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ASSESSING THE INTERCONNECTEDNESS BETWEEN CROSS-BORDER SHADOW BANKING SYSTEMS

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Assessing the interconnectedness between cross-border shadow banking systems

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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 fully 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

[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.

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 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 demand from institutional investors are the most important. After controlling for effects of these driving factors, the interconnections are

[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.

generally insignificant, except the shadow banking system in North America remains influential worldwide. The results show the shadow banking system in that region is far more complicated than those in other economies and so the system needs closer scrutiny before concluding its spillover risk.

The contributions of this study are threefold. First, this study is one of a few to examine interconnectedness of shadow banking in economies. Some studies focus on the spillover impact of financial shocks on the banking system, sovereign bond markets, and real sectors (e.g., Abad et al., 2017; Cetorelli, 2014; Fischer, 2015; Kroszner et al., 2007; Pozsar et al., 2013). 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 (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

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

[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.

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

There are various way to define non-bank financial intermediation in literature. 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-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,

[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.

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 financial crisis in 2008 (Figure 6).

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.

3. Data and empirical methods

[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.

3.1 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$2.1 trillion (Table 2).[11] 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 3 summarises the results of the Augmented Dickey-Fuller (ADF) test for the time series of OFIs for each economy.[12] 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. 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

[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] Cayman Island is excluded in this calculation and empirical estimation given limited information of some independent variables. When the economy is included, the OFI asset is US$ 2.9 trillion on average.

[12] We also report a brief summary on GDP and bank size for reference and find the results quite similar except that the time series of the bank size tends to be I(2) or higher. Details of each test statistic will be available upon request.

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 examples, the average correlations between Asian developed and North American economies and between Asian emerging and North American economies are 0.60 and 0.52 respectively. 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 within North American economies are strongly correlated, when 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 $\Delta OFI_{i,t}$, for i = 1,…, N) on the OFI growth of the j-th economy (denoted by $\Delta OFI_{j,t}$ for j = 1,…, N) and other variables:

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

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

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

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

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

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

Several factors are considered important for the growth in shadow banking in the empirical literature, which include search-for-yield, capital stringency, demand from institutional investors, economic fundamentals and funding support from the banking sector. IMF (2014) offers a summary of plausible explanations for the similar factors. First, the shadow banking system often supplies higher-yielding assets for investors compared with government bonds and the stock market, and therefore a higher investors' risk appetite towards risky assets could drive the growth of shadow banking assets (Goda and Lysandrou, 2014). Second, 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 financial markets (IMF, 2014; Pozsar, 2011). Third, tighter bank regulation encourages institutions to circumvent it through non-bank intermediation and promptly increases the shadow banking activities (Barth et al., 2013; Duca, 2016). Fourth, a stronger growth in the assets of banking sector provides a stronger funding support for the shadow banking sector given that banks and its holding companies play a vital role in the credit intermediation chain (Cetorelli and Peristiani, 2012; Mandel et al., 2012). Finally, stronger economic fundamentals would mean higher economy's productivity and financial market developments which complements the growth in shadow banking (Watkins, 2011; Barbu et al., 2016).

In literature, one possible explanation behind the interconnectedness of shadow banking systems is that investors' portfolio balancing/rebalancing activities drive the co-movement of shadow banking assets across borders. These activities are regarded as one of the motives in exchange-rate theory (Kouri, 1982; Branson and Henderson, 1985), in which domestic investors would repatriate some of the foreign investment when their foreign investment returns are substantially higher than their domestic holdings'. The primary motivation behind such funds' repatriation is to reduce currency risk exposure (Hau and Rey, 2004).[13] There are growing evidence supporting that the reallocations are also motivated by (i) a return-chasing tactic towards markets that will subsequently outperform (Curcuru et al., 2014); (ii) a stronger demand for assets denominated in different currencies (Gabaix and Maggiori, 2015); and (iii) an international diversification influenced by the degree of diversification (proxied by fund size) and cost of rebalancing (proxied by asset liquidity) (Camanho et al., 2018). Over the past

[13] In a world in which all exchange rate risk is perfectly hedged, the global investor generally holds the world equity market, and any increase in the value of foreign equity in this world-market portfolio should not trigger any portfolio rebalancing. However, exchange-rate exposure under imperfect risk-trading reduces the benefit of foreign investment. When the share of wealth in foreign assets increases, the home resident may seek to reduce his increasing FX risk exposure by selling foreign shares to foreign residents who do not face the corresponding FX risk. When the portfolio weights shift due to exchange-rate change itself, the home resident holds an increasing amount of FX risk exposure after the foreign appreciation. He may there be less willing to hold these foreign assets, and therefore we should observe foreign-equity outflows.

decade, these portfolio rebalancing activities have played an increasingly important role in driving the co-movement of shadow banking assets (Puy, 2016; Raddatz and Schmukler, 2012; Curcuru et al., 2014; Jotikasthira et al., 2012).

When attributing to the interconnectedness of shadow banking across borders, our selected factors are closely related to the motive of portfolio rebalancing. First, the search-for-yield factor is highly determined by investors' return-chasing behaviour, during which economies with a higher investment return in shadow banking tends to move closely together given a higher investors' risk appetite. Second, a stronger demand from institutional investors could increase these investors' demand for assets in foreign economies and for international diversification. As a considerable part of shadow banking entities, long-term institutional investors (such as pension funds) have played a more active role in participating portfolio rebalancing activities over the past decades and contribute to a stronger co-movement in assets of shadow banking (e.g., Kakes, 2008; Bikker et al., 2012; De Haan and Kakes, 2011). Finally, an economy's capital stringency, funding support in the banking sector, and economic healthiness would help investors identify the risk profile of the economy. In particular, lower banks' liquidity and credit availability could affect banks across borders and their capital flows in the sector (Bruno and Shin, 2015). Thus, the shadow banking systems among economies with a similar risk profile (e.g., developed vs emerging markets) tend to be regarded as a group when rebalancing, resulting that the co-movement of these economy groups would be stronger especially in times of financial stress. The co-movement is also consistent with Jotikasthira et al. (2012)'s findings which explains why investor flows to funds domiciled in developed markets force significance changes in these funds' emerging market portfolio allocations when rebalancing the funds.

According to these considerations, we use the following variables as proxies in our estimation. Table 4 reports data source of these variables, including:

(i) Search-for-yield effect is proxied by three variables to provide different perspectives on the effect, including forward earnings yield of the MSCI World Index (general forward earnings yield) and those of individual stock markets (individual forward earnings yield), and survey-based measures of consumer confidence. The first variable is defined as forecasting earnings per share of the MSCI World Index divided by the current price of the MSCI World Index, which measures a company's profitability in major markets at a future level of earnings, providing a barometer of potential stock market returns in general.[14] Apart from this general measure of forward-looking returns, the second variable is a market-specific measure of market returns. Both variables reflect that a lower forward earnings yield would decrease investors' investment in stocks and bonds but increase their investment in shadow banking, suggesting that the coefficient sign is expected to be negative. The last variable is provided by consumer surveys conducted among a random sample of households in each economy,[15] which is regarded as a good proxy for investor sentiment (Qiu and Welch, 2004). Thus, the higher the level is, the higher investors' risk appetite will be in the near term, with an expected positive coefficient of the yield in the specification.

(ii) Demand from institutional investors is proxied by the asset size of institutional investors (institutional investor size), which is measured by the total asset size of pension funds and insurance companies for each jurisdiction. A higher asset growth in institutional investors

[14] Alternatively, IMF(2014) uses term spread and real short-term interest rate to measure the search-for-yield effect. However, we find that these variables do not have significant impact on the asset growth of shadow banking. This can be arising from the fact that these price-based variables reflect only past changes in market sentiment and do not help predict future movement in investor sentiment.

[15] In our study, we standardize the consumer confidence to zero mean and unit variance in each cross section, such that the data across economies would be comparable. Details of individual surveys can be found in Appendix.

would be associated with stronger demand from these investors. Thus, the coefficient sign is expected to be positive.

(iii) Capital stringency in the banking sector is proxied by bank concentration,[16] which is measured by the ratio of the assets of an economy's three largest banks to the assets of all commercial banks in that economy. A higher bank concentration in an economy may be associated with more inefficiency in the banking sector followed by a weaker financial stability, and subsequently, a tighter stringent capital regulation standard in the banking sector,[17] triggering more demand for shadow banking sector products. Therefore, the coefficient sign is expected to be positive between the bank concentration and assets of shadow banking.

(iv) Banks' funding support is proxied by asset size of the banking sector (bank size), given that a sizable banking sector would be associated with more credit availability in the financial markets. Therefore, the coefficient sign is expected to be positive between the bank size and assets of shadow banking.

(v) The factor of economic fundamentals is proxied by the economy's gross domestic product (GDP) in nominal level. A larger economy is expected to have stronger economic fundamentals and thus larger OFI assets. Thus, it suggests a positive relationship between the sizes of the economy and shadow banking assets.

[16] The data is sourced from the Financial Development and Structure Dataset. For details, please see http://www.worldbank.org/en/publication/gfdr/data/financial-structure-database. We also consider two alternative proxies for the capital stringency, including financial freedom index sourced from the Heritage Foundation and rule of law index sourced from the Worldwide Governance Indicators (WGI) project. The former is an indicator of bank efficiency, while the latter reflects the effect of the independence of the legal system and the quality of institutions that protect property rights on the stringency of capital regulations. These empirical results are largely consistent with those found by the bank concentration, so these results are not reported in this study.

[17] This is in line with Kara (2016)' concentration-fragility hypothesis which suggests that an increase in bank concentration reduces the stability of the banking sector, and regulators would respond to higher concentration by tightening capital regulations.

Tables 2 and 3 report major descriptive statistics of these variables and results of unit root tests respectively. Consistent with the OFI assets, we consider all the selected explanatory variables are I(1), although some of them appear to be stationary or integrated of higher orders. Arising from this notable nonstationary pattern in the explanatory variables, some variables are found to be highly correlated. As shown in Table 5 which presents the pairwise correlations of selected variables with the OFI assets, highly correlated variables include asset size of institutional investors, GDP, and bank size (ranging from 0.71 to 0.85), which are found to have an increasing trend over the past years.

Econometrically, we apply a linear dynamic panel data regression to an individual economy's data.[18] 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 $OFI_{j,t}$ (for j = 1,…, *N*), 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. Apart from these factors, we add a lagged term of OFI assets to the regression as a control variable for the second round effect of the system. Note that we do not introduce the three proxies of search-for-yield variables together but individually into the specification in estimation to see whether these different measures offer consistent empirical results.

The empirical model is subject to an assumption that the responses of shadow banking assets to driving factors are identical across all economies or specific economy groups (such as AEs, EMEs, etc.). This assumption, however, could be considered too strong when these responses are not constant across economies. To check model adequacy, we build a specific statistical test for the constancy of coefficients across economies. Specifically, we suppose that the "true" panel data model for the OFI assets of the *j*-th economy (for *j* = 1,…, *N*) to be estimated is

$$OFI_{j,t} = \theta_0 + \theta_{1,j} MV_{j,t}^1 + \sum_{k=2}^{K} \theta_k MV_{j,t}^k + \gamma OFI_{j,t-1} + \epsilon_{j,t}^1 \tag{5}$$

where $\epsilon_{j,t}^1$ is a random error with mean zero and variance σ_j^2, and the marginal responses of the OFI assets to the factor $MV_{j,t}^1$ (i.e., $\theta_{1,j}$) vary across economies while the marginal responses to other factors (i.e., $\theta_{2,j}$,…, $\theta_{K,j}$) remain the same. When we run our regression based on Equation (4), the part of misspecification (i.e., difference between Equations (4) and (5), which is known as $(\theta_{j,1} - \theta_j) \cdot MV_{j,t}^1$) will get absorbed by the error term and we will actually estimate:

$$OFI_{j,t} = \theta_0 + \sum_{k=1}^{K} \theta_k MV_{j,t}^k + \gamma OFI_{j,t-1} + \epsilon_{j,t}^* \tag{6}$$

where $\epsilon_{j,t}^* = (\theta_{1,j} - \theta_j) \cdot MV_{j,t}^1 + \epsilon_{j,t}^1$. Except that all economies have the same response (i.e., $\theta_{1,j} = \theta_j$), $\epsilon_{j,t}^*$ will exhibit the same characteristic as the $OFI_{j,t}$, whose marginal responses to $MV_{j,t}^1$ are different across economies. We then estimate the following random coefficient model:

$$\epsilon_{j,t}^{*} = \beta_{1,j} MV_{j,t}^{1} + \epsilon_{j,t}^{1} \ , \tag{7}$$

where $\beta_{1,j}$ is assumed to follow normal distribution with mean zero and variance s_j^2, and perform a statistical test of the responses for constancy across economies (i.e., H_0: $\beta_{1,1} = \beta_{1,2} = \cdots = \beta_{1,N}$). Asymptotically, the test statistic derived under the H_0 follows a chi-squared distribution with N-1 degree of freedom (Swamy, 1970). When the null hypotheses cannot be rejected, we may consider that our empirical model with constancy of response to $MV_{j,t}^{1}$ is adequate. By the same token, we conduct the test for other factors (i.e., $MV_{j,t}^{k}$ for k = 2,…, K), or specifically,

$$\epsilon_{j,t}^{*} = \beta_{k,j} MV_{j,t}^{k} + \epsilon_{j,t}^{k} \tag{8}$$

to assess constancy of responses (i.e., H_0: $\beta_{k,1} = \beta_{k,2} = \cdots = \beta_{k,N}$, for k = 2,…, K). This helps understand how strongly the assumption of constancy in our empirical models would be.

A more general specification in Equation (8), such as the following equation:

$$\epsilon_{j,t}^{*} = \sum_{k=1}^{K} \beta_{k,j} MV_{j,t}^{k} + \zeta_{j,t}^{k} \tag{9}$$

and a joint test for constancy of responses to all factors (i.e., H_0: all $\beta_{k,j}$ are equal at the same time, for k = 1,…, K, and j = 1,… N) can be considered as an alternative approach for adequacy check. However, this alternative may not have an advantage over our approach in this application. First, our approach is more parsimonious since it tests constancy of each response each time in a single-variable regression which allows more degree of freedom in estimation and is desirable for a smaller panel dataset like ours. Second, it is possible that not all coefficients of factors are varying across economies at the same time. For example, the varying response to a factor across economies could be due to some omitted explanatory variables in the specification, and so the response would become constant after controlling for other factors in another regression. Therefore, our approach would be more favourable than others in this application.

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 and World Bank Financial Development and Structure Dataset. All the coefficients in the specification are estimated with white heteroskedasticity-consistent standard errors and covariance.

Table 6 summarises the estimated coefficients of α, β, $\alpha + \delta$, and $\beta + \gamma$ in four matrices reported in four panels.[19] 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

[19] Lagged OFIs is dropped from Equation (1) since it is statistically insignificant most of the time. Relevant empirical results are not reported but will be available upon request.

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 0.06 and 0.19 respectively. They represent, on average, a constant growth of six percentage points in the OFIs of an Asian developed economy, with an additional increase of 19 percentage points in OFI assets when the OFIs of an EMEA economy increases by 100 percentage points. Note that these changes are on a yearly basis and insignificant coefficients at a 5% 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 0.05 and the z-statistic of 0.77 (reported in parenthesis), reflecting that the OFI assets of an economy have an annual constant growth of five percentage points on average, although it is statistically insignificant at any conventional level of significance. In particular, Asian emerging economies have the largest average growth in OFI assets (20 percentage points). The growths in European developed and North American economies are much smaller (both at one percentage point). 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 0.21 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 21 percentage points on average, other things being equal, although the estimate is statistically insignificant (with a z-statistic of 1.09). Among all regions, the responsiveness of an economy to Europe developed and North American economies are found to be larger with an average responsiveness of 0.37 and 0.39 respectively (see the column average under the two regions), reflecting that OFI asset growths of the developed 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., 0.03), reflecting that the influential power of Asian emerging economies is 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 0.15. 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 1.02 on average under the high VIX level (see the fourth panel). The estimate is statistically significant (with a z-statistic of 2.30), suggesting that a 100 percentage-point increase in the OFI assets of one economy would increase the OFI assets of another economy by 102 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 1.61. The weakest one is found in European developed economies with an average responsiveness of 0.53. 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., 1.10 for the Asian developed economies and more than 1.30 for the remaining two groups).

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 to the growth in shadow banking

Table 7 presents the estimation results of Equation (4) based on all AEs and EMEs (columns A to C). In estimating Equation (4), the estimation sample is also divided into EMEs (columns D to F) and AEs (columns G to I). 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.

Column A reports the regression of the OFI assets of all economies on general forward earnings yields as a proxy of search-for-yield factor together with other selected variables. As shown in the column, the within R-Squared is 0.78, suggesting that 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 bank concentration and GDP, all the other factors have significantly effects on OFI assets, with the effect of general forward earnings yields being negative and others' being positive. The results suggest that lower investment returns perceived by stock investors in the near term, stronger demand from institutional investors and banks' funding support would complement a stronger growth in shadow banking assets. Based on the other two alternative proxies for the search-for-yield factor (i.e., columns B and C), the results remain largely the same except that bank concentration and GDP are statistically significant (see column B), suggesting that stronger economic fundamentals and tighter capital stringency in the banking sector could give rise to stronger growth in shadow banking.

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 D), we find that the variables of general forward earnings yields and asset size of institutional investors are the main attributes of the OFI assets, with the former's magnitude being larger than the latter's by some distance. This reflects that the growth of shadow banking in EMEs is driven mainly by the search-for-yield factor and marginally by demand from institutional investors. Considering the two alternative search-for-yield measures, we find that the variables of general forward earnings yields (columns E and F) and banks concentration (column E) are statistically significant, suggesting that capital stringency in the banking sector could also attribute to the assets of shadow banking. For AEs (i.e., columns G to I), all the selected factors have a significant attribution to the OFI assets with most of them being similar in magnitude. 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.

Table 8 presents the test results for model adequacy. The test statistics for EMEs and AEs are calculated based on residuals extracted from Equation (4) reported in Table 7 (see columns J, L, and O). Focusing on all economies, we see that all the factors except search-for-yield factors are significant, meaning that the constancy of response to these factors across economies is rejected in general.

When focusing on EMEs (column M), we can see that, except for the factors of banks concentration and GDP (with the test statistics of 35.1 and 23.5 respectively), all the tests are statistically insignificant at a 5% level. Further investigation on the two exceptions reveals that, the results after removing a few economies that have an extreme coefficients in the sample (see the number of economies being removed in the bracket in column N), become insignificant (see the test statistics of 5.3 and 9.1 for banks concentration and GDP respectively in column E), suggesting that the insignificance in the beginning is mainly arising from a few outliers. When focusing on AEs (column P), we find that four out of seven test statistics are insignificant at a 5% level. Three of them, which test the constancy of responses to institutional investors, bank sizes, and GDP, are found to be significant, but further investigation also find that the test results become insignificant after removing a few extreme cases from the tests (column Q).

In sum, these test results show that the constancy of responses to our selected factors cannot be accepted when we consider all economies together in the test. When we test AEs and EMEs separately, the constancy of coefficients in each group cannot be rejected in most of the tests. The rejected cases are found to be largely due to a few economies that have extreme responses. After removing these extreme economies from the groups, the constancy of coefficients cannot be rejected for each of the groups. Therefore, we may consider that the responses of the shadow banking assets to our selected factors are the same within AEs and within EMEs in general. This consideration would not be too rough because the two economy groups are consistently classified by international organisations and major investment banks under different risk categories in macro-surveillance (e.g., FSB's shadow banking reports, IMF's world economic outlook survey, MSCI World Index classifications, S&P Global BMI, etc.).

4.2.2 Can these factors fully explain the spillover effect?

In this section, we re-assess the spillover effect based on an adjusted OFI asset growth in shadow banking by the driving factors in Equation (4). Specifically, we regress the OFI asset 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 on average (i.e., 0.27). The findings suggest that North American economies could be systemic when there is unexpected liquidity shock originating from these economies.

Table 9 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 -0.03 and 0.06 on average with z-statistics of -0.21 and 0.27 respectively, reflecting that the residuals are statistically zero in mean during the whole sample periods. The estimated β and $\beta + \gamma$ are -0.08

and 0.32 respectively on average with z-statistics of 0.37 and 0.65 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 under a high VIX level, given that the column average of $\beta + \gamma$ is 0.78. In particular, the responsiveness of Asia emerging economies is the largest. This suggests that North American economies are influential among most of the regions, particularly, in Asia emerging economies, in times of tightening global liquidity.

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 in times of shrinking liquidity.

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.[20] 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

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

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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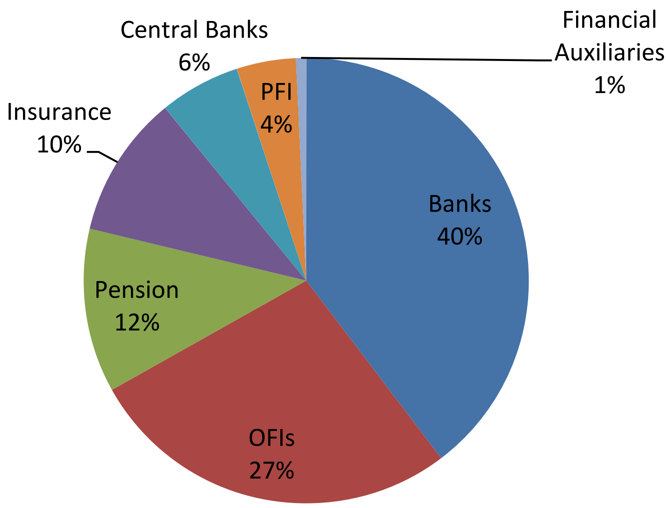


Fig 1. Composition of financial system in 28 economies in 2015. OFIs refers to other financial intermediaries which includes MMFs, hedge funds, other investment funds, real estate investment trusts (REITs) and real estate (RE) funds, trust companies, finance companies, broker-dealers, structured finance vehicles, central counterparties, and captive financial institutions and money lenders. PFI refers to public financial institutions.
Sources: FSB (2017) (which reports findings for years prior to 2016) and HKMA staff calculation.

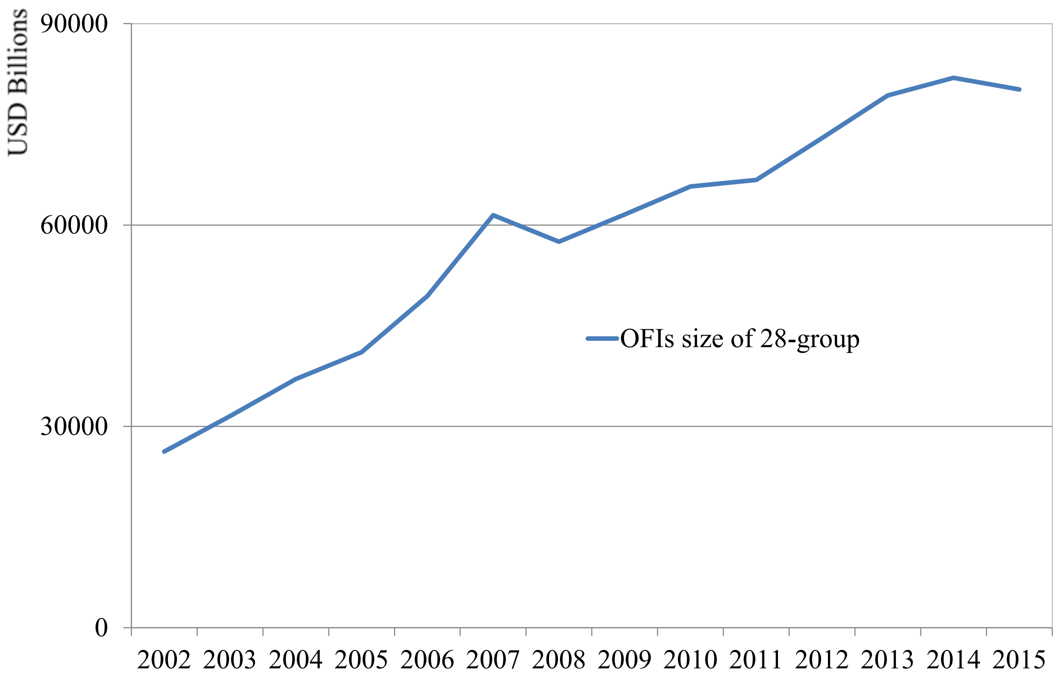


Fig 2. Aggregate size of OFIs in 28 economies. The trend of OFIs size is increasing in the period, albeit a significant decline during the global financial crisis in 2008.
Source: FSB (2017) (which reports findings for years prior to 2016)

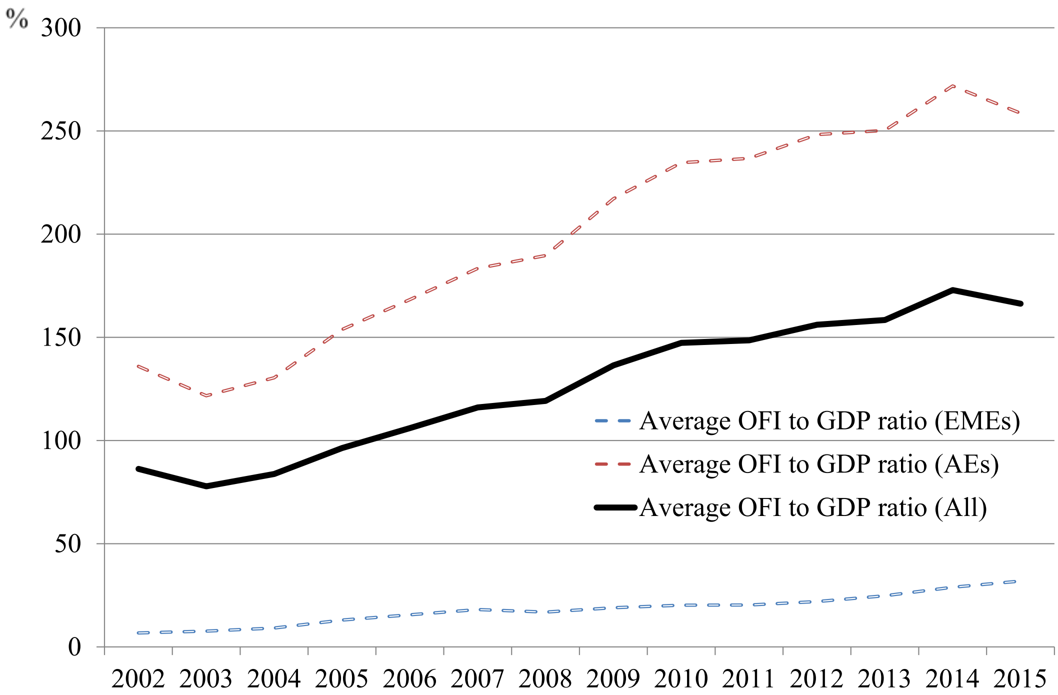


Fig 3. Aggregate size of OFIs as a percentage of GDP (based on 27 economies with Cayman Islands being excluded). Advanced economies (AEs) is in red dotted line and emerging market economies (EMEs) is in blue dotted line. Cayman Islands is excluded due to unusual fluctuations in the data series. The increasing trend demonstrates a persistent growth in shadow banking systems relative to economic system. The OFIs to GDP ratio of AEs is consistently and remarkably higher than that of EMEs.
Sources: FSB (2017) (which reports findings for years prior to 2016) and HKMA staff calculation.

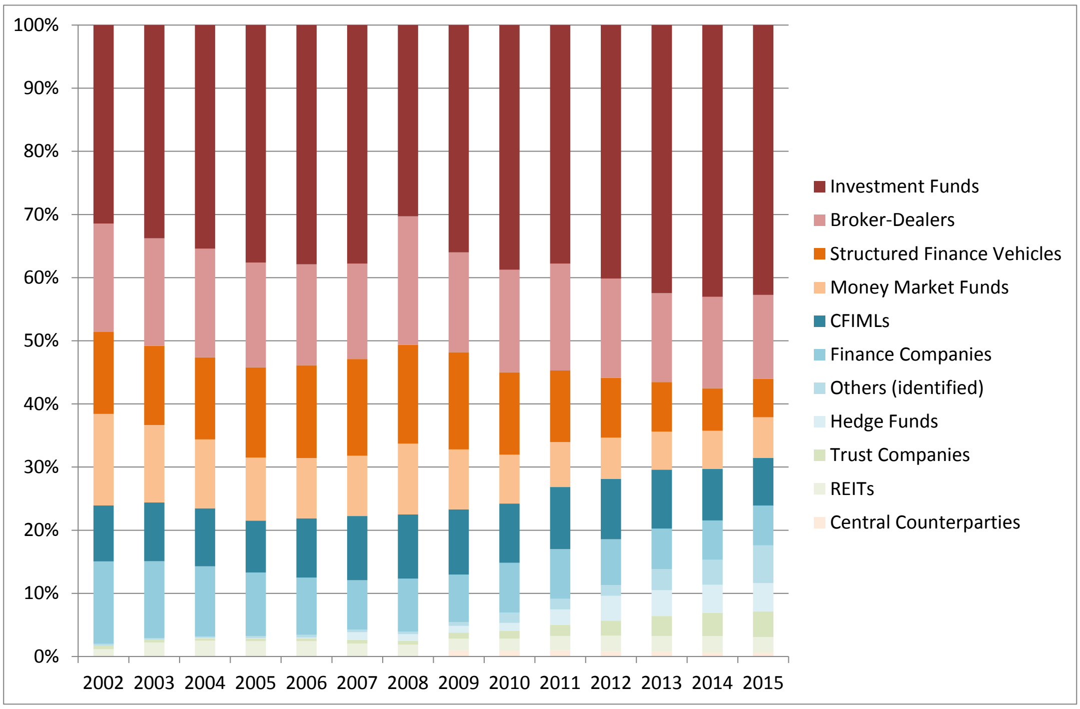


Fig 4. Time series of major OFI sectors in 28 economies. CFIMLs refers to captive financial institutions and money lenders. REITs refers to Real Estate Investment Trusts and Funds. Investment funds is the major subsector of OFIs and its proportion has been increasing particularly since the global financial crisis in 2008.
Sources: FSB (2017) (which reports findings for years prior to 2016) and HKMA staff calculation.

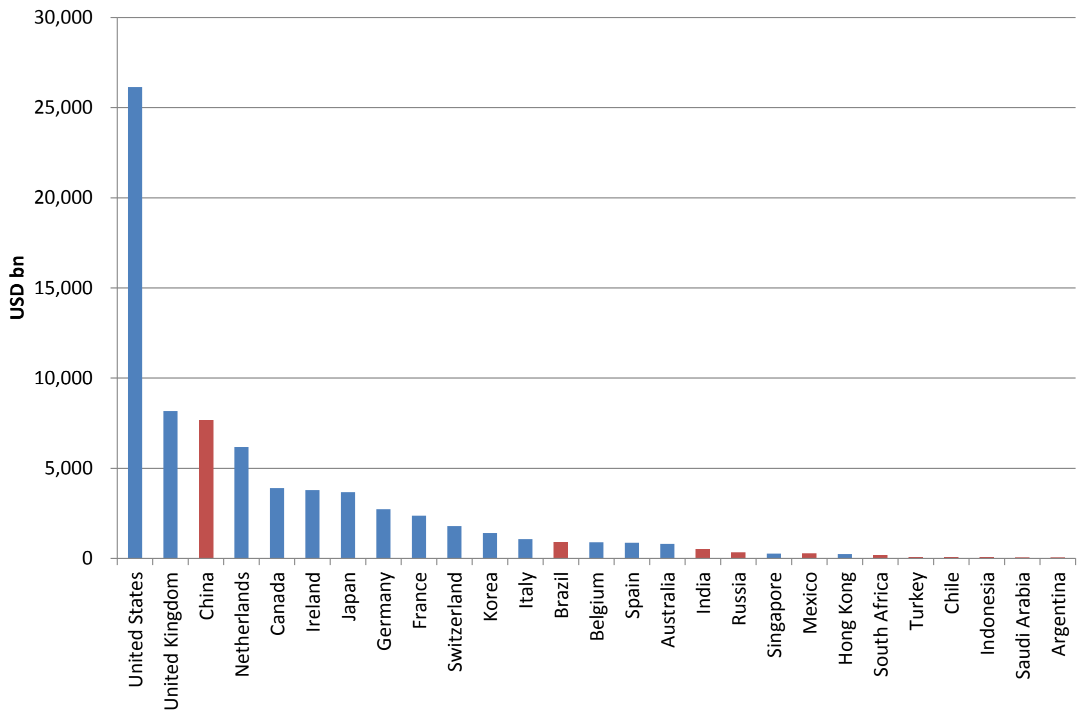


Fig 5. OFI size by individual economy in 2015. The figure compares the size of OFIs of 27 economies (excluding Cayman Islands). Advanced economies are marked in blue and Emerging market economies (EMEs) are highlighted in red. United States is the dominating economy, while China has the largest OFIs size among EMEs. Source: FSB (2017) (which reports findings for years prior to 2016)

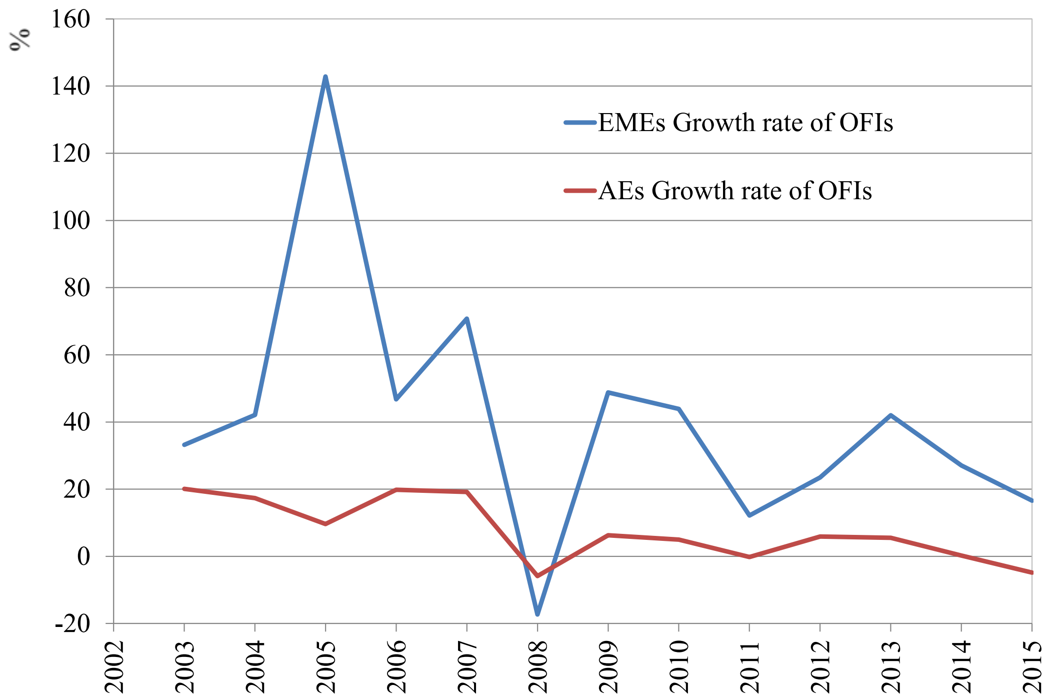


Fig 6. Growth of OFIs (in terms of %). Growth rate of OFIs of advanced economies (AEs) and emerging market economies (EMEs) are plotted in red and blue respectively. There was substantial positive growth for EMEs during the period except during the global financial crisis in 2008.
Sources: FSB (2017) (which reports findings for years prior to 2016) and HKMA staff calculation.

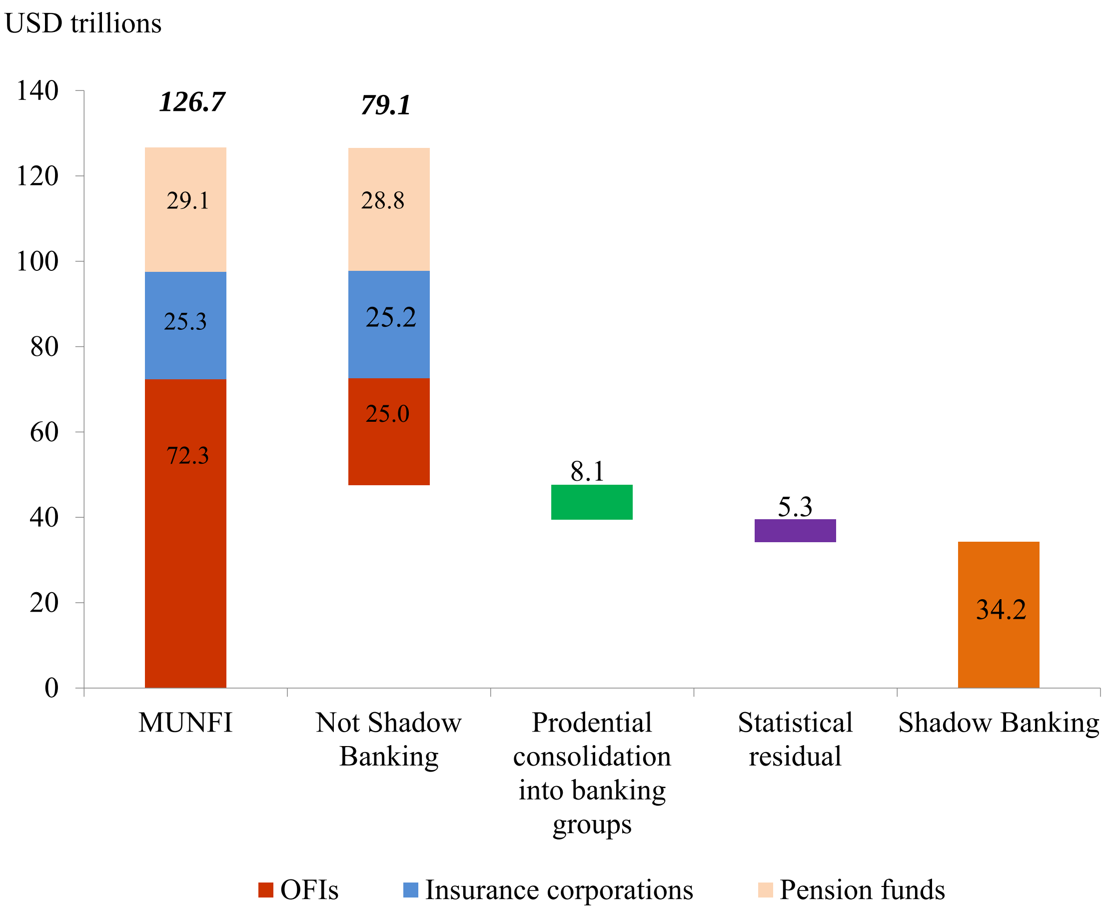
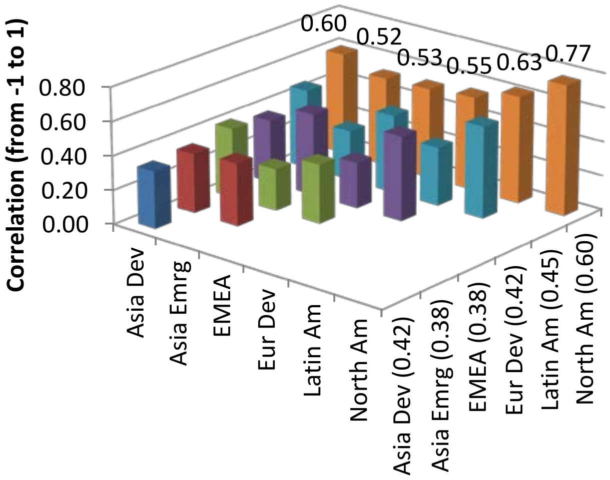
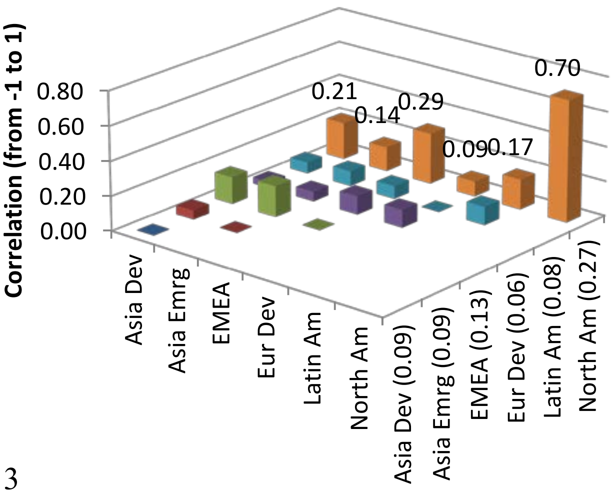


Fig 7. Narrowing down shadow banking. "MUNFI" refers to Monitoring Universe of Non-bank Financial Intermediation, includes OFIs, pension funds, insurance corporations, and financial auxiliaries; OFIs also includes captive financial institutions and money lenders; "Prudential consolidation into banking groups" refers to assets of classified entity types which are prudentially consolidated into a banking group; "Statistical residual" refers to reported residual OFIs generated by the difference between total OFIs and the sum of all known sub-sectors therein.
SBEG's monitoring exercise adopts 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, which is the narrow measure of shadow banking (dark orange bar). The figure demonstrates that the narrow measure of shadow banking is principally contributed by OFIs.
Sources: FSB (2017) (which reports findings for years prior to 2016).



Average = 0.45

Fig 8. Pairwise correlations between OFIs size growth by economic region. This chart depicts the average correlations of OFI growth among the economic regions defined in table 1. Only the upper triangular part of the matrix is presented due to the symmetric characteristic of correlation matrix. For examples, the average correlation between Asian developed and North American economies is 0.60 while the average correlation between Asian emerging and North American economies is 0.52. The figures in parenthesis next to the axis report the average correlation of the specific region with rest of the regions. For example, the average correlation between the North American and other regions is 0.60. The correlation of all region pairs is 0.45 on average.
Source: HKMA staff estimation



Average = 0.13

Fig 9. Pairwise correlations between adjusted OFI size growth by economic region. This chart depicts the average correlations of adjusted OFI growth among the economic regions. Adjusted OFI growth is defined by the regression residual of Equation (4) using the independent variables in column 1 of Table 7. Correlations with p-value less than 0.05 are considered insignificant in the estimation and treated as 0 in calculation. Only the upper triangular part of the matrix is presented due to the symmetric characteristic of correlation matrix. For example, the average correlation between Asian developed and North American economies is 0.21 while the average correlation between Asian emerging and North American economies is 0.14. The figures in parenthesis next to the axis report the average correlation of the specific region with rest of the regions. For example, the average correlation between the North American and other regions is 0.27. The correlation of all region pairs is 0.13 on average, substantially smaller than that of original OFIs (0.45) in Figure 8. This finding suggests that the significant determinants in Equation (4) are the major spillover factors of OFIs, albeit North American economies still has a relatively substantial correlation with other regions. Three missing values of bank concentration are linearly interpolated during the process. Saudi Arabia is not included due to data scarcity.

Source: HKMA staff estimation

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		

Classification of 28 economies into economic regions. The economies 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 size and other variables.

Period: 2002-2015	Min	Median	Mean	Max	SD	N
Asset data (US$ billion)						
OFIs size	1	694	2,085	26,490	4,402	375
Institutional investors size	9	485	1,854	25,777	4,071	334
Bank size	56	1,578	3,993	27,470	5,613	371
Country-specific data						
Individual forward earnings yield (%)	2.6	6.9	7.6	36	3.2	298
Consumer confidence	-2.6	0.0	0.0	2.4	1.0	334
Bank concentration (%)	20.5	60.3	60.6	100	18.8	372
GDP (US$ billion)	68	881	1,858	18,037	2,945	378
Global financial variables						
General forward earnings yield (%)	5.5	6.2	6.6	9.1	1.0	378
VIX Index	11.6	18.3	19.9	40	7.2	378

This table is the summary statistics of OFIs and other variables in the analysis. All variables are defined in session 3.3. There are 14 years and 27 economies (Cayman Islands is excluded).
Sources: FSB (2017), World Bank, the Heritage Foundation, Bloomberg and HKMA staff calculation

Table 3. Unit root test for individual economies.							
	I(0)		I(1)		I(2) or above		
Time trend	No time trend	With time trend	No time trend	With time trend	No time trend	With time trend	total
OFIs size	2	2	17	13	7	10	27
General forward earnings yield	27	0	0	27	0	0	27
Individual forward earnings yield	19	18	6	7	0	0	27
Consumer Confidence	6	5	14	10	5	7	25^
Institutional investors size	3	3	18	13	5	9	26#
Bank size	0	0	7	8	20	14	27
Bank concentration	5	2	18	18	3	5	27
GDP	2	0	13	12	12	13	27

The table shows the results of ADF test for the time series of OFIs and explanatory variables for each economy. The figures are the number of economies under each order of integration under 5% significant level. Majority of the series are integrated of order 1 (i.e. I(1)) or higher.
Note# : Saudi Arabia is excluded due to data scarcity. ^ Saudi Arabia and Switzerland are excluded due to scarcity of year-end data.
Source: HKMA staff estimation

Table 4. Data definition and source.

Variable	Definition	Data Source
OFIs asset size	Other Financial Intermediaries (OFIs) is measured by the sum of assets of all financial corporations that are not classified as central banks, banks, insurance corporations, pension funds, public financial institutions, or financial auxiliaries.	FSB (2017)
General forward earnings yield	The reciprocal of MSCI World Index forward PE which is the price divided by the Bloomberg estimated trailing 12 months earnings per share.	Bloomberg
Individual forward earnings yield	The reciprocal of individual economy's major stock index forward PE which is the price divided by the Bloomberg estimated trailing 12 months earnings per share.	Bloomberg
Consumer confidence	Consumer confidence tracks sentiment among households or consumers. The results are based on the most popular survey conducted among a random sample of households in each economy.	Bloomberg
Institutional investors size	Asset size of institutional investors is measured by the sum of size of pension funds and insurance companies for each economy.	FSB (2017)
Bank size	Bank asset size is measured by all assets of deposit-taking corporations for each economy.	FSB (2017)
Bank concentration	Ratio of the assets of top three largest banks to the assets of all commercial banks for each economy.	World Bank Financial Development and Structure Dataset
GDP	Gross domestic products, current prices (USD billion)	FSB(2017), Datastream, IMF WEO
VIX Index	CBOE volatility index which is the implied volatility of S&P 500 index options over the next 30-day period.	Bloomberg

This table reports the definition and data source of OFI assets and other selected variables in estimation.

Table 5. Correlation matrix of OFI size and explanatory variables.

(in log)	OFIs size	General forward earnings yield	Individual forward earnings yield	Consumer Confidence	Institutional investors size	Bank size	Bank concentration	GDP
OFIs size	1.00	0.10	-0.15	-0.02	0.91	0.84	0.10	0.67
General forward earnings yield	0.10	1.00	0.49	-0.36	0.03	0.10	-0.07	0.10
Individual forward earnings yield	-0.15	0.49	1.00	-0.32	-0.24	-0.04	-0.03	-0.04
Consumer Confidence	-0.02	-0.36	-0.32	1.00	0.02	-0.04	-0.02	-0.01
Institutional investors size	0.91	0.03	-0.24	0.02	1.00	0.85	0.07	0.71
Bank size	0.84	0.10	-0.04	-0.04	0.85	1.00	0.03	0.80
Bank concentration	0.10	-0.07	-0.03	-0.02	0.07	0.03	1.00	-0.37
GDP	0.67	0.10	-0.04	-0.01	0.71	0.80	-0.37	1.00

This table presents the correlations of OFIs size (in log) and explanatory variables in the regression of Equation (4). All variables are defined in session 3.3.
Source: HKMA staff calculation.

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

	Asia Developed	Asia Emerging	EMEA	Europe Developed	Latin America	North America	Row Average
<u>α</u>							
Asia Developed	0.11	0.03	0.06	0.07	0.03	0.04	0.06
Asia Emerging	0.20	0.21	0.23	0.21	0.19	0.18	0.20
EMEA	0.01	0.00	0.00	0.01	0.00	0.00	0.00
Europe Developed	0.02	0.01	0.02	0.02	0.01	0.01	0.01
Latin America	0.03	0.02	0.03	0.07	0.04	0.02	0.03
North America	0.01	0.01	0.02	0.02	0.01	0.02	0.01
Column Average	0.06	0.05	0.06	0.07	0.04	0.05	0.05 (0.77)
<u>β</u>							
Asia Developed	0.06	0.06	0.19	0.24	0.13	0.63	0.22
Asia Emerging	0.31	0.00	0.06	0.60	0.20	0.25	0.24
EMEA	0.17	-0.07	0.02	0.17	0.16	0.17	0.11
Europe Developed	0.24	0.11	0.12	0.52	0.10	0.77	0.31
Latin America	0.11	0.06	0.17	0.21	0.19	0.53	0.21
North America	0.17	0.02	0.10	0.48	0.24	0.00	0.17
Column Average	0.18	0.03	0.11	0.37	0.17	0.39	0.21 (1.09)
<u>α + δ</u>							
Asia Developed	0.03	-0.09	0.06	-0.05	0.02	0.07	0.01
Asia Emerging	0.16	-0.04	0.26	0.06	0.16	0.27	0.15
EMEA	-0.04	-0.11	0.04	-0.11	-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	0.04	-0.05	0.00	0.03	-0.01
North America	0.00	-0.11	-0.01	-0.04	-0.02	0.00	-0.03
Column Average	0.03	-0.07	0.08	-0.03	0.03	0.08	0.02 (0.22)
<u>β + γ</u>							
Asia Developed	1.28	0.74	0.86	1.44	0.86	1.45	1.10
Asia Emerging	1.46	1.43	1.41	2.03	1.35	2.00	1.61
EMEA	1.29	0.82	1.11	1.46	0.95	1.81	1.24
Europe Developed	0.63	0.38	0.38	0.79	0.37	0.61	0.53
Latin America	1.01	0.50	0.69	1.15	0.62	1.11	0.85
North America	0.93	0.35	0.64	0.99	0.61	1.17	0.78
Column Average	1.10	0.70	0.85	1.31	0.79	1.36	1.02 (2.30)

This table reports the results of Equation (1) using OFIs growth. α and β are the constant term and slopes during periods of normal market liquidity respectively, while $\alpha + \delta$ and $\beta + \gamma$ are that during periods of liquidity shocks defined by VIX exceeding its third quartile during the sample period. The reported figure in each cell is the averages of the estimated coefficients with insignificant coefficients at a 10% level are assumed to be zero when averaging. The numbers in the parenthesis are the z-values to test whether the average of the estimated coefficients in the matrix are different from zero.

Note: The estimated coefficients with absolute value of larger than 8 are considered as outliers, which 2 out of 2808 estimation coefficients are removed in the process.

Source: HKMA staff estimation

Table 7. Estimation results of for the determinants of shadow banking size by Equation (4).

	Dependent variable: OFIs size in log-level								
Independent variable	All economies			EMEs			AEs		
(in log)	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
General forward earnings yield	-0.356***			-0.553***			-0.180***		
Individual forward earnings yield		-0.297***			-0.402***			-0.099***	
Consumer Confidence			0.140***			0.176*			0.091***
Institutional investors size	0.255***	0.125**	0.201***	0.224*	0.041	0.115	0.128*	0.236***	0.098
Bank size	0.329***	0.138*	0.425***	0.044	0.077	0.309	0.104*	0.089*	0.133**
Bank concentration	0.140	0.421***	0.245**	0.203	0.469***	0.330	0.079	0.219**	0.077
GDP	0.049	0.229***	-0.087	0.307	0.283	-0.027	0.019	0.085*	0.053
Lag dependent variable	0.517***	0.637***	0.545***	0.575***	0.753***	0.611***	0.715***	0.574***	0.716***
Constant	-2.779***	-3.490***	-1.976***	-3.564***	-4.124***	-1.821	-0.539	-0.967*	-0.410
N	309	271	285	112	99	111	197	172	174
Sargan statistics	184.130	238.359	171.913	88.960	117.228	91.481	173.687	179.454	143.856
Within R^2	0.784	0.782	0.760	0.720	0.756	0.705	0.877	0.816	0.852

The dynamic panel data regression results in this table examine the determinants of OFIs size of all economies (columns A-C), EMEs only (columns D-F) and AEs only (columns G-I). All variables are defined in session 3.3. The Sargan statistics of all models are large enough to reject the null hypothesis of over-identifying restrictions on the instrumental variables of the panel data regression. 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. The sample period is from 2002 to 2015.
Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.
Source: HKMA staff estimate.

Table 8. Test results for coefficient constancy by random coefficient specification in Equations (7) and (8).

Independent variable (in log and demeaned)	All economies		EMEs			AEs		
	Res. from the col. in Table 7 (J)	All economies (K)	Res. from the col. in Table 7 (L)	All EMEs (M)	EMEs excl. outliers (no.of outliers) (N)	Res. from the col. in Table 7 (O)	All AEs (P)	AEs excl. outliers (no.of outliers) (Q)
General forward earnings yield	A	18.64	D	9.32		G	12.81	
Individual forward earnings yield	B	20.30	E	4.37		H	9.19	
Consumer confidence	C	22.01	F	6.21		I	18.35	
Institutional investors size	A	78.69*	D	11.16		G	32.92*	17.764 (2)
Bank size	A	164.85*	D	13.68		G	92.44*	16.496 (3)
Bank concentration	A	50.64*	D	35.09*	5.255 (2)	G	21.54	
GDP	A	278.76*	D	23.46*	9.055 (1)	G	107.28*	22.069 (1)
Number of sample		309		112			197	
Number of economies		26		10			16	

The random coefficient regression results in this table examine the varying responsiveness of residual (see columns J, L, and O for where the residual is extracted from in Table 7) of OFIs size among all economies, EMEs, and AEs. The dependent variable is the OFIs residual which is defined by the residual of Equation (4). Each independent variable is regressed separately as specified in Equation (8). Columns K, M and P reports the chi-squared for comparison test statistics (under the null hypothesis that all individual countries share the same coefficient) among all economies, EMEs and AEs respectively. Columns N and Q reports the test statistics after removing number of outliers reported in parenthesis, which shows that the variables would have consistent coefficient after removing certain outlying economies.

Note: * Significant at 5%. The critical value for rejecting null hypothesis under 5% significant level of columns K, M, and P are 37.7, 16.9 and 25.0 respectively.

Source: HKMA staff estimate

Table 9. Estimated coefficient matrices by adjusted OFI growth by economy group in Equation (1)							
	Asia Developed	Asia Emerging	EMEA	Europe Developed	Latin America	North America	Row Average
α							
Asia Developed	-0.20	-0.32	-0.32	-0.20	-0.28	-0.41	-0.29
Asia Emerging	-0.17	0.00	-0.03	-0.02	-0.03	-0.23	-0.08
EMEA	0.05	0.01	0.02	-0.19	0.01	-0.20	-0.05
Europe Developed	0.00	0.07	0.07	0.07	0.05	0.04	0.05
Latin America	0.12	0.01	0.08	0.01	0.01	-0.02	0.04
North America	0.18	0.14	0.12	0.21	0.19	0.02	0.14
Column Average	0.00	-0.01	-0.01	-0.02	-0.01	-0.13	-0.03 (-0.21)
β							
Asia Developed	-0.14	-0.02	0.14	0.01	0.09	0.53	0.10
Asia Emerging	-0.25	0.00	0.16	-0.26	-0.02	0.34	0.00
EMEA	0.19	0.15	0.00	-0.31	0.14	0.38	0.09
Europe Developed	0.00	-0.03	0.26	0.10	-0.03	0.04	0.06
Latin America	0.02	-0.21	0.14	0.02	0.02	0.17	0.03
North America	0.02	0.00	0.23	0.02	0.09	0.73	0.18
Column Average	-0.02	-0.02	0.16	-0.07	0.05	0.37	0.08 (0.37)
α + δ							
Asia Developed	-0.09	-0.36	-0.15	0.00	-0.17	-0.41	-0.20
Asia Emerging	0.18	0.14	-0.02	0.17	0.44	-0.67	0.04
EMEA	0.04	0.04	0.03	0.16	0.22	-0.14	0.06
Europe Developed	0.07	0.16	0.13	0.10	0.09	0.23	0.13
Latin America	0.19	0.07	0.13	0.14	0.15	0.03	0.12
North America	0.33	0.11	0.20	0.21	0.23	0.02	0.18
Column Average	0.12	0.03	0.05	0.13	0.16	-0.16	0.06 (0.27)
β + γ							
Asia Developed	0.18	0.68	0.52	-0.18	0.01	1.04	0.38
Asia Emerging	1.03	0.00	0.79	-0.19	0.60	1.78	0.67
EMEA	0.40	0.42	1.37	0.09	0.27	0.68	0.54
Europe Developed	-0.21	-0.17	-0.23	-0.15	-0.15	-0.39	-0.22
Latin America	0.26	0.38	0.40	-0.01	-0.21	0.76	0.26
North America	0.34	0.30	0.38	-0.15	-0.05	0.82	0.27
Column Average	0.33	0.27	0.54	-0.10	0.08	0.78	0.32 (0.65)

This table reports the results of Equation (1) using adjusted OFI growth which is defined by the regression residual of Equation (4) using the significant independent variables in column 1 of table 7. α and β are the constant term and slopes during periods of normal market liquidity respectively, while α + δ and β + γ are that during periods of liquidity shocks defined by VIX exceeding its third quartile during the sample period. The reported figure in each cell is the average of the estimated coefficients with significance at a 5% level. The numbers in the parenthesis are the z-values, which tests whether the average of the estimated coefficients in the matrix are different from zero.

Note: Three missing values of bank concentration are linearly interpolated during this process. India, Saudi Arabia and Singapore are not included due to data scarcity. The estimated coefficients with extreme value are considered as outliers, in which 5 out of 2208 estimation coefficients are removed in the process.

Source: HKMA staff estimation

Appendix Table 1. Consumer confidence details by economy

Economy	Full name	Bloomberg ticker	Source
Argentina	Argentina Capital Consumer Confidence UTDT	ARCCCAP Index	Universidad Torcuato di Tella
Australia	Westpac-Melbourne Institute Consumer Confidence Consumer Sentiment	WMCCCON% Index	Westpac Banking Corporation
Belgium	European Commission Consumer Confidence Indicator Belgium	EUCCBE Index	European Commission
Brazil	Brazil CNI Consumer Confidence	BZCCI Index	CNI - Confederacao Nacional das Industrias
Canada	OECD Canada Consumer Opinion Confidence Composite National	OECALCAB Index	OECD
Chile	Chile Adimark Consumer Confidence Overall Index	CLACIPEC Index	Adimark Chile
China	China Consumer Confidence Index	CHCSCONF Index	National Bureau of Statistics of China
France	France Consumer Confidence Overall Indicator SWDA	FRCCO Index	INSEE National Statistics Office of France
Germany	GfK Consumer Confidence	ECO1GFKC Index	GfK SE
Hong Kong	MasterCard Asia Pacific Consumer Confidence - Hong Kong	MCCCHK Index	MasterCard Advisors
India	MasterCard Asia Pacific Consumer Confidence - India	MCCCIN Index	MasterCard Advisors
Indonesia	Bank Indonesia Consumer Confidence Index	IDCCI Index	Badan Pusat Statistik Indonesia
Ireland	European Commission Consumer Confidence Indicator Ireland	EUCCIE Index	European Commission
Italy	Italy Consumer Confidence Indicator	ITPSSA Index	ISTAT
Japan	Japan Consumer Confidence Overall Nationwide	JCOMACF Index	Economic and Social Research Institute Japan
Korea	South Korea Consumer Confidence Index	SKCOEXPC Index	Statistics Korea
Mexico	Mexico Consumer Confidence Index	MXCFCONF Index	INEGI
Netherlands	Netherlands Consumer Confidence Economic Climate	NECCECC Index	Dutch Statistics Office
Russia	Russia Consumer Confidence Overall	RUCNCNCF Index	Federal Service of State Statistics
Saudi Arabia	BAYT.COM Consumer Confidence Index Saudi Arabia	BACISRC Index	BAYT.com
Singapore	MasterCard Asia Pacific Consumer Confidence - Singapore	MCCCSG Index	MasterCard Advisors
South Africa	South Africa Consumer Confidence	SACWC Index	Bureau For Economic Research
Spain	European Commission Consumer Confidence Indicator Spain	EUCCES Index	European Commission
Switzerland	Switzerland Consumer Confidence EU Compatible	SZCCEUCM Index	State Secretariat for Economic Affairs
Turkey	Turkey Consumer Confidence	TUCDCONF Index	Turkish Statistical Institute
United Kingdom	GFK UK Consumer Confidence Indicator	UKCCI Index	GfK NOP (UK)
United States	University of Michigan Consumer Sentiment Index	CONSSENT Index	University of Michigan