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DO LONG-TERM INSTITUTIONAL INVESTORS CONTRIBUTE TO FINANCIAL STABILITY? – EVIDENCE FROM EQUITY INVESTMENT IN HONG KONG AND INTERNATIONAL MARKETS

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Do long-term institutional investors contribute to financial stability? – Evidence from equity investment in Hong Kong and international markets*

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Abstract

This paper assesses whether long-term institutional investors help stabilise or destabilise Hong Kong and international stock markets. We use a novel dataset based on individual funds issued by insurance companies and pension funds worldwide. This allows us to examine each economic region in conjunction with the remaining regions, not in isolation as in bilateral flow-based analysis. Overall, our results indicate that these institutional investors would be counter-cyclical (i.e., they buy past losers and sell past winners) for most stock markets (including Hong Kong) during normal market conditions, which could temper upward and downward movements in asset prices. During adverse market conditions, these investors would become pro-cyclical for some stock markets in advanced economies, which could exacerbate price volatility. This implies that these long-term institutions would have a destabilising impact on these markets during the market downturns. The pro-cyclicality may reflect that some AEs were the epicentre of several major stock market crashes during the sample period. Moreover, the influence of pro-cyclicality would be reinforced by the LTIIs' herding behaviour.

Keywords: Long-term investment, institutional investors, insurance companies, pension funds, portfolio rebalancing, pro-cyclicality, financial stability, panel data, time series analysis

JEL Classification: C22, C23, G01, G11, G15, G23

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1. Introduction

The contributions of insurance companies and pension funds (ICPFs) to financial stability are debatable in literature. While providing long-term funding to non-financial and financial firms, the ICPFs would rebalance their portfolios away from safer assets and towards riskier ones. Such value-trading strategies could temper upward and downward movements in asset prices, resulting in a counter-cyclical impact on financial systems (e.g., see Dutch pension funds and insurers in de Haan and Kakes, 2011). However, these investors would behave pro-cyclically during financial market turbulence (e.g., see most of the global long-term institutional investors in Papaioannou et al., 2013), during which they would rebalance their portfolios away from riskier assets and towards safer ones to meet short-term liquidity needs. Such a flight-to-quality strategy tends to overvalue short-term gains and put less value on long-term investments, which cause or exacerbate financial instability.

These studies, however, commonly consider the risk in isolation of the spillovers from global markets in the funds' portfolio. The spillover effect could be contagious and affect the funds' portfolio rebalancing strategies, especially in a financial downturn, since these institutional investors tend to have consistent trading strategies for markets facing similar risk in the portfolio. Empirical studies have found compelling evidence that, when taking global fund flows and asset reallocation across global markets into consideration, some investment funds behave pro-cyclically and their consequences will be contagious for markets in the portfolio (Puy, 2016; Raddatz and Schmukler, 2012; Curcuru et al., 2014; Jotikasthira et al., 2012). Its potential adverse impact also catches attentions of international organisations and central banks (e.g., BOE, 2014; FSB, 2017; OECD, 2010; Papaioannou et al., 2013). Papaioannou et al., (2013) also urges these long-term investors to develop effective portfolio rebalancing rules to create investment discipline and avoid pro-cyclical behaviour amid the protracted low-yield environment.

Over the past decade, ICPFs have played an increasingly important role in financial stability, since these investors manage a substantial part of global financial assets. According to the Financial Stability Board (FSB)'s Global Shadow Banking Monitoring Report 2017, the total financial assets of insurance corporations and pension funds in 29 reporting jurisdictions have grown steadily at 5% each year since 2008. It reached $60 trillion in 2016 with a share of 18% of global financial assets (Figure 1). After a long period of low economic growth and a low interest rate environment, some investors may have already faced higher liquidity pressures. This

is because (i) the low-yield environment amid weak economic conditions has eroded interest income due to generally declining returns on investments and increased re-investment risk from maturing fixed income assets; and (ii) declining asset returns and rising liabilities due to lower discount rates have increased the funding deficits of pension plans. Therefore, these investors would have a higher incentive to rebalance their portfolio away from risky assets, therefore affecting financial market sentiment during periods of financial turmoil.

This study discusses fund flow dynamics across international markets in the portfolio of ICPFs. It also discusses their role in the funds' cyclical investment behaviour towards these markets, which helps identify markets that could move in tandem in times of financial stress. Therefore, this study attempts to address some new research questions: How strong is the co-movement among the ICPFs' investment in the international financial markets? How different are the co-movements between normal and stressful market periods? How do these investors respond to declines in stock market prices? The answers can shed light on the impact of portfolio rebalancing activities, particularly in times of financial stress.

We address these questions in three steps. First, we use a novel dataset from portfolio flows emanating from a vast number of equity funds issued by ICPFs between 2001 Q1 and 2017 Q1. As of 2016 Q4, the dataset collects information from 63,559 individual funds invested in 56 mature and 181 emerging markets. We primarily focus on the ICPFs' investment in the Hong Kong stock market, given that the Hong Kong stock market is one of the most liquid and transparent equity markets without capital control.[2] We also examine these funds' international equity exposures to uncover the fund flow dynamics among international markets in the ICPFs' portfolio. Second, after adjusting the fund flows for individual fund characteristics and macroeconomic and financial conditions, we apply a dynamic fixed-effect panel data regression to the adjusted flows to examine the cross-border fund flow dynamics. This is useful to illustrate where contagion spreads and with what intensity. Given these fund flow dynamics, in the final step we determine the relationship between the expected fund flows and past returns of the underlying equity markets.

Our major findings on the ICPFs are as follows. Focusing on ICPFs' equity investment in Hong Kong, we find that the fund flow dynamics between Hong Kong and international markets change notably in times of extreme market fear. In

[2] As of 31 October 2017, Hong Kong ranks seventh among major stock exchange groups in terms of market capitalisation.

particular, equity fund flows to Hong Kong, usually correlated with those to developed European economies, would be significantly correlated with those to Asia Pacific economies during periods with a high VIX level. Given these fund flow correlations, the ICPFs would behave counter-cyclically for their equity investment in Hong Kong during stressful market periods. For the funds' equity investment in other regions, the ICPFs would respond counter-cyclically to declines in global stock market prices during normal market conditions. However, these funds would behave pro-cyclically for some major developed stock markets in times of financial crisis.

Taken together, our results contribute to the growing literature on ICPFs' contribution to financial stability in several respects. First, we examine ICPFs' trading behaviour from a broader perspective by considering past-return trading of the entire portfolio of equity assets. To date, most contributions have focused on evidences for ICPFs in individual economies, rather than in global markets, due to limited data availability. Our data allows us to examine each region in conjunction with the rest of the portfolio, not in isolation, as in bilateral flow-based analysis. Second, our measure on fund flows is more useful for analysing the impact of portfolio rebalancing in times of financial crisis, compared to most studies using either bilateral fund flows or flow momentum to measure ICPF trading behaviour. After controlling for various important determinants, including fund-specific characteristics and macroeconomic and financial conditions, our measure allows us to identify how the ICPFs respond differently to their past returns given different fund flow correlations in normal market conditions and market downturns. Finally, we apply an empirically sound econometric method. This is a dynamic panel data regression estimated by a generalised method of moment, to address concerns about the endogeneity among fund flows in the portfolio of ICPFs under a regression framework when identifying the funds' cross-border spillover effects.

The paper is organised as follows. The next section discusses recent trends of ICPFs' investment and the dataset we employed. Sections 3 and 4 detail our empirical methods and summarise our empirical findings. The last section concludes.

2. Data and stylised facts

2.1 Dataset on funds issued by ICPFs

Our data is sourced from Morningstar, a private data vendor tracking a vast number of funds invested in global financial markets.[3] As at the end of 2016, the database

[3] Note that Morningstar's data providers do not guarantee the accuracy, completeness or timeliness of any information provided by them and shall have no liability for their use.

contained information from 63,559 individual funds issued by the ICPFs, which invested in more than 56 developed and 181 emerging markets. There were 6,872 funds that have exposure to the Hong Kong equity market, whose assets totalled HK$7.96 trillion in 2016 Q4. Among these funds, 95% of these assets were held by only 1,010 major funds.

Focusing on these major funds, we find that equity assets are their primary investment assets and most of these equity exposures are invested in developed markets. These can be seen in Figures 2 and 3a, which show the distribution of funds by asset type (i.e., equity, fixed income and others) and by geographical region (i.e., Developed Asia, Emerging Asia, Australasia, Developed Europe, Emerging Europe, Middle East and Africa – or EMEA in short, North America and Latin America). As shown, two-thirds of these assets are invested in equity, 23% in fixed incomes and 4% in others. Moreover, 80% of these equity assets are invested in developed markets in North America and Europe, while the rest of the equity assets are invested in Asia Pacific and emerging markets. This geographical distribution is also highly consistent with those found by the FSB (2017) (see Figure 3b). This suggests that our data sample is not biased towards specific regions and has an adequate representation of ICPFs worldwide. Compared to sizable exposures in developed markets, Hong Kong shares only 1% of the total equity exposures. The share is small but the asset size is comparable to the stock market's daily turnover in Hong Kong. As of 2016, the asset size represented 79% of the average daily turnover of stocks listed on the Main Board of the Hong Kong Stock Exchange.[4]

In this study, we focus on the ICPFs' equity investment in Hong Kong and in the seven regions to simplify our discussion. Details of economies covered in these regions are reported in Appendix A1. Fund flows among individual economies in the portfolio can be identified from the dataset, however, the data work and econometric analysis becomes complicated.

2.2 Our fund flow measure

Following major studies in literature,[5] net flows of each fund invested in a stock market is measured by the percentage change in the fund's total net assets (TNA) invested in the market, in excess of the fund's investment return in the market. Specifically, fund j's TNA invested in a stock market in the k-th region ($TNA_{j,t}^{k}$) at the

[4] Sourced from HKEx Securities and Derivatives Markets Quarterly Report, the average daily turnover is HKD 63.9 billion during the quarter.

[5] Major studies using a similar measure include Cao et al. (2008), Del Guercio and Tkac (2002), Ferreira et al. (2013), Jotikasthira et al. (2012), and Raddatz and Schmukler (2012).

time t is defined as

$$TNA_{j,t}^{k} = TNA_{j,t} \times W_{j,t}^{k} \quad (1)$$

and fund flows to the k-th region are defined as

$$f_{j,t}^{k} = \left(TNA_{j,t}^{k} - TNA_{j,t-1}^{k}\right)/TNA_{j,t-1}^{k} - r_{t}^{k} \quad (2)$$

where $W_{j,t}^{k}$ denotes the weighting of fund j on its equity investment in the k-th region, $TNA_{j,t}$ denotes the TNA of fund j, and r_{t}^{k} denotes the returns of the fund invested in the k-th region. Since equity exposure returns for each individual fund (i.e., $r_{j,t}$) are not available from the data source, we use the index return of the k-th region as a proxy. In other words, all funds invested in the k-th region are assumed to experience the same return as the index return of the k-th region.[6] For the Hong Kong stock market, we use the Hang Seng Index (HSI) return as a proxy for the funds' return on equity. For the seven regions, we use the returns of the MSCI regional indices as a proxy for the funds' return invested in the corresponding regions. These indices are reported in Table 1.

Therefore, the fund flow measure here is considered as changes in ICPFs' exposure to the k-th region. In other words, a positive (negative) change in the fund flow means that the ICPFs increase (decrease) their exposures to the k-th region. This concept is consistent with the net-buy measure in Timmer (2018), which reflects changes in quantity (i.e., fund flows that rule out the price effect) and is more in line with changes in the funds' asset allocation.[7]

We impose a restriction on the flows data to exclude abnormally volatile fund flows. Specifically, we remove gross fund flows and equity fund flows to each region being not less than -150% and not greater than 500%. The restriction on the outflow limit assumes that the fund can be redeemed fully by 100% with a room of short-selling. On the outflow limit, the restriction aims to avoid outliers due to low base impact or data error. After imposing the restriction on the major funds, the final sample includes

[6] This assumption may not be too strong given the documented synchronicity of returns across assets within countries, especially in developing financial markets (Morck et al., 2000).

[7] Unlike our measure, Timmer's (2018) measure is directly the net-buy measure by the nominal value of debt securities, which does not contain price movement instinctually. This kind of measure reflects mainly investment decisions of fund managers rather than fund investors since the portfolio weighting in the measure is mainly determined by the fund managers' strategy in asset allocations. This consideration is also in line with some major studies that employ portfolio weighting to understand investment fund managers' performance (e.g, Bikker, et al., 2010; Morris et al., 2017).

921 individual funds.

2.3 Stylised facts: How strong is the co-movement in the portfolio flows?

This section highlights several properties of the co-movement in the equity fund flows from individual funds issued by ICPFs: (i) fund flows are heavily skewed to inflows and considerably correlated in the sample period; (ii) the ICPFs' fund flows to Hong Kong are negatively correlated with the stock market performance; and (iii) the relationships between equity fund flows to international markets and the stock market performance are mixed. Note that the following results are simply based on the original fund flows measured by Eq. (2) without controlling for the effects of macroeconomic and financial factors and are based on regional flows in isolation from flows in other regions. Therefore, these results are only preliminary and may not be fully comparable with the empirical results discussed in the next section.

Table 2 reports some descriptive statistics of aggregate fund flows to equity markets of Hong Kong and other regions. The flows to Hong Kong are asymmetric and are heavily skewed to the right during the sample period, given that their skewness substantially deviates from zero. For other regions, all the fund flows are also skewed to the right with those to developed economies (including developed Asia, developed Europe and North America) being notably higher.

Table 3 presents a pairwise correlation matrix of these flows. Fund flows to Hong Kong are positively correlated to all the regions, in which the correlations with developed Asia and developed Europe are slightly larger than those to other regions. For other regions, the fund flows are notably correlated across regions. In particular, the correlations among developed economies in Asia, Europe and North America are noticeably higher, with the correlations being more than 0.5.

Figure 4 depicts the aggregate equity fund flows measured by Eq. (2) and the (lagged) stock market returns, which are useful to have an overview of the ICPFs' trading behaviour in equity markets. Focusing on Hong Kong (Figure 4a), we find that the two variables often appear to move in opposite directions throughout the whole period (with a simple correlation of -0.32). This negative relationship appears to be more apparent from 2008 to 2009 (see the shaded area) during which the financial markets underwent the global financial crisis (with a correlation of -0.44).

Focusing on other markets, we find that most of the relationships are positive (with correlations ranging from 0.06 to 0.29) in the sample period, while those in

Australasia (Figure 4d) and Latin America (Figure 4g) are negative. During the crisis period, the relationships in developed economies are positive (ranging from 0.13 to 0.56), while those in EMEA and Latin America are negative (-0.02 to -0.51). Emerging Asia appears to be the only exception among emerging markets, with the correlation being 0.77.

Taken together, our results reflect that the funds have a higher chance of inflow than outflow in a quarter. The correlations of these fund flows among developed economies tend to be stronger than those between other pairs. Therefore, a poorly (well) performed Hong Kong stock market in the last quarter would increase (decrease) the funds' exposure to the Hong Kong stock market in the next quarter and this phenomenon would be stronger in times of financial crisis. For other regions in the portfolio, the relationships between the two variables appear to be mixed in the whole period but become conclusive in the crisis period.

2.4 Data on explanatory variables

We consider fund-specific and macroeconomic and financial factors as major drivers of fund flows to equity market. Their definitions, expected coefficient signs and data sources are described in Appendix A2. These variables include:

Fund-specific factors

Several fund-specific factors on the funds' financial fundamental/healthiness are considered important for driving equity fund flows to the region (Fong et al., 2017). Four factors are useful to directly address our research questions, including:

(i) Individual fund return (i.e., $r_{j,t}$) – The variable is useful to control for the overall performance of the fund investment. A positive (negative) sign of the variable means positive (negative) returns are associated with inflows into (outflows from) the region (Raddatz and Schmukler, 2012; Brandao-Marques et al., 2015).[8]

(ii) Cash ratio – The ratio reflects a fund's liquidity, since a typical fund with more cash can satisfy more investors' redemption without requiring the fund to immediately liquidate its underlying assets. Therefore the coefficient sign is

[8] Gruber (1996) proposed the smart money hypothesis that investors display some fund selection ability as they tend to invest in funds with subsequent good performance. He shows that funds experiencing net cash inflows (in the past three months) perform significantly better than funds that experience outflows. However, Sapp and Tiwari (2004) argue that the smart money effect is explained by momentum. Ferreira et al. (2013) find no evidence of a statistically significant relation between flows and subsequent performance in the sample of US funds. In contrast, they find that non-US funds that receive more new money perform better subsequently than those that receive less new money.

positive.[9] The coefficient can be negative for two reasons. First, the ratio may represent an opportunity cost due to loss of investment opportunities (Nascimento and Powell, 2010). In other words, a fund with more cash means that it invests less in other financial instruments and reduces the fund's potential long-term return. Second, the cash ratio also reflects fund managers' precautionary behaviour (Morris et al., 2017). In other words, if current redemptions are an indication of future redemptions, fund managers would like to hoard more cash to be better prepared for future redemptions in the face of current redemptions.

(iii) Fund size – It controls for the effect that large funds benefit from economies of scale. Large funds may enjoy lower research and administrative expenses, lower lending fees and better trading commissions and so the sign is positive (see Rompotis, 2007; Khorana et al., 2009). However, the coefficient could be negative because larger fund managers must necessarily trade larger volumes of stock, which attracts the attention of other market participants and therefore suffers higher price impact costs (see Chen et al., 2004). Larger funds would also find it harder to have a close relationship with their clients (Del Guercio and Tkac, 2002).

(iv) Debt-to-capital ratio – It measures a fund's financial leverage. The higher the debt-to-capital ratio, the more vulnerable the fund is during market stress and the more likely the funds will flow out. Therefore, the coefficient sign is expected to be negative (see Fong et al., 2017).

Macro-economic and financial factors

Some macro-economic and financial factors are considered important in driving the fund flows (Timmer, 2018). They include:

(v) 10-year government bond yield – It controls for the search-for-yield factors and business cycles (Pozsar et al., 2011, 2013). It is expected to have a positive impact on fund flows, in other words, an increase in sovereign bond yields would increase the size of fund flows.

(vi) Inflation rate – It erodes the purchasing power or opportunity cost of the investors. We would expect more inflows to equity markets when inflation rises. Therefore, the coefficient sign is expected to be positive.

(vii) GDP growth – It measures the size of the real sector of an economy and examines whether the local business cycle has any influence on aggregate fund flows to equity markets. Therefore, the coefficient sign is expected to be

[9] In exceptional circumstances, when there is heavy redemption pressure and capital is immediately demandable, funds without significant cash reserves have no choice but to sell holdings quickly.

positive.

(viii) Short-term interbank rate – It controls for the effect of short-term funding costs on fund flows. A lower short-term market rate tends to ease the rebalancing conditions for the whole economy, so the institutional investors are expected to buy more in such a scenario. Therefore, the coefficient sign is expected to be negative.

Standardisation of fund flows and explanatory variables

In this empirical analysis, dependent and independent variables are statistically standardised so their means and variances are zero and unity respectively. The advantage of this transformation is that the coefficients estimated by our empirical models, discussed later, ignore the variables' scale of units, which makes identification of the relative importance of the selected driving factors easier. In other words, the larger the coefficient magnitude, the more sensitive the independent variable to the fund flows will be.

3. Methodology

This section discusses three major steps in examining the investment behaviour of ICPFs. First, we filter out the effects of major fund-specific and macro factors from the fund flows based on a panel data regression model. Second, taking the residual of the panel data regression as the adjusted fund flows, we estimate the fund flow dynamics among international markets in times of normal market conditions and market downturns. Given the fund flow dynamics, we assess the responsiveness by expected fund flows to past returns in the final step.

3.1 Filtering out fund-specific characteristics from the fund flows

Econometrically, we use cross-section fixed-effect panel least squares to relate the fund flows to a region to fund-specific and macro-economic and financial variables. Specifically, we estimate a model for fund i's equity flows to the k-th region at quarter t, denoted by $f_{i,t}^{k}$ for k = 1, …, K-th region:

$$f_{i,t}^{k} = \gamma^{k\prime} X_{i,t-1} + \phi^{k\prime} Z_{t-1}^{k} + \alpha_i^{k} + \varepsilon_{i,t}^{k} \qquad (3)$$

where $X_{i,t}$ is the vector of fund-specific variables including individual fund return, cash ratio, debt-to-capital ratio and fund size; the vector Z_{t}^{k} controls for macro-economic and financial factors, including the regional weighted average 10-year government bond yield, inflation rate, real GDP growth and short-term interbank rate; α_i^{k} is the cross-sectional fixed effect; and $\varepsilon_{i,t}^{k}$ is the residual of the

model, which is regarded as the adjusted (filtered) fund flows to region k after controlling for the fund-specific characteristics and macro variables captured by $\gamma^{k\prime}$and $\phi^{k\prime}$'. All independent variables are lagged by one time period to circumvent the issue of endogeneity.

3.2 Fund flow dynamics in the international portfolio

Based on the adjusted fund flows, we estimate the fund flow dynamics among international markets. The dynamics are evaluated by regressing the adjusted fund flows to one region on the adjusted fund flows to other regions and its own lag. To differentiate the effects between normal market conditions and market downturns, we introduce a dummy variable based on the VIX index as a proxy of global stock market uncertainty.[10] The sign and magnitude of the coefficients reflect the level of co-movement of fund flows between the two regions.

Specifically, we consider the following panel regression for each region k:

$$\varepsilon_{i,t}^{k} = \left(\sum_{\substack{j=1 \\ j\neq k}}^{K} \theta^{k,j}\varepsilon_{i,t}^{j} + \delta^{k}\varepsilon_{i,t-1}^{k}\right) \times (1 - V_t) + \left(\sum_{\substack{j=1 \\ j\neq k}}^{K} \varphi^{k,j}\,\varepsilon_{i,t}^{j} + \rho^{k}\varepsilon_{i,t-1}^{k}\right) \times V_t + w_i^{k} + u_{i,t}^{k} \quad (4)$$

where ε^{k} is the adjusted fund flow to the j-th region estimated in Eq. (3); u^{k} is the error term of the regression estimation; w_i^k is the cross-section fixed effect; and V_t is a dummy variable defined as 1 when the global liquidity condition proxied by the level of stock volatility index (or VIX) exceeds a level of C, or, specifically,

$$V_t = \begin{cases} 1 & \text{if } VIX_t > C \\ 0 & \text{otherwise} \end{cases}.$$

In this specification, δ^k and $\theta^{k,j}$ are the coefficients representing the autoregressive effect of adjusted fund flows to region k and the spillover effect from region j to region k respectively during normal market conditions, while ρ^k and $\varphi^{k,j}$ are their effect during periods of liquidity shocks. Therefore, we could capture an overall picture of global equity portfolio rebalancing by the ICPFs during normal market conditions (i.e., $\theta^{k,j}$) and market downturns (i.e., $\varphi^{k,j}$). All the coefficients in Eq.(6) are estimated by the panel GMM approach suggested by Arellano and Bond (1991),

[10] It is captured by the CBOE volatility index, which is the implied volatility of S&P 500 index options over the next 30-day period. The index also reflects global liquidity conditions (see Bruno and Shin, 2014).

Arellano and Bover (1995) and Blundell and Bond (1998) to estimate Eq. (4).

3.3 Measuring investment behaviour of ICPFs

One way of identifying ICPF investment behaviour in the literature is to examine whether the ICPFs will substantially increase or decrease their equity investment when stock market prices decline. If the ICPFs increase (decrease) their equity investments during a stock market slump, changes in the ICPFs' exposures will be negatively (positively) correlated with the stock market returns and, therefore, the contribution of ICPFs are regarded as counter-cyclical (pro-cyclical) to the stock market. The regression principle is advocated by Abbassi et al. (2016) who empirically verify that trading banks in Germany increased their investments in securities during crisis. This method is also followed by Timmer (2018) to test the pro-cyclicality of German financial institutions.

Taken into account the fund flow dynamics during the sample period, we use the in-sample predicted values of the fund flows in Eq. (4) since it is a direct measure of the expected fund flows on the flow dynamics in the portfolio. We then identify the investment behaviour of ICPFs by regressing the expected fund flows on the past market returns in a fixed-effect panel data regression model.

Specifically, the expected fund flows to region k are calculated as follows:

$$\hat{\varepsilon}_{i,t}^{k} = \begin{cases} \sum_{\substack{j=1 \\ j\neq k}}^{K} \hat{\theta}^{k,j} \varepsilon_{i,t}^{j} + \hat{\delta}^{k} \varepsilon_{i,t-1}^{k} + \hat{w}_{i}^{k} & \text{if VIX>C} \\ \sum_{\substack{j=1 \\ j\neq k}}^{K} \hat{\varphi}^{k,j} \varepsilon_{i,t}^{j} + \hat{\rho}^{k} \varepsilon_{i,t-1}^{k} + \hat{w}_{i}^{k} & \text{Otherwise} \end{cases} \quad (5)$$

where $\hat{X}$ is an in-sample forecast of the variable X estimated in Eq.(4). This expected fund flows is then regressed by the following specification for each region:

$$\hat{\varepsilon}_{i,t}^{k} = \beta_{0}^{k} MR_{t-1}^{k} \times (1 - V_{t-1}) + \beta_{1}^{k} MR_{t-1}^{k} \times V_{t-1} + \alpha_{i}^{k} + \eta_{i,t}^{k} \quad (6)$$

where MR_{t}^{k} is the stock market return in the region proxied by the return of the HSI or the MSCI regional indices; V_{t} is the dummy variable of VIX exceeding a level of C; α_{i}^{k} is the fixed effect; and $\eta_{i,t}^{k}$ is the error term. Note that the independent variables are all lagged by at least one quarter to: (1) prevent contamination of the price effect due to massive trading decisions and (2) take into account that the reported returns may not be available when executing the trading decisions (Timmer,

2018). All the coefficients are estimated by the fixed-effect least squares method with white heteroskedasticity-consistent standard errors and covariance.

In the specification, β_0^k and β_1^k reflect the investment behaviour of the ICPFs in response to past returns in times of normal market conditions and market downturns respectively. A positive (negative) coefficient indicates a pro-cyclical (counter-cyclical) behaviour of the funds concerned, which implies that the ICPFs would decrease (increase) their equity investment when observing market slumps and vice versa.

4. Empirical findings

4.1 Results on the fund investment in Hong Kong

Table 4 summarises the regression results of (i) the equity fund flows to Hong Kong on their major determinants specified in Eq. (3) (see panel A of Table 4); (ii) the fund flows to Hong Kong adjusted for the major determinants on fund flows to other regions specified in Eq. (4) (panel B); and (iii) the expected fund flows to Hong Kong equities on past stock market returns specified in Eq. (6) (panel C). Since all the variables are in normalised scale, we can compare the relative importance of the variables based on the magnitude of the coefficients.

Some determinants of the fund flows

Our regression results show that all the fund-specific variables and one macro variable have a significant effect on the fund flows to Hong Kong equities (Panel A). This suggests that fund flows are more subject to their fund-specific factors, rather than our selected macro variables. The coefficient of fund size is estimated to be the largest (i.e, -0.245) among all determinants. Its negative sign may support the arguments of (i) large funds suffering higher price impact costs than small funds in Chen et al (2014); and (ii) the diminishing return of client relationship building in Del Guercio and Tkac (2002). In comparison, other variables have a much smaller coefficient in terms of magnitude, ranging from -0.055 to +0.043. The smaller magnitude reflects a smaller impact on the fund flows, however, their impact remains significant statistically.[11]

How strong are the co-movements? How different is it between market conditions?

Panel B of Table 4 summarises the estimation results of Eq. (4). We set the threshold C to be the 75th percentile of the VIX level in the sample period. This threshold is

[11] Since the inflation rate is highly correlated with some variables, to avoid endogeneity issues, we consider a specification of all variables in real terms as an alternative to the current one introducing the variable of inflation rate directly to the specification. Results on the above analysis are found to be largely consistent. Detailed estimation results are reported in Appendix A3.

chosen because of two major considerations: (i) it represents a chance of 25% seeing this event in the sample period which can be regarded as extreme but plausible in the financial markets and (ii) too extreme a VIX level would result in a smaller number of events for estimation, which may lead to bias in the empirical results.

During periods of a lower VIX level, the flow of funds invested in Hong Kong is positively correlated with most of those invested in other region, suggesting that these funds would move in the same direction during normal market conditions. The largest correlation is found between Hong Kong and Developed Europe (i.e., 0.152), followed by Australasia (i.e., 0.107), Developed Asia (i.e., 0.086) and Latin America (i.e., 0.057). In comparison, the correlations with Emerging Asia, EMEA, and North America are found to be insignificant.

During periods of a higher VIX level, we find three major changes in the correlation pattern. First, the correlations between Hong Kong and Asia Pacific increase notably, in which the correlations with developed Asia (i.e., 0.326), emerging Asia (i.e., 0.146) and Australasia (i.e., 0.171) are noticeable, although the increase with Australasia is insignificant based on Wald test statistics. Second, the correlation with EMEA drops significantly to negative (i.e., -0.174), suggesting that the fund flow directions to Hong Kong and to EMEA would be opposite. Finally, the correlation with developed Europe decreases sharply and is not significant statistically.

There are two major implications. First, the results reflect a substantial change in fund flow relationship between Hong Kong and other regions in times of financial crisis. The link between Hong Kong and Asia Pacific strengthens notably in times of market downturns, suggesting that the systemic risk in the region could materialise in times of financial stress. Second, the direct spillover effects from developed Europe and North America remain limited in comparison. That said, their impact on Hong Kong could be indirectly through other regions. This is evidenced in our preliminary fund flow correlation analysis. This shows that these developed economies are strongly linked with Asia Pacific and in our fund flow correlations between international markets.

How do the investors respond to declines in stock markets prices?

Panel C of Table 4 presents the estimation results of Eq. (6). It examines the effect of the past stock market return on expected fund flows given fund flow dynamics in normal markets and market downturns. As shown in the table, the lagged stock market returns are negatively correlated with the expected fund flows to Hong Kong equities

during both normal markets and market downturns. This suggests that the current fund flows would increase when the stock market prices decline in the previous quarter. In particular, the coefficient for market downturn is significantly larger than that for the normal markets, suggesting that the response of fund inflows to declines in stock market prices would be significantly stronger in market downturns.

The empirical results show that the ICPFs would increase their equity investments in Hong Kong in response to declines in stock market prices and the response is significantly stronger during market downturns. This arguably suggests that the ICPFs would rebalance their portfolio towards stocks in Hong Kong in times of adverse market conditions.

4.2 Results on the ICPF fund investment in other regions

Some determinants of fund flows

Table 5 presents the regression results of international fund flows on their fund-specific variables and macro-economic and financial variables. Among these variables, the magnitude of fund size is consistently the largest among all determinants for all the regions. Their coefficient signs are consistently negative, which supports arguments from Chen et al. (2004) and Del Guercio and Tkac (2002). Apart from this variable, the cash ratio is also consistently significant for all the seven regions. The positive coefficient supports the argument about funds' liquidity and is free from immediately liquidating its underlying assets due to short-term needs. On other variables, the estimation results are mixed, reflecting that the contributions of these determinants vary over regions.

What are the fund flow dynamics among other regions in the portfolio?

Table 6 reports the full estimation results of Eq. (4) for each region. Figure 5 depicts all the correlation coefficients of the adjusted fund flows reported in Table 6 to help visualise how the cross-region correlations change over the two VIX regimes (i.e., the VIX level is below, or over its 75th percentile).

During periods of a normal VIX level (see the upper panel), Figure 5 shows that the interactions between developed and emerging markets are not significant. The influences of developed Europe and developed Asia have a larger impact on developed economies, with the average correlation of 0.23 (see the first column), than on emerging markets, with average correlations of less than 0.1 (i.e., 0.06 and 0.09 respectively, see the second column). Among emerging economies, Latin America has a larger impact on emerging markets, with an average correlation of 0.23 (see the

second column), than on developed economies, with an average correlation of 0.03 (see the first column).

In times of high VIX levels (see the lower panel), the overall influence of developed economies increases. On developed economies, the impacts of North America and developed Asia increase notably with the average correlations of 0.16 and 0.28 respectively. On emerging markets, the impact of developed Europe increases substantially (i.e., 0.13), with sharp increases on emerging Asia (i.e., 0.32) and EMEA (i.e., 0.21). The influences of emerging markets on developed markets also increase, however, the increase is only noticeable in developed Asia (i.e., 0.21 and 0.16 for the spillovers from emerging Asia and EMEA respectively).

These results show that the fund flows led by institutional investment can change substantially in market downturns, during which the spillovers of developed markets would increase considerably to other regions.

How do the investors respond to declines in stock market prices?

Table 7 reports the estimation results for the relationship between the ICPFs' expected fund flows and lagged stock market returns given fund flow correlations in normal periods and market downturns. As can be seen, during normal VIX levels, all the said fund flows are negatively correlated with the lagged stock market returns. During a high VIX level, the correlations for most of the developed economies (including Australasia, developed Europe and North America) are positive, while some emerging markets remain negative. For developed Asia and emerging Asia, the correlations are found to be different from the groups. These suggest that the fund flows to all the economies in the current quarter would normally increase when the stock market prices decline in the previous quarter. However, those to the major developed economies and emerging Asia would decrease during periods with a higher VIX level.

The empirical results reflect that the ICPFs would behave counter-cyclically in response to declines in global stock markets prices during normal market conditions. However, during market downturns, these investors would behave pro-cyclically for some major developed markets.

5. Conclusion

This paper studies the effect of portfolio rebalancing activities of long-term

institutional investors on stock markets internationally. We use a novel dataset on individual funds issued by ICPFs worldwide. This allows us to examine each continental region in conjunction with the rest of the region in the portfolio, not in isolation, as in bilateral flow-based analysis. Overall, our results indicate that ICPFs tend to be counter-cyclical (i.e., they buy past losers and sell past winners) for global stock markets during normal market conditions. This shows that these long-term institutional investors help stabilise stock markets in normal periods. However, in times of market downturns, their responses become pro-cyclical for stock markets in some major developed economies,[12] which could result in an increase in price volatility in the financial markets.

The difference in the impact on developed economies and emerging markets may be attributable to two factors. First, it could be arising from the fact that these developed economies were the epicentre of several major stock market crashes triggered by recessions in Europe and the US in the early 2000s, the 2008 global financial crisis and the European debt crisis, suggesting that the counter-cyclical effect would depend on where a shock originates from. Second, the influence of pro-cyclicality would be reinforced by the ICPFs' herding behaviour. In some AEs, the herding could be resulted from similar industry practices for the ICPFs' asset allocation decisions.[13] These practices include: (i) the ICPFs have similar liability structures; (ii) the ICPFs use asset managers who manage ICPF assets as agents according to specific mandates, which may include benchmarks that reference either other asset managers in the industry or industry-wide indices; (iii) the investment decisions of ICPFs are influenced by investment consultants who could have a significant effect on institutional asset allocation; and (iv) ICPFs may face similar regulatory constraints. Hence, the extent to which these long-term institutional investors can fulfil the stabilising role for financial stability would largely depend on their own characteristics and external circumstances.

There are three major limitations in this empirical analysis. First, the ICPFs' counter-cyclical behaviours in Hong Kong, developed Asia and some emerging markets during market downturns could stem from the absence of crisis events originating from these economies in the sample period. Second, our fund data comes from a single data source that regularly collects survey-based data. The data quality is

[12] The pro-cyclical effect is also evidenced in several studies. For examples, during 2008-2009, the effect is found apparent in pension funds of the US, Portugal, and Spain (see Papaioannou et al., 2013 and OECD, 2010), and in insurers of the US, France, and the UK (see BOE, 2014).

[13] Details can be seen in BOE (2014).

therefore highly subject to the survey's response rates and the coverage of the overall asset management sector. Finally, our sample may include some types of funds that are particularly illiquid in the sample period. That said, this study underscores the potential outcomes of these investors' investment behaviour which could be important not only for individual investors and policyholders but also for the economy as a whole. How these investors contribute to financial stability should therefore come under careful scrutiny..

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Table 1. Name of MSCI Index for each region

Region	**MSCI Index**
North America	MSCI North America Index
Developed Europe	MSCI Europe Index
Developed Asia	MSCI AC Asia Index
Australasia	MSCI Australia Index and MSCI New Zealand Index (average return)
Emerging Asia	MSCI EM Asia Index
Latin America	MSCI EM Latin America Index
EMEA	MSCI EM Europe Middle East and Africa Index

Table 2. Descriptive statistics of equity fund flows and other variables

Period: 2001-2017	Min	25 Pc	Median	75 Pc	Max	SD	Skewness	N
Fund flows in the portfolio								
Hong Kong (%)	-135.4	-10.4	1.7	17.2	496.2	50.5	3.3	23783
Developed Asia (%)	-132.0	-5.0	2.2	11.7	482.6	35.2	4.7	23783
Emerging Asia (%)	-132.9	-7.1	2.2	19.6	495.7	56.6	3.4	23783
Australasia (%)	-122.1	-7.7	0.5	14.2	496.4	47.0	3.6	23783
EMEA (%)	-131.6	-8.1	0.4	15.9	499.3	50.4	3.2	23783
Developed Europe (%)	-134.1	-5.6	1.5	10.6	496.7	34.6	4.7	23783
Latin America (%)	-137.0	-10.3	0.0	14.8	494.6	52.4	3.1	23783
North America (%)	-116.4	-4.8	0.2	9.3	492.0	39.8	4.5	23783
Stock market returns								
Hong Kong (%)	-23.7	-5.0	2.9	7.2	35.4	9.9	0.0	23783
Developed Asia (%)	-20.7	-2.8	1.1	6.3	27.5	8.1	-0.1	23783
Emerging Asia (%)	-24.0	-1.6	1.7	6.7	32.9	10.1	-0.1	23783
Australasia (%)	-17.9	-2.9	2.7	5.4	20.4	6.7	-0.5	23783
EMEA (%)	-34.0	-8.6	1.4	7.6	31.6	11.5	-0.2	23783
Developed Europe (%)	-23.3	-3.5	3.6	5.8	17.4	7.8	-0.6	23783
Latin America (%)	-34.8	-4.1	2.7	7.1	37.0	13.4	-0.3	23783
North America (%)	-23.6	-0.3	3.0	5.6	16.4	7.0	-1.0	23783
Other variables								
Fund return (%)	-38.3	-2.7	2.3	6.0	29.6	7.4	-0.3	23448
Cash ratio (%)	-90.8	1.9	4.3	8.8	100.0	9.0	1.1	23783
Debt-to-capital ratio (%)	0.0	30.7	34.0	36.8	57.9	7.2	-1.8	23717
Fund size (in log)	9.0	20.6	21.4	22.5	27.7	1.6	-0.7	23783
Stock returns (%)	-23.7	-5.0	2.9	7.2	35.4	9.9	0.0	23783

Sources: Morningstar, Bloomberg and HKMA staff calculation.

Table 3. Correlation matrices of equity fund flows to Hong Kong and other regions

Fund flows	Hong Kong	Developed Asia	Emerging Asia	Australasia	EMEA	Developed Europe	Latin America	North America
Hong Kong	1.00							
Developed Asia	0.45	1.00						
Emerging Asia	0.27	0.38	1.00					
Australasia	0.37	0.46	0.25	1.00				
EMEA	0.31	0.41	0.37	0.29	1.00			
Developed Europe	0.45	**0.70**	0.35	0.47	0.38	1.00		
Latin America	0.26	0.36	0.34	0.23	0.35	0.34	1.00	
North America	0.35	**0.51**	0.31	0.37	0.32	**0.53**	0.30	1.00

Source: HKMA staff calculation.

Table 4. Estimation results of HK equity flows (full sample period: 2001-2017)					
Independent variables	Raw fund flows	Adjusted fund flows			Expected fund flows
		VIX<=75pct	VIX>75pct	Wald test	
Panel A:					
Fund-specific variable					
Fund size	-0.245**				
Debt-to-capital ratio	-0.055**				
Fund return	-0.029**				
Cash ratio	0.043**				
Macro variable					
Inflation rate	0.028**				
Interbank rate	-0.019				
GDP growth	0.007				
Government bond yield	-0.004				
Constant	-0.063**				
Panel B:					
Adjusted fund flows					
North Am		-0.023	-0.079	-0.524	
Dev Eur		0.152**	-0.148	-2.260**	
Dev Asia		0.086**	0.326**	2.290**	
Aus Asia		0.107**	0.171**	0.942	
Em Asia		0.016	0.146**	1.690*	
Latin Am		0.057**	0.078	0.280	
EMEA		0.020	-0.174**	-2.337**	
Lag of HK		-0.117**	-0.073*	0.905	
Panel C:					
Lagged market returns					
Market return at normal period					-0.017
Market return at crisis period					-0.049**
Constant					-0.021**
Periods included	60		57		57
Cross-sections	921		856		856
Total panel observations	20404		15276		15290
R-squared	0.079				0.0256
Log likelihood	-24993				-15930
Durbin-Watson stat	1.988				1.9266
Wald test statistics of market return at normal and crisis period					2.183**

Note: '**' and '*' denote significance levels of 5% and 10% respectively.
Source: HKMA staff estimate.

Table 5. Estimation results of Equation (3) (full sample period: 2001-2017)							
	Dependent variable: Regional equity fund flow						
Independent variables	North Am	Dev Eur	Dev Asia	Aus Asia	Em Asia	Latin Am	EMEA
Fund return	0.007	0.006	0.026**	0.003	0.029**	0.006	0.003
Cash ratio	0.055**	0.066**	0.033**	0.086**	0.041**	0.037**	0.040**
Debt-to-capital ratio	0.001	0.016*	-0.031**	0.021*	-0.021	0.008	0.014
Fund size	-0.266**	-0.328**	-0.318**	-0.252**	-0.198**	-0.190**	-0.188**
Government bond yield	0.047**	0.109**	0.009	0.064**	-0.029	-0.082**	-0.102**
Inflation rate	-0.027**	0.020**	0.001	0.001	-0.025**	0.035**	0.011
GDP growth	-0.006	-0.017**	0.025**	0.040**	-0.014**	-0.013	0.033**
Interbank rate	-0.003	-0.058**	0.018	-0.015	0.003	0.108**	0.071**
Constant	-0.023**	0.000	-0.044**	0.007	-0.046**	-0.004	-0.025**
Periods included	60	60	60	60	60	60	60
Cross-sections	921	921	921	921	921	921	921
Total panel observations	20404	20404	20404	20404	20404	20404	20404
R-squared	0.088	0.135	0.118	0.094	0.069	0.069	0.072
Log likelihood	-24459	-22662	-23467	-25381	-26216	-26250	-25958
Durbin-Watson stat	1.954	1.979	1.949	1.963	2.042	1.982	1.992

Note: All independent variables are lagged by one quarter. '**' and '*' denote significance levels of 5% and 10% respectively.
Source: HKMA staff estimate.

Table 6. Estimation results of Equation (4) of 7 regions (full sample period: 2001-2017)

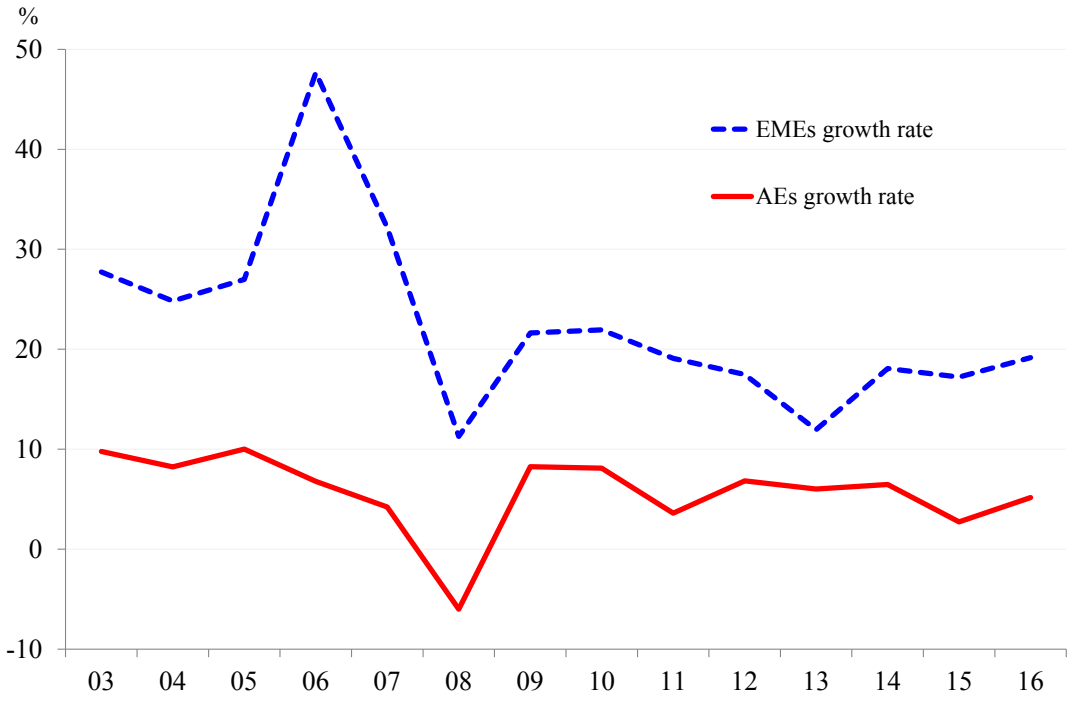
	Dependent variable: Adjusted Fund Flows of the region						
Independent variables: Adjusted fund flows	North Am	Dev Eur	Dev Asia	Aus Asia	Em Asia	Latin Am	EMEA
VIX<=75 pct							
HK	0.040	0.058**	0.116**	0.055*	0.087**	0.042	0.168**
North Am		0.128**	0.077**	0.085**	0.051	0.046**	0.007
Dev Eur	0.175**		0.317**	0.185**	-0.014	0.115**	0.069
Dev Asia	0.093**	0.430**		0.175**	0.055*	0.091**	0.118**
Aus Asia	0.030	0.078**	0.188**		0.057**	-0.027	0.037
Em Asia	0.084**	-0.042*	0.016	0.046**		0.225**	0.117**
Latin Am	0.053**	-0.025	0.118**	-0.045**	0.215**		0.250**
EMEA	0.064**	0.003	-0.017	0.086**	0.182**	0.084**	
Lag of dep var	-0.040	-0.053**	0.015	-0.048*	-0.064**	-0.017	0.029
VIX>75 pct							
HK	0.009	0.030	0.110**	0.074	0.050	0.040	-0.008
North Am		0.208**	0.072	0.187*	0.046	0.268**	-0.079
Dev Eur	0.034		0.348**	-0.052	0.322**	-0.130	0.207**
Dev Asia	0.085	0.567**		0.199**	0.007	0.290**	-0.013
Aus Asia	0.033	0.072**	-0.020		0.023	0.062	0.032
Em Asia	-0.035	-0.042	0.213**	0.088		-0.051	0.383**
Latin Am	0.113**	-0.012	0.068	-0.052	-0.040		0.224**
EMEA	0.073	-0.074*	0.161**	-0.087	0.074	0.168**	
Lag of dep var	-0.147*	0.111	-0.285**	0.012	0.030	0.121	-0.006
Wald test							
HK	-0.606	-0.733	-0.103	0.201	-0.716	-0.026	-2.771**
North Am		0.891	-0.050	0.944	-0.054	2.168**	-0.679
Dev Eur	-1.375		0.228	-1.358	3.037**	-2.114**	1.206
Dev Asia	-0.130	1.035		0.266	-0.538	2.171**	-1.353
Aus Asia	0.079	-0.121	-2.965**		-0.663	1.505	-0.063
Em Asia	-1.671*	0.000	1.793*	0.449		-2.768**	2.891**
Latin Am	1.153	0.328	-0.688	-0.098	-4.424**		-0.379
EMEA	0.166	-1.975**	3.216**	-1.869*	-1.705*	1.136	
Lag of dep var	-1.275	1.439	-2.608**	0.522	1.647*	1.276	-0.529
Periods included	57	57	57	57	57	57	57
Cross-sections	856	856	856	856	856	856	856
Total observations	15276	15276	15276	15276	15276	15276	15276
Instrument rank	16	16	16	16	16	16	16

Note: '**' and '*' denote significance levels of 5% and 10% respectively.
Source: HKMA staff estimate.

Table 7. Estimation results of Equation (6) (full sample period: 2001-2017)							
	Dependent variable: Regional rebalancing-induced fund flows						
Independent variables	North Am	Dev Eur	Dev Asia	Aus Asia	Em Asia	Latin Am	EMEA
Market return at normal period	-0.021	-0.071**	-0.049**	-0.024**	-0.056**	-0.003	-0.034**
Market return at crisis period	0.014	0.055**	-0.035**	0.085**	0.055**	-0.041**	-0.097**
Constant	-0.003	0.004	-0.011*	0.002	-0.006	-0.022**	-0.029**
Periods included	57	57	57	57	57	57	57
Cross-sections	856	856	856	856	856	856	856
Total panel observations	15290	15290	15290	15290	15290	15290	15290
R-squared	0.0248	0.0377	0.0321	0.0361	0.0288	0.0298	0.0268
Log likelihood	-16580	-15737	-15984	-17235	-18557	-18935	-19721
Akaike info criterion	2.2810	2.1707	2.2030	2.3667	2.5395	2.5891	2.6919
Schwarz criterion	2.7094	2.5992	2.6314	2.7951	2.9680	3.0175	3.1203
Durbin-Watson stat	1.8307	1.8866	1.9014	1.9676	2.0057	1.9587	2.1785
Wald test statistic	-1.942*	-8.058**	-0.969	-6.734**	-6.031**	2.329**	3.860**

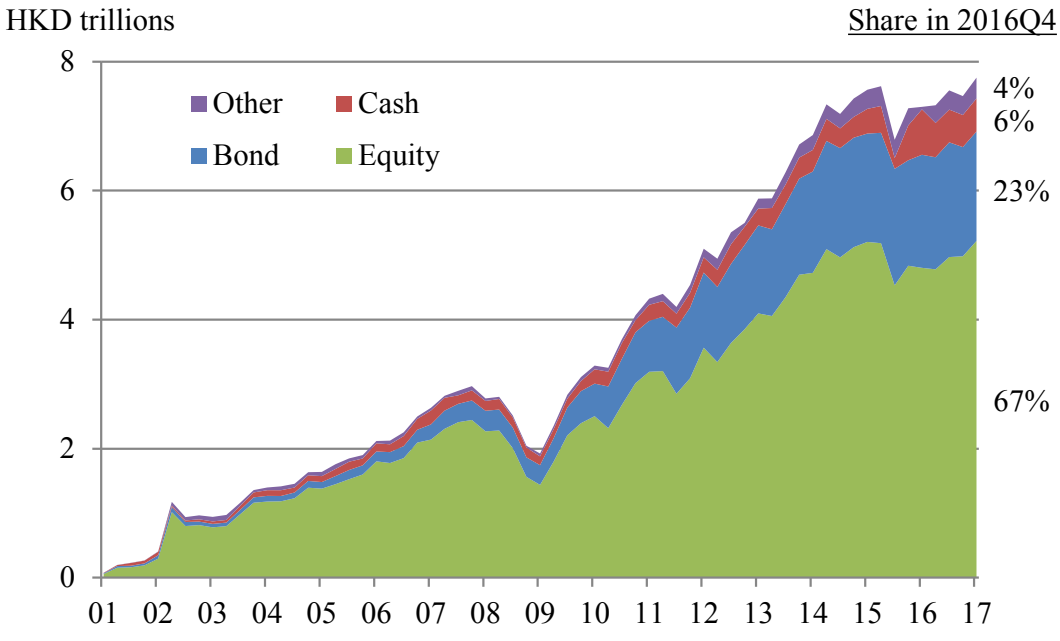
Note: All independent variables are lagged by one quarter. '**' and '*' denote significance levels of 5% and 10% respectively.
Source: HKMA staff estimate.

Figure 1. Growth in aggregate size of insurance corporations and pension funds in 29 economies



Source: FSB Global Shadow Banking Report 2017 and HKMA staff estimate

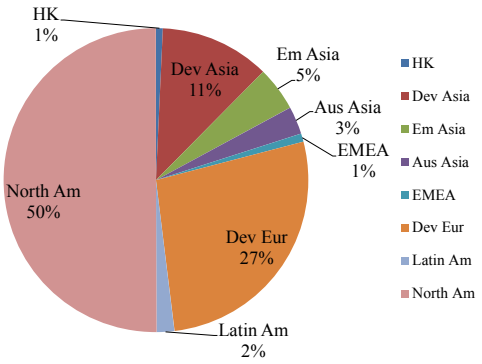
Figure 2. Composition of insurance and pension funds with Hong Kong equity market exposures



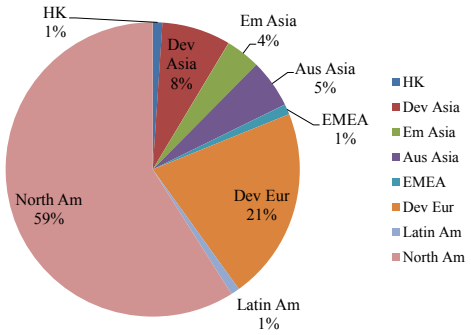
Source: Morningstar and HKMA staff estimate

Figure 3. Geographical distribution of the global ICPF equity investment in 2016 Q4

(a) FSB (2017) data



(b) Morningstar data

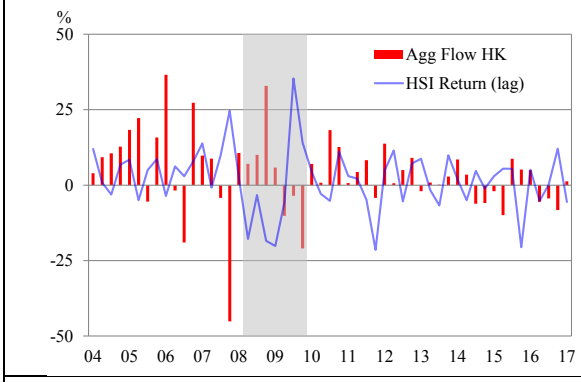


Source: Morningstar and HKMA staff estimate

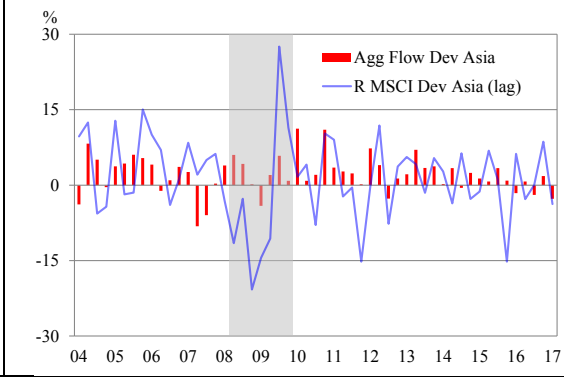
Notes: (i) The investment in Figure (b) covers only funds with Hong Kong equity exposures; (ii) the two charts show that our data is a typical sample of global insurance companies and pension funds, the regional distributions of the equity exposure are highly corresponding to regional distributions of assets from global insurance companies and pension funds.

Figure 4. Distribution of flows and lagged returns by regions (in percentage)

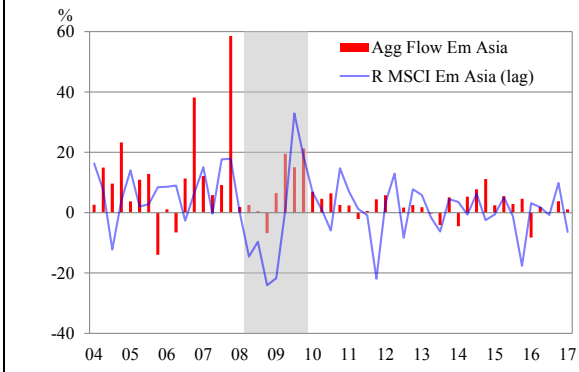
(a) Hong Kong (Full period: -0.32, crisis period: -0.44)



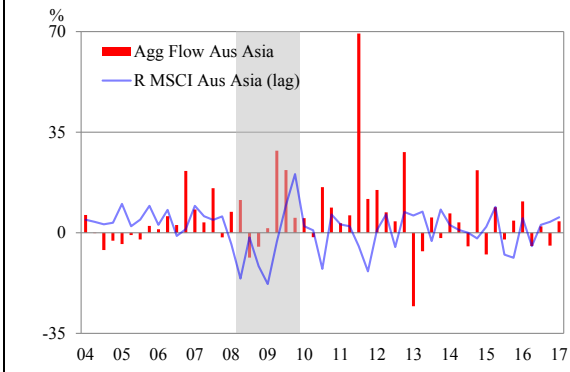
(b) Developed Asia (0.22, 0.50)



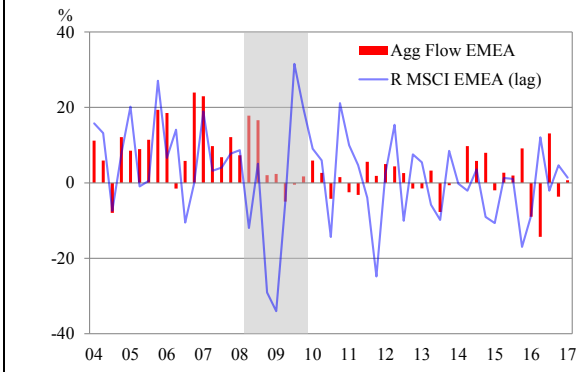
(c) Emerging Asia (0.29, 0.77)



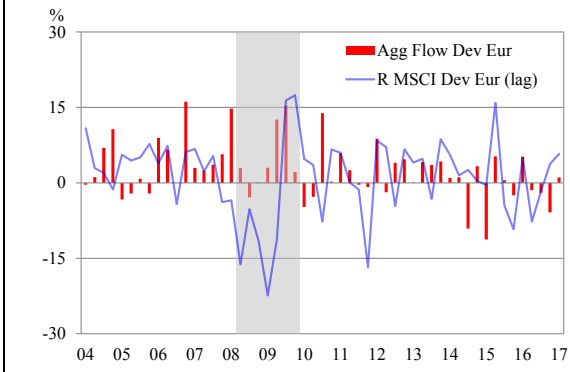
(d) Australasia (-0.13, 0.13)



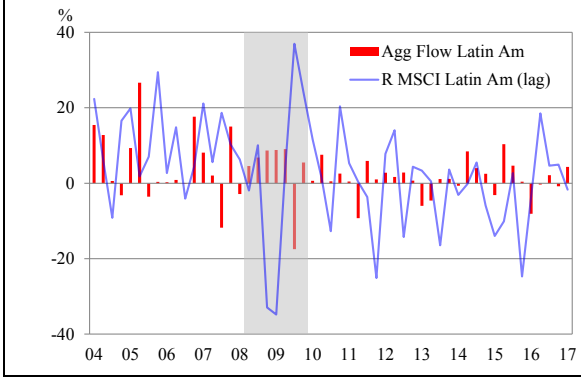
(e) EMEA (0.16, -0.02)



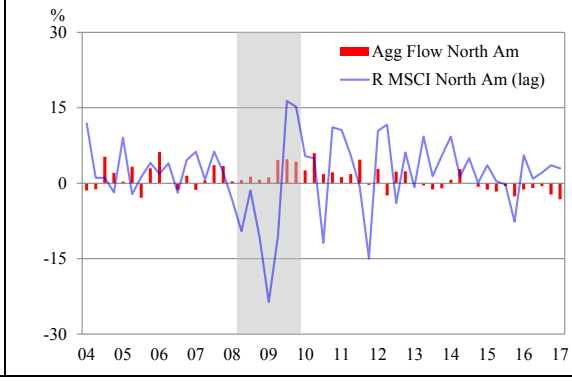
(f) Developed Europe (0.06, 0.32)



(g) Latin America (-0.13, -0.51)

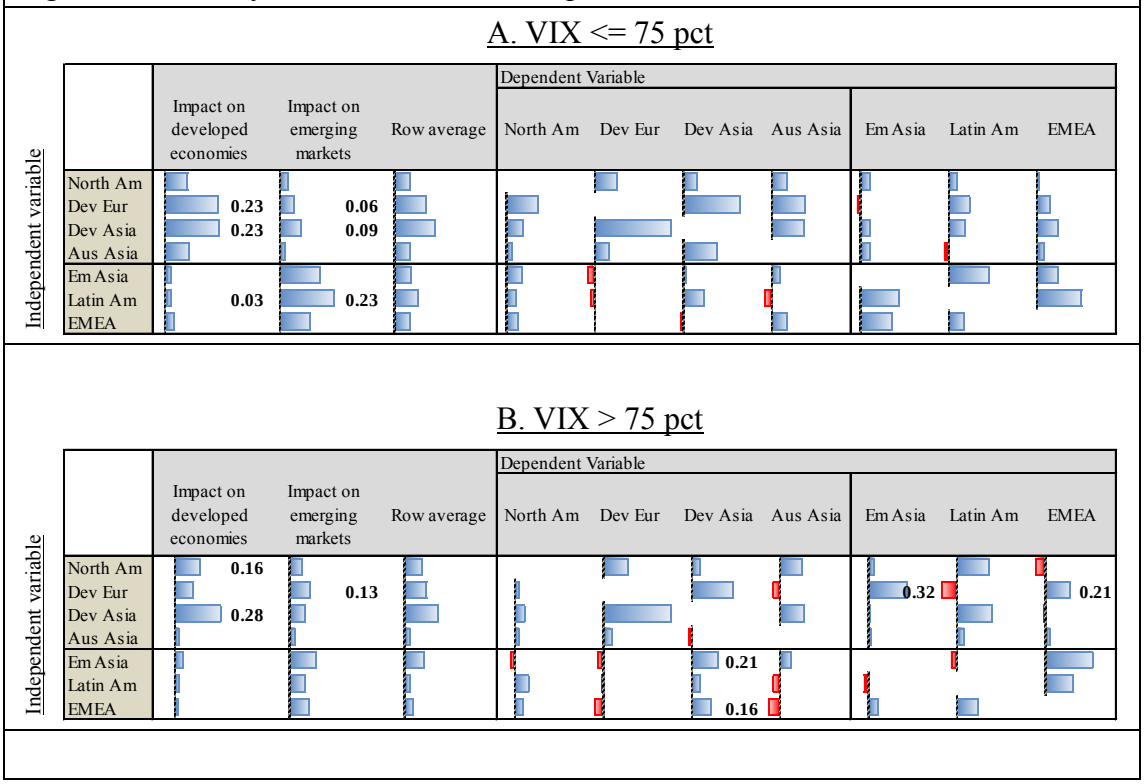


(h) North America (0.06, 0.56)



Note: (i) Aggregate flow is calculated by the percentage change in aggregate regional equity asset in the sample minus the return of regional stock index. (ii) Shaded area indicates the lagged period of global financial crisis.

Figure 5. Summary of estimation results reported in Table 6



Source: Morningstar, Bloomberg and HKMA staff calculation.

Appendix A1: Economies in each region

Developed Asia

Brunei	Hong Kong	Singapore	Taiwan
French Polynesia	Japan	South Korea	
Guam	Macau	New Caledonia	

Emerging Asia

Afghanistan	Fiji	Mongolia	Solomon Islands
American Samoa	Georgia	Nauru	Sri Lanka
Armenia	Heard & McDonald	Nepal	Tajikistan
Azerbaijan	India	Niue	Thailand
Bangladesh	Indonesia	Norfolk Island	Tokelau
Bhutan	Kazakhstan	North Korea	Tonga
Burma	Kiribati	Northern Mariana Isl.	Turkmenistan
Cambodia	Kyrgyzstan	Pakistan	Tuvalu
China	Laos	Palau	Uzbekistan
Christmas Island	Malaysia	Papua New Guinea	Vanuatu
Cocos Islands	Maldives	Philippines	Vietnam
Cook Islands	Marshall Islands	Pitcairn Islands	Wallis & Futuna Isl.
East Timor	Micronesia	Samoa	

Australasia

Australia	New Zealand

Emerging Europe, Middle East and Africa

Albania	Egypt	Macedonia	Serbia & Montenegro
Algeria	Equatorial Guinea	Madagascar	Seychelles
Angola	Eritrea	Malawi	Sierra Leone
Bahrain	Estonia	Mali	Slovakia
Belarus	Ethiopia	Mauritania	Somalia
Benin	Gabon	Mauritius	South Africa
Bosnia & Herzegovina	Gambia	Mayotte	St. Helena
Botswana	Ghana	Moldova	Sudan
Bouvet Island	Guinea	Morocco	Swaziland
Bulgaria	Guinea-Bissau	Mozambique	Syria
Burkina Faso	Hungary	Namibia	Tanzania
Burundi	Iran	Niger	Togo
Cameroon	Iraq	Nigeria	Tunisia
Cape Verde	Israel	Oman	Turkey
Central African Rep.	Jordan	Poland	Uganda
Chad	Kenya	Qatar	Ukraine
Comoros	Kuwait	Reunion Island	United Arab Emirates
Congo	Latvia	Romania	West Bank and Gaza
Cote d'lovire	Lebanon	Russia	Western Sahara
Croatia	Lesotho	Rwanda	Yemen
Czech Republic	Liberia	Sao Tome & Principe	Zambia
Dem. Rep. of Congo	Libya	Saudi Arabia	Zimbabwe
Djibouti	Lithuania	Senegal	

Developed Europe

Andorra	Germany	Liechtenstein	Slovenia
Austria	Gibraltar	Luxembourg	Spain
Belgium	Greece	Malta	Svalbard
Cyprus	Greenland	Monaco	Sweden
Denmark	Iceland	Netherlands	Switzerland
Faroe Islands	Ireland	Norway	Vatican City
Finland	Isle of Man	Portugal	United Kingdom
France	Italy	San Marino	

Latin America

Anguilla	Chile	Guadeloupe	Peru
Antigua & Barbuda	Colombia	Guatemala	Puerto Rico
Argentina	Costa Rica	Guyana	St. Kitts & Nevis
Aruba	Cuba	Haiti	St. Lucia
Bahamas	Curacao	Honduras	St. Vincent & the Grenadines
Barbados	Dominica	Jamaica	Suriname
Belize	Dominican Republic	Martinique	Trinidad & Tobago
Bermuda	Ecuador	Mexico	Turks & Caicos
Bolivia	El Salvador	Montserrat	Uruguay
Bonaire	Falkland Islands	Netherlands Antilles	US Virgin Islands
Brazil	French Antilles	Nicaragua	Venezuela
British Virgin Islands	French Guiana	Panama	
Cayman Islands	Grenada	Paraguay	

North America

Canada	U.S.

Appendix A2. Variable definitions, expected signs and data sources

Variable	Definition	Exp. sign	Data sources
Dependent Variable			
Fund flows to the region	The percentage change in the fund's TNA that invested in the region, net of return of the regional equity market. Using Hong Kong as an example: $TNA_{j,t}^{HK} = TNA_{j,t} \times W_{j,t}^{HK}$ and $flow_{j,t} = (TNA_{j,t}^{HK} - TNA_{j,t-1}^{HK})/TNA_{j,t-1}^{HK} - r_t^{HK}$		Morningstar
Macroeconomic factors			
Government bond yield	All yields are measured by10-year generic yields.	+	Bloomberg.
GDP growth	Seasonally adjusted real GDP are used to calculate the quarterly growth. If seasonally adjusted real GDP is not directly available for particular economies, the real GDP would be adjusted by census X-12 before calculating quarterly growth.	+	CEIC
Inflation rate	They are calculated by year-on-year percentage change of CPI in the region.	+	CEIC
Real government bond yield	They are compiled from the generic yield minus inflation in each economy.	-	Bloomberg and CEIC
Short term interbank rate	This variable is measured by 3-month interbank rates.	-	CEIC
Regional stock market returns	Returns are measured by (a) Hang Seng Index return for Hong Kong and (b) MSCI regional index returns for other regions.	+/-	Bloomberg
VIX index	Global stock market uncertainty is measured by CBOE volatility index, which is the implied volatility of S&P 500 index options over the next 30 day period.	-	Bloomberg
Fund specific data			
Cash ratio	The percentage of the fund's assets in cash	+/-	Morningstar
Debt-to-capital ratio (leverage)	It is the ratio of long-term debt (excluding other liabilities) divided by total capitalisation (the sum of common equity, preferred equity, and long-term debt)	-	Morningstar
Fund size	The asset size of the fund in natural logarithm	+/-	Morningstar
Individual fund return	According to Morningstar, the total return is determined monthly by taking the change in monthly net asset value, reinvesting all income and capital-gains distributions during that month, and dividing by the starting NAV. Our quarterly return is the compound return of the previous three months.	+	Morningstar

Source: Morningstar.

Note: Since most of the variables including generic government bond yield, GDP growth, inflation rate, real short-term rate and short-term market rate are variables by economies, they have to be transformed into regional variables for the analysis of regional fund flows. With reference to (a) FSB Global Shadow Banking Monitoring Report, (b) Morningstar region breakdown and by considering the actual data availability, some major specific economies are selected to represent each regional group. The time series of each economy data are conversed into regional data by averaging across quarter, weighted by nominal GDP in terms of USD at each quarter.

Appendix A3. Robustness check of estimation results of Eq. (3)

	Table A3. Robustness check of estimation results of Eq. (3) (full sample period: 2001-2017)							
	Dependent variable: Regional equity fund flow							
Independent variables	HK	North Am	Dev Eur	Dev Asia	Aus Asia	Em Asia	Latin Am	EMEA
Fund return	-0.029**	0.010	0.028**	0.027**	0.008	0.026**	0.011	0.018**
Cash ratio	0.043**	0.056**	0.066**	0.033**	0.086**	0.039**	0.036**	0.042**
Debt-to-capital ratio	-0.056**	-0.004	-0.003	-0.035**	0.020*	0.004	0.010	0.011
Fund size	-0.245**	-0.271**	-0.347**	-0.320**	-0.259**	-0.193**	-0.185**	-0.177**
Real bond yield	-0.034**	0.032**	0.011	0.001	0.025**	0.021**	-0.058**	-0.043**
GDP growth	0.008	-0.003	-0.024**	0.025**	0.036**	-0.015**	-0.012	0.036**
Interbank rate	-0.014	0.011	0.038**	0.027**	0.030**	-0.003	0.096**	0.021**
Constant	-0.064**	-0.033**	-0.022**	-0.049**	0.001	-0.022**	0.011	0.000
Periods included	60	60	60	60	60	60	60	60
Cross-sections	921	921	921	921	921	921	921	921
Total panel observations	20404	20404	20404	20404	20404	20404	20404	20404
R-squared	0.079	0.088	0.132	0.118	0.093	0.069	0.068	0.068
Log likelihood	-24993	-24461	-22697	-23467	-25390	-26221	-26252	-26002
Durbin-Watson stat	1.987	1.952	1.977	1.948	1.961	2.042	1.982	1.982

Note: Real bond yield is calculated by 10-year generic government bond yield minus inflation rate. All independent variables are lagged by one quarter. '**' and '*' denote significance levels of 5% and 10% respectively.
Source: HKMA staff estimate.