Cross-border arbitrage and cross-listed stocks: Evidence from mutual fund flows†

Abstract

We re-evaluate the effectiveness of cross-border arbitrage by measuring the impact of mutual fund flow–driven price pressure on cross-listed stocks in the United States and 44 international markets. Our tests show that liquidity barriers are greater than information barriers between markets, in that non-US stock returns are more strongly associated with US stock returns than with liquidity-driven US-based mutual fund price pressure. Our procedure shows that higher barriers to cross-border arbitrage exist for small-cap, narrowly-held, and actively-traded stocks that are cross-listed in Latin American, Caribbean, and Asian-Pacific emerging markets, and for funds that are experiencing outflows. We do not find that large outflows (i.e., fire sales) lead to stronger price divergences across markets for cross listed stocks.

Keywords: mutual fund flows; price pressure; fire sales; cross-listing; cross-border arbitrage; spillovers.

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1. Introduction

Expected security returns and conclusions about market efficiency depend on how smoothly the arbitrage process functions in financial markets (De Long, Summers, Shleifer, and Waldmann, 1990; Shleifer and Vishny, 1997). Market frictions that may impede the arbitrage process include trading costs, taxes, capital constraints, and imperfect information. A rich stream of research documents a variety of situations where limits to arbitrage cause prices of otherwise similar securities to diverge, with valuable implications for our understanding of how information and liquidity spills over across markets.

Cross-listed stocks are securities traded in multiple markets, but where political, legal, and transaction-cost barriers to arbitrage often exist. At the same time, substantial amounts of capital, information, and motivation are deployed to exploit arbitrage opportunities (Gagnon and Karolyi, 2009, 2010). An expansive literature documents the existence, duration, and geographic extent of cross-border arbitrage of cross-listed stocks, or lack thereof. Karolyi (1998) provides an early summary of the literature. More recent work includes Gadhab (2018), Pavlidis and Vasilopoulos (2020), and Poutré, Dionne, and Yergeau (2022). Despite abundant research on the extent and duration of price divergences for cross listed stocks, fewer studies examine the trading process that generates asymmetric demand for domestic and foreign stock listings. We identify mutual fund (MF) flows as a largely unexamined force driving potential cross-border price divergence for cross-listed stocks. In doing so, we provide new inferences on which securities are susceptible to mispricing, as well as the market characteristics and types of fund flows that are associated with barriers to arbitrage.

Our analysis begins with a series of tests to confirm that United States (US)-based mutual fund flows generate patterns consistent with price pressure for US-listed stocks. We show that this US-based mutual fund price pressure (MFPP) is distinct from price pressure arising from foreign fund flows. We then conduct a variety of tests to measure the extent to which US and foreign cross-listing pairs of stocks display a divergence in returns in the presence of MFPP. Last, we explore a variety of stock level, market-level, and fund flow characteristics that characterize the nature of cross-border MFPP-driven price discrepancies that are consistent with barriers to arbitrage.

Our initial tests confirm that fund flows in non-US markets are largely uncorrelated with US MF flows. Therefore US-based MFPP provides a useful tool to evaluate how a pricing shock to US stocks is (or is not) transmitted across borders. Next, we find that the spread between US and foreign stock listings diverges in a statistically and economically significant manner when US stock listings experience MFPP, consistent with limits to cross-border arbitrage for cross-listed stocks. This divergence in prices is stronger for stocks that are smaller, more actively traded, and more narrowly held by funds. Barriers to arbitrage appear largest for stocks from emerging markets, or are located in the Latin American, Caribbean, or Asia-Pacific regions. In developed markets, prices diverge only in the presence of unexpected fund flows. Last, we show that the returns on cross-listed stocks diverge in the presence of fund outflows, in general, rather than only for fund experiencing large “fire sale” outflows.

Because we associate mutual fund flows with potential security mispricing, our work is closely related to the burgeoning literature on mutual fund fire sales and the extent to which fire sales represent exogenous shocks to security prices. Coval and Stafford (2007) argue that MFPP, especially for fire sales, is unrelated to underlying stock fundamentals. Notable examples of recent papers that treat fire-sale fund flows as exogenous security price shocks include Bian, He, Shue, and Zhou (2018), De Jesus (2018), Capponi, Glasserman, and Weber (2020), Chernenko and Sunderam (2020), Giannetti and Jotikasthira (2022), and Honkanen and Schmidt, 2022. However, work by Edmans, Goldstein, and Jiang (2012), Berger (2017), Wardlaw (2020), and Schmickler (2020) raise concerns about the exogeneity of MFPP relative to the fundamental values of funds' holdings. Our analysis provides a useful new diagnostic on the extent to which mutual fund flows, in general, and fund fire sales, in particular, are associated with security mispricing.

Our analysis suggests that under appropriate conditions, returns on cross-listed stocks can act as potential instruments for expected domestic security returns, correcting for the endogeneity of domestic fund flows. We can thereby estimate the exogenous component MFPP with a procedure that is independent from those methods that have been used to calibrate the impact of MFPP in past studies, such as the size of reversals (Coval and Stafford, 2007; Schmickler, 2020), flow scaling (Edmans, Goldstein, and Jiang, 2012; Wardlaw, 2020), and sample selection procedures (Berger, 2017). Our results confirm that MFPP represents a liquidity shock to stock returns in the manner originally suggested by Coval and Stafford (2007). However, in our context, this characterization of MFPP as an exogenous shock to security returns applies only to particular stocks, in certain markets, in response to limited types of fund flows.

Our work makes contributes to the fields of portfolio performance measurement and international liquidity spillovers. We demonstrate that information easily permeates international borders while barriers exist to liquidity spillovers. We document this by showing that while returns are highly correlated between US and foreign markets, mutual fund flows and MFPP are often segmented. Our work can therefore be used to better infer when mutual fund derived shocks to stocks can reasonably be expected to lead to meaningful movements in stock prices, either as the basis of a trading strategy by investors or as a proxy for exogenous liquidity shocks by researchers.

In addition, our analysis provides new measures of the extent to which certain markets operate efficiently in the transmission of information and liquidity across borders, while others exhibit apparent arbitrage opportunities of potential interest to regulators, market participants, and academic researchers.

2. Methodology and hypotheses

2.1 Liquidity spillovers and mutual fund flows

Before we evaluate the impact of mutual fund price pressure across borders, we must first characterize the extent to which mutual fund flows are correlated across markets. While mutual fund flows have been studied extensively within national markets such as the USA, there exists surprisingly little academic research on how mutual fund flows are correlated across countries. An extensive literature exists on the determinants and correlations of international portfolio flows on a broad scale (see for example, Brennan and Cao, 1997; Froot et al., 2001; and DeSantis and Luhrmann, 2009). However, this stream of research does not consider mutual fund flows, in particular, and therefore mixes in the drivers of mutual fund price pressure with other sources of liquidity. To our knowledge, only the current work by Nguyen and Rakowski (2022) explicitly models the correlation of retail mutual fund flows across countries. They show that there exists surprisingly little correlation of fund flows across international markets, especially relative to the well-known and strong correlations that exist for returns across countries.

We begin our analysis by taking aggregate mutual fund flow data from national markets and we compute the correlation of mutual fund flows across countries. When then replicate and confirm that the results of Nguyen and Rakowski (2022) hold during our sample period for funds in US and non-US markets.

Our approach is comparable to that taken by Froot and Ramadorai (2008) to measure price pressure and information spillovers in international markets. Froot and Ramadorai use a proprietary sample of institutional portfolio flows as a potential measure of country-level price pressure. They then associate these flows with deviations in closed-end fund market prices and net asset values (NAVs). However, while Froot and Ramadorai focus on country-level flows of money to generate price pressure, we control for flows between countries and examine how domestic security-level flows generate price pressure for individual securities in one national market but not the other. Froot and Ramadorai then examine how price pressure drives closed-end fund discounts or premiums in each national market. In contrast, we look at how prices between individual cross-listed securities diverge from each other due to price pressure.

We define the excess return, $USX_{i,t,}$ as the return on the US-listing for stock i at time t minus the return on the non-US listing of the same stock. The US-listed return includes the liquidity-trading impact arising from flows into and out of US-based mutual funds. Our foreign stock-listings should reflect a higher proportion of informed trading to the extent that foreign mutual fund flows are not perfectly correlated with US fund flows (Nguyen and Rakowski, 2022). We confirm that the assumption of low correlation between US MFPP and foreign stock returns is valid for our data.

2.2 Research Hypothesis

Our first hypothesis is that US MFPP causes US-listed returns to deviate from non-US-listed returns. Therefore, we expect that $USX_{i,t}$ is negatively associated with our measures of MFPP for stock i at time t. In equation (1), $MFPP_{,i,t}$ measures US-domiciled mutual fund trading of the

US-listing of stock *i* at time *t*. $\boldsymbol{X}$ is matrix of control variables for the US listing of stock *i* in month *t* and includes measures of the log of the number of US funds holding stock *i*, the log trading volume of stock *i*, and the log price of stock *i*:

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(MFPP_{i,t-1}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (1)$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t}\ . \quad (2)$$

The first null hypothesis is that $MFPP_{i,t}$ is unrelated to $USX_{i,t}$. Our first alternative hypothesis implies a negative coefficient estimate, α_2, in models (1) and (2).

We include three measures of *MFPP*: total dollar MFPP, MFPP as a percent of market capitalization for stock *i* in month *t-1*, and MFPP as a percent of average daily trading volume for stock *i* in month *t-1*. Following Warther (1999), our measures of unexpected MFPP are the residuals from an auto-regressive model with 3 lags (AR(3)). We require at least 24 valid monthly observations for a stock to be included in any subsample, to allow sufficient observations to compute stock fixed effects.

To characterize liquidity spillovers, we examine variation in the estimates from equations (1) and (2) across types of stocks, markets, and fund flows. Stocks are classified along three dimensions: market capitalization, the number of funds holdings stock *i*, and stock trading activity. Large capitalization and small capitalization are defined as inclusion in the top or bottom quartiles, respectively, of observations of market capitalization for the US listing of stock *i*. High turnover stocks are those stocks in the top quartile of average monthly US-listing volume divided by average monthly US shares outstanding, while low turnover stocks are in the bottom quartile. Widely-held stocks are defined as those stocks in the top quartile based on the number of funds holding that stock, while narrowly-held stocks are in the bottom quartile.

Foreign listings are classified based on four regional groups for the foreign listing of stock *i*: Latin America & the Caribbean, Canada, Europe, or Asia-Pacific. Canada is treated as its own region because it has the largest number observations and its near-synchronous trading hours with US markets allowed for inferences about any potential non-synchronous trading effects. We then classify markets into groups based on emerging or developed market status.

Variation across flow types is characterized based on the direction and scale of the total flows to each to stock *i* in month *t*. We form subsamples for stocks that experience net inflows, net outflows, large inflows (i.e., the top decile of flows, as a percentage of market capitalization across stocks in month *t*), and fire sales (i.e., the bottom decile of flows, as a percentage of market capitalization, across stocks in month *t*).

An additional method to evaluate our hypothesis is to replace USX in equation (1) with the US returns and the non-US returns on $stock_{i,t}$ in two separate models. If *MFPP* drives liquidity trading that contains no information about firm values, then we should find *MFPP* to be significantly positively associated with US returns but unrelated to non-US returns. Any significant association with non-US returns would represent an informative component of *MFPP* that spills-over across markets where liquidity-motivated trading in one market provides information that is relevant in the second market. The models used to test these aspects of our hypothesis are:

$$US\ returns_{i,t} = \alpha_1 + \alpha_2(non\text{-}US\ Returns_{i,t}) + \alpha_3(MFPP_{i,t}) + \alpha_4(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (3)$$

and

$$non\text{-}US\ returns_{i,t} = \alpha_1 + \alpha_2(US\ Returns_{i,t}) + \alpha_3(MFPP_{i,t}) + \alpha_4(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t}\ . \quad (4)$$

As in the estimations of equations (1) and (2), lagged $MFPP_{i,t}$ is replaced with unexpected $MFPP_{i.t}$ in additional specifications.

3. Data

Our data are collected from several sources. Initial analysis draws on aggregate domicile level fund flows over the 2006-2019 period. Our main analysis combines US MF holdings of cross listed stocks over the 2006-2021 period.

The initial sample is drawn from the Center for Research in Security Prices (CRSP) and Morningstar databases, which provide monthly fund flow data for individual US MFs that we aggregate for all US-domiciled funds. The *informa FinancialIntelligence* EPFR database provides monthly aggregate fund flows and returns for non-US domiciled mutual funds. Aggregate domicile level fund flows are available from 2006 until year-end 2019.

The main analysis is based on cross-listed stocks that are identified from the Compustat-Capital IQ North American and Global databases. First, we extract the GVKEY identifiers of all common stocks traded on US exchanges but headquartered outside the US[1]. We match these to all stocks traded on non-US exchanges and we retain the intersection of the two datasets. We use the Compustat issue codes and manual checks verify that these stocks represent the same security traded on both US and non-US exchanges. We exclude non-identical securities, such as American Depository Receipts (ADRs) and Chinese N-shares, because the security design can lead to predictable differences in returns (Gagnon and Karolyi, 2010; Puthenpurackal, 2006) that are not attributable to MFPP. When a security trades in more than one non-US market, we include all non-US listings that pass our filters for at least 24 valid monthly observations. In untabulated robustness

[1] We exclude US-headquartered firms listed outside the US (e.g., General Electric, London Stock Exchange ticker: GEC, New York Stock Exchange (NYSE) ticker: GE) because the non-US trading volume of these firms represents only a small fraction of overall trading activity. We also exclude non-US headquartered or domiciled firms for which the primary listing is in the US (e.g., Accenture PLC, headquartered in Dublin, Ireland, NYSE ticker: ACN). In untabulated robustness checks, we confirm that our results are similar when we include non-US firms with a primary listing in the US.

checks, we confirm that we find similar results to those reported below when we restrict our sample to the top non-US listing for each stock (i.e., the listing with the highest number of monthly observations).

Data downloaded from Compustat include variables to compute monthly returns, volume, shares outstanding, listing information, trading venues, headquarters location, firm identifiers, and share adjustment factors. For US stock listings, corresponding data are also collected from the CRSP stock database. US returns from Compustat are validated against returns from CRSP and any discrepancies are manually corrected or dropped from the sample. All cross-listed common stocks with normal-status and valid non-zero trading activity are retained. Outlier values for non-US listed stocks are validated against data from Datastream and are manually corrected or discarded if correct values cannot be determined.

We recognize tradeoffs in using either US dollar (USD) or local currency returns to compute *USX*. A broad analysis of cross-border arbitrage is best specified when using USD returns of non-US stocks, as this accurately captures exposure of US-based arbitrageurs, including thier exposure to changes in value of the US dollar. However, a narrow focus on the impact of MFPP is better specified using local returns of non-US listings, as the exchange rate component of price divergence is unlikely to be driven by MFPP to individual stocks. As an alternative justification for using local currency returns for cross-listed stocks, we note that both aggregate MF flows and the value of the US dollar have increased substantially over our sample period (ICI Factbook, 2022; Board of Governors of the Federal Reserve System, 2022). Therefore, the use of USD-denominated returns for non-US listings risks spuriously attributing any association between *USX* and *MFPP* to the positive correlation between US aggregate fund flows and USD appreciation. To be conservative, we therefore report *USX* using the local currency returns of non-US listings. For robustness, Online Appendix A reports regression results using USD-denominated non-local returns. Consistent with inflated estimates of the association between *MFPP* and *USX*, we observe stronger results (i.e., larger *t*-statistics) for almost all models reported in Online Appendix A, relative to the results reported in the sections below.

Cross-listed stock data are matched to the holdings of all US-listed open-end MFs. MF holdings data are obtained from the CRSP and Morningstar Direct mutual fund databases. We require the CRSP PERMNO for each MF holding map directly to the Compustat GVKEY of our return data via the CRSP-Compustat mapping file provided by Wharton Research Data Services (WRDS). We use the security header information from CRSP and Compustat to confirm that each US MF holding is for the US listing of each security. We then manually confirm the accuracy of the mapping and holding identities by examining the US and non-US security names. The mapping requirement ensures that the US MF holding matches the share class and security type (e.g., common stock) of each cross-listing. To correct for possible erroneously reported holdings, we manually confirm any observations that are not in the intersection of the CRSP and Morningstar MF holdings data. Quarterly and semi-annually reported fund holdings are converted to inferred monthly holdings based on the closest available reporting dates, with changes to holdings assumed to occur at the end of each reporting period. Holdings from reports that appear missing for more than 6 months are dropped from the sample for that period.

Mutual fund trades are computed from the change in inferred holdings from one month to the next for each stock. Mutual fund trades are then aggregated across all US-listed funds that report holdings of each stock. Only funds with at least 24 valid monthly mutual fund holding observations are retained for analysis. Additional MF characteristics (e.g., TNA and investment objectives) are taken from the CRSP MF database. Separate share classes of a fund are aggregated at the portfolio level, weighted by the TNA of each share class.

Table 1 presents country-level summary statistics on our sample of US stock listings held by US MFs, with cross-listings in thirty-six non-US markets. Our sample covers a net $201 billion in US mutual fund trades of 586 cross-listings, drawn from 352 unique stocks. Cross-listed stocks in our sample are held by about 2,176 US MFs in a typical month, with 13,773 distinct US MFs present in our sample. Stocks appear in the sample for an average of about 74 months, out of a total possible 180 months.

Our exclusion of non-identical cross-listed securities, such as ADRs, leads to a slightly different sample distribution compared to ADR-focused research, such as Gagnon and Karolyi (2010). For example, we retain better coverage of stocks listed on the Frankfurt Stock Exchange (79 stocks) but have relatively few observations from markets that are affiliated with the Euronext family of exchanges (ten sample firms are listed in Amsterdam, eleven in Milan, and zero in Paris). We speculate that the paucity of Euronext-listed observations in our sample stems from the popularity of ADR cross listings for stocks listed on Euronext-affiliated exchanges.

Canada provides the largest number of sample observations, with 106 cross-listed stocks, yielding 10,218 stock-month observations (about one-fifth of our sample). Sample stocks are traded on an average (median) of 1.6 (1.0) different non-US exchanges. Nokia Oyj Corporation has the most listings, with returns reported on eight different non-US exchanges, plus the NYSE. Teva Pharmaceuticals (NYSE: TEVA, Tel Aviv Stock Exchange ticker: TEVA) is the most widely held (by US MFs) stock in our sample, being held by up to 815 MFs per month. There are seven markets that have only one US cross-listed stock in our sample, although these stocks are each held by multiple US MFs. For example, Turkey contributes one firm to our sample, Turkcell

İletişim Hizmetleri A.Ş. (Borsa Istanbul ticker: TCELL; NYSE ticker: TKC), which provides 171 stock-month observations and is held by about 32 US MFs per month.

Table 2 presents descriptive statistics for our sample of 53,683 listing-month observations. The aggregate monthly flow from US mutual funds to each stock, *MFPP*, is $3.76 million on average, but with substantial variation across funds and over time (standard deviation of $11.01 million). *MFPP* as a percent of market capitalization or volume is close to zero on average, but average absolute *MFPP* is 8.11% of a security's market capitalization and 6.10% of volume. The unexpected component of *MFPP* is close to zero on average, as it should be, but with a standard deviation of $6.30 million. We observe an average market capitalization of about $6.8 billion for the US-listing, of which about $624 million (9.1%) is held by US MFs. Sample listings have higher non-US returns than US returns, although median US and non-US returns are closer, with a difference of about six basis points (bps). This is consistent with the comparison of cross listed stocks by Gagnon and Karolyi (2009) and suggests that average return differences are larger than median differences due to a small number of outlier observations[2].

4. Results

4.1 Fund flow correlations across countries

We begin with an examination of country-level aggregate fund flows. Bekaert, Hodrick, and Zhang, 2009, provide an introduction to the large literature on cross-country stock return comovement. In contrast to the stock return correlations summarized by Bekaert, et al., Nguyen

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[2] A manual examination of extreme values of return differences indicates that outliers are concentrated in emerging markets during political or economic crises. For example, some of the largest individual values for *USX* are for cross listings in Argentina during the monetary crisis of 2018. These extreme observations generally add noise to our estimates. Filters for extreme returns lead to stronger results in our regression models (i.e., larger and more significant coefficient estimates in the sections below). To be conservative, we retain these extreme, but valid, return observations.

and Rakowski (2022) document that cross country mutual fund flows correlations are generally weak and insignificant, especially relative to cross-country return correlations. Table 3 reports country-level Pearson correlations for our measures of non-US domiciled and US-domiciled fund flows drawn from the EPFR data. Column 1 of Table 3 provides contemporaneous flow correlations and column 2 provides the correlation with lagged US flows. Consistent with the results of Nguyen and Rakowski (2022), we observe that for most countries, correlation coefficient levels are low and *p*-values are weak, indicating that country flows are largely uncorrelated with both contemporaneous and lagged US flows. On average, the correlation of country-level fund flows with US fund flows over time is only 19.7% (average *p*-value = 0.1979), while average correlation with lagged US flow is negative 4.1% (average *p*-value 0.3831). Half of the countries with valid flow data display positive flow correlations with the US and half do not. The strongest flow correlations are for relatively less developed financial markets and offshore financial centers, with Brazil, India, Monaco, Hungary, the Bahamas, and Russia displaying the strongest correlations with US fund flows.

The lack of correlation between US and non-US fund flows simplifies our later analysis by confirming that US fund flows, and thus MFPP originating from US funds, are generally exogenous to non-US mutual fund flows. Non-US stock prices should be less contaminated by the influence of US MFPP than US listings, making non-US cross-listed stock returns potential instruments for the returns on the expected US-listings of those stocks. The absence of strong correlations between non-US and US aggregate fund flows is made more interesting by the strong correlations that exist between non-US and US stock returns. In untabulated tests, we confirm the results of numerous past studies on market integration (for example, Bekaert and Urias, 1996) and find that average contemporaneous correlation in our sample between US and non-US returns is at least 89% for all markets, with all *p*-values less than 0.01. We find that non-US returns are uncorrelated, on average, with lagged US returns. In untabulated results, we confirm the robustness of these associations (or lack thereof) between US and non-US fund flows and returns for subsamples grouped by MF investment objectives and over alternative time horizons (i.e., quarterly rather than monthly).

4.2 Results: Mutual fund price pressure and return spreads

Table 4 presents the results of our regression equations (1) and (2). The return spread, *USX*, is the dependent variable. Control variables are included in estimations of all models but are not tabulated, as they have little impact on our variables of interest. In untabulated robustness tests, we confirm that the reported results are similar to estimates obtained with modifications to, or elimination of, the control variables, including the use of controls for the foreign stock listing, rather than the US listing. In further untabulated robustness checks, we confirm that models with standardized independent variables (i.e., mean zero and standard deviation set to one) yield similar coefficient signs and significance levels as the results reported in the text below. We do not report standardized regression results because effect sizes for standardized independent variables are difficult to interpret in the analysis, by groups, reported in the sections below.

Table 4 shows that *USX* is positively and significantly associated with fund flow price pressure, *MFPP*. The economic significance of this impact is large. The coefficient on signed log *MFPP* of 0.0169 in column 1 implies that if *MFPP* were to double from the median value of approximately $200,000 per month to $400,000, then the gap between US and foreign monthly stock returns would increase by approximately 22 bps. Alternatively, a one standard deviation increase in log *MFPP* would imply an increase of 29 bps per month for *USX*. As the median (mean) value for *USX* is negative six bps (-19 bps) per month, our estimates represent large impacts on relative price differences across markets. These estimates are consistent with the negative gap between US and foreign returns being eliminated, or reversed, when US stock listings experience *MFPP* (i.e., the negative gap between US returns and foreign returns widens when US MFs experience outflows). *USX* is unrelated to lagged or unexpected *MFPP*.

Table 4, column 3, yields a positive and significant coefficient estimate when *MFPP* is normalized by capitalization, but no significant effect when normalized by volume (column 4). The strong results for *MFPP* as a percent of capitalization implies a stronger effect of *MFPP* on smaller-cap stocks. The relatively weaker effect for *MFPP* as a percent of volume implies that *MFPP* may have a less impact on stocks that are more liquid. We explore these possibilities in more detail in the sections below. The R^2 measures show little variation across models in Table 4, indicating that our four specifications of *MFPP* all capture a similar association between *MFPP* and *USX*.

Overall, the results of Table 4 suggest that we can reject the null hypothesis that US *MFPP* is unrelated to the gap between US and non-US returns. US *MFPP* causes US returns to diverge from non-US returns in the direction that we would expect from liquidity-driven trading in US markets: when US-based MFs experience inflows (outflows), we observe the US-listed returns of stocks held by that fund increasing (decreasing) relative to non-US listings of the same firm.

In Table 5 we present estimates from equation (4) when the independent variables are sequentially entered to evaluate the increase in explanatory power for non-US returns provided by US *MFPP*. In the benchmark model (column 1), control variables and firm and time fixed effects are included, giving a the R^2 of 10.54%. When *MFPP* is added to the model (column 2) the R^2 increases to 13.04%, an increase of 2.50 percentage points. When US returns are added (column 3), the model R^2 rises to 42.05%. If we take 42.05% as the total variation in non-US returns that is explained by US-based MF flow and return information, then these models suggest that US returns account for about 69.0% of this variation, *MFPP* accounts for 5.9% of the variation, and controls account for 25.1%.

4.3 Variation across stocks

Table 6 reports estimates for equations (1) and (2) for subsamples of large-cap (Panel A) and small-cap (Panel B) stocks. The association between *MFPP* and USX is apparent for both small and large cap stocks. Lagged *MFPP* is significant for small cap stocks, while unexpected *MFPP* is significant for large cap stocks. The significance of unexpected *MFPP* only for large cap stocks is consistent with more efficient pricing for these securities.

Table 7 presents results when the sample is partitioned by trading turnover, allowing us to shed light on the inconsistent and weak results for *MFPP* when normalized by trading volume. Panel A presents results for those stocks in in the bottom quartile of turnover, with turnover computed as the average monthly US-listing volume divided by average monthly US shares outstanding. Panel B presents results for in the top quartile of trading turnover. For low-turnover stocks, a positive and significant association exists between *USX* and *MFPP,* lagged *MFPP,* and unexpected *MFPP* (columns 1 and 2 of Panel A). For high turnover stocks, we observe significant coefficient estimates only when *MFPP* is normalized by capitalization or volume. If high-turnover is taken to represent high-liquidity, then the results in columns (1) and (2) imply that in low-trading environments, larger dollar trading by MFs leads to price divergences across markets. Columns (3) and (4) suggest that for more liquid stocks, MF trades must achieve sufficient scale, relative to either capitalization or volume, before these trades are drive price divergence across markets.

A test for the role of barriers to arbitrage in determining spillovers across markets is to consider the number of funds holding a particular stock, and how this is associated with the impact of *MFPP* on *USX*. If more funds holding a stock represent more potential arbitrageurs, then more widely-held stocks should display less impact of *MFPP* on *USX*. Table 8 reports results for subsamples of narrowly-held and widely-held stocks. The association between dollar *MFPP* and *USX* is strong and significant for the narrowly-held subsample, but weaker for widely-held stocks. For widely-held stocks, MFPP is most strongly associated with a divergence in US and non-US prices when MF trading is large relative to trading volume (Panel B, column 4). If the widely-held subsample is interpreted as those stocks that are held by MFs engaging in herding behavior, then these results imply that herding is not a barrier to cross-border arbitrage, as those stocks subject to MF herding are associated with a smaller impact of MF trading on price divergence. Alternatively, MFs may herd more strongly in those stocks that are less susceptible to flow-based price pressure. We note that the number of funds holding a stock is an untabulated control variable in all models.

4.4 Variation across markets

One concern with our full sample is that non-synchronous trading across different time zones may lead to apparent, but actually non-viable, arbitrage opportunities. It is also possible that barriers to arbitrage are driven by geographic and cultural distances between markets. Table 9 reports estimates for equations (1) and (2) for subsamples grouped by four geographic regions[3]: (1) Latin America and the Caribbean; (2) Canada; (3) Asia-Pacific; and (4) Europe.

When we restrict our sample only to the Americas (Table 9, Panel A), where trading is relatively closely aligned with the US markets, we observe a strong (about three times the magnitude of our baseline regressions reported in Table 4) and significant association between dollar *MFPP* and *USX*. Canadian markets (Panel B), which operate nearly synchronously with the US, display no significant associations between MFPP and USX. Asia-Pacific markets (Panel C),

[3] We use the World Bank regional classifications at https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html. We drop South Africa from the regional analysis.

with the highest amounts of non-synchronous trading relative to the US, also display weak results. Instead, it is the European markets, which have partially synchronous trading with the US, that display strong coefficient estimates. Because the degree or synchronicity with the US is unhelpful in explaining regional differences in impact of MFPP, we next examine the level of market development instead.

Table 10 reports estimates for equations (1) and (2) for subsamples grouped by level of financial market development[4]. Consistent with the results reported in Table 9, the association between *USX* and *MFPP* is present only for cross-listed stocks from emerging markets. For developed markets, we observe that unexpected *MFPP* is associated with *USX*, but there are no significant associations between *USX* and any other measure of *MFPP*. These results are consistent with an efficient cross-border arbitrage process in developed markets when flows are predictable. In contrast, emerging markets display evidence consistent with substantial barriers to cross-border arbitrage.

4.5 Variation across types of fund flow

Tables 11 and 12 provide estimates when the sample is constructed only from funds that experience certain levels and directions of flow. Panel A of Table 11 reports estimates for *MFPP* arising only from funds that experience inflows during month *t*. We observe no significant association between *MFPP* and *USX* in columns 1, 3, or 4, and a significant coefficient only in column 2 (controlling for lagged *MFPP*). Panel B of Table 11 illustrates that coefficient estimates in columns 1 through 3 are positive and significant in the case of *MFPP* (as well as lagged and unexpected *MFPP*) arising from fund outflows. Coefficient estimates are substantially larger than in our baseline models reported in Table 4. The stronger results for outflows are consistent with

[4] We use the MSCI market classifications at https://www.msci.com/our-solutions/indexes/market-classification.

the larger literature on fund outflows, fire sales, and price pressure (e.g., Coval and Stafford, 2008). Fund trades driven by inflows may be dispersed across the investable universe of stocks, but fund outflows must be concentrated in those stocks that a fund already holds.

The results from Table 12 allow a refinement of Table 11 by reporting only for those stocks experiencing price pressure from large fund inflows or from large outflows (i.e., “fire sales”). The results arising from the firesale subsample are all insignificant, while the large inflow subsample generally display large and significant estimates. Therefore, although outflows are more strongly associated with price divergence across markets, in general (Table 11), large inflows are more impactful than large outflows. This implies that studies using fire sales to make inferences about cross-border arbitrage may be miss-specified, and the use of all fund flows is more advisable.

4.6 Exchange rates and supplemental tests for market segmentation

Table 13 reports the results of tests to ascertain the extent of segmentation between US and non-US markets. To do so, we test whether or not non-US returns remain correlated with US MFPP after correcting for the influence of US returns. USD returns are computed by discounting the monthly non-US stock returns by the monthly return of the local currency relative to the USD. USD/non-USD exchange rates are obtained from the Federal Reserve and Datastream. We drop any monthly observations where the currency of denomination changes or is unavailable. Exchange rate data are available for 518 of our sample stocks, comprising 42,896 stock-month observations.

Table 14 shows that both US returns and non-US returns are positively and significantly associated with US *MFPP* even when simultaneously correcting for the influence of US returns. Panel A of Table 14 shows that US returns are significantly associated with both contemporaneous foreign returns and with US *MFPP*. Panel B, columns 3 and 4, show that non-US returns are also strongly and significantly associated with US *MFPP*. The results are inconsistent with US *MFPP* representing uninformed liquidity trading in one market with no spillovers across borders. Instead, Table 14 suggests that price pressure from US-based mutual fund flows quickly spills over to foreign listings of cross listed stocks. Therefore, we can conclude that *MFPP* represents more than simple liquidity trading, and that flow-based uninformed liquidity shocks spillover across international markets.

5. Conclusions

Our results provide new inferences about the nature of cross-country arbitrage. We observe meaningful impacts of *MFPP* for across large cap and small cap stocks, high and low turnover stocks, and widely-held and narrowly-held stocks. The impact of MFPP is concentrated in emerging markets, especially in Europe, Latin America, and the Caribbean. Fund outflows drive price divergences more than fund inflows, although large inflows are more impactful than large outflows. Overall, we find that fund flows are associated with liquidity spillovers across markets in ways that are not immediately obvious from intuition or past research.

Our results are important for researchers who use mutual fund flows or fire sales as a tool to identify trades that are exogenous to firm fundamentals. We confirm the general conclusions of Coval and Stafford (2007), in that *MFPP* can proxy for liquidity trading that is largely exogenous to fundamental information about firm values. When US-based mutual funds experience fund flows, and especially unexpected fund flows, the returns on US stock listings diverge from returns on the foreign listings of the same stocks. Therefore, domestic *MFPP* does lead to changes in domestic stock prices that are exogenous to changes in fundamental security values, where fundamental values are inferred from foreign cross listings not subject to domestic *MFPP*.

However, the applicability of these conclusions varies widely across stocks, markets, and types of flows.

Our findings complement those of Wardlaw (2020) and Schmickler (2020) by providing an independent procedure to estimate the extent that *MFPP* can instrument for non-fundamental security price changes. Our results also confirm the findings of Lang, Maffet, Omartian, and Silvers (2020), who document changes in mutual fund holdings of cross-listed stocks following revisions to cross-border regulatory practices. Our work adds to that of Lang, et al., by suggesting that the flows examined in their work also drive a divergence in prices of certain cross-listed stocks.

In terms of the spillover between US and non-US markets, the information from US stock returns explains about 70% of the variation in non-US returns, while liquidity spillovers associated with US-based *MFPP* explain an additional 6% of this variation. The segmentation of mutual fund flow-driven liquidity behind national boundaries provides a potential explanation for why the mutual fund flow-performance relationship differs so much cross countries (Ferriera, et al., 2012) even when information and capital move more freely. Reverse causality, where fund flows respond to price discrepancies between cross-listed stocks, is unlikely to explain our results, as any individual cross-listed stock only makes up a small portion of any of our fund portfolios.

Our results also show that liquidity-based trading in one market can give the appearance of information-based price changes in other markets. It is well known that information spills over between tightly integrated financial markets (Eun and Sabherwal 2003; Gagnon and Karolyi, 2009 and 2010). There is also substantial evidence on the spillovers in liquidity that arise from the actions of institutional investors (Raddatz and Schmulker 2012; Manconi, Massa, and Yasuda 2012; Jotikasthira, Lundblad, and Ramadorai 2012). However, it can be difficult to disentangle these information spillovers from liquidity spillovers (Bartram, Griffin, Lim, and Ng, 2015). Our methods provide a new means to evaluate these spillovers and show that information moves far more freely than liquidity provided by institutional investors.

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Table 1: Summary statistics of US MF holdings of cross-listed stocks

This table presents summary statistics of our sample of the US-listing of cross-listed stocks that are held by US MFs over our sample period from 2006 to 2021. US-listed holdings are aggregated each month across all US MFs that hold the US listing of each cross listed stock, with summary statistics aggregated across all cross listed stocks for each market. Column (1) lists the total number of cross-listed stocks held by US MFs for each market. Column (2) provides the total number of stock-month observations for each market. Column (3) lists the average number of US MFs that hold cross-listed stocks from each market each month. Column (4) reports the median monthly US dollar value held by each sample MF of each cross-listed stock in each market. Column (5) reports the cumulative US dollar MF trades of all US listings of cross-listed stocks over the sample period for each market. Holdings and trades are reported in millions of US dollars.

Market	(1) Stocks	(2) Stock-months	(3) Average US MFs	(4) Median holding	(5) Cumulative trades
Canada	106	10218	74.7	$2.73	$65,120.73
Germany	102	8058	67.8	$2.84	$42,741.71
UK	57	4851	63.8	$4.23	$33,680.07
Mexico	52	4394	74.2	$2.26	-$3,460.27
Japan	23	2551	23.7	$1.29	$2,251.90
Hong Kong	19	2442	29.7	$1.40	$1,345.93
Argentina	27	2421	43.2	$1.26	-$4,256.39
Brazil	29	2286	52.1	$2.10	-$1,127.10
Spain	29	2239	59.3	$2.85	-$105.36
China	10	1364	16.3	$0.82	-$488.36
Italy	11	1229	51.4	$2.03	$6,959.95
South Korea	8	1177	42.7	$4.55	-$4,734.40
South Africa	11	1141	39.6	$6.38	-$7,946.14
India	11	1062	64.5	$1.85	$4,957.90
Chile	9	973	39.0	$1.71	$1,622.16
Netherlands	10	851	52.4	$2.93	$15,363.61
Switzerland	8	841	69.7	$6.36	$11,209.91
Australia	8	803	42.9	$0.78	-$837.01
Sweden	7	708	79.3	$5.42	$19,911.57
Taiwan	5	603	96.1	$2.02	$13,808.98
Russia	7	440	71.4	$2.49	$1,982.98

Table 1 (continued)

Market	(1) Stocks	(2) Stock-months	(3) Average US MFs	(4) Median holding	(5) Cumulative flow
Belgium	5	360	71.2	$3.05	-$306.09
Ireland	4	331	60.1	$7.55	-$995.15
Norway	5	325	76.0	$1.15	-$293.28
Singapore	5	307	22.3	$1.08	-$368.48
Israel	4	299	40.0	$0.46	$6,585.79
New Zealand	2	209	12.3	$1.39	-$66.94
Peru	3	176	70.2	$7.10	$1,674.13
Turkey	1	171	31.7	$2.92	$148.82
Finland	1	169	82.2	$4.82	-$2,593.51
Denmark	1	150	78.8	$14.02	$2,410.35
Colombia	1	140	53.9	$2.40	$158.01
Luxembourg	2	132	61.6	$3.22	$2.37
Portugal	1	97	9.9	$0.47	$13.26
Bermuda	1	88	79.5	$13.68	-$2,615.36
Greece	1	77	16.5	$1.44	-$75.34
Total	586	53,683			$201,680.93

Table 2: Descriptive statistics of US MF holdings of cross-listed stocks

This table provides summary statistics for our sample of monthly US domiciled MFs holdings of the US listing of cross listed foreign stocks. Holdings amounts are computed each period for each listing by summing the US listed market value held by all US MFs. Row (1) reports summary statistics on the holding amount of each stock across all stock-month observations. Row (2) reports the statistics on the total change in holdings each month, row (3) reports values for the change in holdings normalized by average daily volume of the US listing of the stock held, and row (4) reports statistics on the change in holding when normalized by the market capitalization of the US listing of the stock held. Rows (5) and (6) report statistics on the absolute values of the change in holdings, as a percent of volume and market capitalization, respectively. Row (7) reports the unexpected change in holdings derived from an AR(3) model of the expected change in holdings. Rows (8) and (9) report statistics on monthly returns for US and non-US listings, respectively. Row (10) reports statistics on the excess US return, computed as the US return minus the non-US return. The sample period is from January 2006 until December 2020. There are 53,683 listing-month observations. All dollar values are reported in millions of USD and returns are monthly percentage USD returns.

		Mean	Median	Standard Deviation
(1)	Holding amount	624.02	140.76	1,577.89
(2)	Change in holdings (*MFPP*)	3.76	0.20	11.01
(3)	Change in holdings (% volume)	-0.36	0.04	43.75
(4)	Change in holdings (% cap)	-0.05	0.04	75.68
(5)	Absolute change in holdings (% volume)	6.10	1.06	43.33
(6)	Absolute change in holdings (% cap)	8.11	1.64	75.25
(7)	Unexpected change in holdings	-0.19	-0.03	6.30
(8)	US returns	0.79	0.54	11.81
(9)	non-US returns	1.05	0.33	15.39
(10)	US excess returns	-0.29	-0.06	12.03
(11)	US capitalization	6,847.34	1,823.37	15,479.07

Table 3: Market level fund flow correlations with US fund flows

This table presents Pearson correlation coefficient estimates and worldwide summary statistics for the correlation of aggregate monthly market-level fund flows for non-US domiciled equity funds with aggregate US equity fund flows during month *t* (column 1) and month *t*-1 (column 2). Market-level aggregate fund flows are computed as the TNA-weighted averages across all equity funds domiciled in each market each month. Column (3) lists the total number of monthly observations and column (4) lists the maximum number of funds per month in each market. We require at least 60 months of valid flow data for a market to be included, as well as non-missing data on cross-listed stocks held by US MFs in that market. Markets are sorted by month *t* correlation with US fund flow. *p*-values are given in parentheses.

	(1)	(2)	(3)	(4)
Market	**US Flow$_t$**	**US Flow$_{t-1}$**	**Months**	**Funds**
Brazil	.5119	.2868	71	255
	(.0000)	(.0146)		
India	.5099	.2965	72	236
	(.0000)	(.0109)		
Monaco	.3160	-.0591	90	82
	(.0024)	(.5778)		
Hungary	.3160	-.0591	90	9
	(.0024)	(.5776)		
Bahamas	.3159	-.0592	90	189
	(.0024)	(.5775)		
Russia	.3159	-.0593	90	102
	(.0024)	(.5769)		
Portugal	.3103	-.0530	90	19
	(.0089)	(.6633)		
Italy	.2660	-.0397	98	79
	(.0081)	(.6968)		
Spain	.2641	-.0413	98	113
	(.0086)	(.6848)		
Greece	.2543	-.0356	115	74
	(.0061)	(.7044)		
South Africa	.2475	-.0413	108	93
	(.0098)	(.6061)		
Luxembourg	.1316	-.1095	152	125
	(.1060)	(.1780)		
Sweden	.1193	-.0621	143	72
	(.1558)	(.4594)		

Market	(1) US $Flow_t$	(2) US $Flow_{t-1}$	(3) Months	(4) Funds
Canada	.0975	-.0818	152	503
	(.2323)	(.3146)		
Turkey	.0846	-.0919	135	86
	(.3295)	(.2873)		
Belgium	.0760	-.0814	152	198
	(.3522)	(.3171)		
Australia	.0741	-.0927	152	187
	(.3645)	(.2546)		
France	.0731	-.0851	152	213
	(.3711)	(.2956)		
Netherlands	.0730	-.0918	152	341
	(.3716)	(.2592)		
Finland	.0722	-.0928	152	318
	(.3767)	(.2539)		
Denmark	.0720	-.0938	152	150
	(.3780)	(.2490)		
United Kingdom	.0707	-.1003	152	550
	(.3869)	(.2174)		
Ireland	.0523	-.0997	152	1176
	(.5223)	(.2201)		
Germany	.0259	-.0928	152	324
	(.7514)	(.2541)		
World Average	.1969	-.0408	124.38	220.5
	(.1979)	(.3831)		
World Median	.1254	-.0718	143	168.5
	(.1309)	(.3051)		

Table 4: The association between return spreads and fund flow price pressure

This table presents estimates from the following regression models:

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (1)$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (2)$$

where $USX_{i,t}$ is the difference in US and Non-US returns for cross-listed stock$_{i,t}$. $MFPP_{i,t}$ is measured by the signed log change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $MFPP_{i,t}$ is also measured by the change in aggregate MF holdings as a percent of market capitalization and as a percent of volume, as indicated. Unexpected $MFPP_{i,t}$ is measured as the signed log residuals from an AR(3) model of $MFPP_{i,t}$. Fixed effects are included at the stock and month level and standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. Control variables are included but not tabulated for the log number of funds holding stock *i*, the log US price of stock *i*, and the log US trading volume of stock *i*. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
MFPP ($)	0.0169***	0.0199***		
	(3.30)	(4.28)		
MFPP (% capitalization)			0.1601**	
			(2.45)	
MFPP (% volume)				0.0033
				(0.08)
lagged MFPP		-0.0006	-0.0544	0.0018
		(-0.09)	(-1.56)	(0.11)
Unexpected MFPP	0.0052			
	(1.41)			
R^2	6.64%	6.63%	6.61%	6.59%

Table 5: The informational content of US mutual fund price pressure (*MFPP)*

This table presents estimates from the following regression models:

$$Non\text{-}US\ returns_{i,t} = \alpha_1 + \alpha_2(US\ Returns_{i,t}) + \alpha_3(MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t}\ . \quad (5)$$

where *US returns*$_{i,t}$ are the local-currency returns on the US-listings of cross listed-stocks and *Non-US returns* for are the returns on the Non-US listing. Mutual fund price pressure (*MFPP*) is given by the signed natural log of $MFPP_{i,t}$ where $MFPP_{i,t}$ is measured by the change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $\boldsymbol{X\varphi}$ is a matrix of control variables and parameters for the log US stock price level, log trading volume, and the log number of funds holding stock *i*. Standard errors are clustered at the stock and month level. The sample contains 29,928 stock-month observations over the period from 2006 to 2018. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. **, and *** indicate significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)
US returns			0.8576***
			(65.52)
MFPP ($)		0.1993***	0.0158***
		(24.80)	(3.02)
Unexpected MFPP			
R^2	10.54%	13.04%	42.05%
Time fixed effects	yes	yes	yes
Firm fixed effects	yes	yes	yes
Control variables	yes	yes	yes

Table 6: Return spreads and fund flow price pressure, by market capitalization

This table presents estimates from regression models (1) and (2):

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (1)$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (2)$$

where $USX_{i,t}$ is the difference in US and Non-US returns for cross-listed stock$_{i,t}$. $MFPP_{i,t}$ is measured by the signed log change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $MFPP_{i,t}$ is also measured by the change in aggregate MF holdings as a percent of market capitalization and as a percent of volume, as indicated. Unexpected $MFPP_{i,t}$ is measured as the signed log residuals from an AR(3) model of $MFPP_{i,t}$. Fixed effects are included at the stock and month level and standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. Control variables are included but not tabulated for the log number of funds holding stock *i*, the log US price of stock *i*, and the log US trading volume of stock *i*. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Large cap stocks (N = 13,398)	(1)	(2)	(3)	(4)
MFPP ($)	0.0086*	0.0154***		
	(1.76)	(3.13)		
MFPP (% capitalization)			2.0846**	
			(2.19)	
MFPP (% volume)				0.0100
				(0.22)
lagged MFPP		-0.0032	-0.1470	0.0024
		(-0.58)	(-0.26)	(0.17)
Unexpected MFPP	0.0124***			
	(3.62)			
R^2	15.27%	15.23%	15.23%	15.18%

Panel B: Small cap stocks (N = 13,245)	(1)	(2)	(3)	(4)
MFPP ($)	0.0452**	0.0345**		
	(2.46)	(2.34)		
MFPP (% capitalization)			0.1552**	
			(2.42)	
MFPP (% volume)				-0.3860
				(-0.94)
lagged MFPP		-0.0056	-0.0664**	0.3303***
		(-0.29)	(-2.02)	(3.05)
Unexpected MFPP	-0.0161			
	(-0.91)			
R^2	5.32%	5.34%	5.28%	5.26%

Table 7: Return spreads and fund flow price pressure, by trading turnover

This table presents estimates from regression models (1) and (2):

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (1)$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (2)$$

where $USX_{i,t}$ is the difference in US and Non-US returns for cross-listed stock$_{i,t}$. $MFPP_{i,t}$ is measured by the signed log change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $MFPP_{i,t}$ is also measured by the change in aggregate MF holdings as a percent of market capitalization and as a percent of volume, as indicated. Unexpected $MFPP_{i,t}$ is measured as the signed log residuals from an AR(3) model of $MFPP_{i,t}$. Fixed effects are included at the stock and month level and standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. Control variables are included but not tabulated for the log number of funds holding stock *i*, the log US price of stock *i*, and the log US trading volume of stock *i*. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Low turnover stocks (N = 13,230)	(1)	(2)	(3)	(4)
MFPP ($)	0.0104**	0.0182***		
	(2.29)	(4.04)		
MFPP (% capitalization)			-0.1325	
			(-0.12)	
MFPP (% volume)				-0.0097
				(-0.28)
lagged MFPP		0.0118**	0.4241	0.0016
		(2.36)	(0.33)	(0.10)
Unexpected MFPP	0.0100**			
	(2.09)			
R^2	16.12%	16.38%	16.03%	16.02%

Panel B: High turnover stocks (N = 13,446)	(1)	(2)	(3)	(4)
MFPP ($)	0.0162	0.0177		
	(1.00)	(1.34)		
MFPP (% capitalization)			0.1533**	
			(2.38)	
MFPP (% volume)				19.1950**
				(2.30)
lagged MFPP		0.0132	-0.0590*	9.5485**
		(0.67)	(-1.81)	(2.46)
Unexpected MFPP	-0.0009			
	(-0.08)			
R^2	5.93%	5.94%	5.94%	5.96%

Table 8: Return spreads and fund flow price pressure, by level of fund holdings

This table presents estimates from regression models (1) and (2):

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (1)$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (2)$$

where $USX_{i,t}$ is the difference in US and Non-US returns for cross-listed stock$_{i,t}$. $MFPP_{i,t}$ is measured by the signed log change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $MFPP_{i,t}$ is also measured by the change in aggregate MF holdings as a percent of market capitalization and as a percent of volume, as indicated. Unexpected $MFPP_{i,t}$ is measured as the signed log residuals from an AR(3) model of $MFPP_{i,t}$. Fixed effects are included at the stock and month level and standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. Control variables are included but not tabulated for the log number of funds holding stock *i*, the log US price of stock *i*, and the log US trading volume of stock *i*. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Narrowly-held stocks (N = 13,221)	(1)	(2)	(3)	(4)
MFPP ($)	0.0444***	0.0398***		
	(3.02)	(4.62)		
MFPP (% capitalization)			0.1179*	
			(1.80)	
MFPP (% volume)				0.0037
				(0.10)
lagged MFPP		-0.0041	-0.1038***	-0.0014
		(-0.71)	(-4.93)	(-0.09)
Unexpected MFPP	-0.0074			
	(-0.46)			
R^2	10.06%	10.10%	9.93%	9.88%

Panel B: Widely-held stocks (N = 13,439)	(1)	(2)	(3)	(4)
MFPP ($)	0.0081	0.0165**		
	(1.08)	(2.49)		
MFPP (% capitalization)			0.7928	
			(1.36)	
MFPP (% volume)				1.0132**
				(2.19)
lagged MFPP		0.0056	0.3369	0.1237
		(0.67)	(1.57)	(0.31)
Unexpected MFPP	0.0147***			
	(3.64)			
R^2	19.79%	19.71%	19.75%	19.69%

Table 9: Return spreads and fund flow price pressure, by region of cross-listing location

This table presents estimates from regression models (1) and (2):

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \tag{1}$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \tag{2}$$

where $USX_{i,t}$ is the difference in US and Non-US returns for cross-listed stock$_{i,t}$. $MFPP_{i,t}$ is measured by the signed log change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $MFPP_{i,t}$ is also measured by the change in aggregate MF holdings as a percent of market capitalization and as a percent of volume, as indicated. Unexpected $MFPP_{i,t}$ is measured as the signed log residuals from an AR(3) model of $MFPP_{i,t}$. Fixed effects are included at the stock and month level and standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. Control variables are included but not tabulated for the log number of funds holding stock *i*, the log US price of stock *i*, and the log US trading volume of stock *i*. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Latin America and Caribbean

(N = 10,316)	(1)	(2)	(3)	(4)
MFPP ($)	0.0434**	0.0463**		
	(2.29)	(2.38)		
MFPP (% capitalization)			0.0772	
			(1.22)	
MFPP (% volume)				0.0164
				(0.23)
lagged MFPP		-0.0271	-0.0988**	-0.0173
		(-0.95)	(-2.02)	(-1.04)
Unexpected MFPP	0.0116			
	(1.00)			
R^2	6.47%	6.47%	6.39%	6.38%

Panel B: Canada (N = 10,218)	(1)	(2)	(3)	(4)
MFPP ($)	-0.0014	-0.0009		
	(-0.54)	(-0.40)		
MFPP (% capitalization)			-0.6247	
			(-1.04)	
MFPP (% volume)				-0.0287
				(-0.69)
lagged MFPP		0.0022	-0.1217	0.0531
		(1.41)	(-0.27)	(1.43)
Unexpected MFPP	0.0003			
	(0.23)			
R^2	76.56%	76.65%	76.60%	76.60%

Panel C: Asia-Pacific (N = 10,816)	(1)	(2)	(3)	(4)
MFPP ($)	0.0102	0.0122*		
	(1.40)	(1.68)		
MFPP (% capitalization)			0.5983	
			(1.03)	
MFPP (% volume)				0.2242
				(0.42)
lagged MFPP		0.0036	0.4285	0.0577
		(0.70)	(0.71)	(0.10)
Unexpected MFPP	0.0027			
	(0.58)			
R^2	11.56%	11.41%	11.52%	11.51%

Panel D: Europe (N = 20,926)	(1)	(2)	(3)	(4)
MFPP ($)	0.0126*	0.0137***		
	(1.95)	(2.83)		
MFPP (% capitalization)			0.1907**	
			(2.39)	
MFPP (% volume)				-0.0365
				(-0.88)
lagged MFPP		0.0059	-0.0468	0.0142**
		(1.42)	(-1.36)	(2.34)
Unexpected MFPP	-0.0006			
	(-0.08)			
R^2	9.98%	10.00%	10.00%	9.96%

Table 10: Return spreads and fund flow price pressure, by market development groups

This table presents estimates from regression models (1) and (2):

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (1)$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (2)$$

where $USX_{i,t}$ is the difference in US and Non-US returns for cross-listed stock$_{i,t}$. $MFPP_{i,t}$ is measured by the signed log change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $MFPP_{i,t}$ is also measured by the change in aggregate MF holdings as a percent of market capitalization and as a percent of volume, as indicated. Unexpected $MFPP_{i,t}$ is measured as the signed log residuals from an AR(3) model of $MFPP_{i,t}$. Fixed effects are included at the stock and month level and standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. Control variables are included but not tabulated for the log number of funds holding stock *i*, the log US price of stock *i*, and the log US trading volume of stock *i*. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Emerging markets (N = 16,425)	(1)	(2)	(3)	(4)
MFPP ($)	0.0343***	0.0366***		
	(2.66)	(2.84)		
MFPP (% capitalization)			0.1548**	
			(2.15)	
MFPP (% volume)				0.0435
				(0.49)
lagged MFPP		-0.0200	-0.0782**	-0.0180
		(-1.12)	(-2.28)	(-0.92)
Unexpected MFPP	0.0089			
	(1.14)			
R^2	6.42%	6.42%	6.35%	6.34%

Panel B: Developed economies (N = 37,258)	(1)	(2)	(3)	(4)
MFPP ($)	0.0061	0.0092***		
	(1.53)	(3.10)		
MFPP (% capitalization)			0.1562	
			(1.23)	
MFPP (% volume)				-0.0391
				(-1.23)
lagged MFPP		0.0065**	-0.0412	0.0201***
		(2.34)	(-0.56)	(2.86)
Unexpected MFPP	0.0029			
	(0.69)			
R^2	10.78%	10.80%	10.78%	10.76%

Table 11: Variation across stocks with fund inflows and outflows

This table presents estimates from regression models (1) and (2):

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (1)$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (2)$$

where $USX_{i,t}$ is the difference in US and Non-US returns for cross-listed stock$_{i,t}$. $MFPP_{i,t}$ is measured by the signed log change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $MFPP_{i,t}$ is also measured by the change in aggregate MF holdings as a percent of market capitalization and as a percent of volume, as indicated. Unexpected $MFPP_{i,t}$ is measured as the signed log residuals from an AR(3) model of $MFPP_{i,t}$. Fixed effects are included at the stock and month level and standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. Control variables are included but not tabulated for the log number of funds holding stock *i*, the log US price of stock *i*, and the log US trading volume of stock *i*. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fund inflows (N = 26,446)	(1)	(2)	(3)	(4)
MFPP ($)	0.0822	0.1017**		
	(1.51)	(1.98)		
MFPP (% capitalization)			0.5577	
			(1.48)	
MFPP (% volume)				0.1081
				(0.72)
lagged MFPP		-0.0020	0.1526	0.0109
		(-0.26)	(0.60)	(0.04)
Unexpected MFPP	0.0050			
	(1.14)			
R^2	7.92%	8.06%	7.93%	7.90%

Panel B: Fund outflows (N = 24,835)	(1)	(2)	(3)	(4)
MFPP ($)	0.0671**	0.0938***		
	(2.44)	(3.37)		
MFPP (% capitalization)			0.1686***	
			(7.65)	
MFPP (% volume)				0.0116
				(0.33)
lagged MFPP		0.0051	0.0739**	0.0096***
		(1.19)	(2.42)	(3.26)
Unexpected MFPP	0.0097***			
	(2.79)			
R^2	18.04%	18.14%	17.98%	17.96%

Table 12: Fire sales and large fund inflows

This table presents estimates from regression models (1) and (2):

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{lagged } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (1)$$

and

$$USX_{i,t} = \alpha_1 + \alpha_2(MFPP_{i,t}) + \alpha_3(\text{unexpected } MFPP_{i,t}) + \boldsymbol{X\varphi} + \varepsilon_{i,t} \quad (2)$$

where $USX_{i,t}$ is the difference in US and Non-US returns for cross-listed $\text{stock}_{i,t}$. $MFPP_{i,t}$ is measured by the signed log change in aggregate holdings of stock *i* in month *t* by US-based mutual funds. $MFPP_{i,t}$ is also measured by the change in aggregate MF holdings as a percent of market capitalization and as a percent of volume, as indicated. Unexpected $MFPP_{i,t}$ is measured as the signed log residuals from an AR(3) model of $MFPP_{i,t}$. Fixed effects are included at the stock and month level and standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. Control variables are included but not tabulated for the log number of funds holding stock *i*, the log US price of stock *i*, and the log US trading volume of stock *i*. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Large fund inflows (N = 1,580)	(1)	(2)	(3)	(4)
MFPP ($)	0.9835***	1.0231***		
	(4.09)	(4.05)		
MFPP (% capitalization)			2.4336*	
			(1.80)	
MFPP (% volume)				0.1751
				(0.19)
lagged MFPP		-0.0015	0.3355	-4.7613***
		(-0.16)	(1.48)	(-3.03)
Unexpected MFPP	0.0093			
	(0.99)			
R^2	34.48%	34.47%	35.49%	33.29%

Panel B: Firesale outflows (N = 1,427)	(1)	(2)	(3)	(4)
MFPP ($)	-0.0272	-0.0057		
	(-0.42)	(-0.08)		
MFPP (% capitalization)			-0.0652	
			(-0.24)	
MFPP (% volume)				1.5705*
				(1.69)
lagged MFPP		-0.0288**	-0.0815	0.1787
		(-2.54)	(-0.36)	(0.20)
Unexpected MFPP	0.0147			
	(1.43)			
R^2	47.49%	47.63%	47.44%	47.68%

Table 13: The association between local currency returns and MFPP

This table presents estimates from the following regression models:

$$US\ returns_{i,t} = \alpha_1 + \alpha_2(Non\text{-}US\ Returns_{i,t}) + \alpha_3(MFPP_{i,t}) + \alpha_4(\text{lagged } MFPP_{i,t}) + \varepsilon_{i,t} \quad (3)$$

and

$$Non\text{-}US\ returns_{i,t} = \alpha_1 + \alpha_2(US\ Returns_{i,t}) + \alpha_3(MFPP_{i,t}) + \alpha_4(\text{lagged } MFPP_{i,t}) + \varepsilon_{i,t}\,. \quad (4)$$

where $US\ returns_{i,t}$ are the local-currency returns on the US-listings of cross listed-stocks and *Non-US returns* for are the returns on the Non-US listing. Mutual fund price pressure (*MFPP*) is given by the signed natural log of $MFPP_{i,t}$ where $MFPP_{i,t}$ is measured by the change in aggregate holdings of stock *i* in month *t* by US based mutual funds. Unexpected $MFPP_{i,t}$ is measured as the log residuals from an AR(3) model of $MFPP_{i,t}$. Standard errors are clustered at the stock and month level. Auto-correlation and heteroscedasticity-consistent *t*-statistics are reported in parenthesis. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dependent Variable: US listing returns

	(1)	(2)	(3)	(4)
Non-US listing returns			0.39.48***	0.3954***
			(5.73)	(5.72)
MFPP ($)	0.1656***	0.2131***	0.1050***	0.1343***
	(23.53)	(28.54)	(9.03)	(9.46)
lagged MFPP		0.0220***		0.0122***
		(5.88)		(3.12)
Unexpected MFPP	0.0761***		0.0473***	
	(18.30)		(9.01)	
R^2	31.60%	30.95%	54.84%	54.47%
Time Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Control variables	no	no	no	no

Panel B: Dependent Variable: Non-US listing returns

	(1)	(2)	(3)	(4)
US listing returns			0.8608***	0.8613***
			(67.59)	(67.03)
MFPP ($)	0.1534***	0.1992***	0.0109**	0.0157***
	(19.58)	(25.27)	(2.07)	(3.22)
lagged MFPP		0.0249***		0.0059
		(3.58)		(0.95)
Unexpected MFPP	0.0729***		0.0074**	
	(14.33)		(2.00)	
R^2	12.19%	11.80%	42.03%	41.83%
Time Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Control variables	no	no	no	no