Global Liquidity Provision and Risk Sharing

INTERNET APPENDIX

(Not for publication)

Feng Jiao and Sergei Sarkissian

Contents:

A.1. Sample Selection Bias

In the present study, we have established that U.S. firms after cross-listing on foreign exchanges enhance firm liquidity during market downturns. Furthermore, our results also demonstrate that the positive impact of foreign listing is stronger in certain types of markets and for firms with certain characteristics. However, the decision to cross-list is endogenous, so that the sample of U.S. firms, which place their shares on foreign exchanges, is not random. Consequently, U.S. firms that decide to cross-list abroad may have unique, but unobservable features that simultaneously affect their decision to cross-list in foreign markets, causing increased global ownership and liquidity gains. Said differently, it is possible that the observed liquidity gains from foreign listing are biased upwards. A cross-listing is frequently associated with time-varying market and industry trends and changes in firms' investment and growth opportunities (see Sarkissian and Schill, 2016).

To address this possible sample selection bias, i.e. to understand whether or not our sample selection affects our findings, we use the Heckman two-stage model (Heckman, 1979). For the first stage estimation, we run a Probit model to predict the probability of U.S. cross-listing on foreign exchanges. The dependent variable is an indicator, $I_{i,j,t}$, which is equal to one after firm *i* cross-lists in a host market *j* at time *t*, and is zero otherwise. Based on the gravity model in Sarkissian and Schill (2016), we include a set of macroeconomics variables, proximity measures, aggregate market conditions, firm level controls, and industry fixed effects as our explanatory variables. The macroeconomic variables include host market GDP (log) and GDP growth rates, as well as the logs of exports from and imports to the United States. All these variables are at annual frequency from the Penn World Tables. We use two static familiarity variables: geographic proximity and cultural proximity. Geographic proximity is the inverse of the logarithm of the great-circle distance between a host country and the United States. Cultural proximity is a dummy that equals to one if the host country has the same colonial heritage or language as the United States (and zero otherwise). We also include U.S. market return, host market return firm return, B/M ratio, and firm size as control variables. All these variables are collected at the end of each year from CRSP and Compustat. International stock market data are from DataStream. All dynamic variables are lagged by one period.[1]

Table A.1 presents the results of both Stage 1 and Stage 2 tests. Along with the point estimates and their absolute t-statistics, the results in Table A.3 also report the number of observations and pseudo R-squared for Stage 1 estimation and adjusted R-squared for Stage 2 estimation. The results of Stage 1 estimation show that the probability of U.S. firms to be listed abroad increases with the proximity and size of the host market, its GDP growth, and imports to the United States. The cross-listing is also more likely with a higher host market return, as well with a larger firm size and foreign income. These results are generally consistent with the determinants on cross-listings found in previous studies (e.g., Pagano, Röell, and Zechner, 2002; Sarkissian and Schill, 2016). Probably the most surprising are the signs of the coefficients on firm return and B/M ratio. Their point estimates only imply that the decision of U.S. firms to be listed abroad is not closely tied to their pre-listing performance. Furthermore, the results of Stage 2 show that the coefficient on $CL_{i,t} \times R_{US,t\text{-}1}$ is still almost identical, both qualitatively and quantitatively, to that in column (4) of Table 3 – our main regression specification. In addition, the inverse Mills ratio coefficient is insignificant. Therefore, the results in Table A.3 provide evidence that our finding on the importance of cross-listing for U.S. firm liquidity enhancement to adverse market conditions is immune to potential sample-selection endogeneity issues.

A.2 Regressions by Firm and Spread-Based Liquidity Measure

Hameed, Kang and Viswanathan (2010) estimate time-series regressions of liquidity innovations on stock returns separately for each individual stock and use a bid-ask spread as their measure of illiquidity. Note that, unlike the bid-ask spread, which is available for a much shorter time period, the Amihud measure allows us to compute stock liquidity over our long sample

[1] Our sample includes all cross-listed firms. In Stage 1, it is constructed by conducting a Cartesian join of each cross-listing *i* and host country *j* in year *t*. We set $I_{i,j,t}$, to unity after firm *i* cross-lists in a host market *j* at time *t*, and zero otherwise. In Stage 2, the sample size is smaller, because the inverse Mills ratio is not available for firms without “Firm Foreign Income”.

period. Therefore, in this section, we restate our main results in Table 3 using individual firm regressions with both Amihud and bid-ask spread liquidity measures.

Corwin and Schultz (2012) derive an implicit bid-ask spread, the high-low spread (HLS) estimator, using stock prices collected over two consecutive trading days. This allows us to estimate the bid-ask spread without settling for a short sample period. In what follows, we briefly present their methodology.

Denote H_t (L_t) the high (low) stock price on day t, $H_{t,t+1}$($L_{t,t+1}$) the high (low) stock price over the two consecutive days t and t + 1. Then, the daily HLS or stock illiquidity estimator is:

$$ILLiq_t = \frac{2\left(e^{\alpha} - 1\right)}{1 + e^{\alpha}}, \quad \text{(A.1)}$$

where

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}, \ \gamma = \left[ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2, \ \beta = \sum_{j=0}^{1}\left[ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2. \quad \text{(A.2)}$$

We calculate the monthly averages of $ILLiq_{i,t}$ for each stock i from its daily values. The illiquidity innovation for each firm i at time t, $\Delta ILLiq_{i,t}$, is the percentage change in its monthly HLS estimator, i.e. $\Delta ILLiq_{i,t}$, = ($ILLiq_{i,t}$ – $ILLiq_{i,t-1}$) / $ILLiq_{i,t-1}$. Corwin and Schultz (2012) note that their HLS can be negative for some two-day periods. In these cases, they suggest changing negative daily values to zero. We follow their recommendation. In addition, to simplify comparisons with our estimations that use the Amihud liquidity measure, we multiply $\Delta ILLiq_{i,t}$ by (-1) to arrive to the liquidity-equivalent innovation measure from the bid-ask spread, $\Delta Liq_{i,t}$.

Thus, for each cross-listed stock, we estimate the equation separately for the pre-cross-listing and post-cross-listing periods,

$$\Delta Liq = \alpha + \beta_1 R_{i,t-1} + \beta_2 R_{US,t-1} + \beta_3 R_{IN,t-1} + Firm\_Controls + MKT\_Controls + \varepsilon, \quad \text{(A.3)}$$

where ΔLiq is the change in liquidity, while other variables are identical to those in Model (1). The results from these estimations are reported in Table A.2. For brevity, we report the estimates, including standard deviations, of the three main variables of equation (A.3), $R_{i,t-1}$, $R_{US,t-1}$, and $R_{IN,t-1}$. The first three columns of the table reflect the test results based on the Amihud liquidity measure; the last three – on the bid-ask spread.

Columns (1) and (4) of Table A.2 show the equally-weighted mean coefficients across all individual firm regressions using the pre-cross-listing subsample. Columns (2) and (5) correspond to these values from the post-cross-listing subsample. Columns (3) and (6) report the difference in the estimated coefficients between pre- and post-cross-listing subsamples and its statistical significance. The test results are largely consistent with our main findings in Table 3. The average sensitivity of stock liquidity in response to U.S. market returns (coefficient β_2) based on Amihud liquidity is 0.217 before cross-listing but drops to 0.067 after cross-listing. This decline is statistically significant at the 5% level. Meanwhile, there are no significant changes in the other two regression coefficients. The results using the bid-ask spread are also similar to Table 3. Cross-listing decreases the liquidity sensitivity of U.S. firms (the coefficient on $R_{US,t\text{-}1}$ drops from 0.891 to 0.416). Statistically, the effect is significant at the 10% level, which is not surprising, since this estimator is less precise than its Amihud counterpart.

A.3. Alternative Controls

We also examine the impact of "bad controls" (Angrist and Pischke, 2009) and non-linearity on the impact of cross-listing on firm liquidity. In our estimations, we control for the observable firm and country characteristics (e.g., volatility, turnover) and find that they do not drive away the beneficial impact of cross-listing on liquidity in weak market conditions. However, one may not exclude the possibility that these variables directly or indirectly depend on the cross-listing decision. For instance, Domowitz, Glen, and Madhavan (1998) and Halling, Pagano, Randl, and Zechner (2008) document big shifts in trading of shares after foreign listing placement. This can impact not only the firm volatility, but also the market-wide volatility and turnover. As a result, controlling for such variables may introduce biases in interpreting our main results. Therefore, in Table A.3, we replace our control variables with the fixed effects composed of the interaction of firm and time fixed effects, as well as the interaction of country and time fixed effects. This change in the estimation specification accounts for unobserved time-varying factors that may influence firm liquidity. The results in column (1) of Table A.3 show that the coefficient on $CL_{i,t} \times R_{US,t\text{-}1}$ and again significantly negative with the point estimate similar to that in Table 3. Then, in column (2), in order to control for any possible association between lagged stock returns and cross-listing, we add an additional term, $CL_{i,t} \times R_{i,t\text{-}1}$. This specification slightly reduces the magnitude of coefficient on $CL_{i,t} \times R_{US,t\text{-}1}$, but it is still negative, large, and statistically significant at the 5% level. Finally, in the last two columns of Table A.3, we add the non-linear terms, first only the lagged squared firm and U.S. market returns, and then alongside with the interaction of these variables with the cross-listing dummy. The assumption underlying this inclusion of squared return terms is that the funding liquidity is more likely to get hit during bad market times characterized by large negative returns. However, controlling for non-linearity does not alter the economic or statistical inference of our previous estimations.

A.3. Return Magnitude around Cross-Listing and Liquidity Sensitivity

It is well known that firms experience substantial changes in returns around their cross-listing dates (e.g., Foerster and Karolyi, 1999; Sarkissian and Schill, 2009). Therefore, we would like to see if the size of returns around the listing date is related to changes in liquidity sensitivity. We address this issue by ranking all U.S. firms based on their cumulative abnormal returns (CARs) around cross-listing events.

First, following Foerster and Karolyi (1999), we compute the CARs over three periods: the pre-listing period (from day -100 to day -2) and the full period around listing events (from day -100 to day +250). The CARs are based on a U.S. market model. For each firm, the U.S. market model is estimated during the 150-day pre-listing period from day -250 to day -101. We require a minimum of 40 observations for the U.S. market model estimation. Then we split this ranked sample by the median and re-run estimations based on Regression (4) from Table 3 on the resulting subsamples.

The test results are shown in Table A.4. Regressions (1) and (3) correspond to the firms with below-median pre-listing, post-listing, and full listing period CARs, respectively; while Regressions (2) and (4) are for those with above-median CARs. Our results reveal that the coefficient of $CL_{i,t} \times R_{US,t\text{-}1}$ is consistently larger in magnitude for the subsamples with above-median CARs. This is quite intuitive. In unreported results, we find that firms with above-median CARs experience larger changes in their market cap, liquidity, trading volume, and foreign ownership upon cross-listing than their below-median counterparts. This implies that a superior stock performance during the listing period is associated with strong demand for it among global investors. As a result, the larger foreign ownership of firms with high CARs facilitates their ownership dispersion channel resulting in larger coefficient on $CL_{i,t} \times R_{US,t\text{-}1}$.

A.4. Foreign Ownership Changes around the Crisis Period

The liquidity provision channel implies that foreign arbitrageurs, unaffected by tighter U.S. funding constraints, may take the advantage of arbitrage opportunities by buying the U.S. equities during U.S. market downturns. This pattern resembles the trading of a market maker, who buys when the public sells (which tends to coincide with falling prices). Consequently, we explore whether foreign investors buy the U.S. cross-listed firms when the U.S. funding constraint tightens, i.e., when the effect of foreign holdings on firm liquidity is maximal.

Figure A.1 summarizes foreign holdings ratio of cross-listed U.S. firms five years before and after the financial crisis year of 2008. Plot A in Figure A.1 shows holdings of both cross-listed firms and the matched U.S. firms without foreign listings. It also shows the average annualized TED spread. In line with the intuition, there is a monotone and profound increase in the TED spread between 2003 and 2008, which suggests a steadily tightening funding liquidity conditions prior to the 2008 financial crisis. However, after 2008, the TED spread drops significantly, remaining below 0.5% on average in annual terms. In support of our expectation, we observe that the proportion of foreign ownership of cross-listed firms also increases from about 12% prior to the crisis to almost 20% after it, to peak by 2009 and then decrease in subsequent years. By contrast, the foreign ownership of matched firms does not experience any increase around the crisis years: the overall change in its proportion within the eleven-year window is below 2%. Therefore, Plot A in Figure A.1 shows that, with an increase in market uncertainty and decrease in funding liquidity, holding of cross-listed firms only becomes more attractive to international investors.

The next logical question to address is what types of institutions are responsible for the observed dynamics of foreign ownership of cross-listed stocks. Plot B of Figure A.1 shows foreign holdings ratios over the same 2002-2013 sample period by type of institution: closed-end funds, exchange traded funds, mutual funds, pension funds, annuity funds, and hedge funds. With regard to these results, the first observation is that, in the years before the financial crisis, the largest foreign institutional owners of cross-listed U.S. firms were closed-end funds and pension funds; however, post-crisis, such largest foreign institutional owners were pension funds and hedge funds. Over time, closed-end funds have very significantly lost their appetite for holding cross-listed securities: while, in 2003, their share of foreign ownership was about 60%, by 2011, it dropped below 20%. The other types of institutional owners maintained low, relatively more stable, or slightly increasing proportions of holdings of cross-listed U.S. stocks. The second and more important observation is that the foreign holdings of both pension funds and hedge funds experience strong run-up prior to the crisis, followed by a gradual decrease and levelling off over some higher level of holdings ratio. The time-series pattern of foreign holding ratios of these two types of institutions effectively explains the aggregate institutional ownership results presented in Plot A (Figure A.1).

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Table A.1
Sample selection bias

This table shows the results from Heckman's selection bias tests. The sample period is 1950-2013. Stage 1 gives Probit model results from regressing the cross-listing indicator on financial and economic characteristics. The dependent variable is an indicator, $I_{i,j,t}$, which is equal to one after firm *i* cross-lists in a host market *j* at time *t*, and is zero otherwise. All macroeconomic variables are at annual frequency from the Penn World Tables. U.S. market return, firm returns, B/M ratio, and firm size are collected at the end of each year from CRSP and Compustat. International stock market data is from DataStream. Geographic proximity is the inverse of the logarithm distance between a host country and the United States. Cultural proximity is a dummy equals to one if the host country has the same colonial heritage as the United States, and is zero otherwise. Firm size is the logarithm of market capitalization. Firm Foreign Income is the proportion of a firm's income generated from non-U.S. sources. Industry fixed effects are constructed using one-digit SIC codes. Stage 2 gives the main regression results from Table 3 after including the inverse Mills ratio (IMR) from Stage 1 as an additional control variable. All other variables are defined as in Table 3. The table also reports the number of observations and pseudo-R^2 in Stage 1 and adjusted R^2 in Stage 2 estimations. The absolute *t*-statistics are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Stage 1: Probit Regression (annual frequency)		Stage 2: Main Regression	
Host GDP (Log)	2.814*** (43.96)	$R_{i,t\text{-}1}$	0.146*** (12.35)
Host GDP Growth	0.112*** (6.71)	$R_{US,t\text{-}1}$	0.246*** (4.16)
Export to the U.S. (Log)	-0.842*** (44.26)	$R_{IN,t\text{-}1}$	0.009 (0.26)
Import from the U.S. (Log)	0.330*** (20.99)	$CL_{i,t} \times R_{US,t\text{-}1}$	-0.230*** (4.52)
Geographic Proximity (Log)	0.104*** (6.68)	$CL_{i,t} \times R_{IN,t\text{-}1}$	0.024 (0.61)
Cultural Proximity	-1.375*** (58.74)	$CL_{i,t}$	-0.008 (0.28)
US Market Return	0.000 (0.01)	IMR	0.095 (0.79)
Host Market Return	0.299*** (6.61)		
Firm Return	-0.181*** (10.12)		
Firm Size	0.279*** (63.41)		
Firm Foreign Income	0.041*** (8.46)		
B/M	0.137*** (10.75)		
		Controls	Yes
Industry FE	Yes	Firm FE	Yes
Intercept	Yes	Intercept	Yes
Obs.	125,037	Obs.	71,970
Pseudo R^2	0.310	Adj. R^2	0.251

Table A.2
Regression by firm and spread-based liquidity measure

This table shows the average coefficients from the regression of U.S. cross-listed firms' liquidity innovation on the lagged firm stock return and the U.S. and international market return variables. The sample period is 1950-2013. It reports the results based on the Amihud liquidity measure and the Corwin and Schultz (2012) high-low spread (HLS) estimator. For each cross-listed stock, we estimate equation (A.3) separately for the pre-cross-listing and post-cross-listing sub-periods. Then, we report the equally-weighted mean coefficients across all individual firm regressions. The U.S. stock market information is from CRSP, and international stock markets data is from DataStream. In columns (1)-(3), the dependent variable is the innovation in Amihud liquidity measure. The dependent variable in columns (4)-(6), is the change in the monthly HLS estimator for each individual firm i at time t multiplied by (-1). The daily HLS estimator is:

$$ILLiq_{i,t} = \frac{2\left(e^{\alpha}-1\right)}{1+e^{\alpha}},\ \alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}},\ \gamma = \left[ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2,\ \beta = \sum_{j=0}^{1}\left[ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2.$$

H_t (L_t) is high (low) price on day t, $H_{t,t+1}$ ($L_{t,t+1}$) is the high (low) price on days t and t+1. The monthly average HLS estimator for each stock is computed from its daily measure. The illiquidity innovation is the percentage change in the monthly illiquidity measure, that is, $\Delta ILLiq_{i,t}$, = ($ILLiq_{i,t}$ - $ILLiq_{i,t-1}$) / $ILLiq_{i,t-1}$. We multiply $\Delta ILLiq_{i,t}$ by (-1) to arrive to the liquidity-equivalent innovation measure of the bid-ask spread. Other variables are as in Table 3 and are winsorized at 1% and 99%. The absolute t-statistics are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

		Amihud Liquidity			High-Low Spread × (-1)		
		Before	After	After - Before	Before	After	After - Before
$R_{i,t-1}$	Mean	0.105	0.139	-0.033	0.201	0.095	-0.106
	SD	0.162	0.270	(1.60)	1.051	0.621	(1.34)
$R_{US,t-1}$	Mean	0.217	0.067	-0.149**	0.891	0.416	-0.476*
	SD	0.992	0.554	(2.01)	3.562	2.177	(1.75)
$R_{IN,t-1}$	Mean	-0.038	0.008	0.047	-0.337	-0.089	0.248*
	SD	0.604	0.375	(1.00)	1.572	1.310	(1.79)

Table A.3
Alternative controls

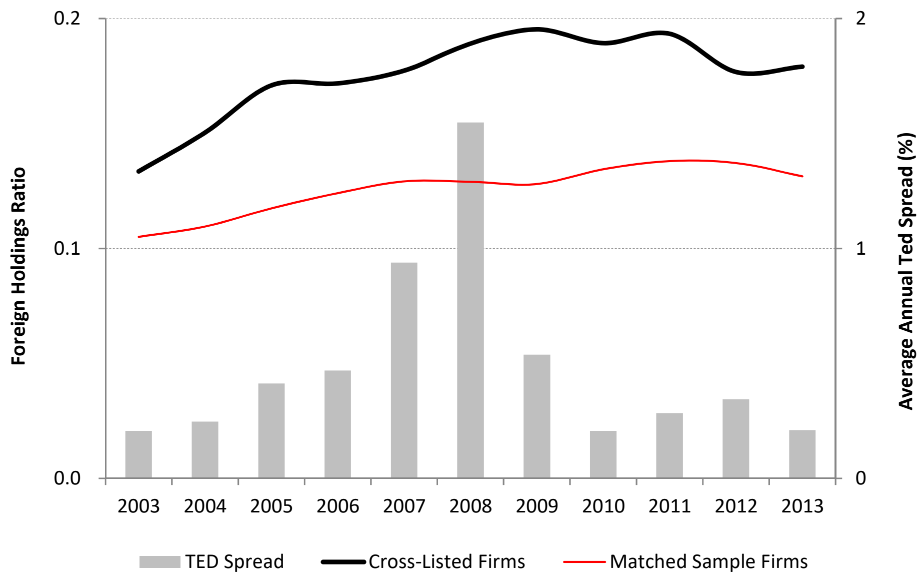
This table shows the main regression results after controlling for additional fixed effects and non-linearity. The sample period is 1950-2013. The U.S. stock market information is from CRSP, and international stock markets data is from DataStream. The dependent variable and explanatory variables are defined as in Table 3. $R_{i,t-1}^2$ is the squared term of $R_{i,t-1}$. Country × Time FE is the interaction of home country and time fixed effects. Firm × Time FE is the interaction of firm and time fixed effects. The time fixed effects are at the annual frequency. The intercept and fixed effects are present in each regression, but their estimates are not shown. The standard errors are clustered by firm and month. The table also reports the number of observations and the adjusted R-squared. The absolute *t*-statistics are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
$R_{i,t-1}$	0.140***	0.178***	0.174***	0.170***
	(9.89)	(5.21)	(5.12)	(4.98)
$R_{US,t-1}$	0.357***	0.315***	0.319***	0.321***
	(4.04)	(3.50)	(3.54)	(3.53)
$R_{IN,t-1}$	0.033	0.029	0.030	0.032
	(0.64)	(0.55)	(0.57)	(0.61)
$CL_{i,t} \times R_{US,t-1}$	-0.259***	-0.206***	-0.207***	-0.209***
	(3.43)	(2.63)	(2.63)	(2.68)
$CL_{i,t} \times R_{IN,t-1}$	-0.023	-0.017	-0.017	-0.021
	(0.49)	(0.37)	(0.37)	(0.43)
$CL_{i,t}$	-0.011	-0.011	-0.011	-0.009
	(1.57)	(1.45)	(1.50)	(1.21)
$CL_{i,t} \times R_{i,t-1}$		-0.050	-0.049	-0.044
		(1.41)	(1.39)	(1.23)
$R_{i,t-1}^2$			0.065	0.134
			(1.43)	(1.41)
$R_{US,t-1}^2$				0.161
				(0.20)
$CL_{i,t} \times R_{i,t-1}^2$				-0.087
				(0.80)
$CL_{i,t} \times R_{US,t-1}^2$				-0.178
				(0.25)
Country × Time FE	Yes	Yes	Yes	Yes
Firm × Time FE	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	91,921	91,921	91,921	91,921
Adj. R^2	0.012	0.012	0.012	0.012

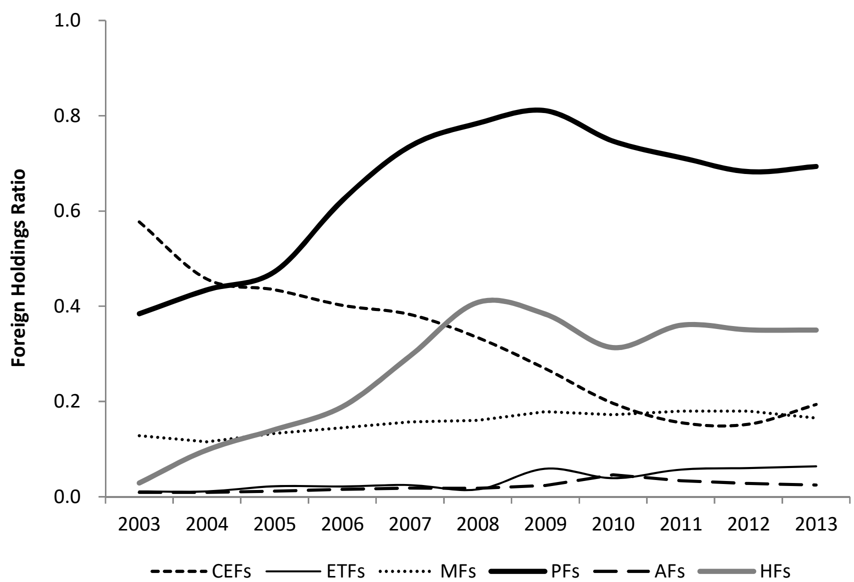
Table A.4
Return magnitude around cross-listing and liquidity sensitivity

This table shows the results from panel regression of the U.S. cross-listed firms' liquidity innovation on the lagged firm stock return and the U.S. and international market return variables depending on the magnitude of pre-listing cumulative abnormal returns (CARs). Columns (1) and (3) show the estimation of liquidity sensitivity for firms with below median CARs (Low CARs); columns (2) and (4) – for firms with above median CARs (High CARs). The U.S. stock market information is from CRSP, and international stock markets data is from DataStream. The dependent variable, $\Delta Liq_{i,t}$, is the change in monthly Amihud liquidity measure for each individual firm *i* at time *t*. First, for each individual stock, we calculate the monthly average Amihud liquidity measure from its daily measure. Then we compute the liquidity innovation as percentage change in the monthly Amihud liquidity measure, i.e. $(Liq_{i,t} – Liq_{i,t-1})/|Liq_{i,t-1}|$. The variables $R_{i,t-1}$, $R_{US,t-1}$, and $R_{IN,t-1}$ are the lagged monthly returns for firm *i*, CRSP total market index, and international markets, respectively. For each firm *i*, $R_{IN,t-1}$ is constructed as the equally-weighted average of MSCI country index return for all hosting markets for its cross-listings at time *t*. $CL_{i,t}$ is a dummy equal to one after the initial cross-listing date by firm *i* and to zero for the time before the listing. The control variables are the same as in Table 3. The CARs are computed over three periods: the pre-listing period (from day -100 to day -2) and the full period around the listing event (from day -100 to day +250). The CARs are based on a U.S. market model. For each firm, the U.S. market model is estimated during the 150-day pre-listing period from day -250 to day -101. The standard errors are clustered by firm and month. The table also reports the number of observations and the adjusted R-squared. The absolute *t*-statistics are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Pre-listing period		Full listing period	
	Low CARs	High CARs	Low CARs	High CARs
$R_{i,t-1}$	0.131***	0.145***	0.142***	0.132***
	(8.13)	(7.17)	(8.17)	(6.41)
$R_{US,t-1}$	0.147	0.352***	0.145*	0.357***
	(1.56)	(4.78)	(1.78)	(4.09)
$R_{IN,t-1}$	0.032	-0.040	-0.019	0.014
	(0.67)	(-0.95)	(-0.45)	(0.30)
$CL_{i,t} \times R_{US,t-1}$	-0.184**	-0.302***	-0.165**	-0.332***
	(2.10)	(3.14)	(2.18)	(3.20)
$CL_{i,t} \times R_{IN,t-1}$	0.044	0.034	0.075	0.006
	(0.73)	(0.77)	(1.44)	(0.12)
$CL_{i,t}$	-0.042	-0.015	-0.018	0.011
	(0.17)	(0.07)	(0.78)	(0.42)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	34,744	33,921	33,906	33,425
Adj. R^2	0.223	0.242	0.236	0.230



Plot A: Foreign holding ratios of cross-listed and matched firms versus the TED spread



Plot B: Foreign holdings ratios by institution type

Figure A.1
Foreign holdings ratio of cross-listed U.S. firms around the crisis period

This figure shows the dynamics of foreign holdings ratios of cross-listed U.S. firms five years before and five years after 2008. Plot A shows holdings of both cross-listed firms and the matched U.S. firms without foreign listings (pseudo cross-listing). It also shows the average annualized TED spread. We first match our sample of cross-listed firms with the FactSet Ownership database that contains institutional holdings data. For each institution (mutual fund, ETF, pension fund, etc.), we categorize it as "foreign" if its headquarters are located outside the United States. Then, we compute the proportion of holdings of cross-listed by foreign institutions at the end of each year. We repeat the same procedure for the matched sample. Plot B shows foreign holdings ratios by the type of institution: CEF – closed-end funds, ETFs – exchange traded funds, MFs – mutual funds, PFs – pension funds, AFs – annuity funds, HFs – hedge funds.