy's data.[12] The method is a regression commonly used to analyse data collected over time (i.e., longitudinal dimension) and the same individuals (i.e., cross sectional dimension). In our context, the model specifically links the OFI assets to a group of driving factors relevant to financial sectors.

Specifically, we regress the OFI asset of the *j*-th economy at time *t*, denoted by $OFI_{j,t}$, on *K* driving factors, denoted by $MV_{j,t}^{k}$ (for *k* = 1,…*K*), or:

$$OFI_{j,t} = \theta_0 + \sum_{k=1}^{K} \theta_k MV_{j,t}^{k} + \gamma OFI_{j,t-1} + \epsilon_{j,t} \tag{4}$$

where $\epsilon_{j,t}$ is the residual of the model. In this specification, all variables are measured in log-level terms, so each coefficient of the factors is regarded in terms of elasticity, which measures how responsive the OFI asset is to change in each of the factors in percentage terms.

Several factors are considered important for the growth in shadow banking in the empirical literature, which include search-for-yield, capital stringency and demand from institutional investors. IMF (2014) offers the following explanations. First, the shadow banking system often supplies higher-yielding assets for investors compared with government bonds and the stock market, and therefore investors' search-for-yield behaviour could be key to the growth of shadow banking assets. Second, tighter bank

[12] More specifically, the model assumes that the unobserved panel-level effects correlate with the lags of the dependent variable. This model is an extension of the Arellano-Bond estimator that accommodates large autoregressive parameters and a large ratio of the variance of the panel-level effect to the variance of idiosyncratic error. This is known as the Arellano-Bover/Blundell-Bond system estimator. This estimator is designed for datasets with many panels and few periods. This method assumes there is no autocorrelation in the idiosyncratic errors and requires the panel-level effects to be uncorrelated with the first difference of the first observation of the dependent variable.

regulation encourages institutions to circumvent it through non-bank intermediation and promptly increases the shadow banking activities (Barth et al., 2013; Duca, 2016). Third, a stronger demand from institutional investors, such as pension funds and insurance companies, has often come along with a stronger asset growth of investment funds and other non-bank intermediations in emerging markets. The growth in shadow banking grew from the demands of institutional cash pools for alternatives to insured deposits and safe assets in some advanced economies. Apart from these factors, our estimation also includes sizes of the real sector and banking sector in each economy. That is because an economy with sound economic fundamentals and stronger funding support from the banking sector is expected to be associated with a stronger growth in shadow banking (Watkins, 2011; Barbu et al., 2016).

According to these considerations, we use the following factors in our estimation. The search-for-yield factors, which would be associated with investment returns and cost of funding, are considered in this study. They include:

(i) MSCI World Index – it checks whether favourable market performance, measured by the MSCI level, can correlate with more OFIs growths.

(ii) Real short-term rate – it tests whether the cost of funding, compiled from sovereign zero coupon yield and inflation in each jurisdiction, has any effect on the scale of OFIs. Theoretically, fund investors shift their portfolio investments more into equity markets/OFIs when real interest rates are lower.

(iii) Term spread – it tests whether the increase in term spread, measured by the difference of two-year and 10-year sovereign zero coupon yields, has a direct effect on the size of OFIs. The term spread is used to capture search-for-yield factors and business cycles. Some studies argue that, at least in the US, other effects related to the quantitative easing by the Federal Reserve have played a role in this period (Pozsar et al., 2011, 2013).

The factors of capital stringency include:

(iv)Top-three-bank concentration ratio[13] – it tests whether a higher concentration in banking sector discourages investment in OFIs. The variable is the ratio of the assets of a country's three largest banks to the assets of all commercial banks in that country. The top three bank concentration ratio is used to capture the risk-taking incentives in the banking sector. The intensity of competition in the banking sector, which is usually measured by the inverse of the concentration ratio, is considered one of the major determinants of bank risk-taking. The conventional concentration-stability predicts large banks in concentrated markets are more efficient and better diversified, and have larger charter values at stake. They are less inclined to take excessive risks, so the financial products they provide may not be sufficient to fulfil the investment need. This might trigger demand for shadow banking sector products. Furthermore, it is easier for regulators and market participants to monitor the health of a few large banks than many small banks. In short, the conventional view asserts that there is a negative correlation between competition and financial stability.

(v) Financial Freedom Index[14] – it tests whether banking efficiency affects growth in OFIs. The Financial Freedom Index is an indicator of banking efficiency and a measure of independence from government control and interference in the financial sector. State ownership of banks and other financial institutions, such as insurers, reduces competition and generally lowers the level of access to credit. The index scores an economy's financial freedom by looking at five areas: (1) the extent of government regulation of financial services; (2) the degree of state intervention in banks and other financial firms through direct and indirect ownership; (3) government influence on the allocation of credit; (4) the extent of financial and capital market development; and (5) openness to foreign competition.

(vi)Rule of law index[15] – to test the effect of the independence of the legal system and the quality of institutions that protect property rights on the stringency of capital regulations on the growth in OFIs. It reflects perceptions of the extent to which agents have confidence in, and abide by, the rules of society,

[13] The data is from the Financial Development and Structure Dataset. For details, please see http://www.worldbank.org/en/publication/gfdr/data/financial-structure-database.

[14] The data is from the Heritage Foundation. For details please see http://www.heritage.org/index/book/methodology.

[15] The data is from the Worldwide Governance Indicators (WGI) project. For details please see http://info.worldbank.org/governance/wgi/index.aspx#home.

and, in particular, the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.

(vii) The factors of economic fundamentals, funding support from the banking sector, and demand from institutional investors include:

(viii) GDP – it measures the size of the real sector of an economy and examines whether the local business cycle has any influence on the growth of OFIs.

(ix)Bank size – it is measured by assets of banking sector size for each jurisdiction. Some studies indicate that banks have sponsored shadow banking activities (Mandel et al., 2012).

(x) Asset size of institutional investors – which is measured by the size of pension funds and insurance companies for each jurisdiction. Stronger growth of institutional investors is associated with higher growth in shadow banking, consistent with complementaries and demand-side effects. Alternatively, this could reflect a general trend in financial development.

Tables 2 and 3 summarise major statistics (e.g., mean, median) of these variables and the correlations among these variables. Note that we add the alternative measure of regulatory factor into the regression to test the effect of regulatory arbitrary, but do not introduce all the variables of regulatory arbitrary at the same time to avoid concerns over endogeneity in estimation since they appear to be highly correlated.

4. Empirical results

4.1 How are shadow banking systems interconnected across borders?

We first estimate Equation (1) for each economy pair. In estimation, the threshold *k* is chosen to be the third quartile of the VIX level, which assumes a probability of 25% that the global liquidity condition goes beyond the VIX level. From a historical perspective, the assumption is considered useful to detect adverse market conditions seen in 2007, 2008 and 2011, when global financial markets underwent the global financial crisis and European debt crisis. Data of OFI assets is obtained from the Global Shadow Banking Monitoring Report 2016 of the FSB, while other macroeconomic and financial data is obtained from Bloomberg.

Table 6 summarises the estimated coefficients of α, β, α + δ, and β + γ in four matrices reported in four panels. Lagged OFIs is dropped from Equation (1) since it is statistically insignificant most of the time.[16] To simplify our discussion, we report our estimation results by geographical region: (1) Asia developed; (2) Asia emerging; (3) emerging Europe, Middle East and Africa (EMEA); (4) Europe developed; (5) Latin America; and (6) North America (Table 1). We report the average value of the estimated coefficients in each cell of the tables. For instance, the estimated coefficients α and β in the first row "Asia developed" and third column "EMEA" are found to be 0.07 and 0.25 respectively. They represent, on average, a constant growth of seven percentage points in the OFIs of an Asian developed economy, with an additional response of a 25-100 percentage-point increase in OFI assets of an EMEA economy. Note that these changes are on a yearly basis and insignificant coefficients at a 10% level are assumed to be zero when averaging.

As shown in the first panel, most of the estimated coefficient α are positive with an average of 0.08, reflecting that the OFI assets of an economy have an annual constant growth of eight percentage points on average, although it is statistically insignificant. In particular, Asian emerging economies have the largest average growth in OFI assets (24 percentage points). The growth in European developed and North American economies are much smaller (two and three percentage points respectively). This indicates that the OFI assets in Asian emerging economies tend to have stronger growth during periods of normal market liquidity, compared to developed markets.

Regarding the responsiveness of economies reported in the second panel, the coefficient β is estimated to be 0.31 on average. This suggests that a 100 percentage-point increase in the OFI assets of one economy would increase the growth in the OFI assets of another economy by 31 percentage points on average, other things being equal, although the estimate is statistically insignificant. Among all regions,

[16] Relevant empirical results are not reported but will be available upon request.

the responsiveness of an economy to North American economies is found to be larger with an average responsiveness of 0.64 (see the column average under North American), reflecting that OFI asset growths of North American economies have a stronger influential power than others in general. In contrast, the average responsiveness to changes in Asian emerging economies are the smallest (i.e., 0.09), reflecting that the influential power of Asian emerging economies are ceteris paribus smaller.

Given a high VIX level, the estimated constant growth (i.e., sum of α and δ) in the third panel drops to 0.02 on average, although the estimated one for Asian emerging economies remains notably positive at 0.16. The results revealed that, during adverse liquidity conditions proxied by the high VIX level, the constant growth in the OFI assets of an economy would slow to two percentage points, except that Asian emerging economies remain responsive to other economies, other things keeping constant.

Furthermore, the estimated responsiveness (i.e., sum of β and γ) increases sharply to 1.10 on average under the high VIX level (see the fourth panel). The estimate is statistically significant, suggesting that a 100 percentage-point increase in the OFI assets of one economy would increase the OFI assets of another economy by 110 percentage points. Comparing the responsiveness of all economies (i.e., row average), the strongest one is found in Asian emerging economies with an average responsiveness of 1.89. The weakest one is found in European developed economies with an average responsiveness of 0.54. Comparing the influence of all economies (i.e., column average), developed economies appear to be more influential than emerging markets, as the average responses to changes in Asian developed, European developed and North American economies are more than unity (i.e., 1.26, 1.48 and 1.41 respectively).

The above results suggest that, while the association of OFI growth between economy groups might be immaterial in normal time, the spillover effect during illiquid market conditions could be substantial. This shows that risks in shadow banking could be systemic in times of shrinking liquidity, during which the collapse of OFI sectors in one region could trigger the shrinkage of OFI sectors in other regions.

4.2 What are the major driving factors behind linkages?

4.2.1 Attributions of economy-specific and global risk factors to the growth in shadow banking

In estimating Equation (4), the estimation sample is divided into developed and emerging market countries. There is an expectation that the relative importance of common factors will vary by the level of economic and financial developments in the shadow banking systems. Apart from economy-specific and global factors, we add a lagged term of OFI assets to the regression as a control variable for the second round effect of the system. The estimation results of Equation (4) based on all economies (columns 1 to 3), AEs only (column 4), and EMEs only (column 5) are reported in Table 7.

Focusing on the regression results in column 1, which reports the regression of the OFI assets of all economies on banks' concentration apart from other variables, the within R-Squared is 0.83. This means the explanatory power of the regression is reasonably high. The Sargan statistic is large enough to reject the null hypothesis of over-identifying restrictions on the instrumental variables of the panel data regression, which means the estimated panel data regression is adequate for explaining the OFI assets at any reasonable level of significance.

Except for the factors of GDP, real short-term rate, and term spread, all the other factors have significantly positive effects on OFI assets. The results suggest that higher investment returns, stronger demand from institutional investors and funding support from the banking sector but tighter capital stringency would complement a stronger growth in shadow banking assets. Among these variables, the coefficient of the MSCI world index is the largest, reflecting that investors' search-for-yield behaviour, led by higher investment returns, is the key to the growth of shadow banking among all the factors. Based on two alternative proxies for capital stringency (i.e., columns 2 and 3), these results remain largely the same except that the variable of rule of law index contributes insignificantly to the OFI assets, albeit marginally.

When estimating AEs and EMEs separately, we find that the relative importance of the driving factors for their asset growths is different to some extent. Focusing on the results for EMEs (i.e., column 4), the variables of the MSCI world index, size of banking sector and bank regulations are the main attributes of the OFI assets. This reflects that the growth of shadow banking in EMEs is mainly driven by investment returns, funding support from the banking sector and capital stringency. For AEs (i.e., column 5), most of the risk factors have a similar attribution to the OFI assets with the size of institutional investors being slightly larger. This reflects that the shadow banking growth in AEs cannot be explained solely by any single risk factors and economy-specific and global risk factors play an equal role in driving the growth in shadow banking.

4.2.2 Can these factors fully explain the spillover effect?

In this section, we re-assess the spillover effect based on an adjusted asset growth in shadow banking by the driving factors in Equation (4). Specifically, we regress the OFI growth on the determinants using Equation (4) and then extract the residuals. We repeat the procedure in session 4.1 to access the spillover effect by the above residuals. In theory, when the residuals are not correlated across economies, there is no spillover effect across residuals and the spillovers of OFIs are all through significant driving factors in Equation (4). When the correlations among residuals are significantly different from zero, part of the spillover of OFIs could be through channels other than the driving factors.

Figure 9 depicts the pairwise correlations between the adjusted OFI asset growths. As can be seen, the average pairwise residual correlation decreases notably to 0.13. With this immaterial correlation, the driving factors in Equation (4) can be regarded as major driving factors of the spillover effect overall. Comparing individual regions, however, North American economies tend to have a higher residual correlation with other regions, especially the EMEA. The findings suggest that North American economies could be systemic when there is unexpected liquidity shock originating from these economies.

Table 8 summarises the estimation results by the adjusted OFI growth (residual of Equation 4). As can be seen, both estimated coefficients, α and $\alpha + \delta$, decline notably to 0.00 and -0.01 on average with z-statistics of -0.08 and -0.14 respectively, reflecting that the residuals are statistically zero in mean during the whole sample periods. The estimated β and $\beta + \gamma$ are 0.17 and 0.14 respectively on average with z-statistics of 0.55 and 0.23 respectively, which means the responsiveness is statistically insignificant at any conventional level during the periods. When focusing on results of individual regions, economies are more responsive to North American economies, given that the column averages of β and $\beta + \gamma$ are 0.71 and 0.92 respectively. This suggests that North American economies are influential among all regions.

The above results demonstrate that the spillover effect of OFI growth across economy groups could be substantially filtered by the determinants of OFI growth. In particular, it shows that, after controlling the determinants, the interconnectedness among shadow banks is significantly reduced to an immaterial level in general. Comparing individual economies, these factors, however, may not fully explain some spillover effects originating from North American economies since its effect remains influential for other regions in transmitting risks of shadow banking.

5. Conclusion

This paper provides an overview of shadow banking in numerous economies and investigates their interconnectedness. We find shadow banking systems are highly interconnected across borders in times of tightening global liquidity conditions. Their interconnectedness is largely through the economy-specific and global risk factors concerned in this analysis. In particular, investors' search-for-yield behaviour, driven by investment returns, funding support from the banking sector, capital stringency and demand from institutional investors, are the key determinants. Comparing economies' spillover effects, the systems in European and North American economies are the most influential, while those in Asian EMEs are the most responsive. After controlling for the effect of driving factors, the shadow banking system in North American economies remains notably influential worldwide. This reflects that the shadow banking system in these economies is far more complicated than those in other economies, as conventional risk factors can only partially explain their contributions to the risk of spillovers.

Our finding highlights that the spillover risk of shadow banking is not limited by national boundaries, which requires policymakers and regulators to co-ordinate closely with their foreign counterparts. It also draws a possible policy implication for introducing necessary macro-prudential policies (including monitoring banks' exposure to shadow banking risk and encouraging supply of alternative safe assets) to mitigate the risk of shadow banking being materialised. In light of these findings, the role played by the sector of shadow banking should require a higher level of scrutiny.

Several caveats merit attention. First, our measure of shadow banking activities focuses on financial intermediations operating primarily outside banks and therefore it may miss out part of those activities that operate in banks (e.g., liquidity puts to securitisation SIVs and collateral operations of dealer banks, repos) and results in underestimating the potential systemic risk.[17] Second, since the time series data is relatively short, robustness of these empirical findings may be highly subject to the validity of assumptions implicitly made in the empirical models. In particular, the study may not fully overcome potential endogeneity problems, and the results should be interpreted primarily as correlations, although many of the findings are consistent with causal interpretations as discussed above. Finally, the shadow banking defined by the SBEG in this study is a broader and conservative measure based on data of FSB jurisdictions. Therefore the results may not be appropriate for interpreting individual economies and non-FSB jurisdictions. Further research is therefore needed to assess the importance of the phenomenon when considering the policy implications of our findings.

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[17] This observation is also consistent with findings in Pozsar and Singh (2011) and Cetorelli and Peristiani (2012).

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Appendix

Box 1. Shadow banking in Hong Kong and its growth determinants

This box provides an overview of Hong Kong shadow banking and its growth determinants. We consider two measures of shadow banking in this study defined by the SBEG of the FSB. The first measure is the size of OFI assets, which is regarded as a broad measure to cast a wide net on shadow banking.[18] The second is a subset of the first that focuses on the assets directly involved in significant maturity or liquidity transformation, or leverage and are typically part of a credit intermediation chain, but not prudentially consolidated into a banking group.

Hong Kong's shadow banking data is sourced from various authorities.[19] The supervisory data is contributed by Financial Services and the Treasury Bureau (FSTB),[20] the Hong Kong Monetary Authority (HKMA),[21] the Hong Kong Mortgage Corporation (HKMC),[22] Insurance Authority[23] and the Securities and Futures Commission (SFC).[24]

I. Overview of Hong Kong shadow banking

Based on the broad measure, the size of the shadow banking sector in Hong Kong is quite small, when comparing its asset size with that of other economies and the Hong Kong banking sector. As shown in Figure B1, at the end of 2015, OFIs in Hong Kong amounted to US$249 billion, which is 0.2% of the total OFIs of all economies concerned and ranks 21st out of 27 economies with the US being the first in the economy list. The ratio of these assets to Hong Kong's GDP was 77%, but it is much smaller than the ratio of Hong Kong banking sector assets to Hong Kong's GDP, which was 830%.

These OFI assets have increased markedly over the past 14 years, but, since 2008, the pace of growth is generally similar to that of banking sector assets in Hong Kong. As a percentage of GDP, OFI assets increased substantially from 13% in 2002 to 60% in 2008 before the global financial crisis and increased with a similar pace of growth to the banking sector (Figure B2).

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[18] There are 10 core OFI subsectors, which is broadly consistent with the way jurisdictions' sector balance sheet statistics are typically structured. They include MMFs, hedge funds, other investment funds, real estate investment trusts (REITs) and real estate (RE) funds, trust companies, finance companies, broker-dealers, structured finance vehicles, central counterparties and captive financial institutions and money lenders.

[19] Unlike Hong Kong, the shadow banking data (e.g., sectors' balance sheet data) of most countries is sourced from national financial accounts statistics (i.e. "Flow of Funds").

[20] The FSTB helps consolidate pension fund data and finance company data. The finance company data is based on the annual survey of money lenders. Total assets of money lenders are used as estimates for total financial assets. To better reflect the habitat of the industry, money lenders with money lending as not their primary business activities, are also included, and those respondents with money lending business less than 1% of their total assets size are removed. As the data is collected through the survey, the respondents each year might be different.

[21] Bank-related data is from Monthly Statistical Bulletin of the HKMA.

[22] Asset of Public Financial Institutions refers to total assets of the HKMC.

[23] For the insurance corporations, the figures provided by the Insurance Authority include only total assets maintained in Hong Kong by general insurers (excluding HKMC) and the total assets of long-term business funds maintained by long-term insurers.

[24] Most of the OFI data is collected by the SFC. The SFC obtains data on entities or products that it regulates or authorises. The SFC has not authorised any structured finance vehicles or structured finance products. With regard to structured products, the SFC authorises retail unlisted structured products (equity-linked and commodity-linked) issued by banking institutions, of which the amounts is relatively small.

Figure B1. Bank assets and OFI assets in Hong Kong

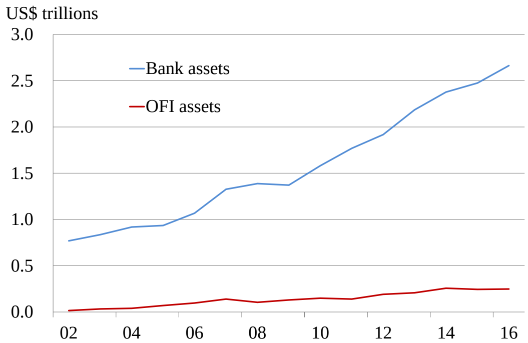
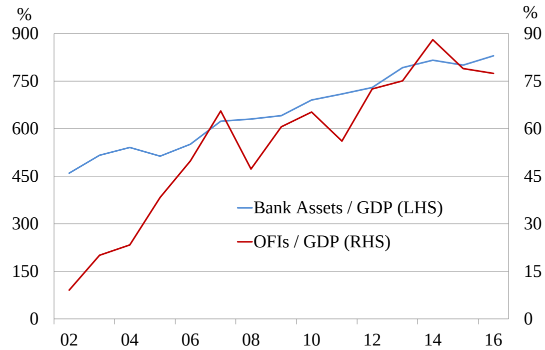


Figure B2. Bank assets and OFI assets as a percentage of GDP in Hong Kong



Regarding the funding source of shadow banks, the share of banks' funding has inched upward since 2014. At the end of 2015, one-third of shadow banking assets were funded by conventional banks in Hong Kong. Despite this material interconnectedness between conventional banks and shadow banks, this funding represented 3.0% of the total assets only in the Hong Kong banking sector (Figure B3). This suggests that the risk of spillovers from shadow banks to banks would be limited.

Figure B3. Interconnectedness between the banking sector and OFIs

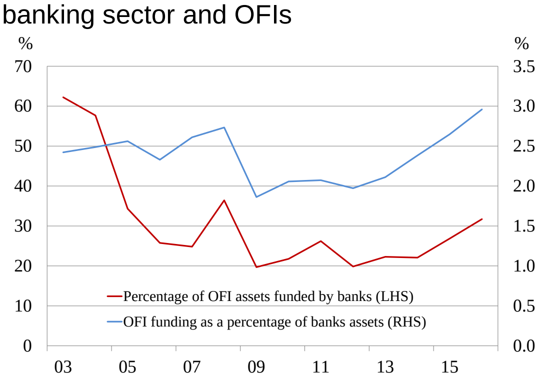
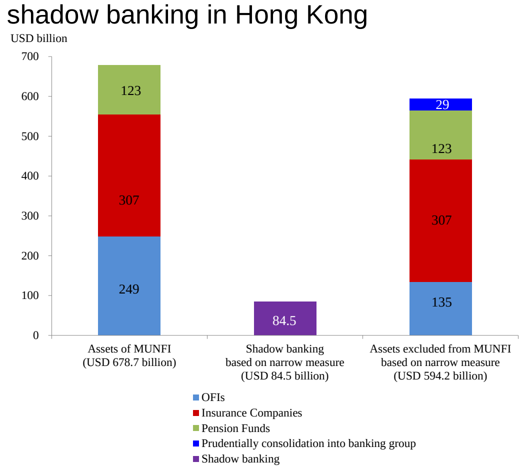


Figure B4. Board and narrow measure of shadow banking in Hong Kong



Based on the narrow measure, Hong Kong shadow banking amounted to US$64.3 billion in 2015 (Figure B4), or 26% of Hong Kong's GDP. In 2015, these assets shared only 0.2% of all 27 jurisdictions' aggregate.[25]

In terms of narrow measure, among all EFs, the shadow banking sector of Hong Kong is dominated by assets associated with "intermediation of market activities dependent on short-term funding". That is namely EF3 (which constitutes 45.5% of the narrow measure), and with "collective investment vehicles with run risk", namely EF1 (which constitutes 40.9% of the narrow measure) in 2015. All of the economies are dominated by assets associated with EF1 (which constitutes 65.0% of the narrow measure for all the economies), followed by EF3 (11.1%).

[25] China's shadow banking in terms of narrow measure is not available in 2015.

Table B1: Narrow measure of shadow banking in 2015 (by economic functions)

Economic Function	Definition	Examples of Classified Entity type	Asset size (US$ bn) & share (%) #	
			Hong Kong (US$ bn &%)	All jurisdictions (US$ trn &%)
EF1	Management of collective investment vehicles with features that make them susceptible to runs	Fixed income funds, money market funds	26.3 (40.9%)	22.2 (65.0%)
EF2	Loan provision dependent on short-term funding	Money lenders	8.5 (13.2%)	2.7 (7.9%)
EF3	Intermediation of market activities dependent on short-term funding or on secured funding of client assets	Broker-dealers	29.3 (45.5%)	3.8 (11.1%)
EF4	Facilitation of credit creation	Insurance companies	0.2 (0.3%)	0.1 (0.4%)
EF5	Securitisation-based credit intermediation and funding of financial entities	Securitisation vehicles	---	3.0 (8.9%)
Unallocated Shadow Banking			---	2.3 (6.7%)
All EFs (amount and share)			64.3 (100%)	34.2 (100%)

Notes:
#: These assets exclude those prudentially consolidated into banking groups.
@: "Unclassified shadow banking assets" refers to assets that contain shadow banking activities but which could not be classified into a specific economic function.

Sources: FSB Global Shadow Banking Monitoring Report 2016 and HKMA staff calculation.

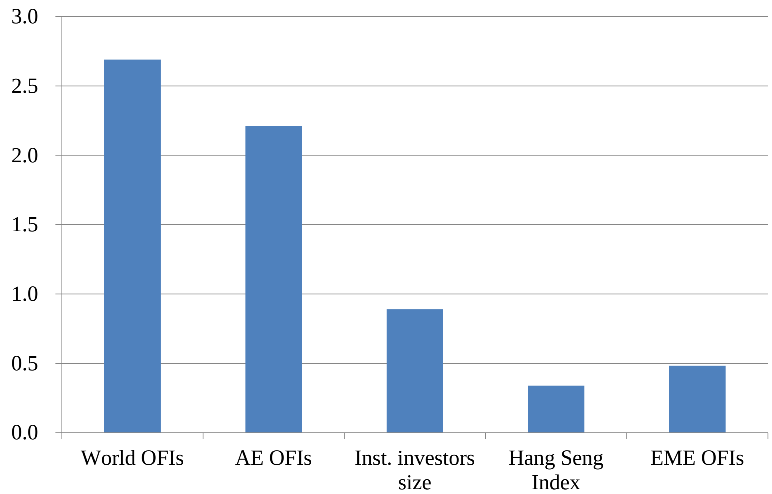
II. Potential growth determinants of Hong Kong shadow banking

We use the OFI assets of Hong Kong as a broad measure to examine to what extent risk factors are correlated with the growth in shadow banking in Hong Kong. Because of concerns about data scarcity, we use a simple linear regression with the OFI assets as the dependent variable and with each of the risk factors discussed in the main text as the explanatory variable.[26] Apart from those risk factors discussed, we also add the aggregate assets of the OFIs of AEs, EMEs and all economies as explanatory variables in the specification to assess the effect of co-movement led by these economies. Other than constant term and lagged of dependent variable, all other variables are included in the regression one by one.

Figure B5 plots all the significant coefficients in the estimated regression. One may find that the OFI growth in Hong Kong is positively associated with the growths in the total OFI assets of AEs and all economies, institutional investors and investment returns. This suggests that the larger the growth of these factors, the larger the growth of the OFI assets in Hong Kong. Among these variables, the OFI asset growth has the largest association with the growth in the total OFI assets of all economies, reflecting that the shadow banking assets in Hong Kong would move in line with global shadow banking. The variables of institutional investors and stock market returns are also significant, suggesting that demand from institutional investors and investors' search-for-yield behaviour may play a significant role in shadow banking, which is consistent with the results for the shadow banking system in EMEs.

[26] Since the time series length is only 12, sophisticated models are not suggested. Having said that, for a robustness check, we also estimate a full regression and estimate a stepwise regression. The results are largely consistent with the regression results on global markets, in which the asset sizes of institutional investors and the banking sector have a significant effect on the Hong Kong OFI assets, with some additional findings on significant contributions by the OFIs of the AEs and all economies. Note that the results may be subject to the underlying assumptions and could be biased given the small degree of freedom in estimation.

Figure B5. Significant coefficients by pairwise estimation for Hong Kong



III. Concluding remarks

This box provides an overview of shadow banking in Hong Kong. Shadow banking in Hong Kong has grown notably over the past 14 years. Its growth is significantly driven by the growth in global shadow banking, demand from institutional investors and investors' search-for-yield behaviour, which are in line with empirical results for global shadow banking. These assets of shadow banking, however, are very small compared to those in global economies, and have a tenuous interconnection with the Hong Kong banking sector. This suggests that the risk of shadow banking and its risk of spillovers to the banking sector would be limited.

Figure 1. Composition of financial system in 28 economies in 2015

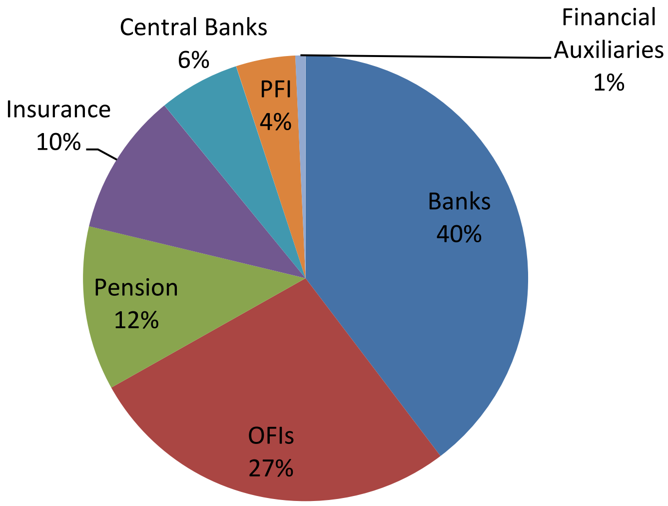


Figure 2. Aggregate size of OFIs in 28 economies

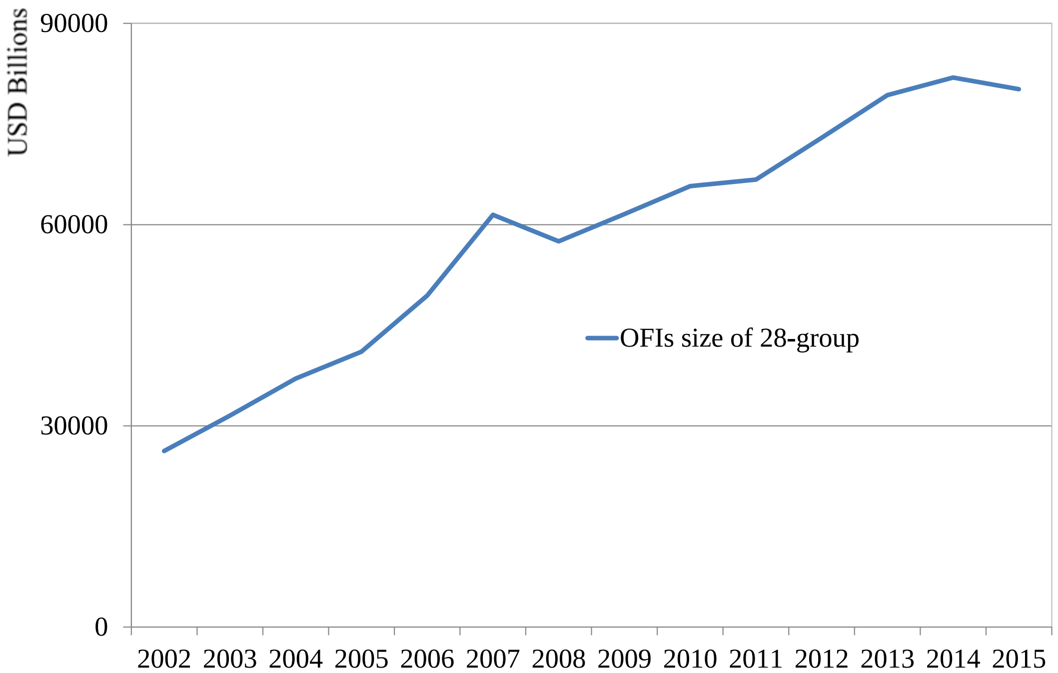


Figure 3. Aggregate size of OFIs as a percentage of GDP (based on 27 economies with Cayman Islands being excluded)

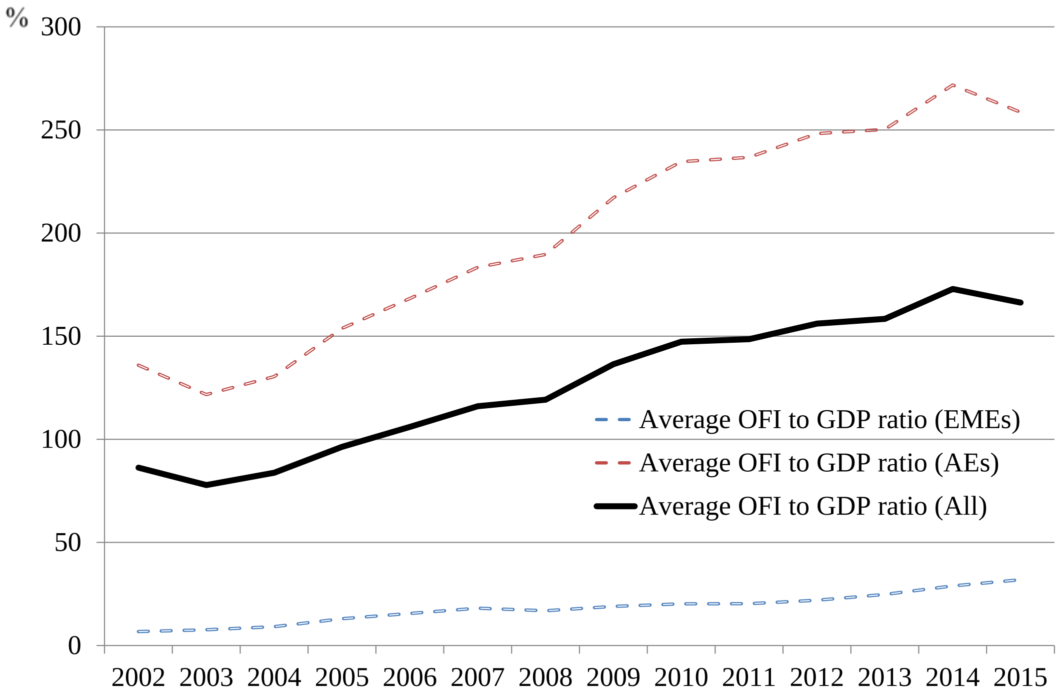
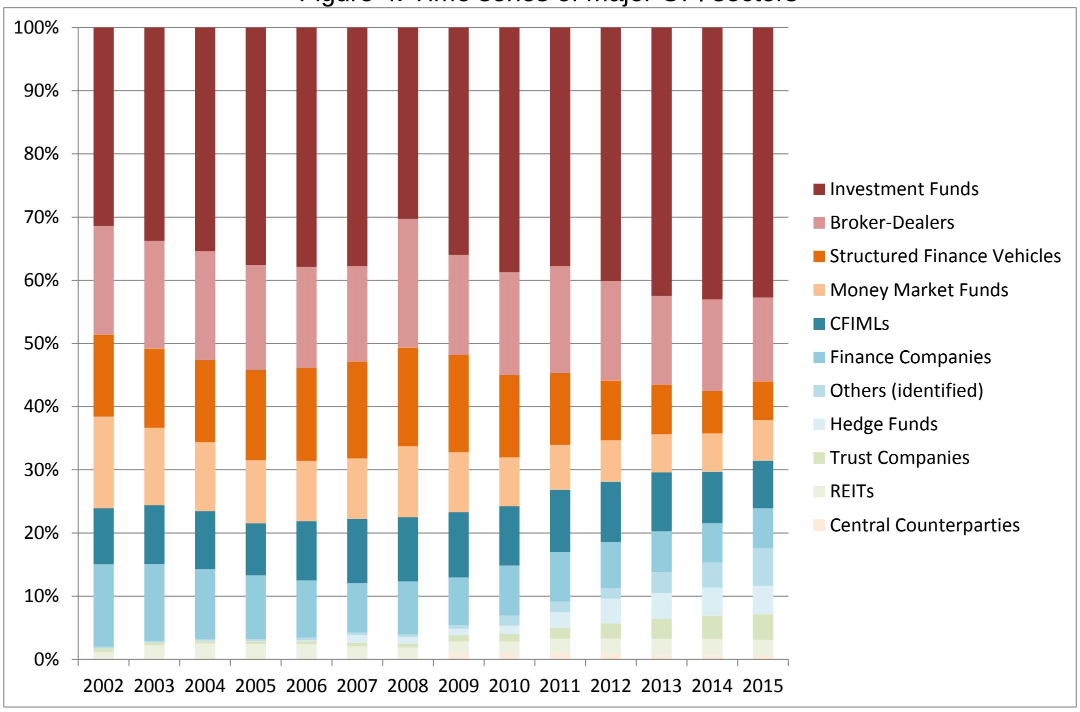
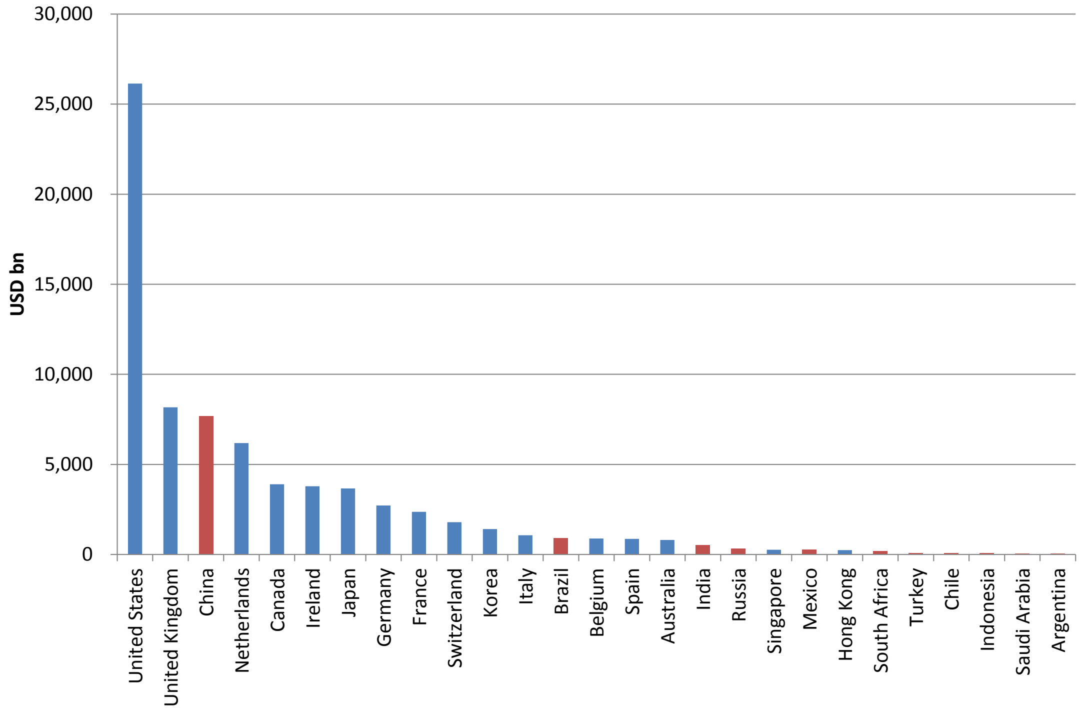


Figure 4. Time series of major OFI sectors



Note: "CFIMLs" refers to captive financial institutions and money lenders
Source: FSB (2017) (which reports findings for years prior to 2016)

Figure 5. OFI size by individual economy in 2015



Note: AEs are highlighted in blue and EMEs are in red.
Source: FSB (2017) (which reports findings for years prior to 2016)

Figure 6. Growth of OFIs (in terms of %)

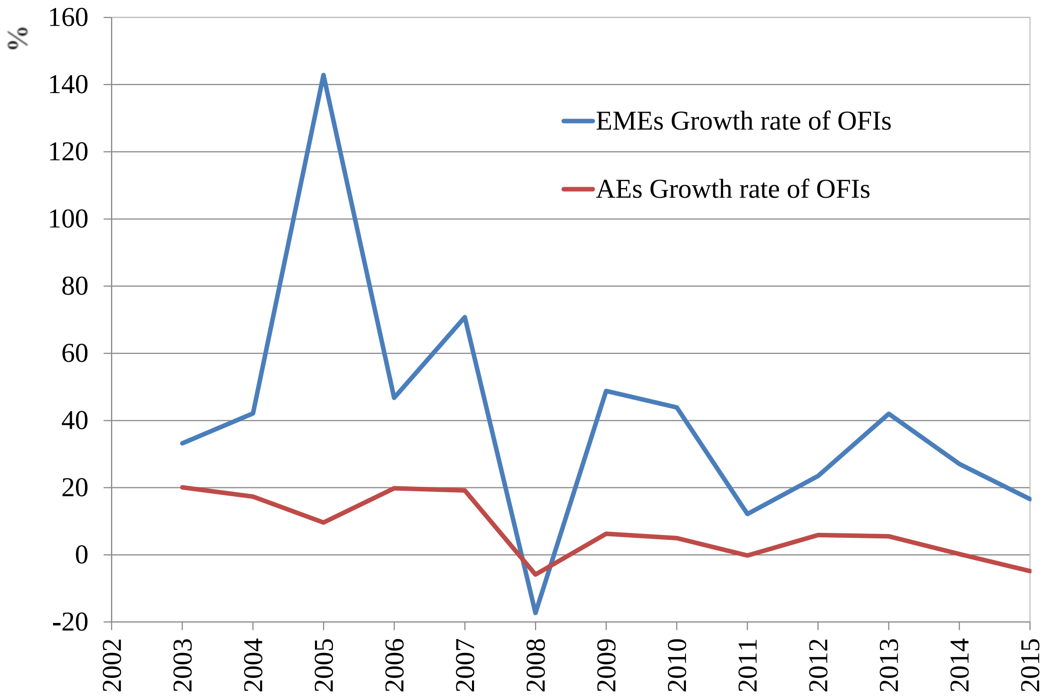
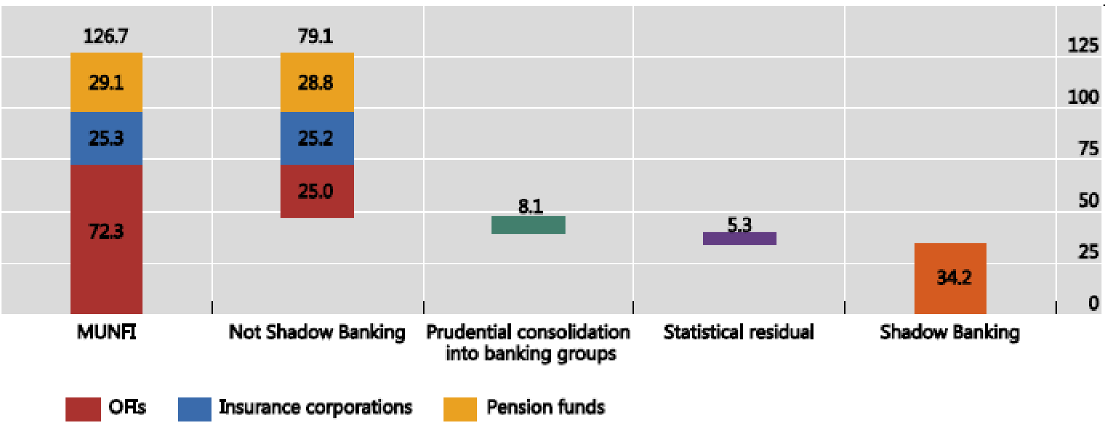


Figure 7. Narrow measure of shadow banking

Narrowing down shadow banking

27 jurisdictions at end-2015, in trillions of US dollars Exhibit 4-2

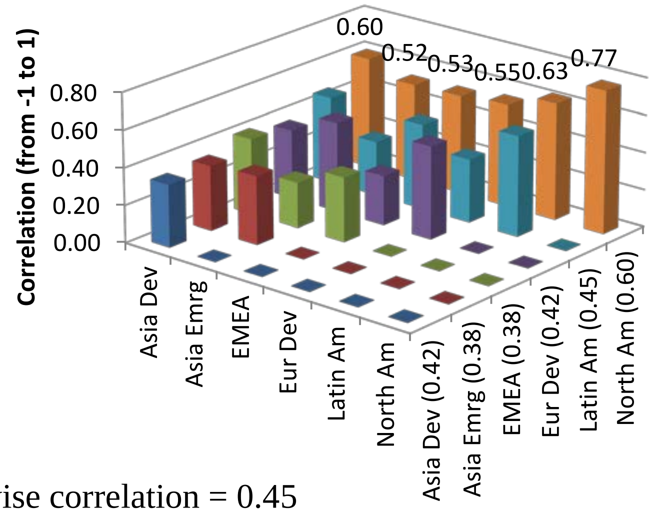


MUNFI = Monitoring Universe of Non-bank Financial Intermediation, includes OFIs, pension funds, and insurance corporations; OFIs also includes captive financial institutions and money lenders; Prudential consolidation into banking groups = assets of classified entity types which are prudentially consolidated into a banking group; Statistical residual = reported residual OFIs generated by the difference between total OFIs and the sum of all know subsectors therein; Shadow banking = narrow measure of shadow banking based on the economic functions.

Sources: National sector balance sheet and other data; FSB calculations.

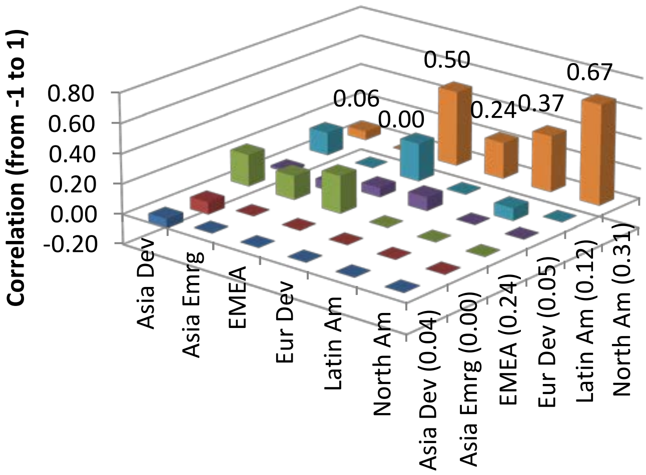
Note: The figure is extracted from the FSB (2017) (which reports findings for years prior to 2016)

Figure 8. Pairwise correlations between OFI asset growths by economic region (upper triangular matrix)



Average pairwise correlation = 0.45

Figure 9. Pairwise correlations between “adjusted” OFI asset growths by economic region (upper triangular matrix)



Average pairwise correlation = 0.13

Table 1. Economies in the SBEG

Advanced economies (AEs)		Emerging market economies (EMEs)	
Asia Developed	Australia, Hong Kong, Japan, South Korea, Singapore	*Asia Emerging*	China, India, Indonesia
Europe Developed	Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland, United Kingdom	*Emerging Europe, Middle East and Africa (EMEA)*	Russia, Saudi Arabia, South Africa, Turkey
North America	Canada, United States	*Latin America*	Argentina, Brazil, Chile, Mexico
Others	Cayman Islands		

Note: The countries listed above are consistent with those listed in the FSB (2017) (which reports findings for years prior to 2016)

Table 2. Descriptive statistics of OFIs and other financial variables

Period: 2002-2015	Min	Median	Mean	Max	SD	N
Asset data (US$ billion)						
OFIs size	1	816	2,869	31,479	5,934	398
Bank size	56	1,671	5,038	42,769	8,061	394
Pension size	0	140	998	17,917	2,770	327
Insurance size	5	300	1,079	9,551	1,884	385
Institutional investors size	9	467	1,882	25,777	4,208	311
Country-specific data						
Term spread (%)	-32.6	0.9	0.6	7.1	3.2	358
Real short-term rate (%)	-7.3	0.1	0.8	57.2	4.9	334
GDP (US$ billion)	-2	881	2142	18037	3423	406
Concentration (%)	20.5	60.6	61.2	100.0	18.9	385
Financial Freedom Index	30.0	70.0	62.4	90.0	19.4	378
Rule of Law Index	-1.0	1.2	0.8	2.0	0.9	392
Financial variables						
MSCI World Index	792	1,269	1,304	1,710	277	406
VIX Index	11.6	18.3	19.9	40.0	7.2	406

Sources: FSB (2017), World Bank, the Heritage Foundation, Bloomberg and HKMA staff calculation

Table 3. Correlation matrix of OFI asset size and other explanatory variables

	OFIs in log	Term spread	Real short-term rate	GDP in log	MSCI World Index in log	Concentration in log	Financial Freedom Index in log	Rule of Law Index	Bank size in log	Institutional investors size
OFIs in log	1.00	0.16	-0.21	0.50	0.21	0.12	0.48	0.60	0.85	0.92
Term spread	0.16	1.00	-0.70	-0.01	-0.08	0.15	0.33	0.28	0.13	0.14
Real short-term rate	-0.21	-0.70	1.00	-0.10	0.00	-0.09	-0.23	-0.29	-0.27	-0.24
GDP in log	0.50	-0.01	-0.10	1.00	0.11	-0.37	-0.07	0.01	0.68	0.71
MSCI World Index in log	0.21	-0.08	0.00	0.11	1.00	-0.03	0.03	0.02	0.14	0.12
Concentration in log	0.12	0.15	-0.09	-0.37	-0.03	1.00	0.44	0.47	0.03	0.08
Financial Freedom Index in log	0.48	0.33	-0.23	-0.07	0.03	0.44	1.00	0.76	0.29	0.41
Rule of Law Index	0.60	0.28	-0.29	0.01	0.02	0.47	0.76	1.00	0.52	0.65
Bank size in log	0.85	0.13	-0.27	0.68	0.14	0.03	0.29	0.52	1.00	0.84
Institutional investors size in log	0.92	0.14	-0.24	0.71	0.12	0.08	0.41	0.65	0.84	1.00

Source: HKMA staff calculation.

Table 4. Unit root test for individual countries						
	Without time trend			*With time trend*		
	I(0)	**I(1)**	**I(2) or above**	**I(0)**	**I(1)**	**I(2) or above**
OFI	Italy	Argentina Belgium Canada Chile Germany Hong Kong India Indonesia Ireland Japan Mexico Russia Saudi Arabia Singapore South Africa South Korea Switzerland Turkey	Australia Brazil China France Netherlands Spain United Kingdom United States	Singapore	Argentina Belgium Canada Chile Germany Hong Kong Ireland Italy Japan Russia Saudi Arabia South Africa South Korea Switzerland Turkey	Australia Brazil China France India Indonesia Mexico Netherlands Spain United Kingdom United States
GDP	Belgium France Italy Netherlands Spain Turkey United Kingdom	Canada Chile Germany Hong Kong India Ireland Japan Mexico Russia Singapore South Africa South Korea Switzerland	Argentina Australia Brazil China Indonesia Saudi Arabia United States	---	Belgium Canada Chile France Germany Hong Kong India Italy Netherlands South Africa Switzerland Turkey United Kingdom	Argentina Australia Brazil China Indonesia Ireland Japan Mexico Russia Saudi Arabia Singapore South Korea Spain United States
Bank	Netherlands South Africa	Argentina Chile China India Indonesia Mexico Russia Saudi Arabia Singapore South Korea Switzerland Turkey	Australia Brazil Canada France Germany Hong Kong Ireland Italy Japan Spain United Kingdom United States Belgium	Russia Switzerland	Argentina China France Germany Hong Kong India Italy Mexico Netherlands South Africa Turkey United Kingdom	Australia Brazil Chile Indonesia Japan Singapore Spain Belgium Canada Ireland Saudi Arabia South Korea United States
Note: For those series with order I(2) or above, the probabilities and critical values are calculated from a small sample size thus may not be accurate.						

Table 5. Panel unit root test						
	I(0)			**I(1)**		
	Statistic	**P-value**	**Significance**	**Statistic**	**P-value**	**Significance**
OFIs	-3.099	0.001	***	---	---	---
Term spread	-5.010	0.000	***	---	---	---
Real short-term rate	-5.917	0.000	***	---	---	---
GDP	-3.083	0.001	***	---	---	---
MSCI World Index[1]	-2.099	0.248		-3.837	0.016	**
Concentration	-6.927	0.000	***	---	---	---
Financial Freedom Index	-2.829	0.002	***	---	---	---
Rule of Law Index	-4.603	0.000	***	---	---	---
Bank size	-1.595	0.055	*	---	---	---
Institutional investors size	-0.102	0.460		-14.628	0.000	***

Notes:
1: For the MSCI World Index, Augmented Dickey-Fuller test is applied.
2. The Levin-Lin-Chu bias-adjusted t-statistic is reported.
3. '***', '**' and '*' denote significance levels of 1%, 5% and 10% respectively.

Table 6. Estimated coefficient matrices by economy group in Equation (1)

	Asia Developed	Asia Emerging	EMEA	Europe Developed	Latin America	North America	Row Average
α							
Asia Developed	0.13	0.10	0.07	0.11	0.04	0.04	0.08
Asia Emerging	0.27	0.21	0.28	0.23	0.23	0.20	0.24
EMEA	0.08	0.09	0.05	0.10	0.01	0.03	0.06
Europe Developed	0.03	0.01	0.03	0.03	0.02	0.01	0.02
Latin America	0.08	0.08	0.07	0.09	0.05	0.04	0.07
North America	0.03	0.02	0.04	0.04	0.03	0.02	0.03
Column Average	0.10	0.09	0.09	0.10	0.06	0.06	0.08
							(1.09)
B							
Asia Developed	0.20	-0.02	0.25	0.35	0.25	0.77	0.30
Asia Emerging	0.31	0.14	0.07	0.73	0.29	0.78	0.39
EMEA	0.32	0.03	0.02	0.30	0.31	0.48	0.25
Europe Developed	0.29	0.20	0.12	0.60	0.24	0.93	0.40
Latin America	0.19	0.12	0.23	0.27	0.49	0.73	0.34
North America	0.22	0.09	0.10	0.48	0.27	0.11	0.21
Column Average	0.25	0.09	0.13	0.45	0.31	0.64	0.31
							(1.33)
α + δ							
Asia Developed	0.02	-0.09	0.06	-0.06	0.02	0.07	0.00
Asia Emerging	0.17	-0.04	0.28	0.06	0.19	0.33	0.16
EMEA	-0.04	-0.14	0.05	-0.09	-0.03	0.06	-0.03
Europe Developed	0.03	-0.01	0.07	0.00	0.05	0.06	0.03
Latin America	0.00	-0.08	0.03	-0.06	0.00	0.03	-0.01
North America	-0.03	-0.11	-0.01	-0.09	-0.02	0.00	-0.04
Column Average	0.03	-0.08	0.08	-0.04	0.04	0.09	0.02
							(0.19)
β + γ							
Asia Developed	1.43	0.74	0.88	1.60	0.90	1.45	1.17
Asia Emerging	2.15	1.43	1.41	2.65	1.39	2.29	1.89
EMEA	1.34	0.82	1.11	1.61	1.14	1.81	1.30
Europe Developed	0.66	0.39	0.39	0.81	0.37	0.61	0.54
Latin America	1.04	0.59	0.70	1.20	0.62	1.11	0.88
North America	0.93	0.54	0.64	0.99	0.61	1.17	0.81
Column Average	1.26	0.75	0.86	1.48	0.84	1.41	1.10
							(2.05)

Table 7. Estimation results of Equation (4) (full sample period: 2002-2015)

	Dep. variable: OFI assets in log-level				
Indep. variable	All economies			EMEs	AEs
(in log-level)	(1)	(2)	(3)	(4)	(5)
Constant	-3.987**	-3.216**	-1.835**	-5.356**	-1.555**
Lag dependent variable	0.560**	0.544**	0.536**	0.571**	0.638**
MSCI World Index	0.340**	0.370**	0.329**	0.533**	0.143**
Inst. investors size	0.230**	0.147*	0.319**	0.154*	0.240**
Bank size	0.218**	0.251**	0.271**	0.391**	0.004
Banks' concentration	0.261**	---	---	0.327**	0.150
Rule of Law Index	---	0.154*	---	---	---
Fin. Freedom Index	---	---	-0.166	---	---
Real short-term rate	0.002	0.001	0.002	-0.001	0.011*
GDP	0.042	0.088	-0.120	-0.125	0.126*
Term spread	0.008	0.006	0.008	0.003	0.000
N	255	259	259	88	167
Sargan statistics	246.541	253.968	249.705	108.723	185.525
Within R^2	0.832	0.836	0.832	0.787	0.883

Note: '**' and '*' denote significance levels of 1% and 5% respectively.
Within R^2 assumes that the total sum of square is $SST = \sum_{i=1}^{n} \sum_{t=1}^{T} (y_{it} - \bar{y}_i)^2$ and the pseudo R^2 is $R^2 = 1 - SSR/SST$. It adjusts the total sum of square for cross section effect.
Source: HKMA staff estimate.

Table 8. Estimated coefficient matrices by unexpected OFI growth by economy group in Equation (1)

	Asia Developed	Asia Emerging	EMEA	Europe Developed	Latin America	North America	Row Average
A							
Asia Developed	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Asia Emerging	0.00	--	0.00	0.02	0.00	0.00	0.00
EMEA	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Europe Developed	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Latin America	0.00	0.00	0.00	0.00	0.00	0.00	0.00
North America	-0.01	0.00	-0.01	-0.01	-0.01	-0.02	-0.01
Column Average	0.00	0.00	0.00	0.00	0.00	0.00	0.00 (-0.08)
B							
Asia Developed	-0.14	0.00	0.15	0.05	0.20	0.43	0.11
Asia Emerging	0.00	--	0.00	0.00	0.00	0.15	0.03
EMEA	0.08	0.00	0.14	0.07	0.22	0.88	0.23
Europe Developed	0.01	0.00	0.00	0.12	0.00	0.40	0.09
Latin America	0.07	0.00	0.19	0.04	-0.09	1.21	0.24
North America	0.00	0.00	0.20	0.18	0.22	1.19	0.30
Column Average	0.00	0.00	0.11	0.08	0.09	0.71	0.17 (0.55)
$\alpha + \delta$							
Asia Developed	-0.04	0.00	-0.01	-0.02	-0.02	0.01	-0.01
Asia Emerging	-0.19	--	0.01	-0.05	0.16	0.00	-0.01
EMEA	-0.03	0.00	0.00	-0.01	-0.02	0.04	0.00
Europe Developed	0.01	0.00	-0.01	0.00	0.00	-0.04	-0.01
Latin America	-0.01	-0.01	0.01	-0.01	0.01	0.07	0.01
North America	-0.05	0.00	-0.01	-0.03	-0.04	0.02	-0.02
Column Average	-0.05	0.00	0.00	-0.02	0.02	0.02	-0.01 (-0.14)
$\beta + \gamma$							
Asia Developed	-0.29	-0.01	0.11	-0.42	0.13	1.24	0.13
Asia Emerging	-0.35	--	-0.83	-0.29	1.30	0.00	-0.03
EMEA	-0.02	0.00	0.15	-0.51	0.04	1.53	0.20
Europe Developed	0.14	0.01	-0.06	0.29	-0.05	-0.79	-0.08
Latin America	0.17	0.01	0.40	-0.26	0.01	1.37	0.28
North America	0.09	0.00	0.17	-0.52	0.08	2.18	0.33
Column Average	-0.04	0.00	-0.01	-0.28	0.25	0.92	0.14 (0.23)