Capital account reform and short- and long-run stock price leadership

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Abstract

This paper studies the effect of capital account liberalization policies on the price discovery of cross-listings in Chinese stocks. We construct a non-linear causality framework that decomposes short- and long-run dimensions of price leadership. Our analysis shows that capital account liberalization has had a profound effect on long-run A- and H- price leadership traits. Specifically, increased inward capital movement from Qualified Foreign Institutional Investors (QFIIs) strengthens long-term leadership in the mainland A- market. Similarly, increased capital outflow from the Chinese mainland galvanizes long-term price discovery processes in the Hong Kong H- market. We thus offer strong evidence that capital account liberalization promotes stock market efficiency in the long-run. The present study's empirical account also suggests that such capital flows inhibit short-term lead-lag effects.

JEL classification: G01; G15; G18

Keywords: Capital account liberalization; A- and H- share cross listings, short- and long-run price leadership.

1 Introduction

The analysis of cross-listed securities provides important insights into issues of cross-border price discovery.[1] The pivotal question is which cross-listed market leads in price discovery terms? The present study answers this question in relation to the effects of China's recent capital control liberalization policies on its leading stocks' cross-listed A- and H- prices. This investigation constitutes a major extension and development of the literature. For instance, while Cai, McGuinness and Zhang's (2011) sub-period analysis identifies rising A- and H- co-integration, the literature offers little guidance on the specific effects of capital flows.[2] Similar sentiments apply in relation to causality or price leadership effects. We go well beyond this analysis by quantifying both inward and outward capital flows between the emerging mainland Chinese and developed Hong Kong markets. Decisively, our analysis identifies the impact of inward and outward capital flows on *short*- and *long-run* dimensions of price leadership.

Our study reveals weakening short-term causality effects in A- and H- prices over an extended 1999-2010 time-frame. These changes dovetail with the iterative, step-by-step liberalization of China's capital account. At the beginning of the study period, China essentially had a closed capital account. By period end, a raft of policy initiatives allowed for considerable permeability.[3] These initiatives include the opening-up and extension of Qualified Foreign and Qualified Domestic Institutional Investor Schemes (QFII and QDII), the establishment and development of the "The Closer Economic Partnership Agreement" (CEPA) between Hong Kong and Beijing (see TID), as well as various moves to encourage partial RMB convertibility. We assess such effects by constructing specific capital inflow and outflow measures. The present study's direct assessment of capital flow movement significantly extends Cai *et*

[1]. See Gagnon and Karolyi (2006, 2010a) for cogent review of this issue.

[2]. As important background, accounts like Bekaert, Harvey, Lundblad and Siegel (2011) demonstrate that capital control restrictions impede arbitrage and price discovery.

[3]. An additional benefit of our estimation approach is that it allows refined insight into whether 'home' (A-) market investors are more or less informed than international (H-) market investors. Chan, Menkveld and Zhang (2008) consider such informational differences in relation to China's A- and B- share markets. Ma *et al*. (2010) frame arguments to support greater price discovery in either local (A-) or offshore (H-) settings. On one hand, domestic 'home' investors may have an information advantage due to their proximity to the state and the rumour-mill engulfing the market. On the other, the sophistication of international investors may be decisive in driving causality from H- to A- shares. Deploying Gonzalo and Granger's (1995) "Permanent and Transitory components" and Hasbrouck's (1993) "Information Share" approaches, Ma *et al.* (2010) suggest greater A- price discovery. We significantly extend such findings by decomposing price discovery into short- and long-run components.

al.'s (2011) sub-period approach as well as Schuppli and Bohl's (2010) study of QFIIs' contribution to Chinese market efficiency[4].

As a key part of our analysis of short- and long-run price leadership traits, we also assess other (i.e., non-capital account based) determinants of causality. By focusing on a range of plausible arguments for short-and long-run causality effects, we go well beyond extant accounts of A- and H- pricing (Wang and Jiang, 2004; Arquette *et al*., 2008; Ma, Swan and Song, 2010; and Cai *et al*., 2011). We conjecture that time-varying A-/H- price causality derives from **three** principal sources: (1) China's capital account liberalization policies, (2) differential market sentiment effects and (3) liquidity issues. As possible mediating factors, we also assess causality in relation to earnings announcements, arbitrage cost issues (Pontiff, 2006; and Gagnon and Karolyi, 2010b), Renminbi appreciation (Arquette *et al*., 2008) and important regulatory initiatives, like China's 'Split Share Reform' (see CSRC, 2005).

To summarize, the analysis of cross-listed securities provides important insights into the general area of cross-border price discovery (see Gagnon and Karolyi, 2006 for detailed review of this general area). A central and overarching facet of price discovery is price leadership. Our present study design allows for two important contributions to this literature. First, we propose an estimation approach capturing the time-varying nature of both short- and long-run dimensions of price leadership. With Engle and Granger (1987) and Granger (1988) as backdrop, we develop a framework that incorporates co-integration (error-correction) and short-run causality (predictability) effects, all within a non-linear (state dependent) framework.[5]

Prior studies either examine co-integration *without* specific control for directional causality (see Harris, McInish, Shoesmith and Wood, 1995; Eun and Sabherwal, 2003; Cai, McGuinness and Zhang, 2011) or the reverse, causality *without* consideration of co-integration effects (see Wang, Rui and Firth, 2002; Gagnon and Karolyi, 2009). Our model approach has wide appeal since it has potential relevance to

[4]. Specifically, Cai et alia (2011) study the cointegration relation between the A- and H- share prices. They utilize a univariate Markov error-correction model and reveal, over the period between January 1999 to March 2009, significant improvement in the two markets' cointegration relation They also adopt sub-period analysis to map key changes in this cointegration relation to important policy and macro-economic changes. The present endeavour marks a major step forward by considering causality, and thus price leadership effects, as well as making specific account of inward and outward capital flows.

[5]. 'Short-term (or Granger) causality' captures short-term lead-lag effects and 'error-correction' causality deriving from the long-run co-integration relationship. The generic 'causality' term we use captures both channels.

the general issue of security and commodity pricing in segmented market settings. Second, as an important extension of the literature on Chinese cross-listed stocks, we find that increased capital account permeability underlies much of the two markets' increased price synchronization. These results complement the existing literature on global market segmentation (see Bekaert, Harvey, Lundblad and Siegel, 2011)[6]. Third, the present study also extends the literature on the migration of stock trading in emerging market issuers (see Domowitz, Glen and Madhavan, 1998; Levine and Schmukler, 2006; Halling, Pagano, Randl and Zechner, 2007; and Baruch, Karolyi and Lemmon, 2007). Virtually all of the evidence amassed on this topic relates to settings where a clearly dominant market (in terms of capitalization and turnover) draws-in issuers from a much less developed one. We add to this literature by uncovering a time-varying pattern of price leadership for synchronized[7] cross-listings in markets of comparable size and liquidity[8].

Moreover, we look at how information is transmitted between the world's leading emerging stock market and its closest developed rival (in terms of proximity, political connections and issuer base). Assessment of the A- and H- cross-pricing issue is also timely given the likelihood that foreign issuers, i.e., those of non-mainland Chinese domicile, will soon be allowed to list on the Shanghai Stock Exchange (SSE).[9] It is also given greater resonance by China's ongoing capital account reform, with the "through-train" trading arrangement between Hong Kong and Shanghai (see Yiu, 2014) constituting the latest major development.

As an overview, the present study reveals beneficial long-run pricing effects wrought by capital account liberalization. First, increased QFII investment has helped promote A- price leadership. Second,

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[6]. The tight capital controls of earlier years, combined with excessive savings rates, combined to ensure that mainland Chinese investors' required rates of return (equity discount rates) were at much lower levels than investors' rates in international markets like Hong Kong. Chinese investors' discount rates have logically risen with the gradual easing of mainland capital account restrictions. This resonates with contentions in Bekeart *et al*. (2011: 3877) on globalization effects.

[7]. Stock trading times overlap for much of the business day. However, HKEx closes one hour later than Shanghai and Shenzhen which suggests that closing prices on HKEx may be more informative than mainland market closing prices.

[8]. According to World Federation of Exchanges' (WFE) statistics for 2010, HKEx ranked as the world's seventh largest exchange in terms of market cap (USD 2,711 billion). Shanghai/Shenzhen combined rank second with a cap value of USD 4,028 billion (see http://www.world-exchanges.org/statistics/annual/2010/equity-markets/domestic-market-capitalization). WFE 2010 turnover statistics reveal that Shanghai/Shenzhen combined ranked second and HKEx ninth (see http://www.world-exchanges.org/statistics/annual/2010/equity-markets/total-value-share-trading).

[9]. Our analysis offers potentially important insight into the cross-border price dynamics that would likely surround the listing of non-mainland PRC companies. Media reports (see, for example, Ren, 2013) suggest that the SSE and CSRC may unveil new listing rules to allow foreign companies, i.e., entities of non-mainland Chinese domicile, to do IPO in Shanghai.

H- market price discovery processes have been galvanized by greater inward capital flows (emanating from mainland China). We thus offer strong evidence that capital account liberalization promotes stock market efficiency. Results also suggest that increased capital flow from the mainland (into Hong Kong) serves a role in weakening short-run causality effects from H- to A- share prices.

2 A non-linear causality model for cross-listed stocks

2.1 Literature review and model development

The extant literature on price discovery in cross-listed stocks mainly focuses on adjustment to a long-term equilibrium path, as typically determined by the respective series' co-integration relation (see, for example, Eun and Sabherwal's, 2003 assessment of error-correction processes for determining long-term price discovery). In contrast, studies like Gagnon and Karolyi (2009) focus on short-run effects. They assess how trading volumes capture information spill-over for cross-listed stocks. How does one reconcile approaches like Gagnon and Karolyi's (2009), which focus on short-run effects, with a long-run equilibrium approach?

Granger's (1988) discussion of the relationship between co-integration and causality offers a way forward in disentangling long-run co-integration and short-run predictability effects. He contends that, "… there are two possible sources of causation of x_t by y_t, either through the z_{t-1} term [error correction term] … or … lagged Δy_t terms" (Granger, 1988, p. 203, brackets as shown). His discussion highlights the importance of considering both types of causality when examining co-integrated series. Most of the existing literature simply addresses the first type of causality (i.e., adjustments to the long-run equilibrium path) while ignoring the second (i.e., short-run lead-lag effects). Although some studies control for short term dynamic effects, the economic meaning of a short-run lead-lag effect is rarely discussed. One possible reason is the presumption of market efficiency and the absence therefore of systematic lead-lag effects. By definition, a causal relationship implies some level of price predictability[10].

[10]. Absolute market efficiency suggests that fundamental information is instantaneously and simultaneously impounded into both markets' prices. Market efficiency therefore precludes causality effects.

With Engle and Granger (1987) and Granger (1988) as backdrop, we develop a framework that incorporates co-integration (error-correction) and short-run causality (predictability) effects, all within a non-linear (state dependent) framework. We develop this literature in three important ways: (1) by examining causality and co-integration effects *simultaneously*; (2) by incorporating a Markov-Switching (MS) dynamic to capture structural changes in the markets' time-varying causality, and (3) delving into the specific determinants of 'short' and 'long' run causality.[11]

2.2 Economic Interpretation of a Co-integration-Causality model for Cross listing stocks

We capture the basic dynamic of cross-listing price discovery by offering an initial model form.

$$\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} = \begin{bmatrix} \mu_A \\ \mu_H \end{bmatrix} + \begin{bmatrix} \phi_A & \psi_A \\ \psi_H & \phi_H \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} + \begin{bmatrix} \kappa_A \\ \kappa_H \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix} \quad (1)$$

where $R_{A,t}$ and $R_{H,t}$ are the first difference of the natural logarithm of exchange rate adjusted A- and H-prices; and $P_{A,t-1} - P_{H,t-1}$ is the log price difference at t-1.

The above system provides a description of the data-generating process for paired A- and H-prices. It reveals two important elements: (1) the level of error-correction in relation to the previous period's mispricing (κ_A and κ_H), and (2) the level of short-term causality, as reflected by parameters (ψ_A and ψ_H)[12]. In the following, we interpret both in relation to price discovery and arbitrage.

A similar framework, to the one above, figures in the study of macroeconomic issues (see, for example, Katsimbris and Miller's, 1993 study of European interest rate linkages). The model framework serves to detect one market's dominance over another. From a cross-pricing perspective, the error-

[11]. Through our assessment of these areas, we shed new light on the A- to H- pricing difference (see Wang and Jiang, 2004; Arquette *et al*., 2008; Ma *et al*. 2010; and Cai *et al*., 2011) and on cross-listing price discovery in general (see Harris *et al.*, 1995; Eun and Sabherwal, 2003; and Gagnon and Karolyi, 2009, 2010a, 2010b). Also see Cai et al. (2011, p. 2126, Note 13) for brief review of Markov estimation approaches in relation to dual-traded securities. Girardin and Liu (2007) employ a Markov set-up in their examination of stocks straddling three markets (Mainland China, Hong Kong and the US).

[12]. Our model embeds one-lag short-term causality effects. We adopt this approach because closing price change in one market (A- or H-) should, if causality effects obtain, spill-over into next-day prices. Similarly, Garbade and Silber (1983) deploy a one-lag causality term in their causality model of cash and futures markets.

correction component measures the contribution to long-term price discovery. Importantly, the magnitude of error-correction in one market reflects the other's contribution to long-term price discovery. The intuition is as follows. Given that the pricing error term in Equation (1) is calculated as A- price minus H-, a negative (positive) κ coefficient in the A- (H-) share equation suggests error-correction. If error-corrections only occur in the A- market, A- prices simply adjust to prior period's H- prices whenever observable differences in period A- and H- prices appear. This would suggest a leading role for the H-market in long-term price discovery. In reality, one or both markets might be error-correcting. When both are error-correcting, the relative magnitude of error-correction coefficients offers insight into the relative contribution of each market to long-term price discovery. This approach underlies Eun and Sabherwal's (2003) examination of US and Canadian cross-listings.

While interpretation of error-correction coefficients is straightforward, the literature suggests some difficulty in the economic interpretation of lagged- variable coefficients (especially, ψ_A and ψ_H). In the macroeconomic context, short-term dynamics are often assumed to reflect cyclical factors, causing a time series to fluctuate around its long-term level (see Akitoby, Clements, Gupta and Inchauste, 2004). In cross-listing price discovery terms, short-term causality coefficients capture short-run leadership.

While leadership in long-run price discovery is driven by fundamental information, short-run leadership might derive from liquidity surges predicated on rumour or transitory sentiment effects. Such short-term effects appear much more likely in the mainland market arena where retail investors dominate. Lee, Li and Wang (2010, p. 121), for example, highlight the overarching influence of retail investors on A- prices. They reveal that institutions account for less than 14 per cent of RMB volumes in SSE180 index stocks. By way of contrast, we note that local and overseas institutions dominate HK$ volumes on Hong Kong Exchanges and Clearing Limited (see HKEx, March 2012, p. 5). In addition, A- market investors' close proximity to issuers may exacerbate short-term trading effects. We thus posit that the A-market leads in short-term price discovery terms, potentially causing transitory spill-over effects into H-prices. In contrast to longer-run price discovery, short-run spillovers characterize market inefficiency.

Because we incorporate both types of causality (long-run error-correction and short-term price adjustment) we are able to distinguish between two types of information leadership. If, for example, a rumour turns-out to be true and affects long-run valuations, adjustment should occur in the (long-run) error-correction coefficient. At an extreme level, where all non-synchronized price movement reflects one market capturing fundamentals more quickly than the other, short-term lead-lag coefficients should be insignificant. The two types of causality offer different implications in relation to arbitrage. First, a larger error-correction coefficient suggests a faster and more complete adjustment to equilibrium. Second, unrestricted arbitrage suggests synchronization of the two markets' short-run prices. Accordingly, there should be an inverse association between short-term causality effects and arbitrage cost. Moreover, the existence of short-term causality presents an arbitrage opportunity. If causality runs from A- to H- prices, a technical increase in the A-price would signal an opportunity to buy the corresponding H- share today with a view to selling it at a higher price tomorrow. Naturally, the easier it is to conduct 'risky' arbitrage, the less pronounced short-term causality effects. Moreover, a range of recently-instituted capital account liberalization moves suggests greater feedback and 'risky' arbitrage trading effects in A- and H- markets.

2.3 A non-linear co-integration-causality model

As pointed out in Gagnon and Karolyi's (2010a, p. 13) survey of cross-listings, linear examination of the price dynamic may "mask" important volatile sub-periods. Unlike other studies, where structural changes are dealt with in terms of sub-period analysis (see Tian and Wan, 2004; Groenewold, Tang and Wu, 2004; Tian, 2007; Pan and Dai, 2008; and Chan, 2011), a Markov-Switching (MS) approach embeds the time-varying nature of causality in the stochastic process itself. Estimation of the MS model also enables us to delve into causality determinants. It is also more flexible than other non-linear designs (see Cai, Faff and Shin, 2010). Moreover, and unlike smooth transition or threshold models, a specific state variable is not required (see Rabinovitch, Silva, and Susmel, 2003).

We combine the Markov-Switching (MS) causality model of Psaradakis, Ravn and Sola (2005) with the co-integration causality model discussed in Section 2.2. The advantage of Psaradakis *et al.*'s

(2005) model framework is its ability to separate causality direction into four regimes. The final form of the MS co-integration causality (MSCC) model is as follows:

$$
\begin{aligned}
\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} &= \begin{bmatrix} \mu_{A,0} + \mu_{A,1} \\ \mu_{H,0} + \mu_{H,1} \end{bmatrix} + \begin{bmatrix} \phi_{A,0} + \phi_{A,1} & \psi_A \\ \psi_H & \phi_{H,0} + \phi_{H,1} \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} \\
&\quad + \begin{bmatrix} \kappa_{A,0} + \kappa_{A,1} \\ \kappa_{H,0} + \kappa_{H,1} \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix}, \qquad \text{if } S_t = 1 \\
\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} &= \begin{bmatrix} \mu_{A,0} \\ \mu_{H,0} + \mu_{H,1} \end{bmatrix} + \begin{bmatrix} \phi_{A,0} & 0 \\ \psi_H & \phi_{H,0} + \phi_{H,1} \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} \\
&\quad + \begin{bmatrix} \kappa_{A,0} \\ \kappa_{H,0} + \kappa_{H,1} \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix}, \qquad \text{if } S_t = 2 \\
\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} &= \begin{bmatrix} \mu_{A,0} + \mu_{A,1} \\ \mu_{H,0} \end{bmatrix} + \begin{bmatrix} \phi_{A,0} + \phi_{A,1} & \psi_A \\ 0 & \phi_{H,0} \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} \\
&\quad + \begin{bmatrix} \kappa_{A,0} + \kappa_{A,1} \\ \kappa_{H,0} \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix}, \qquad \text{if } S_t = 3 \\
\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} &= \begin{bmatrix} \mu_{A,0} \\ \mu_{H,0} \end{bmatrix} + \begin{bmatrix} \phi_{A,0} & 0 \\ 0 & \phi_{H,0} \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} \\
&\quad + \begin{bmatrix} \kappa_{A,0} \\ \kappa_{H,0} \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix}, \qquad \text{if } S_t = 4
\end{aligned}
\tag{2}
$$

In Regime 1 there is two-way causality between A- and H- shares. Regime 2 allows for only one way causality from A- to H- prices; while Regime 3 constraints causality in the opposite direction (from H to A prices). Finally, Regime 4 reflects the possibility of no causality in either direction. The MSCC model in (2) above offers three main advantages. First, states of nature are directly defined from causal relationships. This provides for a clear classification of states at each and every observation. Second, and as noted in Psaradakis *et al*. (2005), the MS model allows for probabilistic inferences about regime change at multiple locations within the sample. Third, the inclusion of both error correction[13] and short-term causality allows for separation of short- and long-run price discovery.

Following estimation, the extent of error-correction (long-term price leadership) in each market can be determined by examining the signs and significances of the error-correction coefficients in the

[13]. Studies like Eun and Saberwal (2003) highlight how error correction helps in identifying price discovery.

state with highest estimated probability. At a given time t, in the state with highest estimated probability, a negative (positive) and significant error correction coefficient in the A- (H-) share equation indicates error-correction in the A-market and long-term price leadership in the H-.

To determine the short-term causality direction in each period *t*, we examine state probabilities and the significance of causal parameters. At a given time t, $R_{H,t}$ Granger causes $R_{A,t}$ if the state with the highest estimated probability is either $S_t = 1$ or $S_t = 3$ and the ψ_A coefficient is statistically significant and positive. A positive and significant causality coefficient is sufficient for causality (see Peiers, 1997). Similarly, $R_{A,t}$ Granger causes $R_{H,t}$ if the state with the highest estimated probability is either $S_t = 1$ or $S_t = 2$ and the ψ_H coefficient is statistically significant and positive.

3 Data, estimation results and price leadership measures

3.1 Data characteristics

As of sample period (January 1999 - December 2010) end, there were 66 Chinese state-owned enterprises with concurrent A- and H- share listings. From this number, 55 had listing in A- share form in Shanghai and the remaining 11 in Shenzhen[14]. In respect of such issuers' A- share listings, a proscription on cross-listings between the Shanghai and Shenzhen stock exchanges meant that all 66 issuers had only one mainland exchange listing venue. In determining the final sample, and to allow for meaningful formulation of the present study's various tests, we imposed a restriction that each entity should have at least 100 trading days of overlapping A- and H- share price data. As of 31 December 2010, only 62 of the 66 issuers were able to meet this important criterion. The majority of the final sample's missing daily returns stems from holidays, rather than non-trading effects. In relation to causality model estimation, we use daily closing price from DataStream. Section 4 sets out the discussion of variables relating to the determinants of causality. The principal sources of data are DataStream and Bloomberg. Table 3 provides a summary of relevant variables that figure as determinants of short- and long-run price leadership.

[14]. We thank HKEx for providing us with a list of issuers, listing dates and trading locales for the A- and H- pairings.

Even though A- and H- share markets occupy the same time-zone, pricing gaps remain. These arise primarily from a trading right difference, in which a given entity's listed A-shares are restricted to trades between domestic mainland Chinese parties while corresponding Hong Kong (H-) listed shares are available for trades between international investor concerns. During our study period, the only foreign parties able to trade A- shares were QFIIs. This access was made possible in late 2002 (CSRC, 2002) with initial quota allotted in 2003. While the clear separation of trading rights on A- and H- shares prevents direct (riskless) arbitrage, greater flexibility in capital account and exchange convertibility (Arquette *et al*., 2008; and Cai *et al*., 2011) throughout the period helped narrow the average A- and H- pricing gap.

In terms of market trading arrangements, both the A- and H- markets employ limit order systems. Market-making systems are thus absent in both settings' stock trading systems. Settlement differences arise however with A- and H-shares subject to respective T+1 and T+2 regimes. In terms of short-sale constraints, an absolute proscription applied on all A- trades during the study period. In contrast, HKEx applied a regulated short-selling regime throughout the 1999 to 2010 period.[15] From a tax standpoint, authorities in both settings exempt stock transactions from capital gains charges. However, A- dividends are subject to standard mainland income tax rates, while H- dividends escape Hong Kong income tax but face a 10 per cent mainland withholding tax.[16] In terms of general trading costs, bid-ask spreads of H-shares are around three times higher than those on A-shares (Cai, 2004, p. 30). Finally, in terms of price synchronization, we note trading overlap for much of the A- and H- markets' business day (see Ma et al., 2010, p. 40). However, the market close in Hong Kong occurs one hour after the corresponding mainland market close; with continuous stock trading on HKEx (Shanghai/Shenzhen) ending at 16:00 (15:00) hours. During our study period, a 30-minute gap in the two markets' continuous call open times is evident (see Ma, Swan and Song (2010, Page 40 for pictorial illustration of the Shanghai/Hong Kong trading day up to 2010). Currently, the SSE and HKEx share the same morning open of 09:30 hours for their continuous call markets. This synchronicity of opening times reflects a 2011 change by HKEx, when it brought its morning session open forward from 10:00 to 09:30 hours (see HKEx, 2011).

[15]. As relevant to the beginning of our study sample, see McGuinness (1999: 78-81) for discussion of the arrangements.
[16]. See Arquette et al., 2008, p. 1924 for further discussion.

Our definition of causality is contingent on measurement interval. Granger (1988) highlights the importance of such a defined interval in the interpretation of causality effects. We choose close-to-close daily return intervals given the important reference points closing prices provide, especially in relation to derivative contracts, index valuation and the unwinding of positions. One further benefit of daily data, over intraday data, is that it allows for examination of price dynamics over long-run horizons. Studies employing intra-day data typically use short-horizons of less than one year. The day-to-day persistence of A- to H- pricing gaps provides further justification for our use of *inter*-day data.

3.2 Model Estimates

We estimate Equation (2) for each pair of available (62) stock pairings using a Maximum Likelihood approach[17]. Following Psaradakis *et al*. (2005), a Ljung and Box C^2 test of residuals determines the relevant autoregressive lag number. For those estimations with residual autocorrelation, additional lags feature. The maximum number of lags in our estimation is three. Overall, there are 22, 17, and 23 pairings with a respective model specification of one, two and three autoregressive lags.

To capture causality, and given our interest in short-term lead-lag effects, we determine a one-lag structure. Such a structure has intuitive appeal when studying lead-lag effects. It also has theoretical backing. Gagnon and Karolyi (2009), for example, select a one lag structure in their model specification of spill-over effects in cross-listed stocks.

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Table 1

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Table 1 summarizes the main parameters from MSCC estimation of Equation (2). Panel A reports summary statistics of coefficient medians as well as the number of estimates from available statistically significant pairings (at the 10% level). As our model's pricing error term is calculated as A-price minus H- price, a negative (positive) coefficient in the A- (H-) share equation suggests error-

[17]. See Hamilton (1994, chap. 22) for background discussion on the approach employed.

correction. Overall, the sign of the error coefficients in all states confirms a long-run co-integration relationship between pairings. These results suggest that when A- values exceed H-, A- (H-) prices adjust downwards (upwards) in the following period to restore balance.

For short-term A- causes H- returns, as reflective of states 1 and 2, the median coefficient is -0.01 (ψ_H), with 40 out of 62 pairs significant (at the 10% level). The small coefficient size suggests that A- price movement has a weak causal effect on H- prices. For H- to A- causality, as reflective of states 1 and 3, the median coefficient is 0.11 (ψ_A), with 41 out of 62 pairs significant (at the 10% level). Comparison of the two short term causality coefficients indicates stronger H- to A- causality effects on average.

Panel B reports mean transition and ergodic probabilities. The transition from one causality regime to another is guided by the transition matrix. When examining the contribution of each market to the causality regimes, we are effectively studying the realization of the transition from one causality regime to another (as guided by the relevant transitional matrices). The transition probabilities suggest considerable state-switching. Ergordic probabilities confirm that the stock pairings' price discovery relationship is most often in the state of no short-term causality (State 4). Regardless of state at time t-1, the next period with highest probability of occurrence is State 4.

3.3 Time-varying Causality

The preceding section's model estimates identify significant state-based causality effects. To achieve an aggregated time series of regime changes for each given day, we count the number of stocks that are in a given regime. Specifically, we construct four aggregated price leadership measures by combining relevant individual stock statistics for each day[18].

Pcnt_A_contr: Percentage of stocks in each period error-correcting in the H-market;

Pcnt_H_contr: Percentage of stocks in each period error-correcting in the A-market;

Pcnt_A→H: Percentage of stocks where A- causes H-;

[18]. While the parameters for each stock are fixed once the regimes are estimated for a given day, different stock combinations exist in different regimes.

Pcnt_H→A: Percentage of stocks where H- causes A-;

Fundamental (i.e., long-run) price leadership issues underlie the first two measures and technical (i.e., short-run) price leadership effects the final two. In classifying a stock into the *Pcnt_A_contr* (*Pcnt_H_contr*) regime, the error-correction coefficient in the H- (A-) share equation, in the state of highest probability, must display the correct sign (i.e., negative for A- and positive for H- return equations) and be significant at the 5% level. In classifying a stock into *Pcnt_A→H* (*Pcnt_H→A*) regime, the causality coefficient ψ_A (ψ_H), if evident in the state of highest probability, must be positive and significant at the 5% level. Intuitively, the first two regimes variables (i.e., *Pcnt_A_contr* and *Pcnt_H_contr*) capture contributions to long-term price discovery, by counting the number of pairs for ***a given day*** in a state with correctly-signed error correction coefficients that are significant at the 5% level. The last two variables [i.e., *Pcnt_A→H* (*Pcnt_H→A*)] capture the level of causality by counting the numbers of state-pairings with a significant causality relationship. Table 2 summarizes the percentage of pairings within each of the two error-correction and two short-term causality regimes. Figure 1 reports time-series plots.

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Table 2 and Figure 1

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The market (A- or H-) which possesses an information advantage should act as price leader. Table 2 and Figure 1 reveal three important findings. First, the H- market has been dominant in terms of its contribution to long-term price discovery, i.e., there is a statistically greater percentage of pairings with error-corrections in the A- market. This is perhaps not too surprising given the developed nature of the Hong Kong market-place and its sophisticated institutional investor base. However, both A- and H-markets' contribution to long-term price discovery has gradually increased over time. Second, there are more stock pairings with short-term H- to A- causality (*Pcnt_H→A*) than the converse (*Pcnt_A→H*). Nonetheless, Figures 1c and d show that short-run causality effects (both A- to H- and H- to A) have

gradually eased over time. Third, in relation to short- and long-run effects, much greater volatility is evident during the recent Global Financial Crisis Period. This is of interest given the growing interest in illiquidity and pricing effects during financial crises (see Yeyati, Schmukler and Van Horen, 2008).

Overall, our univariate evidence questions the existence of 'home' market advantage. Instead, there is greater evidence of causality from 'foreign' (H-) to 'home' market (A-) settings. This is perhaps due to international investors' scale of trading and their reliance on fundamentals. Results are also consistent with 'noisy' trading in the 'home' market, brought-about by a dominant retail investor presence.

In sum, as the two markets' prices have converged, short-term lead-lag effects have diminished. This is consistent with Bekaert *et al*.'s (2011) view that greater "financial openness" and "local financial market development" reduce market segmentation.[19] In the following section we explore the important determinants of short- and long-run pricing effects.

4 Determinants of Price Leadership

In relation to the overarching issue of cross-border price discovery (see Gagnon and Karolyi's, 2006 review of cross-listing studies), we identify *three* principal types of determinant. First and foremost, we consider China's iterative, step-by-step capital account liberalization programme, which began towards the beginning of our study period. Specifically, at the open of our sample period (1999), China had a closed capital account. By sample period end (2010), a non-trivial amount of permeability had been achieved, brought-on by a raft of policy initiatives as well as moves to allow partial RMB convertibility. We hypothesize that such capital flows have been pivotal in moderating short- and long-run price leadership effects. Our second and third hypotheses relate to sentiment and liquidity effects. To help contextualize the three determinants, we also consider a range of control effects.

[19]. This is also consistent with harmonization of regulatory and governance structures. However, even at an intra-country level, industry segmentation effects may persist (see Carrieri, Errunza and Sarkissian, 2004).

4.1 Policies Related to Capital Account Liberalization

Theoretical models of multimarket trading (Chowdhry and Nanda, 1991; Domowitz *et al*., 1998; and Baruch *et al*., 2007) rely on the ability of informed or liquidity traders to freely choose trading location. In such accounts, unfettered capital flows are essential in purging mispricing.[20] Capital restrictions impede this process (see Bekaert *et al*., 2011). The relaxation of any pre-existing capital control measures, in one or more market where a stock has cross-listing, should therefore boost price discovery. This issue is particularly relevant to China given recent capital account liberalization policies and earlier evidence of A- share market segmentation (Wang and Di Iorio (2007).

At the beginning of our study period, China effectively ran an impenetrable capital account. The increased capital mobility brought about by various capital account liberalization initiatives (principally the introduction and enlargement of QFII and QDII programmes in various stages) in subsequent years should have facilitated greater price discovery between A- and H- prices. We construct two variables, *QFII* and *ChinInv*, to examine the effects of capital account liberalization. *QFII*, as determined from data at China SAFE's website on the accumulated quota available to qualified foreign institutional investors[21], captures the scale of inward capital flow into the A-share market. *ChinInv* captures mainland Chinese investors' contribution to HKEx turnover.[22]

Potentially, *QFII* participation serves to imbue the A- market with a stronger focus on fundamentals and on longer-term or less speculative trading strategies. Specific to China, Schuppli and Bohl (2010) find that QFIIs enhance A- market stability and pricing efficiency. Frino, Webb and Zheng (2012), in respect of Australian-traded derivative products, show that overseas-initiated fund flows enhance domestic price discovery. They demonstrate that removal of investment "barriers" enhances price discovery in cash and related derivative markets. Thus at face value, QFII investment offers a mechanism for enhancing long-run A- price leadership.

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[20]. See Gromb and Vayanos (2010) for a survey of the theoretical literature on the limits of arbitrage.

[21]. See http://www.safe.gov.cn.

[22]. Framed using HKEx 2010/11 (http://www.hkex.com.hk/eng/stat/research/Documents/cmts11.pdf and 2005/6 surveys (http://www.hkex.com.hk/eng/stat/research/cmts/documents/cmts06.pdf). In determining *ChinInv* we refer to Figure 2 ("Distribution of cash market trading value by investor type") and Figure 7 ("Distribution of overseas investor trading in cash market by origin") in the above. HKEx defines each year from 1 October to 30 September.

In the present analysis, we utilize QFII quota as an overall proxy for foreign investment in the A-share market (and not specifically a measure for A- share investment in cross-listed entities). Nonetheless, survey evidence (Tan, 2009: p. 358) suggests that QFIIs typically invest in large cap stocks, specifically the top-100 cap stocks in the A- market. As cross-listed entities are predominantly within this upper echelon, we conjecture that change in QFII quota is a valuable proxy for inward foreign investment into our sub-sample of firms. Accordingly, Hypothesis 1A posits that,

Hypothesis 1A: **The A- share market's contribution to long- (short-) term price leadership has increased (decreased) with commensurate increases in inward capital flow, i.e. QFII investment.**

If QFII investment enhances price discovery processes, cross-listed A- and H- share prices should be better synchronized. A corollary of this would be weaker short-term causality or lead-lag effects.

In a related hypothesis (H1B), we consider the effects of capital outflow from the Chinese mainland into Hong Kong. It is not clear as to which type of investor (i.e., foreign institutional or mainland Chinese domestic investor) bears greater influence on price discovery processes. For review of the literature on the influence of either or both channels, see Chan et al., (2008: p. 159-160). Hypothesis 1B recognizes the possibility that domestic mainland Chinese investor flows might promote price discovery in H- prices. It is conceivable that foreign institutional flows (into the A- market) and domestic investor flows (into the H- market) could simultaneously support price discovery processes in respective A- and H- settings. Specifically, Chinese investors' localized or home information advantage may contribute to enhanced price leadership in the H- market. Accordingly, Hypothesis H1B contends that,

Hypothesis 1B: **Growing mainland Chinese investment in the H- market has resulted in an increase (decrease) in the H- market's contribution to long- (short-) term price leadership.**

On the other hand, as Chinese investors are overwhelmingly retail, and have been schooled in an emerging market environment, mainland capital outflows could add noise and volatility (Bekaert and Harvey, 1997), and thus reduce the "informativeness" of H- prices.

4.2 Market Sentiment Effects

A given market's sentiment level also plays an important role in influencing the pricing behaviour of the majority of stocks listed in that setting (see Wang and Jiang, 2004; and Xu and Green, 2013 for respective Hong Kong and Shanghai-based studies). Further afield, Baker and Wurgler (2006) demonstrate that surges in investment sentiment have much greater impact on markets subject to arbitrage restrictions and on securities with more uncertain prospects. Mian and Sankaraguruswamy (2012) demonstrate greater mispricing of "good ("bad") earnings news" during surging (waning) sentiment, while Stambaugh, Yu and Yuan (2013) reveal more anomalous pricing during ebullient trading periods.

If notable inefficiencies exist in the pricing of cross-listed stocks, investors may infer value from both fundamental factors and sentiment effects. Weaker longer- (short-) term price leadership traits are naturally ascribed to a market where sentiment effects (fundamentals) dominate. Following Arquette *et al*. (2008), we capture market sentiment in relation to general price-to-earnings (PE) levels. However, unlike Arquette *et al*. (2008), we examine *changes* in such levels rather than absolute magnitudes. For the A-market, we define variable Δ***PE_A20***, the percentage change in the A- market's overall PE level over a preceding 20 trading day period (equivalent to around one month's trading). For robustness reasons, we also examine market sentiment effects over 60- (3 months) and 120- trading day (6 months) periods[23].

We hypothesize that rising price levels act to boost short-term causality and blunt long-term price leadership. Accordingly, Hypothesis 2 contends that,

Hypothesis 2A: **Increasing A- market sentiment helps weaken (strengthen) the A-market's contribution to long- (short-) term price leadership.**

Similarly, we capture market sentiment for the H- market by looking at changes in the market's general PE level (Δ*PE_H20*). This allows us to test the related hypothesis, H2B.

[23]. We use Datastream for daily PER values of the Hang Seng Index and Bloomberg for the Shanghai A-share Total Stock index (Datastream does not provide a PER series for the A-share index).

Hypothesis 2B: **Rising H- market sentiment serves to weaken (strengthen) the H-market's contribution to long- (short-) term price leadership.**

4.3 Liquidity and Trading Activities

In modelling the effect of market liquidity on multimarket trading, Chowdhry and Nanda (1991) show that weaker market depth (i.e., the greater the price impact of an informed trade and the greater the trading cost) results in a lower likelihood of informed trading. Price "informativeness" is therefore inversely related to transaction cost. Price impact (or market depth) is one important dimension of liquidity. Essentially, the ease with which trading volumes are able to move prices captures the extent of price impact. Price impact is thus increasing in illiquidity. Amihud (2002) reports a strong positive association between price impact (i.e., illiquidity) and US excess market returns. We conjecture that A- (H-) leadership weakens in long-term price discovery as A- (H-) illiquidity increases. Likewise, A- (H-) market leadership weakens in short-term price discovery as A- (H-) illiquidity increases.

Similarly, we note the importance of differential trading activities as a measure of liquidity. Volume also serves as a powerful indicator of where fundamental information is revealed. Baruch *et al*.'s (2007) analysis of order fragmentation in cross-listed stocks demonstrates that the market that more readily captures private information likely dominates in volume terms. Nonetheless, volumes reveal much less information in emerging markets dominated by noise traders (Bekaert and Harvey, 1997).

The literature on liquidity trading also provides a useful guide on the 'informativeness' of volume. Admati and Pfleiderer (1988), Foster and Viswanathan (1990) and George, Kaul and Nimalendran (1994) identify an inverse association between liquidity trading and information asymmetry levels.

Eun and Sabherwal's (2003) examination of co-integration and two-way price adjustment effects for Canadian stocks listed in Toronto and the US is also pertinent. They find that the US contribution to price discovery (as measured by error-correction coefficients) is positively related to the US proportion of a stock's overall volume as well as "to the ratio of proportions of informative trades" (p. 549). They also note a weakening effect on US price discovery as the US to Toronto bid-ask spread ratio rises.

By assessing Chinese issuers, and a long time-series, we extend Eun and Sabherwal (2003). Accordingly, we anticipate that the A- (H-) market's long- and short- run leadership roles strengthen as A- (H-) trading volume increases. Accordingly, Hypothesis H3 contends that,

Hypothesis 3A: **Increasing A- market liquidity strengthens the A- market's contribution to long- and short- term price leadership.**

Hypothesis 3B: **Increasing H- market liquidity strengthens the H- market's contribution to long- and short- term price leadership.**

We construct two liquidity (illiquidity) measures, the first of which is based on the Amihud (2002) measure.[24] Accordingly, *Illiq_A* (*Illiq_H*) is the average ratio of daily absolute returns to the RMB value of A- (H-) share trading, and is calculated for each firm i on day t using a 20-day rolling window of observations (from t-20 to t-1). Second, following Gagnon and Karolyi (2009), we capture differential share volume using a natural logarithm volume metric as below.

$$Tov\_A_t = \left(\log(Tov_{A,t} + a) - \frac{1}{20} \sum_{1}^{20} \log(Tov_{A,t-i} + a) \right) 100$$

$$Tov\_H_t = \left(\log(Tov_{H,t} + a) - \frac{1}{20} \sum_{1}^{20} \log(Tov_{H,t-i} + a) \right) 100 \qquad (3)$$

Where $Tov_{A,t}$ and $Tov_{H,t}$ is the turnover ratio of a stock at day t for A- and H- market trading. This is defined as the day's trading volume divided by the total number of shares in issue. This is de-trended by subtracting the 20-day moving average of prior days' volumes. Following Gagnon and Karolyi (2009), we add a constant (a=0.00000255) to avoid problems with zero volumes.

[24]. Yeyati, Schmukler and Van Horen (2008) consider the Amihud (2002) measure in assessing illiquidity effects during crises. Gagnon and Karolyi (2010b) consider it in assessing illiquidity issues in cross-listed ADRs.

4.4 Control Variables

In addition to *QFII*, *ChinInv*, Δ*PE_A30*, Δ*PE_H30*, *AccAnn*, *Illiq_A*, *Illiq_H*, *Tov_A* and *Tov_H*, which are central to our three hypotheses, we specify a number of control variables.

Information Risk: Greater price discovery should emerge as information gaps narrow. We capture differences in the two markets' processing of information in relation to year-end earnings announcements. In theory, such announcements provide insights into fundamentals and should help bolster long-term price discovery processes. For a given issuer, we construct a dummy variable with value one for each of the 20 trading days in the period 10 days prior to 10- days post year-end earnings announcements. By aggregating across all pairings, we arrive at dummy *AccAnn*.

The A- ('home') market may have an advantage in 'interpreting' the broader background to important corporate and macro/policy announcement (Lee, Li and Wang, 2010). Moreover, Lee e*t al*. (2010) show that retail investors in the A- market trade more aggressively in relation to major corporate disclosures and key market pronouncements. Rather than bolstering long-term price discovery, such announcements might accelerate short-term A- to H- causality effects. At the same time, Li, Brockman and Zurbruegg (2015) reveal that H- prices are more efficient in capturing "firm-specific information".

We also control for **idiosyncratic risk**. Recent analyses in Pontiff (2006) and Gagnon and Karolyi (2010b) point to the overarching role of idiosyncratic risk in limiting arbitrage. Gagnon and Karolyi's (2010b) assessment of more than 500 ADRs demonstrates that the greater the idiosyncratic risk level of a stock the larger the home-to-ADR pricing gap. Therefore, causality effects should be increasing in arbitrage cost. Accordingly, stocks with greater idiosyncratic risk should exhibit stronger causality effects. Pure or riskless arbitrage is severely constrained by short-sale proscriptions in the A- market as well as the non-fungible nature of A- and H- share trading. However, China's recent capital account liberalization reforms, have given impetus to indirect or 'risky' arbitrage. Our analysis of arbitrage relates to this 'risky' form. Nonetheless, the absence of A- and H- fungibility relegates the issue of idiosyncratic risk to second-order status in this study.

We measure idiosyncratic risk using the Gagnon and Karolyi (2010b, p. 63) approach. Accordingly, *Idio* captures the standard deviation of residuals obtained from regressing each stock pairing's return difference against Shanghai A- and Hang Seng index market returns and the RMB/HKD exchange rate using 60-day rolling data.

$$R_{A-H,t} = \alpha + \beta_1 R_{SH,t} + \beta_2 R_{HS,t} + \beta_3 R_{FX,t} + \varepsilon_t \quad (4)$$

$R_{A-H,t}$ is the return difference between cross-listed shares; $R_{SH,t}$ ($R_{HS,t}$) is the return of the Shanghai A- share (Hang Seng) index; $R_{FX,t}$ is the RMB/HKD exchange rate.[25]

We also control for expectations of **currency appreciation**. Arquette *et al*. (2008) highlight the importance of exchange rate change in realigning A- and H- prices. To capture the general uncertainty surrounding the RMB/HKD exchange rate we compute *FwdPrem*.

FwdPrem= (Fwd rate –Spot rate)/Spot rate

(5)

Where *Fwd rate* is the Renminbi's (relative to US dollar) 12-month non-deliverable forward (NDF) price; and *Spot rate* is the relevant exchange rate for immediate delivery. *FwdPrem* is based on Arquette *et al*.'s (2008) measurement of the forward pricing premium on the NDF.

Finally, we control for one of the study period's most important equity market reforms, namely China's Split Share Reform.[26] The Reform entailed widespread conversion of non-tradable (principally state-held) stock into tradable form. One would expect increased float size to support to price discovery.

[25]. Unlike Gagnon and Karolyi (2010a), and due to A-/H- trading overlap, we measure specific risk without lead/lag adjustment.

[26]. For discussion, see McGuinness, 2009. As background, the Scheme began in 'Pilot' form in April 2005 and continued for much of the remainder of our sample period, 2005-10. The Scheme's basic thrust was to transform non-tradable stock into tradable A- share form. Given the potentially deleterious impact on A- prices arising from disposals, extensive trading moratoria were applied to newly tradable stock. Various other safeguards were also applied as a means of dampening any risk premium on state share disposals. These included bonus payments to existing A- share investors and, decisively, CSRC thresholds and SASAC approval requirements for disposals. The various protections and lock-ins imposed on the newly transformed stock helped stem market participants' fears of large-scale state share disposals. Such fears had risen palpably in the years prior (2001-4) to the Reform but were largely dispelled by the programme's successful implementation in 2005-6. A scheme announced in 2001, enabling state-owners to sell existing holdings via A- share IPO, triggered a sell-off. Even though the scheme was subsequently cancelled, the risk surrounding future possible state share disposals lingered over the A-share market.

Specifically, we contend that an increase in the proportional tradable A- float contributes to enhanced long-term A- price leadership. We deploy variable *ΔNontrade_A* to capture the changing A- float resulting from 'Split Share Reform'. This variable is framed as the 20- day rolling change in the aggregate number of non-tradable A- shares to the total number of tradable and non-tradable shares outstanding.

5 Empirical assessment of the Determinants of causality

Tables 3 and 4 summarize variable forms and descriptive statistics.

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Tables 3 and 4

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Table 4 reveals a mean quota for the QFII scheme (relative to the size of China's stock market) of only 0.37 basis points with a mean change of 0.02 basis points. In terms of *ChinInv*, mainland Chinese investors contributed on an average to 2.4 per cent of Hong Kong's total turnover. In contrast to Hong Kong's price-to-earnings ratio (PER), Shanghai's PER generally fell across the sample period. This observation is reflected by the negative (positive) mean PER changes we observe for Shanghai (Hong Kong). The large range in PER change suggests considerable variation in market sentiment over the study period. For instance, the percentage monthly change in Shanghai's PE ratio ranges from -35 to 23 percent.

Descriptive data for the price impact measure (*Illiq*) reveals the A- market to be considerably more liquid than the H- market. The average A- price impact is 0.16 per cent return per million RMB of trading value, as compared to 5.79 per cent for the H- market. The inference to be drawn is that for the two markets to have the same proportionate price impact, trading activity in the A- market would need to be 36 times that of the H- market. A smaller figure applies when focusing on the median gap. Market turnover also declined over time (i.e., average de-trended turnovers, *Tov_A* and *Tov_H,* are negative).

Statistics for variable *AccAnn* indicate that companies' earnings occur within a relatively narrow reporting season. The idiosyncratic risk measure *Idio* exhibits substantial variation over the study period. Finally, descriptive statistics for variable *FwdPrem* reveal a pronounced discount on the 12-month RMB forward contract. This is suggestive of an average expectation of RMB appreciation (against the USD) across the 12-year period. As expected, the proportion of non-tradable A- stock fell over the 1999-2010 time-frame; declining at an average rate of 0.16 per cent per month.

The final set of variables in Table 4 present the relative market characteristics of our sample of A- and H- stocks. The exchange adjusted market capitalization variables (*Market_Cap_A* and *Market_Cap_H*) highlight the significantly larger H-float size relative to A-. Despite this, average daily RMB volumes are considerably higher for a cross-listed entity's A-share float.

In order to test the three hypotheses (**H1-H3**) of price leadership, we employ a generalized least square (GLS) regression approach. The dependent variables (i.e., Pcnt_A_contr, Pcnt_H_contr, Pcnt_A→H and Pcnt_H→A) are functions of estimated causality parameters discovered from our first stage estimations in Section 3. We adopt Saxonhouse's (1976) weighted procedure to address a potential *generated regressor problem* in the two-stage estimation set-up[27]. As Hornstein and Greene (2012) stress, when the dependent variable in the second stage regression is a non-linear function of estimated parameters from the first, the weighting matrix should be the inverse of the variance of the estimated function of the parameter (rather than the variance of the estimated parameter itself). We follow Hornstein and Greene (2012) in computing the variance of the variance of the indicated dummy in terms of the A-market's contribution to long run price discovery (Pcnt_A_contr). This is as follows:

[27]. In this approach, the inverse of the variance of estimated parameters from stage one is used to weight observations in second stage GLS regressions (see Waring, 1996 and Greene et al., 2009 for relevant applications).

$$
\begin{aligned}
&Var(I(\kappa_H/\sigma_{\kappa_H}>1.645))\\
&=\Pr(\kappa_H/\sigma_{\kappa_H}>1.645)\times Var(I(\kappa_H/\sigma_{\kappa_H}>1.645)\,|\,\kappa_H/\sigma_{\kappa_H}>1.645)\\
&\quad+\Pr(\kappa_H/\sigma_{\kappa_H}\le 1.645)\times Var(I(\kappa_H/\sigma_{\kappa_H}>1.645)\,|\,\kappa_H/\sigma_{\kappa_H}\le 1.645)\\
&\quad+\Pr(\kappa_H/\sigma_{\kappa_H}>1.645)\times\left(E\left(I(\kappa_H/\sigma_{\kappa_H}>1.645)\,|\,\kappa_H/\sigma_{\kappa_H}>1.645\right)-E\left(I(\kappa_H/\sigma_{\kappa_H}>1.645)\right)\right)^2\\
&\quad+\Pr(\kappa_H/\sigma_{\kappa_H}\le 1.645)\times\left(E\left(I(\kappa_H/\sigma_{\kappa_H}>1.645)\right)-E\left(I(\kappa_H/\sigma_{\kappa_H}>1.645)\,|\,\kappa_H/\sigma_{\kappa_H}\le 1.645\right)\right)^2\\
&=\Pr(\kappa_H/\sigma_{\kappa_H}>1.645)\times 0+\Pr(\kappa_H/\sigma_{\kappa_H}<1.645)\times 0\\
&\quad+\Pr(\kappa_H/\sigma_{\kappa_H}>1.645)\times\left(1-\Pr(\kappa_H/\sigma_{\kappa_H}>1.645)\right)^2\\
&\quad+\Pr(\kappa_H/\sigma_{\kappa_H}<1.645)\times\left(\Pr(\kappa_H/\sigma_{\kappa_H}>1.645)-0\right)^2
\end{aligned}
\qquad (6)
$$

Where $I(.)$ is an indicated function, which takes on value one when the stated condition is met and zero otherwise. κ_H and σ_{κ_H} are the mean and standard error of the parameters estimated from Equation (2). The $\Pr(\kappa_H/\sigma_{\kappa_H}>1.645)$ is calculated, on the assumption that κ_H follows a normal distribution $N\sim(0,\sigma_{\kappa_H})$. The aggregate function for the variable for a given day is

$$
\text{Pcnt\_A\_contribute}=\frac{1}{N}\sum_{i=1}^{N} I(\kappa_H/\sigma_{\kappa_H}>1.645)\,. \qquad (7)
$$

The κ_H parameter is selected for each stock pairing from the state with highest probability. The variance of this aggregated function is calculated by summing the variance of each indicated function and dividing by the square of the number of stocks (N). The underlying premise is that stock pairing parameters are independently distributed parameters among the stock parings. We obtain the variance of other indicated functions, for the remaining error correction parameter κ_A, and the two short-term causality parameters ψ_H and ψ_A, in a similar manner. The inverse of the variance is used as the weighting matrix in second stage GLS regressions.

We also adjust for autocorrelation in residuals using lagged dependent variables of up to five lags. To address potential heteroscedasticity induced by a *generated regressor problem*, we apply White's (1980) heteroscedasticity-consistent correction. A VIF of less than five highlights the general absence of multicollinearity effects. Table 5 reports regression results. As mentioned earlier, due to Hong Kong closing one hour after the Shanghai and Shenzhen stock exchanges, closing prices on HKEx may be more informative than mainland closing prices. Potentially, the later HKEx close could give it a price discovery

advantage. Such an effect, if it exists, should be captured by the intercept term in relevant regressions. Consistent with this view, we document larger intercept terms in regressions for both long- and short-term H- price discovery (relative to those for long- and short-term A-price leadership)[28].

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Table 5

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5.1 Policies Related to Capital Account Liberalization (**H1**)

We first note that greater external fund flows, as evident from the significant positive coefficient on ΔQFII (ChinInv) in Model 1 (2), galvanize the contribution of the A- (H-) market to long-run price discovery. Furthermore, greater mainland Chinese investor participation on HKEx appears to weaken short-term H- to A- causality. Overall, the findings support the contentions in Hypotheses H1A and H1B. That is, relaxation of capital controls boosts long term price discovery processes and inhibits short-term lead-lag effects. More specifically, results suggest that capital account liberalization boosts information transmission (Bekaert *et al*., 2011).[29] Our findings also reinforce evidence that external fund flows enhance local price discovery (Frino *et al.*, 2012) and efficiency (Schuppli and Bohl, 2010).

5.2 Differential Market Sentiment (**H2**) & Liquidity and Trading (**H3**) Effects

The negative coefficient on Δ*PE_A* and Δ*PE_H* in respective Models (1) and (2) of Table 5 indicates that stronger sentiment in a given setting weakens that market's contribution to long-term price discovery. A given market's leading role thus weakens with rising PER levels; this is especially so for the H-share market where the relevant coefficient is highly significant. This finding is consistent with greater mispricing in momentum- or sentiment-driven markets (Mian and Sankaraguruswamy, 2012; and

[28]. We thank the reviewer for alerting us to this possible non-synchronous trading effect.

[29]. In the Chinese market context, the tight capital controls of earlier years, allied to excessive savings rates, combined to keep mainland Chinese investors' required rates of return at much lower levels than their international counterparts. Chinese investors' discount rates have logically risen with the gradual easing of capital restrictions. Such effect is also consistent with arguments in Bekeart *et al.* (2011: 3877) on globalization effects on discount rates. Of additional interest, Chang, Luo and Ren (2013) show that A- share IPO underpricing is exacerbated by the "anchoring" of the offer price to the stock's pre-existing H-share price.

Stambaugh, Yu and Yuan, 2013). Interestingly, rising sentiment also weakens short-term causality (see Models 3 and 4). Taken together, our findings suggest that sentiment in one market does not necessarily spill-over to the other related market setting. Overall, and in long-run price discovery terms, results offer some support for Hypotheses H2B.

Results in Table 5 point to a strong inverse association between price impact (i.e., illiquidity) and long-term price leadership. This applies in respect of both *Illiq_A* and *Illiq_H* (Models 1 and 2) and is consistent with hypotheses **H3A** and **H3B**. Moreover, the results support predictions in Chowdhury and Nanda (1991) that higher price impact (as an indicator of lower liquidity) discourages informed trading.

There is also some indication that higher price impact inhibits short-term price leadership. This holds for the H- market (Model 4), which generally has lower liquidity than the related A- market. For the A- market, the picture is a little different. In respect of Model 3, while *Illiq_A* is positive short-term A- to H- causality effects are nonetheless insignificant.

For the second measure of liquidity, Tov_A and Tov_H, results show that higher volumes boost long-run price leadership. This holds in relation to both A- (Model 1) and H- markets (Model 2). This finding complements results for developed markets (see Baruch *et al*., 2007 and Gagnon and Karolyi, 2009). Increased trading activity also appears to boost short-term price discovery processes, especially in relation to H- to A- causality (Model 4). Overall, and in relation to the illiquidity and trading activity measures we employ, hypotheses **H3A** and **H3B** receive a strong measure of support. Our analysis provides a new application in the price impact literature (Amihud, 2002; and Gagnon and Karolyi, 2009) by assessing liquidity in relationship to Chinese A- and H- markets price leadership issues.

5.3 Control Effects

Arbitrage risk: In periods with greater levels of idiosyncratic risk, the H- market appears to play a more dominant role in long-term price discovery. This is consistent with H- market investors being more adept at identifying firm specific risk factors. This evidence complements analyses in Pontiff (2006)

and Gagnon and Karolyi (2010b). For the present study, the H- market exhibits a longer-term price discovery advantage over the A- market for stocks with high idiosyncratic (specific) risk levels.

Information risk: In respect of Models 1 and 2, results for *AccAnn* indicate that the A-share market plays less of a long-run leadership role during earnings announcement periods. Furthermore, consistent with a possible 'home' advantage effect, results for Model 3 indicate stronger short-term A- to H- causality during such periods. However, the weakening of the long-run effect suggests that any 'home'-based information advantage is transitory and probably the result of 'noisy' spillovers. This finding is broadly consistent with Lee, Li and Wang's (2010: p. 116) account of greater A- market retail trading (a proxy for noise effects) around key corporate reporting dates.

Currency Expectation & 'Split Share Reform': Table 5 reveals that rising expectations of RMB appreciation (i.e., lower *FwdPrem* values) strengthen the H- market's long- and short- run leadership roles. Results in Models 2 and 4 suggest that firming expectations of RMB appreciation induce greater foreign investment in China-related stocks. In this sense, increased H- investment boosts market liquidity and helps squeeze the long-term H- to A- pricing discount (see Arquette *et al*., 2008).[30]

Results in Table 5 (Model 1) also suggest that the conversion of non-tradable stock into tradable A-form has bolstered the A- market's contribution to long-term price discovery.

5.4 Robustness Check

To check for robustness of results, we conduct two alternative specification tests. First, due to the absence of QFII quota prior to 2003, the pivotal *ΔQFII* variable takes-on value zero in the early part of our sample-frame, 1999-2002. To confirm that overall results are robust after exclusion of this sub-period, we re-estimate models using the later 2003 to 2010 subsample. Table 6 reports relevant results. Principal findings remain. However there is a noticeable difference in the significance of the negative effect of sentiment on long-term price discovery. Specifically, Table 6 reveals that stronger sentiment in the A-

[30]. Global investors' increased demand for offshore Chinese investments may also be accompanied by domestic mainland Chinese investors' reluctance to sell RMB assets. This second observation would account for reduced short-term A- to- H- causality (Model 3), especially when expectations of RMB appreciation are on the up.

market significantly weakens A- market leadership. Sentiment effects in relation to H- leadership (Model 2) remain at very similar levels in Table 5 and 6 results.

In a second set of robustness tests we further deepen findings by considering relative differences in market sentiment, liquidity and activity measures. This area of analysis (Table 7) complements our findings in relation to the absolute sentiment, liquidity and activity measures of a given (A- or H-) market (Tables 5 and 6). Additional regression results in Table 7 incorporate the relative measures *PE_change_A_H*, *Illiq_A_H* and *Tov_A_H* (see Table 3 for variable definitions and Table 4 for associated descriptive statistics). Results in Table 7 help to extend our findings in regard to sentiment, liquidity and activity effects. Specifically, the relative measures reveal that higher A- price impact (relative to H-) coincides with greater one-way causality effects from H- to A- prices. In terms of activity, greater A-market turnover (relative to H-) is congruent with stronger A-price leadership. This last result reinforces the findings in Table 6. Results in Tables 6 and 7 are thus complementary in revealing how strong daily turnover in the A-market (both in absolute terms and relative to H- market volumes) underlies long-run A- to H-share price leadership effects.

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Tables 6 and 7

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6 Conclusions

The present study offers two major contributions. First, we decompose price leadership into short- and long-run dimensions. As a contribution to the literature on cross-listings, for both Chinese (Wang and Jiang, 2004; Arquette et al., 2008; Ma et al., 2010; and Cai et al., 2011) and global issuers (Gagnon and Karolyi, 2010a), we identify varying degrees of short- and long- term price leadership. The second contribution relates to our assessment of the determinants of long- and short- run price leadership. We find that capital control reform is central to changes in the short- and long-run price discovery dynamic between A- and H- prices. Specifically, the A- market's role in long-term price discovery

strengthens with increased capital inflow (i.e., ΔQFII investment). Consistent with this picture, greater mainland Chinese capital outflow into Hong Kong accentuates long-term price discovery in H- prices. Such capital movement also inhibits short-term causality effects (especially from H- to A- when Chinese capital outflow is on the up). Our findings strongly suggest that capital account liberalization boosts long-run price discovery (Bekaert et al., 2011) and reduces short-term non-synchronicity of prices. Results are consistent with external fund flows galvanizing domestic market price discovery (Frino et al., 2012). By deploying specific inward and outward capital flow measures, we significantly extend prior work on A- and H- pricing (most specifically Cai et al., 2011) and market efficiency (Schuppli and Bohl, 2010).

As an important subsidiary finding we report that a given market's long- and short- term price discovery function generally weakens as its price-to-earnings move strongly upward. Such findings are consistent with surging investor sentiment promoting greater amounts of mispricing and detracting from price discovery (Mian and Sankaraguruswamy, 2012 and Stambaugh, Yu and Yuan, 2013). In addition, we find that greater price impact (i.e., lower market depth or greater illiquidity) in a particular setting weakens that market's contribution to long-run price discovery. Such results support predictions in Chowdhury and Nanda (1991) by suggesting that higher price impact discourages informed trading. Consistent with results on price impact, higher trading volumes galvanize long- and short-run price discovery (see Baruch et al., 2007 and Gagnon and Karolyi, 2009).

Additionally, we examine a number of other effects potentially relevant to cross-border price discovery. These relate to earnings announcement effects, arbitrage costs (Pontiff, 2006; and Gagnon and Karolyi, 2010b) and key structural changes to China's issuers and its macro-economic environment. Among other things, expectations of RMB currency revaluation are significant in driving causality effects. However, information effects from earnings, China's 'Split Share Reform' and arbitrage risk (or idiosyncratic cost) appear as second-order factors in explaining price discovery.

Finally, there are three overarching reasons why our study of cross-listed A- and H- pricing is of international importance. First, suggestions of an impending move by the Shanghai Stock Exchange to

introduce an international board may mean that foreign issuers will soon be able to list on the Chinese mainland (see Ren, 2013 for recent discussion).

Second, reforms to ramp-up existing QFII and RQFII (i.e., RMB QFII) schemes will undoubtedly invite greater international investor penetration, and thus further galvanize A- and H- price-discovery processes.[31] Indeed, a number of business media outlets highlight the role of QFII in supporting A-share prices (see, for example, Ye, 2014 for recent discussion of the effects of additional QFII quota on Shanghai market sentiment). Expansion and development of the longstanding QFII scheme and the more recently-implemented RQFII initiative also offer important tools for policy-makers in influencing A-share market demand. Of particular import is the effect of the November 2014 launch of the Shanghai-Hong Kong Connect initiative (see HKEx, 2015) on the aggregate quota assigned both QFII and RQFII (for further discussion, see Yiu, May 2015). Capital outflow from the Chinese mainland into Hong Kong plays a similarly important role in influencing H-share prices. One vehicle for such outflow is QDII [see Cheng (2006) for topical discussion of its effects on Hong Kong market sentiment]. The present study's findings are instructive given the array of capital account reforms that will inevitably impact on China's existing menu of liberalization initiatives (i.e., QFII, QDII, RQFII, Shanghai-Hong Kong Connect) as well as likely new ones, most notably Shenzhen-Hong Kong Connect (see Yiu, July 2015).

As a third important international contribution, our analysis significantly extends the empirical literature on capital flows between developed market settings and/or for securities traded in major overseas markets (see, for example, Eun and Sabherwal, 2003; Grammig, Melvin and Schlag, 2005; Pascual, Pascual-Fuster and Climent, 2006; and Frino et al., 2012). More particularly, we offer insights for a unique setting in which emerging and developed markets co-exist in close proximity, but differ in terms of regulatory/legal structures. This special Chinese environment allows refined insights into the impact of capital reform on price discovery processes. In a general sense, the present study's findings offer important background for policy makers in other settings where capital account reform is on the horizon.

[31]. RQFII was announced in late 2011 and implemented in its first stage in early 2012 through Hong Kong. This development coincided with Hong Kong's growing role as an offshore deposit-base for Renminbi. For detailed comparison of RQFII and QFII schemes, see Tan (2014).

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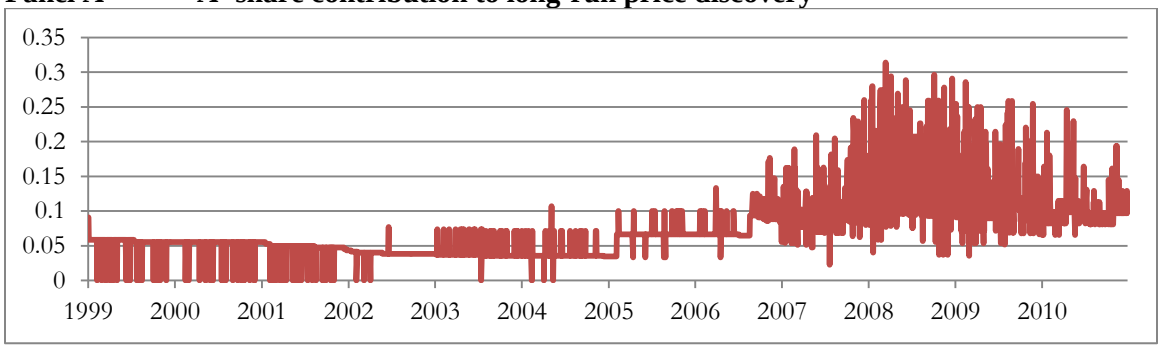
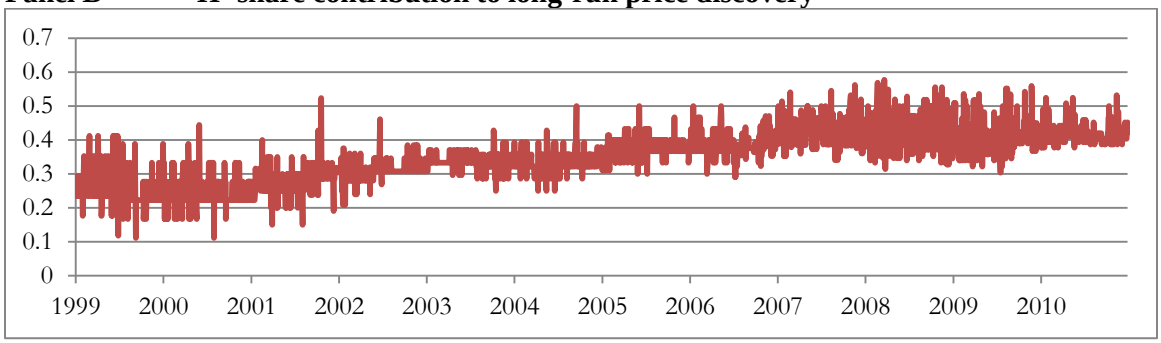
Figure 1 **Time-varying causality charts: 1999-2010**

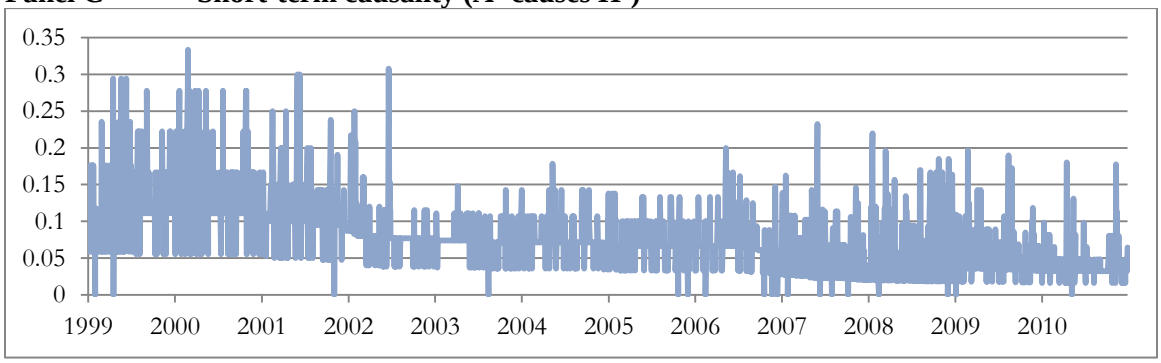
Panel A **A- share contribution to long-run price discovery**



Panel B **H- share contribution to long-run price discovery**



Panel C **Short-term causality (A- causes H-)**



Panel D **Short-term causality (H- causes A-)**

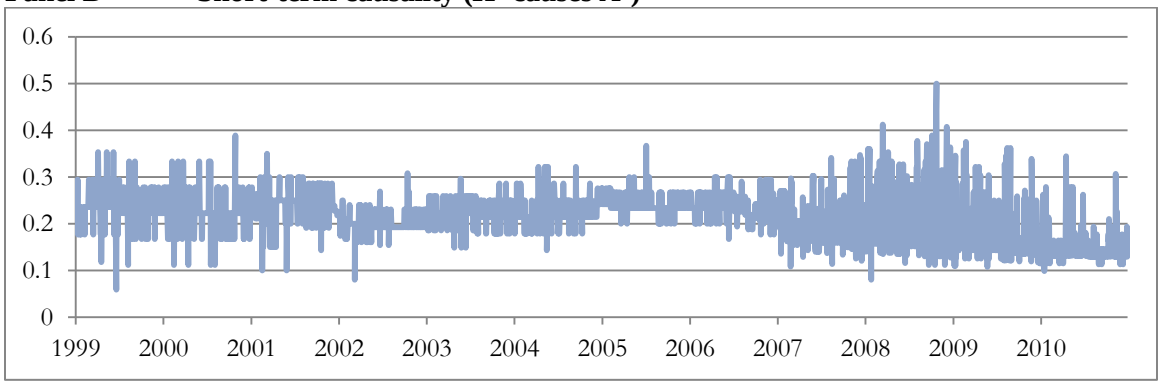


Table 1 Summary of MS-VAR estimates

This table summarizes the MS-VAR estimation of Equation (2). Panel A reports a summary of the parameters estimated for the 62 pairs of cross-listed companies. The large font-size Arabic numerals show median coefficients and the numerals in smaller-font the number of estimated pairs statistically significant (at the 10% level) from the 62 available. Only the first lag of autoregressive parameters is reported.

Panel B reports the mean transition and ergodic probabilities.

Panel A Summary of Estimation Results

$$\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} = \begin{bmatrix} 0.46 \\ {\scriptstyle 45} \\ -0.1 \\ {\scriptstyle 43} \end{bmatrix} + \begin{bmatrix} 0.13 & 0.11 \\ {\scriptstyle 34} & {\scriptstyle 41} \\ -0.01 & 0.20 \\ {\scriptstyle 40} & {\scriptstyle 45} \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} + \begin{bmatrix} -1.19 \\ {\scriptstyle 48} \\ 1.04 \\ {\scriptstyle 45} \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix}, \quad \text{if } S_t = 1$$

$$\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} = \begin{bmatrix} 0.14 \\ {\scriptstyle 29} \\ -0.1 \\ {\scriptstyle 43} \end{bmatrix} + \begin{bmatrix} -0.02 & 0 \\ {\scriptstyle 39} & \\ -0.01 & 0.20 \\ {\scriptstyle 40} & {\scriptstyle 45} \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} + \begin{bmatrix} -0.11 \\ {\scriptstyle 32} \\ 1.04 \\ {\scriptstyle 45} \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix}, \quad \text{if } S_t = 2$$

$$\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} = \begin{bmatrix} 0.46 \\ {\scriptstyle 45} \\ -0.06 \\ {\scriptstyle 35} \end{bmatrix} + \begin{bmatrix} 0.13 & 0.11 \\ {\scriptstyle 34} & {\scriptstyle 41} \\ 0 & -0.01 \\ & {\scriptstyle 35} \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} + \begin{bmatrix} -1.19 \\ {\scriptstyle 48} \\ 0.27 \\ {\scriptstyle 33} \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix}, \quad \text{if } S_t = 3$$

$$\begin{bmatrix} R_{A,t} \\ R_{H,t} \end{bmatrix} = \begin{bmatrix} 0.14 \\ {\scriptstyle 29} \\ -0.06 \\ {\scriptstyle 35} \end{bmatrix} + \begin{bmatrix} -0.02 & 0 \\ {\scriptstyle 39} & \\ 0 & -0.01 \\ & {\scriptstyle 35} \end{bmatrix} \begin{bmatrix} R_{A,t-1} \\ R_{H,t-1} \end{bmatrix} + \begin{bmatrix} -0.11 \\ {\scriptstyle 32} \\ 0.27 \\ {\scriptstyle 33} \end{bmatrix} \left(P_{A,t-1} - P_{H,t-1} \right) + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{H,t} \end{bmatrix}, \quad \text{if } S_t = 4$$

Panel B Matrix of Markovian transition probabilities

	State$_{t-1}$				
State$_t$	**1**	**2**	**3**	**4**	**Ergodic Probability**
1	0.170	0.307	0.256	0.168	0.126
2	0.151	0.188	0.242	0.087	0.117
3	0.116	0.195	0.105	0.036	0.033
4	0.563	0.311	0.397	0.709	0.725

Table 2 Percentage of A- and H- stock pairings classified by state of causality regime

This table reports the summary statistics for the key dependent variables.

Definitions:

Pcnt_A_contr = Percentage of stocks in each period that are error-correcting in the H- market;
Pcnt_H_contr = Percentage of stocks in each period that are error-correcting in the A- market;
Pcnt_A→H = Percentage of stocks where A- causes H-;
Pcnt_H→A = Percentage of stocks where H- causes A-;

We report time series means, minimum, median and maximum values and observation numbers for each variable below. The test columns report significant levels for tests on the difference between causality measures in A- and H- share markets.

t- test and signed rank tests are applied to the difference in means and medians.
*** Indicates the significance of such test at the 1 per cent level.

	Long term			Short term		
	pcnt_A_contr	**pcnt_H_contr**		**pcnt_A→H**	**pcnt_H→A**	
Mean	7.37	34.86	***	7.71	21.24	***
Median	6.45	35.71	***	7.14	21.88	***
Min	0.00	11.11		0.00	5.88	
Max	31.37	57.69		33.33	50.00	
Std	4.46	7.31		4.36	4.48	
N	3067	3067		3067	3067	

Table 3Variable definitions: Determinants of one-way and two-way causality effects

Variable	Definition
Variables capturing capital account policy	
QFII	Ratio of accumulated quota assigned to all qualified foreign institutional investors to China's total stock market capitalization, multiplied by 10,000. Quota data are obtained from China's State Administration of Foreign Exchange website.
ΔQFII	De-trended QFII =ΔQFII [= QFII-lag(QFII)]
ChinInv	Percentage contribution of mainland Chinese investment to overall HKEx turnover. Two HKEx surveys, one for 2010/11 (http://www.hkex.com.hk/eng/stat/research/Documents/cmts11.pdf) and one for 2005/6 (http://www.hkex.com.hk/eng/stat/research/cmts/documents/cmts06.pdf), serve in the determination of annual data values for 1997-2010. HKEx defines a year for the period from 1 October to 30 September. The constructed variable is then interpolated into daily observation using a cubic spline conversion method.
Variable capturing differential market sentiment effects	
ΔPE_A (H)	ΔPE_A (H) measures the rolling percentage changes in the price-earnings ratios (PERs) of Shanghai A-share Total Stock index (Hang Seng Index's) in past 20 trading days.
ΔPE_A_H	ΔPE_A_H measures the difference between changes in the price-earnings ratios (PERs) of Shanghai A-share Total Stock index (Hang Seng Index's) in past 20 trading days (= ΔPE_A - ΔPE_H).
Variable capturing differential liquidity and trading activity effects	
Illiq_A(H)	A measure of the daily price impact of the order flow in the A- (H-) share market. Following the definition proposed by Amihud (2002), we calculate this measure for each firm on a daily basis as the rolling 20 day average of the absolute-return to RMB-value-of-trading ratio in the A- (H-) share market, where absolute return is measured in percentage terms and RMB-value-of-trading in millions of RMB.
Illiq_A_H	Illiq_A_H measures the difference of the illiquidity measure in A- and H- share markets (= Illiq_A-Illiq_H).
Tov_A(H)	Tov_A_t and Tov_H_t are respective de-trended turnover levels in A- and H-trades on day t. $$Tov\_A_t = \left\{\log(Tov_{A,t}+a) - \frac{1}{20}\sum_{1}^{20}\log(Tov_{A,t-i}+a)\right\} 100$$ $$Tov\_H_t = \left\{\log(Tov_{H,t}+a) - \frac{1}{20}\sum_{1}^{20}\log(Tov_{H,t-i}+a)\right\} 100$$ Where $Tov_{A,t}$ and $Tov_{H,t}$ are the turnover ratio of a stock at day t for A- and H-market trading respectively. They are defined as the day's trading volume divided by the total number of shares in issue. This is de-trended by subtracting the 20-day moving average of prior days' volumes. Following Gagnon and Karolyi (2009), we add a constant (a=0.00000255) to avoid problems with zero volumes.
Tov_A_H	Tov_A_H measures the difference in the turnover ratio in the A- and H- market trading (= Tov_A - Tov_H).
Additional control variables	
AccAnn	Percentage of companies in the year-end earnings announcement period, defined as the 20-day period beginning 10 days prior to announcement and ending 10 days after.

Idio	An idiosyncratic risk measure developed by Gagnon and Karolyi (2010a, page 63), equal to the standard deviation of residuals from regressing each pair's 60-day rolling return difference against returns on the Shanghai A-share index and HSI as well as the RMB/HKD exchange rate. We obtain the rolling average of the residuals in the past 20 days to capture the overall measure of idiosyncratic risk in the market. This measure is scaled by 100.
FwdPrem	*[(RMB forward rate –RMB spot rate)/RMB spot rate]*100* Forward and spot rates are in RMB/USD format, whereby *forward* rate captures the 12-month RMB non-deliverable forward contract price relative to the USD and *spot rate is* the 'cash' price for immediate or spot delivery. A premium (discount) indicates an expected depreciation (appreciation) of the RMB against USD.
ΔNontrade_A	Measure the 20-day rolling changes in the average percentage of non-tradable A-shares, measured as number of non-tradable A-shares divided by total number of shares outstanding.
Other descriptive variables	
Market_Cap_A (H)	Market_Cap_A (H) measures the average market capitalization of the A- (H-) shares in millions of RMB.
Volume_A (H)	Volume_A (H) measures the average daily volume of the A- (H-) shares in millions of RMB.

Table 4 Descriptive statistics of explanatory variables

See Table 3 for variable definitions.

	Mean	Min	Q1	Median	Q3	Max	Std
QFII	0.37	0.00	0.00	0.32	0.60	1.28	0.36
ΔQFII	0.02	-13.67	-0.15	0.00	0.09	12.02	1.05
ChinInv	2.43	0.29	1.36	2.31	3.35	4.96	1.37
ΔPE_A	-0.31	-34.83	-4.79	0.06	5.63	23.19	9.78
ΔPE_H	0.34	-25.29	-4.75	0.89	4.88	28.51	8.79
ΔPE_A_H	-0.65	-41.42	-7.00	-0.54	5.83	37.96	11.08
Illiq_A	0.16	0.01	0.04	0.11	0.24	0.79	0.15
Illiq_H	5.79	0.06	0.46	2.17	6.14	50.20	9.34
Illiq_A_H	-5.63	-50.11	-5.99	-1.97	-0.38	0.02	9.29
Tov_A	-2.32	-95.71	-34.66	-3.21	27.81	133.29	46.30
Tov_H	-2.19	-110.29	-32.20	-2.57	25.06	150.10	48.15
Tov_A_H	-0.12	-226.67	-30.30	0.87	30.71	200.10	51.78
AccAnn	0.07	0.00	0.00	0.00	0.00	0.82	0.16
Idio	3.22	1.72	2.50	3.00	3.76	5.78	0.94
FwdPrem	-1.35	-11.46	-4.11	-1.88	0.88	12.93	3.86
ΔNontrade_A	-0.16	-5.62	-0.12	0.00	0.00	1.27	0.92
Market_Cap_A	11652	566	1511	1718	18632	78485	18307
Market_Cap_H	18091	408	1748	4803	38426	84267	22114
Volume_A	2195	1	78	383	2160	93258	5135
Volume_H	381	2	54	224	536	3931	471

Table 5 Determinants of error-correction and causality: Regression with de-trended QFII

The sample contains 3,047 observations, for trading days from January 1999 to December 2010. All explanatory variables are as defined in Table 3. AR1 to AR5 variables are included in regressions to control for serial correlation in the error term. We also report heteroscedasticity consistent t statistics, which when marked by ***, ** and * are significant at 1, 5 and 10 per cent significance levels, respectively.

		Long-term price discovery models						**Short-term price discovery models**					
		(1)			**(2)**			**(3)**			**(4)**		
		pcnt_A_contr			**pcnt_H_contr**			**pcnt_A→H_1way**			**pcnt_H→A_1way**		
Hypothesis	**Variable**	Coeff	t Value		Coeff	t Value		Coeff	t Value		Coeff	t Value	
	Intercept	2.594	6.11	***	8.363	8.45	***	0.214	0.37		17.317	12.34	***
Capital flow	ΔQFII	1.391	10.608	***				-0.200	-0.762				
	ChinInv				1.043	9.508	***				-1.484	-10.610	***
Sentiment	ΔPE_A	-0.009	-0.961					-0.026	-1.845	*			
	ΔPE_H				-0.041	-3.085	***				-0.038	-2.611	***
Liquidity	Illiq_A	-4.955	-8.399	***				2.664	1.512				
	Illiq_H				-0.037	-3.327	***				-0.047	-4.154	***
Activity	Tov_A	0.008	4.217	***				0.001	0.280				
	Tov_H				0.011	5.737	***				0.011	4.639	***
Others	Idio	0.101	1.065		0.315	2.283	**	0.443	1.842	*	0.157	1.013	
	AccAnn	-1.578	-1.793	*	-1.753	-1.638		3.898	3.594	***	-1.655	-1.811	*
	FwdPrem	-0.053	-1.636		-0.153	-3.623	***	0.159	3.667	***	-0.111	-2.589	***
	ΔNontrade_A	-0.165	-1.990	**	-0.067	-0.642		0.068	0.705		-0.056	-0.486	
Control	AR1	0.109	3.966	***	0.164	6.584	***	0.107	1.385		0.002	0.060	
	AR2	0.195	6.024	***	0.146	4.951	***	0.212	4.467	***	0.105	3.462	***
	AR3	0.158	5.158	***	0.184	6.418	***	0.081	2.107	**	0.111	3.652	***
	AR4	0.148	5.198	***	0.087	3.178	***	0.117	2.253	**	0.098	3.252	***
	AR5	0.117	4.228	***	0.084	3.084	***	-0.016	-0.235		0.012	0.430	
	Adj R-Sq	0.558			0.655			0.320			0.348		
	NumObs	3047			3047			3045			3047		
	Max VIF	1.852			3.934			1.617			3.302		

Table 6 Determinants of error-correction and causality: Subsample analysis from QFII quota commencement (2003) to 2010

The sample contains 1,978 observations, for trading days from June 2003 to December 2010. All explanatory variables are as defined in Table 3. AR1 to AR5 variables are included in regressions to control for serial correlation in the error term. We also report heteroscedasticity consistent t statistics, which when marked by ***, ** and * are significant at 1, 5 and 10 per cent significance levels, respectively.

		Long-term price discovery models						**Short-term price discovery models**					
		(1)			**(2)**			**(3)**			**(4)**		
		pcnt_A_contr			**pcnt_H_contr**			**pcnt_A→H_1way**			**pcnt_H→A_1way**		
Hypothesis	**Variable**	Coeff	t Value		Coeff	t Value		Coeff	t Value		Coeff	t Value	
	Intercept	3.213	6.41	***	11.287	8.84	***	1.054	1.56		25.463	13.28	***
Capital flow	ΔQFII	1.402	10.796	***				-0.169	-0.669				
	ChinInv				0.921	6.318	***				-2.476	-11.990	***
Sentiment	ΔPE_A	-0.024	-2.339	**				-0.026	-1.859	*			
	ΔPE_H				-0.053	-3.324	***				-0.053	-3.048	***
Liquidity	Illiq_A	-8.063	-9.014	***				2.416	1.020				
	Illiq_H				-0.106	-1.772	*				0.089	1.647	*
Activity	Tov_A	0.012	5.011	***				0.001	0.178				
	Tov_H				0.017	6.036	***				0.020	6.099	***
Others	Idio	0.502	3.332	***	0.758	3.765	***	0.236	0.897		0.426	1.956	*
	AccAnn	-2.030	-1.864	*	-1.761	-1.355		4.382	3.364	***	-2.211	-1.985	**
	FwdPrem	-0.009	-0.197		-0.071	-1.212		0.059	1.333		0.024	0.391	
	ΔNontrade_A	-0.136	-1.471		-0.072	-0.625		0.050	0.552		-0.015	-0.118	
Control	AR1	0.083	2.995	***	0.128	4.568	***	0.059	0.676		-0.055	-1.703	*
	AR2	0.173	5.337	***	0.127	3.842	***	0.178	3.488	***	0.052	1.619	
	AR3	0.138	4.448	***	0.188	5.819	***	0.074	1.857	*	0.065	1.948	*
	AR4	0.123	4.283	***	0.070	2.315	**	0.117	2.007	**	0.054	1.693	*
	AR5	0.090	3.217	***	0.070	2.217	**	-0.064	-0.903		-0.036	-1.220	
	Adj R-Sq	0.481			0.340			0.143			0.377		
	NumObs	1978			1978			1978			1978		
	Max VIF	1.685			2.667			1.357			3.643		

Table 7 Determinants of error-correction and causality: Utilizing relative measures ΔPE_A_H, Illiq_A_H and Tov_A_H

The sample contains 3,047 observations, for trading days from January 1999 to December 2010. All explanatory variables are as defined in Table 3. AR1 to AR5 variables are included in regressions to control for serial correlation in the error term. We also report heteroscedasticity consistent t statistics, which when marked by ***, ** and * are significant at 1, 5 and 10 per cent significance levels, respectively.

		(1) pcnt_A_contr			(2) pcnt_H_contr			(3) pcnt_A→H_1way			(4) pcnt_H→A_1way		
Hypothesis	**Variable**	Coeff	t Value		Coeff	t Value		Coeff	t Value		Coeff	t Value	
	Intercept	1.657	4.23	***	7.863	7.80	***	0.472	0.81		16.942	11.62	***
Capital flow	ΔQFII	1.371	10.509	***				-0.174	-0.674				
	ChinInv				0.877	8.111	***				-1.482	-10.368	***
Relative Sentiment	ΔPE_A_H	0.010	1.422		0.016	1.876	*	-0.024	-1.576		0.461	0.510	
Relative Liquidity	Illiq_A_H	0.045	5.063	***	0.034	3.073	***	-0.056	-1.979	**	0.047	4.222	***
Relative Activity	Tov_A_H	0.003	2.004	**	-0.002	-1.257		0.000	0.090		-0.001	-0.481	
Others	Idio	0.058	0.605		0.185	1.360		0.311	1.405		0.032	0.210	
	AccAnn	-0.685	-0.767		-1.064	-0.998		3.660	3.461	***	-0.958	-1.060	
	FwdPrem	-0.036	-1.036		-0.144	-3.344	***	0.134	3.176	***	-0.110	-2.552	**
	ΔNontrade_A	-0.174	-2.068	**	-0.071	-0.674		0.090	0.931		-0.054	-0.451	
Control	AR1	0.121	4.342	***	0.175	6.989	***	0.122	1.609		0.013	0.411	
	AR2	0.210	6.436	***	0.154	5.209	***	0.220	4.486	***	0.115	3.749	***
	AR3	0.174	5.688	***	0.191	6.572	***	0.085	2.251	**	0.117	3.789	***
	AR4	0.164	5.742	***	0.093	3.360	***	0.121	2.475	**	0.104	3.343	***
	AR5	0.130	4.716	***	0.088	3.198	***	-0.015	-0.218		0.014	0.507	
	Adj R-Sq	0.548			0.650			0.319			0.339		
	NumObs	3047			3047			3045			3047		
	Max VIF	1.824			3.703			1.609			3.288		