Dual-Listed Shares and Trading

Clark Liu
HKUST

Mark S. Seasholes
HKUST

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Abstract

We study companies with dual-listed shares in China (mainland) and Hong Kong. When China has a short-sale ban, Chinese stock prices are 1.8× as high as Hong Kong prices (on average). Stock pairs with higher fundamental volatilities or more volatile order flows have higher price disparities (on average). The average stock pair's return difference is volatile and has a standard deviation of 8.8% *per week*. This paper shows that order flows can affect both a company's fundamental price and/or its transitory prices. In Hong Kong, transitory variance accounts for 39% of a stock's *total* variance. These results are surprising because the average market capitalization is over USD 8 billion for the Hong Kong-listed shares and the turnover is over 2.5× per annum. We exploit a quasi-natural experiment in which the short-sale ban is lifted for some Chinese stocks but not others. After the ban is lifted, the affected shares trade at parity. We estimate that lifting the short-sale ban in China (mainland) reduces weekly transitory volatility in Hong Kong by 49 bp per week because it enables a hedging mechanism.

Keywords: Dual-Listed Shares, Trading Imbalances, Cost of a Short-Sale Ban

JEL Number: G12, G14

Note: All referenced appendices are in the associated Internet Appendix.
Please see: *http://dl.dropbox.com/u/6555606/AHpremXsecAppendix.pdf*

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1 Introduction

Consider a company with shares listed in two markets/countries. How do the relative prices of the shares behave? When are the share prices at parity? A central focus of this paper is the interaction of trading behavior and market frictions (such as a short-sale ban and limited risk bearing capacity). Do the frictions cause the company's prices to deviate in a predictable fashion? What are the relations between stock-level order flows and relative prices in both the time-series and cross-sectional dimensions? How volatile are the relative prices and associated returns? Finally, how can we use our research design along with a quasi-natural experiment to estimate the cost of a short-sale ban?

To answer the above questions, we study a sample of 43 companies with dual-listed shares in China (mainland) and Hong Kong.[1] The companies are chosen because they have been, at some point in time, part of a well-publicized index that tracks stock price disparities across the two markets. The companies are large, highly visible, and have high turnovers. In fact, the average company's total market capitalization is USD 32.6 billion, of which USD 8.2 billion is listed in Hong Kong. Throughout this paper we follow convention and refer to China (mainland) as the a-share market and Hong Kong as the h-share market.[2]

We propose a parsimonious theoretical framework to give structure to the questions in the opening paragraph. We consider a single company with two non-fungible securities that trade in two separate markets. The securities are otherwise identical and have claims on exactly the same dividends. Each market is populated by informed traders and noise traders that are specific to the market. In addition, there are arbitrageurs who can trade in both

[1] We use the term "dual-listed shares" to differentiate these shares from cross-listed shares (which are typically fungible), dual-listed companies (which refer to a specific corporate structure), and dual-class shares (which typically have different voting or dividend rights). Our shares have none of these features.

[2] Our sample of 43 companies has recently been studied by Seasholes and Liu (2011). Comparisons and contrasts between their paper and the current manuscript are in Section 1.1 and Appendix Q.

markets. The arbitrageurs are risk-averse and face a short-sale constraint in one of the markets only. The two main frictions studied in this paper are limited risk-bearing capacity and a short-sale constraint in one market (only).

The theoretical framework produces seven testable implications. For example, when there is no short-sale constraint, we expect prices to trade at parity ($P_t^a = P_t^h$) because arbitrageurs have a perfect way to hedge any position. When there is a short-sale constraint in the a-market, we expect a-shares to trade at a premium to h-shares ($P_t^a \geq P_t^h$) because arbitrageurs can easily trade against upward movements in P_t^h but not in P_t^a. In our data, we see the price of the average company's a-shares typically sell for 1.8× the price of its h-shares. At times, prices in China (mainland) can be 2×, 3×, or even 4× prices in Hong Kong. Following market convention, we refer to the ratio of a company's a-share to h-share prices (times 100) as its "AH Premium" and a value of 100 indicates that a share pair is trading at parity. An AH Premium of 182.1 indicates a-share prices are 1.8× as high as h-share prices.

More surprisingly (and perhaps more interestingly), the relative prices of a dual-listed share pair are far from constant. In other words, a given company's share price difference varies considerably over time. For the average company, the AH Premium has a volatility of 39.5 per week. If the company's AH Premium starts a week with a value of 182.1, a one standard-deviation upward movement leads the AH Premium to end the week with a value of 221.6 (indicating prices in the a-market are 2.2× prices in the h-market). A one standard-deviation downward movement leads the AH Premium to end the week with a value of 142.6, indicating that prices in the a-market are 1.4× prices in the h-market.

As mentioned in the opening paragraph, a central focus of this paper is the interaction between trading behavior and market frictions. Our theoretical framework produces testable implications regarding order imbalances and prices. For example, in a market with limited risk-bearing capacity, order flows are positively correlated with price movements—a result seen in papers such as Grossman and Miller (1988). If order flows are uncorrelated across markets, the log change in a company's AH Premium (i.e., the difference in a company's two returns across markets) is positively correlated with the difference in order flows. Seasholes and Liu (2011) empirically study this relation at the index level. Our paper focuses on the stock-pair level and our model predicts the level of a company's AH Premium is positively correlated with the amount of trading volatility and a company's fundamental volatility.

To refine our empirical analysis, we estimate a state-space model. Our estimation methodology starts with the standard assumption that a stock's observed price consists of two unobservable components. The first component is called the stock's "efficient price" (or fundamental price) and is assumed to follow a random walk with drift. The second component is the "transitory price" and is assumed to be stationary. One can think of the second component as a (temporary) deviation from fundamental price. A key feature of dual-listed stocks is that they share the same fundamental price.

We estimate relations between order flows and the unobserved components of stock prices. A one standard-deviation shock to order flow in China (Hong Kong) leads to a 150 basis points or "bp" (112 bp) change in the associated transitory price. We next decompose a stock's total variance into a part coming from the efficient component and a part coming from the transitory component. Focusing on Hong Kong (the developed market), we find that transitory variance represents 39.2% of <u>total</u> variance at a weekly frequency. Our results provide support for findings in Hendershott et al. (2010), who find that the transitory variance is 25% of the monthly <u>idiosyncratic</u> variance. If the idiosyncratic variance is half the total variance, then the magnitude of transitory variance in Hong Kong is roughly 3$\times$ larger than the magnitude reported in Hendershott et al. (2010).

The state-space model allows us to test cross-sectional predictions from our theoretical framework. Specifically, we show that a company's average AH Premium is positively correlated with its fundamental volatility (a quantity that is only observable after our estimation procedure.) Companies with fundamental volatilities one standard deviation above (below) the mean have AH Premiums of 274.6 (83.34), indicating the result is economically significant. The premium is also positively correlated with the volatility of order flows.

We end the paper by exploiting a quasi-natural experiment that allows us to estimate the cost of a short-sale ban. Starting on 31-Mar-2010, Chinese authorities allowed 21 of our 43 companies' a-shares to be shortable. The other 22 a-shares remained non-shortable and serve as a control group. After the ban was lifted, affected shares traded at parity while the AH Premium of the non-shortable shares was near 150. We find the weekly h-share transitory volatility of the shortable group fell 49 basis points (bp) around the lifting of the ban, while the h-share transitory volatility of the non-shortable group rose slightly. Our paper provides theoretical and empirical evidence of a friction in one market affecting prices in other markets by limiting the hedging options of arbitrageurs. In our case, the friction in an emerging market (China mainland) is shown to affect prices in the world's fifth largest stock market (Hong Kong).

1.1 Literature Review

Our study of Chinese dual-listed shares adds to a substantial group of empirical papers documenting transitory price movements (please see Appendix A). Our paper also complements a number of other literature strands. First, there is a large strand of literature about cross-listed shares. Karolyi (2010) surveys corporate finance issues relating to cross-listing. Gagnon and Karolyi (2010a) review recent papers on international cross-listings. There are also three relatively new papers on multi-market trading that include Baruch, Karolyi, and Lemmon (2007), Gagnon and Karolyi (2010b), and Halling, Moulton, and Panayides (2011). The second one is most similar to our paper except that the authors study intra-day prices and quotes and they find small deviations from price parity. Our paper, on the other hand, studies large and volatile price deviations at a weekly frequency.

The second strand studies dual-listed companies such as Royal Dutch and Shell—see Rosenthal and Young (1990). Froot and Dabora (1999) find that differences between share prices appear to be correlated with the markets on which the shares are traded most. Chan, Hameed, and Lau (2003) expand our understanding of location-of-trade effects using Jardine Group stocks. DeJong, Rosenthal, and Van Dijk (2009) evaluate trading strategies designed to profit from the price discrepancies of dual-listed companies. Our paper complements these papers by linking trading imbalances to high levels of relative-price volatility.

A third strand of literature studies dual-listed shares that trade only within China (mainland). A-shares were initially designated for local Chinese citizens while b-shares were for foreign investors. Chan, Menkveld, and Yang (2007) show that, prior to Feb-2001, most price discovery used to happen in the a-share market. Chan, Menkveld, and Yang (2008) construct a measure of information asymmetry to explain the b-share discount. Mei, Scheinkman, and Xiong (2009) find that speculative trading motives help explain the a-share premium over b-shares. Fourth, state-space statistical models have been used to study round-the-clock price discovery for cross-listed stocks by Menkveld, Koopman, and Lucas (2007). The models have also been used to look at price pressure at a daily frequency by Hendershott and Menkveld

(2010) and at a monthly frequency by Hendershott et al. (2010). More detailed comparisons and contrasts between our paper and Hendershott et al. (2010) can be found in Appendix R.

Froot and Ramadorai (2008) study cross-border equity flows, closed-end funds' NAVs, and price returns. They find cross-border flows are linked to fundamentals, while closed-end fund flows are a source of price pressure. Scruggs (2007) studies Siamese twin stocks and Chan, Kot, and Yang (2010) study a- and h-share prices, neither makes use of trading imbalances. Likewise, Lauterbach and Wohl (2001) study price deviations of equal-payoff government bonds from Israel. These bonds have a mean absolute spread of 20.5 bp with a 22.7 bp standard deviation. These magnitudes are far smaller than what we document in Hong Kong. Finally, in a recent paper, Seasholes and Liu (2011) study trading and the index of AH prices. Our paper differs from the earlier work in six main dimensions: i) We present an economic model. ii) Our paper focuses on the stock level. iii) The use of dual-listed shares represents a new identification strategy for better understanding transitory price. iv) We exploit a quasi-natural experiment to estimate the cost of a short-sale ban. v) We use a state-space model to estimate unobserved fundamental and transitory price series. vi) We have cross-sectional predictions and tests about the size of a stock pair's AH premium. More detailed comparisons and contrasts between our paper and Seasholes and Liu (2011) can be found in Appendix Q.

2 Theoretical Framework

We model an economy with a single firm that has two claims to its dividends (i.e., two types of shares). The claims are equal in all respects except that they are non-fungible and trade in two separate markets (denoted "a" and "h"). Please see Appendix B for proofs and additional details.

The Economy: There are four dates $t = \{0, 1, 2, 3\}$ and two risky assets that each pay $\tilde{D}_3$ units of the consumption good at t=3. The cashflow can be written as $D_3 = \bar{D}+\epsilon_1+\epsilon_2+\epsilon_3$, where $\epsilon_t \sim N[0, \sigma_t^2]$. We denote P_t^a and P_t^h as the prices of the stocks in these two markets at time t, with $P_3^a = P_3^h = D_3$ on the final date. There is a single riskless asset. Without loss of generality, the price of the riskless asset is normalized to one each period.

Investors Specific to Market a: There are two groups of investors specific to market a. Informed investors are labeled "$\iota(a)$" and adjust their demands in response to information releases. Noise traders are labeled "$\eta(a)$" and have inelastic demands at each date. Each group is assumed to have a mass of one and an initial endowment of W_0. Holdings of the two groups at time t are denoted $X_t^{\iota(a)}$ and $X_t^{\eta(a)}$.

Investors Specific to Market h: There are two parallel groups in market h denoted "$\iota(h)$" and "$\eta(h)$" with holdings $X_t^{\iota(h)}$ and $X_t^{\eta(h)}$.

Arbitrageurs and a Short-Sale Constraint: A separate group of informed investors is labeled "α" and are free to trade in both markets. The group has a mass of one and an initial endowment of W_0. Since these "arbitrageurs" can hold both types of shares, their holdings at time t are denoted $\{X_t^{\alpha(a)}, X_t^{\alpha(h)}\}$. Group α's holdings in market a are constrained to be nonnegative, so that $X_t^{\alpha(a)} \geq 0$ for all time t. This assumption captures situations in which one of the markets has a short-sale constraint. There are no such constraints in market h.

Timing of the Model and Shocks: Part of the assets' final dividends (ϵ_1) is revealed to all informed investors at t=1, a second part (ϵ_2) is revealed at t=2, and a third part (ϵ_3) is revealed at t=3. Noise trader holdings are subject to exogenous shocks at time t and denoted $\Delta X_t^{\eta(a)}$ and $\Delta X_t^{\eta(h)}$ with $\Delta X_t^{\eta(a)} \sim N[0, \sigma_a^2]$ in market a and $\Delta X_t^{\eta(h)} \sim N[0, \sigma_h^2]$ in market h.

Shocks are independently and identically distributed across time and across markets.

Agents' Maximization Problems: Informed traders maximize their expected utility of wealth at t=3, which is denoted as $\mathbb{E}\big[U(W_3)\big]$. We assume all agents have exponential utility functions of the form $-e^{-\lambda W_3}$, where the λ coefficient of risk aversion could be different for each group of investors.[3]

Equilibrium Prices and Holdings: Using backward induction, we solve for prices, holdings, changes in prices (returns), and changes in holdings (order imbalances) at each date. Agents at date t take expectations of prices and quantities at date t+1. We also solve for a contemporaneous price disparity across the markets and call this quantity a company's "AH Premium" or "$AH\ Prem_{i,t}$" for a given company i. Positive (negative) values indicate that the share price in market a is above (below) the price in market h.[4] Appendix B provides analytical expressions for all quantities. Appendix C provides a numerical analysis of our model.

Testable Implications: The ability to calculate prices, returns, holdings, and order imbalances at each date allow us to produce seven testable implications.

> *Implication #1: Relative Prices.* With no short-sale constraint, $P_t^a = P_t^h$ since arbitrageurs can perfectly hedge any position. When a short-sale ban is in place, $P_t^a \geq P_t^h$. In the model, the short-sale constraint only applies in market a. Therefore, the arbitrageurs can easily trade against mispricings when $P_t^a < P_t^h$, but are limited in their actions when $P_t^a > P_t^h$.

> *Implication #2: Mean Reversion.* Our model has limited risk-bearing capacity and both of a company's stock prices are mean reverting, similar to Grossman and Miller (1988). If a given company's order imbalances are uncorrelated across markets, the company's $AH\ Prem_{i,t}$ is also

[3]Solutions become unwieldy if three λs are used. Therefore, we impose a restriction on the λs. Specifically, we set $\lambda = \lambda^{\iota(a)} = 0.5\lambda^{\iota(h)} = 0.5\lambda^{\alpha}$. This assumptions captures the idea that investors in market a are more risk-tolerant than both those in market h and the arbitrageurs. The notion that investors in market a are more risk-tolerant than those in market h carries through to our numerical analysis in Appendix C (which gives additional insights into our model). The risk tolerance of the noise traders plays no role in this framework since these investors have inelastic demands.

[4]In a CARA-normal framework, and due to issues related to taking the ratio of two normal variables, the theoretically calculated AH Premium is based on price differences. In Section 3, and in practice, the premium is based on the price ratio. Note that using differences vs. ratios is the same if parameters are chosen such that $P_t^h = 1$.

mean reverting.

Implication #3: Cross-Market Return Correlations. A given company's stock returns are positively, contemporaneously correlated across the two markets because the stocks have the same fundamental component.

Implication #4: Price Pressure. Trades in a given market are positively correlated with returns in that market. If trades are uncorrelated across markets, cross-market differences in trading are positively correlated with cross-market return differences (i.e., changes in $AH\ Prem_{i,t}$). This implication is a stock-level analog to the index-level findings in Seasholes and Liu (2011).

Implication #5: Trading and Returns. The correlation of returns with order imbalances is stronger in market a than in market h. This implication comes from the fact that arbitrageurs cannot easily trade against upward price movements in market a.

Implication #6: Fundamental Volatility and AH Premiums. The average level of a company's AH Premium increases with underlying (fundamental) volatility. This result comes from fundamental volatility causing risk to arbitrageurs, who then trade less aggressively and demand greater compensation for taking on a position.

Implication #7: Trading Volatility and AH Premiums. The average level of a company's AH Premium increases with the amount of trading volatility in either market. This result comes from arbitrageurs being more reluctant to take positions when there is a greater chance of suffering losses.

3 Data and Overview Statistics

3.1 Sample Selection

We study companies with dual-listed shares in Hong Kong and China (mainland). All companies have been, at some time, part of a well-publicized index that tracks the price discrepancies of dual-listed shares. Our sample of 43 companies begins on 03-Jan-2006 and ends on 30-Apr-2009. Throughout this paper, we report trading and price variables at a weekly frequency, with 173 weeks of total data.[5] Weeks run from the close-of-market Wednesday through the close-of-market the following Wednesday.

[Insert Table I About Here]

[5] Our sample of 43 companies is the same as that studied in Seasholes and Liu (2011). Columns 1, 2, 3, and 6 in our Table I highlight this fact. Background on the China (mainland) and Hong Kong markets can be found in their paper. More information about the AH Premium Index can also found in their paper. Our sample start date is the start of the published index data. The end date is when we downloaded the trading data. Section 5 focuses only on prices and extends the sample period through 2010 in order to exploit a quasi-natural experiment.

Table I, Panel A shows the names and tickers of the 43 companies in our sample. We report market capitalizations in millions of USD and as of 30-Apr-2009. The average company's total market capitalization is USD 32.7 billion and the median is USD 9.5 billion. For the Hong Kong-listed shares (only), the average market capitalization is USD 8.2 billion. We provide each company's industry based on Global Industry Classification Standard (GICS) codes and weeks of available data. As part of our robustness checks, we repeat all tests after restricting our sample to the 27 companies with 87 or more weeks of data.

3.2 Stock Market Data and Stock-Level AH Premiums

We obtain daily stock prices and returns from Datastream. Returns are compounded to a weekly frequency. All monetary values in this paper are converted to United States dollars (USD) because Hong Kong-listed stocks are quoted in Hong Kong dollars (HKD) and Chinese (mainland)-listed stocks are quoted in renminbi (RMB). Datastream provides HKD-USD and RMB-USD exchange rates.

The price ratio of a company's *a*-shares and its *h*-shares is called the company's "AH Premium." Below, $P^a_{i,t}$ is Wednesday's closing price in China (mainland) after converting to USD. $P^h_{i,t}$ is Wednesday's closing price in Hong Kong, also after converting to USD. A value of 100 indicates that shares are selling for the same price on the two exchanges. A value greater than 100 indicates that the price in China (mainland) is higher than the price in Hong Kong.

$$AH\ Prem_{i,t} = \frac{P^a_{i,t}}{P^h_{i,t}} \times 100 \tag{1}$$

Table I, Panel B gives overview statistics related to companies' AH Premiums. The average company has a share price in China (mainland) that is 1.8× as high as its Hong Kong share price. More importantly, the average company has a standard deviation of *AH* $Prem_{i,t}$ that is 39.5 *per week*. Understanding these high levels of variation is one goal of this paper.

[Insert Figures 1 and 2 About Here]

Figure 1 graphs the 25%, 50%, and 75% percentiles of *AH* $Prem_{i,t}$ over time. While premiums are relatively low in the first part of our sample, they grow noticeably in the latter part. The median firm ends the sample with a value just under 200, indicating that its China (mainland) shares are selling for almost double the price of its Hong Kong shares. The interquartile range also grows over time. In the first part of the sample, the range is approximately 50, while it is well over 100 in the latter part. Finally, we note that Figure 1 shows the high level of volatility associated with AH Premiums.

Figure 2 plots three companies' AH Premiums over time and we again see high levels of relative-price volatility. These companies represent the 25%, 50%, and 75% percentiles of average *AH* $Prem_{i,t}$ over our sample period. For one of the companies, Jiangxi Copper, in early 2008, the price of its Chinese (mainland) shares is almost 4× the price of its Hong Kong-listed shares.

Table I, Panel B gives evidence supporting *Implication #1* from Section 2. In the third column of numbers we see that $P^a \leq P^h$ for only 8% of stock-weeks. The fourth column supports *Implication #2*, because the average *AH* $Prem_{i,t}$ has a 0.84 *AR(1)* coefficient. We are measuring the variable's level, so a coefficient $0 \leq AR(1) < 1$ indicates mean reversion with no overshooting. A first-order autocorrelation coefficient of 0.85 implies that shocks have half-lives of 4.3 weeks. Consistent with *Implication #3*, the final column of numbers shows that $r^a_{i,t}$ and $r^h_{i,t}$ are positively correlated for all 43 stock pairs. The average correlation is 0.47, while the correlation is 0.50 for the median company.

3.3 Order Imbalance Data

Order imbalance data come from the Thomson Reuters Tick History (TRTH) database. The database contains trades and quotes for stocks listed around the world. Data fields include a ticker code, local date, local time, and a variable indicating whether the record pertains to a trade or a quote. For each trade, the database provides a transaction price in local currency and number of shares traded. For each quote, there is a bid price and bid size or an ask price and ask size.

To compute the order imbalance for a given stock over a given day, we employ a trade-signing algorithm like the one proposed by Lee and Ready (1991). Trades that take place above the current midpoint of the bid and ask prices are classified as buyer-initiated. Trades below the midpoint are classified as seller-initiated.

For the 43 stocks in our sample, and during our 2006 to 2009 sample period, the TRTH database contains over 563 million trades of a shares and over 61 million trades of h shares. For each stock i, each day k, and each market (a or h), we calculate buyer-initiated volume and seller-initiated volume. In China (mainland) these quantities are denoted $Buy^a_{i,k}$ and $Sell^a_{i,k}$. Appendix D contains notes on the steps to calculate the order imbalance numbers.

Table I, Panel C provides an overview of the order imbalance data. Columns 2 and 3 show the free floats in each market (as fractions of shares outstanding). The average company has 24% of its China-listed shares available for trading in China. Of shares listed in Hong Kong, 89% of shares are available for trading on average.

Panel C also shows each company's average turnover in each market. Each week, we calculate a stock's turnover as the number of shares bought divided by the number of shares available to trade (free float). Low free floats and high volumes of trading in China (mainland) lead to a very large average turnover of 0.13. By comparison, the average turnover in Hong Kong is 0.05 per week, which is over 2.5× per annum.

Finally, Panel C shows the correlation of each company's order imbalances. For the average company, the correlation of $OIB^a_{i,t}$ and $OIB^h_{i,t}$ is 0.01, while the median value is 0.04. The low correlation is consistent with our model's assumption that noise trader shocks are uncorrelated across markets.[6]

4 State-Space Model and Empirical Results

We estimate a state-space model (SSM) using the assumption that stock i's observable price can be decomposed into two unobservable components. The first component is called the stock's "efficient price" and is denoted $m_{i,t}$. The second component is called the "transitory price" and is denoted $s_{i,t}$. The efficient price is assumed to follow a random walk with drift, while the transitory price is assumed to be stationary.[7] Here, $p_{i,t}$ denotes the natural log of stock i's price as of week t.

[6] We note that Seasholes and Liu (2011) show a positive and contemporaneous relationship between changes in the AH Premium Index and the difference in aggregate order imbalances (from market-a minus market-h). Their paper is focused on relations at the index level. Please see Table 2 on p.134 of their paper. We take the existing results as a starting point of our analysis. Please see Appendix Q for a complete description on how our analysis is different from theirs.

[7] Appendix F outlines an alternative estimation methodology based on an ARMA (statistical) model. We have thought about, but decided against, also presenting estimates from a VAR. Such work would be motivated by papers such as Hasbrouck (1993). Expanded materials are available from the authors upon request.

In the case of dual-listed shares, there are two observable stock prices, which are denoted $p^a_{i,t}$ and $p^h_{i,t}$. Economically, we assume a given company has a single fundamental value at each point in time, but any observable price can deviate from this fundamental value. The system of equations below represents our state-space (statistical) model:

$$
\begin{aligned}
p^a_{i,t} &= m_{i,t} + s^a_{i,t} + c_i \\
p^h_{i,t} &= m_{i,t} + s^h_{i,t} \\
m_{i,t} &= m_{i,t-1} + \delta_{i,t} + w_{i,t} \\
w_{i,t} &= \kappa^a \tilde{O}IB^a_{i,t} + \kappa^h \tilde{O}IB^h_{i,t} + u_{i,t} \\
s^a_{i,t} &= \phi^a s^a_{i,t-1} + \gamma^a OIB^a_{i,t} + \epsilon^a_{i,t} \\
s^h_{i,t} &= \phi^h s^h_{i,t-1} + \gamma^h OIB^h_{i,t} + \epsilon^h_{i,t}
\end{aligned} \tag{2}
$$

In Equation (2), c_i is a constant that captures average price differences between company i's two stocks. One can think of c_i as a company-specific fixed effect. It can capture unobserved differences in a company's a-share and h-share prices. Alternatively, in segmented markets, two otherwise identical shares may sell for different prices due to differences in risk-aversion across markets. The c_i can capture such an effect as well. Next, $\delta_{i,t}$ is the required rate of return, including a market component of the efficient stock price increases. It is defined as: $\delta_{i,t} = r_{f,t} + \beta_i(1.08^{\frac{1}{52}} - 1) + \beta_i f_t$. Here, $r_{f,t}$ is the riskless rate over week t, β comes from a regression of stock i's returns on the market's returns in market h, and f_t is the demeaned return of the MSCI Broad China Index, defined as $f_t = r_{m,t} - \bar{r}_m$.

$OIB^a_{i,t}$ and $OIB^h_{i,t}$ are defined in Section 3.3. $\tilde{O}IB^a_{i,t}$ is a residual from a regression of $OIB^a_{i,t}$ on four of its own lags. This captures the surprise component of order imbalances, because this is the part that affects the efficient price. $\tilde{O}IB^h_{i,t}$ is an analogous measure for market h.

4.1 Parameter Estimates

We estimate the system of equations shown in Equation (2) on a stock-by-stock basis. Estimation is by maximum likelihood using statistical software called `Ox` along with an add-on pack called `ssfpack`. See Koopman, Shephard, and Doornik (1999) for additional information about related estimation procedures. Appendix E has information about implementing the estimation, and Hendershott et al. (2010) discuss the advantages of using a state-space model in a setting related to studying dual-listed shares.

For two of the 43 stocks in our sample, we do not have enough observations to estimate the state-space model. Therefore, Table II reports cross-sectional average parameter estimates and standard errors across 41 stocks.[8]

[Insert Table II About Here]

In Table II, the estimates of κ^a, κ^h, and σ_u are from the efficient price equations. The κ^a coefficient of 0.0022 and standard error of 0.0005 show that order imbalances in market a (China) have a statistically significant influence on a company's efficient price. In other words, fundamental information appears to be incorporated into prices via trading in the a-share market. The result is consistent with Chan, Menkveld, and Yang (2007).

The second set of estimates are from the transitory price equations. The ϕ^a and ϕ^h estimates are 0.8524 and 0.8430 respectively, showing that the two transitory components are highly autocorrelated. A first-order autocorrelation coefficient of 0.85 implies that shocks

[8] Appendix G reports results similar to those shown in Table II, but the sample is restricted to the 27 companies with at least 87 weeks of data.

have half-lives of 4.3 weeks. The γ coefficients of 0.0052 and 0.0038 indicate that order imbalances affect the transitory prices in both the a and h markets. This finding is consistent with Implications #4 and #5. Both γ coefficients are statistically significant at all conventional levels.

4.2 Economic Magnitudes

To better understand economic magnitudes, we multiply the estimated coefficients by the standard deviations of our trading variables. Results are reported in basis points per week.

[Insert Table III About Here]

In Table III, Panel A, we can see that a one standard-deviation change in Chinese OIB^a is associated with a 62 bp change in a stock's efficient price and a 150 bp change in a stock's transitory price. Likewise, a one standard-deviation change in the Hong Kong OIB^h is associated with essentially no change in a stock's efficient price and a 112 bp change in a stock's transitory price. The finding that $\gamma^a \cdot \sigma(OIB^a)$ is larger than $\gamma^h \cdot \sigma(OIB^h)$ is consistent with Implication #5.

4.3 Variance Decomposition

To further understand economic magnitudes, we decompose the variances of stock returns. The first step is to rewrite the fundamental expression for prices from Equation (2). The first expression below, starts with the expressions for $p^h_{i,t}$ and for $p^h_{i,t-1}$ and then takes differences.

As we are using log prices, the first difference represents a stock's return.

$$\Delta p^h_{i,t} = \Delta m_{i,t} + \Delta s^h_{i,t} \tag{3}$$

$$\sigma^2(r^h_{i,t}) = \sigma^2(\Delta m_{i,t}) + \sigma^2(\Delta s^h_{i,t}) + 2Cov(\Delta m_{i,t}, \Delta s^h_{i,t}) \tag{4}$$

We use a smoother to estimate the changes of transitory and efficient prices shown in Equation (3). We then decompose the variance of stock i's returns to those parts shown in Equation (4). Appendix H shows the standard deviation of the stock returns for each company in our sample.

In Table III, Panel B, and for Hong Kong, efficient price variance accounts for 47.5% of the average stock's total variance. Transitory variance accounts for 39.2% of total variance. While σ_u and σ_ϵ are orthogonal by design, there is no such requirement for $m_{i,t}$ and $s_{i,t}$. The table shows, $m_{i,t}$ and $s_{i,t}$ are slightly positively correlated such that the covariance term accounts for 13.3% of total return variance.

The finding that transitory variance accounts for 39.2% of total variance is a contribution of this paper and supports earlier results in Hendershott et al. (2010). One difference between the two papers is that we report a fraction of *total* variance while the earlier paper reports a fraction of *idiosyncratic* variance. If, as Appendix H suggests, idiosyncratic variance is half of total variance, the amount of transitory variance in our study is approximately three times as large as that reported in Hendershott et al. (2010).

4.4 Back-of-the-Envelope Calculations

For readers who are new to, or skeptical of, state-space estimation, we provide two additional calculations. These so-called "back-of-the-envelope calculations" are possible because our research design focuses on dual-listed shares. We are able to combine readily observable summary statistics (variances and correlations) with a few assumptions. These calculations help set our research apart from existing papers.

Transitory Variance: We provide a quick and easy way to estimate the ratio of transitory variance to a stock's total variance. From Appendix H we see that the variance of the typical a-share is $(7.73\%)^2$ and the variance of the typical h-share is $(9.24\%)^2$. Although not reported, the variance of the average company's log-change in $AH\ Prem_{i,t}$ is $(8.82\%)^2$. Using these three numbers, and two rather weak assumptions, Appendix N shows how we can we estimate the ratio of transitory variance to total variance. We estimate this ratio is 45.6%, which is not too different from the 39.2% estimated from the state-space model. Appendix N provides details of the associated calculations.

Autocorrelation: We provide a quick estimate of the transitory component's first-order autocorrelation coefficient. For this calculation, we need an estimate of the average stock pair's first-order autocorrelation. Table I, Panel B shows this number is 0.84 for the typical stock pair. Under some fairly strong assumptions, we estimate the first-order autocorrelation of transitory prices is 0.84, which exactly matches the 0.84 estimated by the state-space model. Appendix O provides details of the calculations.

4.5 Cross-Sectional Predictions

We test the cross-sectional predictions from our model. Implication #6 suggests that AH Premiums are cross-sectionally related to fundamental volatility. Such a test highlights the power of the state-space model. Fundamental volatility is unobservable. Stock price volatility may not be a good proxy for fundamental volatility in markets with limited risk-bearing capacity (since trading shocks also affect stock volatility).

We use the Kalman filter to extract estimates of fundamental volatility, $\sigma(w)$, from our SSM. Note that $\sigma(w)$ is a function of $\kappa^a \cdot \sigma(OIB^a)$, $\kappa^h \cdot \sigma(OIB^h)$, and $\sigma(u)$. We regress each stock's average $AH\ Prem_{i,t}$ on a constant and on its $\sigma_i(w)$. As shown in Table IV, Panel A, Reg1 the regression coefficient on $\sigma(w)$ is 0.30 with a 2.98 t-statistic. Economically, our results are also significant. Companies with fundamental volatilities one standard deviation above (below) the mean have AH Premiums of 274.6 (83.34). The regression result is consistent with Implication #6 and represents one of the more novel contributions of our model. Reg2 confirms results by controlling for the natural log of a stock's market capitalization. Reg3 uses $AH\ Prem_{i,t}$ at a single point of time.

[Insert Table IV About Here]

Our model suggests that AH Premiums are cross-sectionally related to trading volatility in both markets. Note that our order imbalance measures ($OIB^a_{i,t}$ and $OIB^h_{i,t}$) have been normalized so we do not include them directly in the tests. Instead, we regress each stock's average $AH\ Prem_{i,t}$ on a constant and 1,000 times its γ^a and γ^h coefficients.[9] The γ co-

[9] Because $OIB^a_{i,t}$ and $OIB^h_{i,t}$ have been normalized, it does not make sense to include the variables in a cross-sectional regression. Also, our single stock model is technically suited to presenting comparative statics. Therefore, and under certain assumptions, we can use γ^a and γ^h in a comparative static (cross-sectional) analysis of the trading volatility risks faced by an arbitrageur.

efficients come from our state-space model. Results from nine regression specifications are shown in Table IV, Panel B. In Reg1, the regression coefficient on 1,000$\cdot\gamma^a$ is 8.68 with a 3.27 t-statistic.

The economic significance in Table IV, Panel B is less than that shown in Panel A. Companies with trading volatilities one standard deviation above (below) the mean have AH Premiums of 210.0 (148.0). The regression result is consistent with Implication #7 and represents another novel contribution of our model. Reg2 uses $\gamma^a \cdot \sigma(OIB^a)$ as the main RHS variable and in place of 1,000$\cdot\gamma^a$.

In Reg5, the regression coefficient on 1,000$\cdot\gamma^h$ is 5.39 with a 2.11 t-statistic. Reg3, Reg4, Reg7, and Reg8 include the natural log of a company's market capitalization as a control variable. Reg9 tests both 1,000$\cdot\gamma^a$ and 1,000$\cdot\gamma^h$ together. We see that, while both coefficients are positive, only γ^a remains statistically significant.

4.6 Robustness Checks

Longer Data Histories: Appendix G reports average state-space parameter estimates using only those companies with 87 or more weeks of data (i.e., at least half of the 173 possible weeks). Results are quantitatively and qualitatively similar to those presented in the main paper. For example, for this subsample, we estimate that 42.7% of a Hong Kong stock's observed variance is due to transitory price movements.

ARMA Estimates: Appendix F reports parameter estimates based on an ARMA (statistical) model. We find that a one standard-deviation shock to order imbalances is associated with a 134 bp change in a stock's transitory price at a weekly frequency. The value of 134 bp is greater than the 112 bp estimate from our state-space model.

Links to Existing Papers: We compare and contrast our results with three existing frameworks. 1) The volatility of our companies' AH Premiums are 3.3× to 16.2× as large as equivalent measures of the Froot and Dabora (1999) Siamese twin stocks. 2) The Roll (1984) model can be used to decompose a stock's return variance. This model estimates that transitory variance represents only 4% of total variance in our sample of Hong Kong stocks. This value is far less than the 39.2% that we estimate, because the transitory price movements in our study are far greater than typical bid-ask spreads. 3) Plugging our values of transitory volatility into the equations developed in Asparouhova, Bessembinder, and Kalcheva (2010), we estimate that expected returns are biased upward by 8.4% due to the transitory "noise" studied in our paper. Appendices K, L, and M provide additional details.

5 Cost of a Short-Sale Ban and a Quasi-Natural Experiment

On 31-Mar-2010, some Chinese (mainland) shares became available for short selling. This event offers us a quasi-natural experiment with which to estimate the cost of a short-sale ban. Of the 43 companies in our sample, we initially make an index of the 21 companies that are shortable called $AH\ Prem_t$*(shortable)*. We also make an index of the 22 companies that remain non-shortable called $AH\ Prem_t$*(non-shortable)*. The non-shortable shares serve as a control group.[10]

We use the word "quasi" because the decisions to lift the short-sale ban were not made 100% randomly. The China Securities Regulatory Commission (CSRC) imposes conditions for a stock to be shortable. Mainly, stocks must be large and have high turnovers. Ap-

[10] Three of the 43 stocks change designation after the initial formations of the shortable and non-shortable indices. We reconstitute the indices as necessary. See Appendix P for the list of the three initial companies and dates of their changes.

pendix P provides a list of CSRC conditions. It turns out that most shortable stocks are included in one of two well-followed indices (the Shanghai 50 Index or the Shenzhen Component Index of 40 stocks).

Appendix P provides overview statistics for the shortable and non-shortable shares. Not surprisingly, the companies with shortable shares are larger than the companies with non-shortable shares since size is one criterion used by the CSRC. Both share types have similar turnovers in both the a- and h-share markets. Order imbalances are slightly more correlated (across markets) for the non-shortable companies.

Other differences between the shortable and non-shortable companies are controlled for by our research design. We look at changes to price behaviors around a specific event (a *difference-in-difference* methodology). In addition, we look at changes to relative share price differences (by stock pair) around the specific event. We focus on two time periods. The "pre-period" is nine months before the ban (from Jul-2009 to Mar-2010). The "post-period" is nine months after the ban (from Apr-2010 to Dec-2010).

Index Levels: The AH Premium of the shortable index falls from a pre-period average of 119.0 to a post-period average of 97.7, which represents a drop of 17.9%. During the pre-period, the shortable index had a standard deviation of 9.2 per week, which fell to 5.9 in the post-period.

The AH Premium of the non-shortable index (our control group) experienced only a slight decline during the same periods. The pre-period average was 155.9 and the post-period average was 145.5, which represents a drop of only 6.7%. During the pre-period, the non-shortable index had a standard deviation of 7.4 per week, which actually rose to 8.1 in the post-period.

Volatilities of Index Changes (Returns) and Transitory Prices: We use the back-of-the envelope methodology described in Section 4.4 to decompose prices and calculate Hong Kong transitory volatilities. As can been seen in Table V, Panel A, the *h*-share volatility of the shortable group drops from 3.63% to 2.78% per week around the lifting of the ban. The *h*-share volatility of $AH\ Prem_t$*(shortable)* drops too. Most importantly, the *h*-share transitory volatility drops from 2.30% to 1.81% during this period.

[Insert Table V About Here]

Using the non-shortable shares as a control group, we see that the total volatility of these *h*-share returns goes up during the same period, as does $AH\ Prem_t$*(non-shortable)*. Most importantly, the transitory volatility these *h*-shares *goes up* by 0.53%.

We conclude that lifting the short-sale ban has two effects. First, dual-listed share price discrepancies can disappear.[11] Second, decreasing frictions in one market can decrease transitory volatility in other markets by enabling hedging mechanisms. Our results show that lifting the short-sale ban in China (mainland) reduces transitory volatility of affected Hong-Kong shares by 49 bp per week. No such reduction happens for the dual-listed *h*-shares with the ban still in place.

6 Conclusions

This paper studies a sample of 43 large, high-profile, high-turnover companies with dual-listed shares in China (mainland) and Hong Kong. One goal is to answer the question:

[11] Appendix I looks at the eight companies in our sample that have shares listed in both New York City and in Hong Kong. Neither market has a short-sale ban. Dual-listed shares in New York and Hong Kong trade at parity. These findings provide additional strong support for the conclusions reached in this paper.

Why do the relative prices of two very similar securities exhibit large and volatile price differences? On average, prices in China are 1.8× prices in Hong Kong. More importantly, a given company's price difference is very volatile.

We focus on two main frictions. The first is a short-sale ban in China. The second is the limited risk-bearing capacity of arbitrageurs. To structure our study, we provide a parsimonious theoretical framework that produces seven testable implications. We are able to make predictions about the level and dynamics of a company's AH Premium, which is the ratio of its China a-share price to its Hong Kong h-share price.

Many of this paper's empirical results come from estimating a state-space model (SSM). The statistical model assumes that a stock's observable price is composed of two unobservable components. For dual-listed shares, we assume a given company has a single efficient price at each point in time and two transitory prices. Using order flows from each market, we have a new method of identifying a company's unobservable components. In addition, our research design allows us to carry out two back-of-the-envelope calculations that confirm the SSM estimates. Finally, an ARMA estimation also confirms our findings. Our paper offers a number of results:

- A one standard-deviation shock to order flow in China (mainland) leads to a 150 bp change in transitory prices in China.
- A one standard-deviation shock to order flow in Hong Kong leads to a 112 bp change in transitory prices in Hong Kong.
- Cross-sectionally, companies with fundamental volatilities one standard deviation above the mean have average AH Premiums of 274.6, while companies one standard deviation below the mean have average AH Premiums of 83.34.

- Cross-sectionally, companies with order flow volatilities one standard deviation above (below) the mean have AH Premiums of 210.0 (148.0).

- Focusing on Hong Kong, we decompose a stock's total variance into a part coming from the efficient component and a part coming from the transitory component. We find that transitory variance represents 39.2% of total variance.

Why do we care about transitory price movements? First, investors worry about prices being temporarily below fundamental values when they need to sell shares to fund consumption. Second, fund managers worry that a stock's price might be temporarily above (or below) its fundamental value when building (or reducing) a position. Third, holders of contingent contracts worry that a stock's price may be above or below its fundamental value at the time of expiry. Fourth, and related to the previous reasons, regulators and exchanges typically work to reduce transitory price movements. Fifth, recent papers by Brennan and Wang (2010), Asparouhova, Bessembinder, and Kalcheva (2010), and Asparouhova, Bessembinder, and Kalcheva (2011) show how noise leads to biases when calculating a stock's expected return. Sixth, highly volatile transitory prices can affect the allocation of resources in the economy—i.e., the role of prices in a market economy is diminished if transitory price movements are large relative to fundamental price movements.

We end the paper by exploiting a quasi-natural experiment to estimate the cost of a short-sale ban. On 31-Mar-2010, China lifted the short-sale ban for 21 of the 43 companies in our sample. For the remaining 22 stocks, the ban stayed in place. Around the time of the ban lifting, we see the AH Premium of the shortable stocks fall to 100, indicating the shares trade at parity. The AH Premium of the non-shortable shares falls to 150, indicating that prices in China are 50% higher than prices in Hong Kong. Thus, one can think of the short-sale cost as the mis-allocation of resources associated with prices being incorrect by

50%.

Alternatively, we show that lifting of the short-sale constraint in China reduces the transitory volatility of the associated Hong Kong shares by 49 bp. There is no reduction in transitory volatility for the shares that remain non-shortable (our control group). In fact, the transitory volatility of the control group actually goes up. The results show that a friction in an emerging stock market can affect prices in a developed market by restricting access to hedging instruments.

There are a number of research agendas that follow naturally from our paper:

- One could incorporate brokerage account data into our state-space estimation. With such data, one might be able to construct order imbalance measures for relatively naive individuals and for relatively sophisticated institutions. Estimates that incorporate these order imbalances may lead to additional insights into the movements of a stock's transitory and fundamental components.

- Economists may want to investigate whether large price impacts associated with order imbalances indicate a need to attract more capital into the market-making (arbitrage) sector of the economy. One might be able to show a decrease in transitory price movements after an increase in market-making capital.

- There may be a link between our findings and investment industry practices. Future work could ask: How do fund managers build (or reduce) a position in markets with high levels of transitory price movements? Since a stock's transitory component ($s_{i,t}$) is not observable, one never knows if a price is temporarily high or low. Waiting incurs opportunity costs. If investors are risk-averse, it may make sense to dollar-cost average over a given period of time (presumably related to the half-life of the transitory shocks).

- Finally, it would be interesting to link the degree of transitory price movements documented in this paper to welfare losses stemming from the inefficient allocation of resources in the economy. To accomplish this goal, one needs a general equilibrium model that allows prices to have non-zero transitory components.

The above list of projects is potentially interesting to finance professionals, economists, and policy makers. Each project builds on the fundamental result of our paper—there is substantial "noise" in prices. This noise is relevant for large stocks in developed markets. The noise is not short lived and may affect prices for weeks and even months.

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Table I — Panel A

Overview of Companies in Our Sample

The table shows the 43 companies in our data sample. A-shares trade in China (mainland). H-shares trade in Hong Kong. Market capitalizations are in millions of US dollars. Industries are based on Global Industry Classification Standard (GICS) codes. The final column shows the number of weeks a company is in our sample.

Name	A Ticker	H Ticker	Tot Mkt Cap (US$ mil)	HK Mkt Cap (US$ mil)	Industry (GICS Codes)	# of Wks of Data
Air China	601111	0753	9,537	2,046	Airlines	140
Anhui Conch	600585	0914	10,644	2,663	Construction Mat.	173
Anhui Expressway	600012	0995	1,106	244	Transport Infra.	165
Bank of China	601988	3988	119,676	27,759	Comm. Banks	147
Bankcomm	601328	3328	44,041	18,183	Comm. Banks	102
Beijing N Star	601588	0588	1,918	150	Real Estate	132
CCB	601939	0939	133,111	127,272	Comm. Banks	82
CHALCO	601600	2600	17,320	2,926	Metals & Mining	104
China Coal	601898	1898	17,451	3,460	Oil, Gas & Fuels	60
China COSCO	601919	1919	15,787	2,068	Marine	96
China East Air	600115	0670	2,531	265	Airlines	60
China Life	601628	2628	97,611	25,587	Insurance	120
China Oilfield	601808	2883	7,712	1,166	Energy Equip.	82
China Rail Cons	601186	1186	17,257	2,877	Constr & Engin.	34
China Railway	601390	0390	17,153	2,861	Constr & Engin.	60
China Shenhua	601088	1088	68,952	9,209	Oil, Gas & Fuels	78
China Ship Dev	600026	1138	5,333	1,440	Marine	173
China South Air	600029	1055	4,249	418	Airlines	86
Chongqing Iron	601005	1053	987	159	Metals & Mining	86
CITIC Bank	601998	0998	24,897	5,633	Comm. Banks	86
CM Bank	600036	3968	32,930	4,850	Comm. Banks	135
CSCL	601866	2866	5,748	881	Marine	69
CSR	601766	1766	7,312	930	Machinery	8
Datang Power	601991	0991	10,441	1,591	Indep Power	123
Dongfang Elec	600875	1072	4,586	418	Elec. Equip.	173
Guangshen Rail	601333	0525	4,643	621	Road & Rail	122
Guangzhou Pharm	600332	0874	786	84	Pharmaceut	173
Guangzhou Ship	600685	0317	1,300	199	Machinery	86
Huadian Power	600027	1071	3,652	379	Indep Power	173
Huaneng Power	600011	0902	12,162	2,093	Indep Power	173
ICBC	601398	1398	197,229	46,189	Comm. Banks	130
Jiangsu Express	600377	0177	4,147	856	Transportation	173
Jiangxi Copper	600362	0358	7,233	1,565	Metals & Mining	173
Maanshan Iron	600808	0323	4,109	666	Metals & Mining	173
PetroChina	601857	0857	293,150	18,104	Oil, Gas & Fuels	73
Ping An	601318	2318	42,977	15,467	Insurance	112
SH Electric	601727	2727	12,568	994	Elec. Equip.	17
ShenzhenExpress	600548	0548	1,391	283	Transportation	173
Sinopec Corp	600028	0386	111,978	12,558	Oil, Gas & Fuels	173
Tianjin Capital	600874	1065	1,040	64	Comm Svcs	173
Tsingtao Brew	600600	0168	3,809	1,521	Beverages	173
Yanzhou Coal	600188	1171	7,980	1,769	Oil, Gas & Fuels	173
Zijin Mining	601899	2899	16,667	3,122	Metals & Mining	52
Average			32,677	8,176		118
Median			9,537	1,591		122

Table I — Panel B

The table provides an overview of weekly prices and returns for the 43 companies in our sample. A-shares trade in China (mainland). H-shares trade in Hong Kong. For a given company, the AH Premium is defined as 100 times the ratio of P^a to P^h. We report the AR(1) of each company's AH Premium. We also report the correlation of each company's weekly returns.

Name	Avg AH Prem$_{i,t}$	Stdev AH Prem$_{i,t}$	Frac weeks $P^a \leq P^h$	AR(1) Coef AH Prem$_{i,t}$	Corr (r^a, r^h)
Air China	206.60	65.10	4%	0.94	0.55
Anhui Conch	104.90	16.80	43%	0.87	0.62
Anhui Expressway	126.00	26.30	24%	0.93	0.15
Bank of China	142.60	28.30	15%	0.94	0.43
Bankcomm	125.00	22.50	24%	0.92	0.58
Beijing N Star	291.00	70.50	0%	0.89	0.55
CCB	124.30	19.80	9%	0.91	0.62
CHALCO	219.00	45.10	0%	0.86	0.50
China Coal	146.70	29.10	2%	0.78	0.53
China COSCO	184.00	46.20	0%	0.84	0.52
China East Air	415.90	90.10	0%	0.86	0.54
China Life	129.10	26.90	18%	0.94	0.58
China Oilfield	230.80	39.10	0%	0.79	0.52
China Rail Cons	106.70	6.30	18%	0.34	0.53
China Railway	120.20	14.90	7%	0.78	0.42
China Shenhua	143.70	15.40	0%	0.61	0.55
China Ship Dev	129.40	30.80	20%	0.91	0.51
China South Air	296.50	58.20	0%	0.88	0.53
Chongqing Iron	242.30	46.70	0%	0.84	0.55
CITIC Bank	176.30	31.00	0%	0.88	0.40
CM Bank	112.40	15.50	21%	0.88	0.66
CSCL	267.50	58.60	0%	0.86	0.46
CSR	145.50	4.60	0%	0.00	0.45
Datang Power	246.40	78.40	0%	0.84	0.22
Dongfang Elec	149.40	36.60	3%	0.92	0.46
Guangshen Rail	158.70	18.90	0%	0.81	0.25
Guangzhou Pharm	219.30	55.90	0%	0.96	0.38
Guangzhou Ship	196.70	41.80	0%	0.81	0.55
Huadian Power	208.30	74.00	5%	0.95	0.21
Huaneng Power	142.10	39.20	22%	0.94	0.21
ICBC	120.90	16.20	8%	0.89	0.60
Jiangsu Express	119.30	12.30	2%	0.73	0.23
Jiangxi Copper	208.70	64.70	0%	0.94	0.57
Maanshan Iron	146.10	43.20	13%	0.93	0.43
PetroChina	198.20	29.00	0%	0.85	0.44
Ping An	113.70	22.60	40%	0.93	0.68
SH Electric	347.50	44.30	0%	0.65	0.63
ShenzhenExpress	153.60	42.80	12%	0.95	0.28
Sinopec Corp	167.50	38.80	1%	0.93	0.43
Tianjin Capital	305.50	134.80	0%	0.98	0.47
Tsingtao Brew	132.90	19.70	9%	0.87	0.47
Yanzhou Coal	152.50	44.50	4%	0.93	0.36
Zijin Mining	157.60	34.50	0%	0.81	0.49
Average	182.10	39.50	8%	0.84	0.47
Median	153.60	36.60	2%	0.88	0.50

Table I — Panel C

The table provides an overview of weekly trading variables for the 43 companies in our sample. A-shares trade in China (mainland). H-shares trade in Hong Kong. Columns 2 and 3 report free floats as percentages of shares listed. Columns 4 and 5 report average weekly turnover, by company, as percentages of shares available to trade (free floats). We also report each company's correlation of weekly order imbalances.

Name	Free Float Mkt a	Free Float Mkt h	Avg Turn(a)	Avg Turn(h)	Corr (OIB^a, OIB^h)
Air China	0.16	0.54	0.17	0.07	0.20
Anhui Conch	0.26	1.00	0.07	0.04	0.12
Anhui Expressway	0.33	1.00	0.10	0.02	0.09
Bank of China	0.03	0.39	0.11	0.07	0.07
Bankcomm	0.25	0.62	0.10	0.03	-0.09
Beijing N Star	0.43	1.00	0.24	0.05	0.11
CCB	0.92	0.20	0.07	0.04	-0.25
CHALCO	0.21	1.00	0.11	0.07	0.12
China Coal	0.18	0.98	0.13	0.05	-0.11
China COSCO	0.20	0.96	0.15	0.10	0.09
China East Air	0.15	1.00	0.13	0.06	-0.11
China Life	0.05	1.00	0.12	0.07	0.07
China Oilfield	0.19	1.00	0.09	0.04	-0.32
China Rail Cons	0.25	0.85	0.11	0.05	-0.08
China Railway	0.26	0.91	0.11	0.05	0.02
China Shenhua	0.11	1.00	0.07	0.05	-0.20
China Ship Dev	0.26	1.00	0.14	0.04	0.11
China South Air	0.35	0.95	0.15	0.07	-0.10
Chongqing Iron	0.30	1.00	0.12	0.05	0.30
CITIC Bank	0.07	0.41	0.07	0.05	0.33
CM Bank	0.46	1.00	0.06	0.07	0.02
CSCL	0.27	0.96	0.09	0.10	0.10
CSR	0.35	0.90	0.21	0.06	-0.06
Datang Power	0.30	1.00	0.15	0.06	-0.07
Dongfang Elec	0.29	1.00	0.11	0.04	-0.09
Guangshen Rail	0.39	1.00	0.14	0.03	0.07
Guangzhou Pharm	0.23	1.00	0.15	0.03	-0.04
Guangzhou Ship	0.50	1.00	0.15	0.06	0.09
Huadian Power	0.21	1.00	0.11	0.05	0.06
Huaneng Power	0.21	1.00	0.08	0.04	-0.03
ICBC	0.04	0.48	0.12	0.06	-0.22
Jiangsu Express	0.09	1.00	0.11	0.03	-0.10
Jiangxi Copper	0.20	1.00	0.21	0.11	0.04
Maanshan Iron	0.22	1.00	0.17	0.10	0.15
PetroChina	0.02	1.00	0.06	0.04	-0.23
Ping An	0.35	0.54	0.09	0.06	0.05
SH Electric	0.07	1.00	0.35	0.07	0.09
ShenzhenExpress	0.20	1.00	0.12	0.02	-0.03
Sinopec Corp	0.06	1.00	0.10	0.05	0.10
Tianjin Capital	0.25	1.00	0.24	0.05	0.04
Tsingtao Brew	0.40	0.50	0.07	0.03	-0.07
Yanzhou Coal	0.15	1.00	0.16	0.07	0.02
Zijin Mining	0.11	1.00	0.34	0.05	0.28
Average	0.24	0.89	0.13	0.05	0.01
Median	0.22	1.00	0.12	0.05	0.04

Table II

Parameter Estimates

This table shows parameter estimates for the state-space model shown in Equation (2) and directly below. We estimate the equations on a stock-by-stock basis and report average coefficients. There is sufficient data to estimate parameters for 41 of the 43 stocks in our sample.

$$\begin{aligned}
p^a_{i,t} &= m_{i,t} + s^a_{i,t} + c_i \\
p^h_{i,t} &= m_{i,t} + s^h_{i,t} \\
m_{i,t} &= m_{i,t-1} + \delta_{i,t} + w_{i,t} \\
w_{i,t} &= \kappa^a \tilde{O}IB^a_{i,t} + \kappa^h \tilde{O}IB^h_{i,t} + u_{i,t} \\
s^a_{i,t} &= \phi^a s^a_{i,t-1} + \gamma^a OIB^a_{i,t} + \epsilon^a_{i,t} \\
s^h_{i,t} &= \phi^h s^h_{i,t-1} + \gamma^h OIB^h_{i,t} + \epsilon^h_{i,t}
\end{aligned}$$

	κ^a	κ^h	σ_u
Param	0.0022	-0.0002	0.0274
Stderr	(0.0005)	(0.0004)	(0.0021)

	ϕ^a	ϕ^h	γ^a	γ^h	$\sigma_{\epsilon(a)}$	$\sigma_{\epsilon(h)}$
Param	0.8524	0.8430	0.0052	0.0038	0.0582	0.0585
Stderr	(0.0067)	(0.0124)	(0.0006)	(0.0006)	(0.0024)	(0.0023)

Table III

Economic Magnitudes and Variance Decomposition

Panel A: Economic Magnitudes

This panel estimates economic magnitudes of parameters from our state-space model. We calculate all economic quantities on a stock-by-stock basis. The table reports average values across 41 of the 43 stocks in our sample for which there is sufficient data.

		Market a		Market h	
Effic Eq	(bp)	Trans Eq	(bp)	Trans Eq	(bp)
$\kappa^a \cdot \sigma(\tilde{OIB}^a)$	62	$\gamma^a \cdot \sigma(OIB^a)$	150	$\gamma^h \cdot \sigma(OIB^h)$	112
$\kappa^h \cdot \sigma(\tilde{OIB}^h)$	-3	$\sigma(\Delta s^a)$	573	$\sigma(\Delta s^h)$	574
$\sigma(w)$	200				

Panel B: Variance Decomposition

This panel decomposes return variance of the Hong-Kong listed stocks in our sample. The decomposition is done on a stock-by-stock basis. The table reports average values across 41 of the 43 stocks in our sample for which there is sufficient data.

$$\Delta p_{i,t}^h = \Delta m_{i,t} + \Delta s_{i,t}^h$$

$$\sigma^2(r_{i,t}^h) = \sigma^2(\Delta m_{i,t}) + \sigma^2(\Delta s_{i,t}^h) + 2Cov(\Delta m_{i,t}, \Delta s_{i,t}^h)$$

	$\sigma^2(r^h)$	$\sigma^2(\Delta m)$	$\sigma^2(\Delta s^h)$	$2Cov(\Delta m, \Delta s^h)$
Average	100%	47.5%	39.2%	13.3%
Stderr	(n.a.)	(7.5%)	(6.1%)	(2.0%)

Table IV

Cross-Sectional Implications for $\boldsymbol{AH\ Prem_{i,t}}$

Panel A: Fundamental Volatility and $AH\ Prem_{i,t}$

This panel shows cross-sectional regression results of $AH\ Prem_i$ on fundamental volatility. In Reg1, the LHS variable is a company's average $AH\ Prem_{i,t}$ over our sample period. In Reg2, we include the natural log of a company's market capitalization as a control variable. In Reg3, the LHS variable is a company's final value of $AH\ Prem_{i,t}$. Each company's $\sigma_i(w)$ comes from our state-space model.

$$AH\ Prem_i \quad = \quad \beta_0 + \beta_1 \sigma_i(w) + \beta_2 ln(MktCap_i) + \varepsilon_i$$

Coef	Reg1	Reg2	Reg3
β_0	118.60	266.11	137.15
(t-stat)	*(5.30)*	*(4.01)*	*(4.57)*
β_1	0.30	0.23	0.32
(t-stat)	*(2.98)*	*(2.31)*	*(2.36)*
β_2		-14.42	
(t-stat)		*(-2.34)*	
Obs	41	41	41
LHS Variable	Average $AH\ Prem_{i,t}$	Average $AH\ Prem_{i,t}$	Final $AH\ Prem_{i,t}$

Table IV — Panel B

Panel B: Trading Volatility and $AH\ Prem_{i,t}$

This panel shows cross-sectional regression results of $AH\ Prem_i$ on trading volatility. In Reg1 - Reg4 we use RHS variables related to order imbalances in market a. In Reg5 - Reg8 we use RHS variables related to order imbalances in market h. In Reg9 we use trading variables from both markets. The RHS variables tested are either 1,000$\cdot\gamma_i^a$, 1,000$\cdot\gamma_i^h$, $\gamma_i^a \cdot \sigma(OIB^a)$, or $\gamma_i^h \cdot \sigma(OIB^h)$, where γ_i^a and γ_i^h are from our state-space model.

$$AH\ Prem_i \quad = \quad \beta_0 + \beta_1^a \left(1000 \cdot \gamma_i^a\right) + \beta_1^h \left(1000 \cdot \gamma_i^h\right) + \beta_2 ln(MktCap_i) + \varepsilon_i$$

Coef	Reg1	Reg2	Reg3	Reg4
β_0	133.82	117.43	274.24	217.14
(t-stat)	*(8.02)*	*(7.93)*	*(4.46)*	*(3.67)*
β_1^a	8.68	0.41	6.95	0.35
(t-stat)	*(3.27)*	*(5.01)*	*(2.66)*	*(4.09)*
β_1^h				
(t-stat)				
β_2			-14.19	-9.84
(t-stat)			*(-2.36)*	*(-1.74)*
Obs	41	41	41	41
Main RHS Variable	1,000$\cdot\gamma_i^a$	$\gamma_i^a \cdot \sigma(OIB^a)$	1,000$\cdot\gamma_i^a$	$\gamma_i^a \cdot \sigma(OIB^a)$

Coef	Reg5	Reg6	Reg7	Reg8	Reg9
β_0	158.73	156.69	313.85	305.82	124.12
(t-stat)	*(11.43)*	*(11.49)*	*(4.95)*	*(4.80)*	*(7.12)*
β_1^a					7.75
(t-stat)					*(2.91)*
β_1^h	5.39	0.20	3.55	0.13	3.88
(t-stat)	*(2.11)*	*(2.37)*	*(1.41)*	*(1.61)*	*(1.61)*
β_2			-16.00	-15.33	
(t-stat)			*(-2.50)*	*(-2.39)*	
Obs	41	41	41	41	41
Main RHS Variable(s)	1,000$\cdot\gamma_i^h$	$\gamma_i^h \cdot \sigma(OIB^h)$	1,000$\cdot\gamma_i^h$	$\gamma_i^h \cdot \sigma(OIB^h)$	1,000$\cdot\gamma_i^a$ and 1,000$\cdot\gamma_i^h$

Table V

Quasi Natural Experiment

Panel A: Index of Shortable Shares

This panel shows results related to an index of shortable share pairs. The index is initially formed using the same methodology as the AH Premium Index but only considers the 21 companies for which the short-sale ban was lifted in China (mainland). We consider two periods: nine months before the short-sale ban is lifted (Jul-2009 to Mar-2010) and nine months after (Apr-2010 to Dec-2010). The column with r^h shows the standard deviation of the Hong Kong shares (only). The column with r^{ah} shows the standard deviation of log changes to the AH Premium Index. The column with s^h shows the transitory volatility of Hong Kong shares (only). Transitory volatility is estimated using the back-of-the-envelope method described in Section 4.4.

Start	End	Stdev(r^h)	Stdev(r^{ah})	Stdev(s^h)
01-Jul-2009	31-Mar-2010	0.0363	0.0325	0.0230
01-Apr-2010	31-Dec-2010	0.0278	0.0256	0.0181
	Diff			-0.0049

Panel B: Index of Non-Shortable Shares

This panel mirrors the panel above, but shows results related an index of non-shortable share pairs. The index is initially formed using the same methodology as the AH Premium Index but only considers the 22 companies for which the short-sale ban was not lifted in China (mainland).

Start	End	Stdev(r^h)	Stdev(r^{ah})	Stdev(s^h)
01-Jul-2009	31-Mar-2010	0.0416	0.0351	0.0248
01-Apr-2010	31-Dec-2010	0.0425	0.0426	0.0301
	Diff			0.0053

Figure 1

Cross-Section of AH Premiums

The figure shows three points in the cross-section of company-level AH Premiums at a weekly frequency. A given company's AH Premium is defined as 100 times the ratio of its China (mainland) a-share price to its Hong Kong h-share price. A value of 100 indicates a company's a-shares are selling for the same price as its h-shares. We show the 25^{th}, 50^{th}, and 75^{th} percentile over time. Data are weekly starting 03-Jan-2006 and ending 30-Apr-2009.

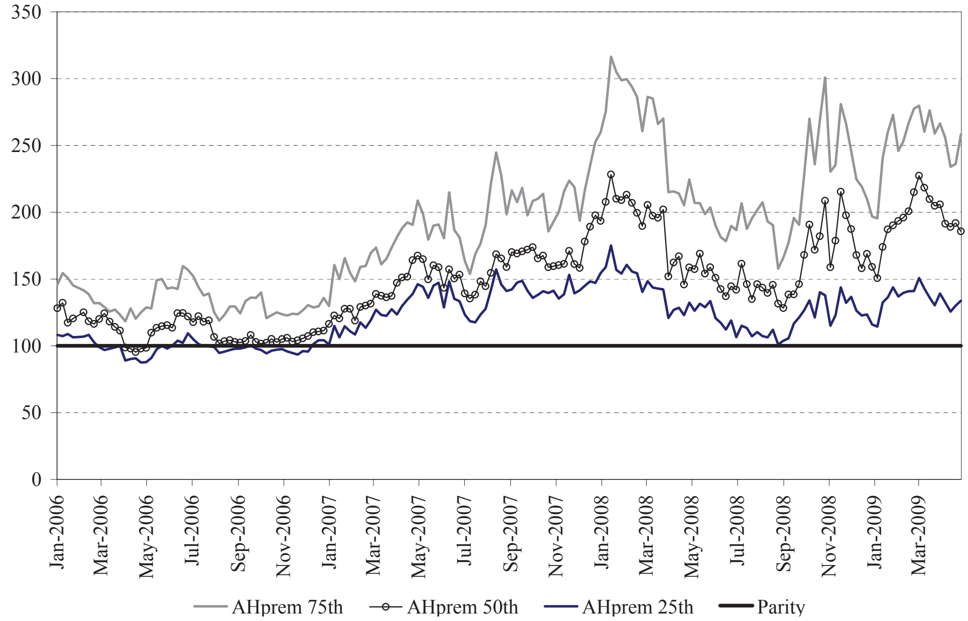

Figure 2

AH Premiums for Three Companies

The figure shows the time-series of AH Premiums for three companies at a weekly frequency. A given company's AH Premium is defined as 100 times the ratio of its China (mainland) a-share price to its Hong Kong h-share price. A value of 100 indicates a company's a-shares are selling for the same price as its h-shares. The first company is Jiangxi Copper. The second company is Shenzhen Expressway. The third company is China Shipping. Data are weekly starting 03-Jan-2006 and ending 30-Apr-2009.